EXPLORING SOCIODEMOGRAPHIC INFLUENCES UPON SENSORIMOTOR CONTROL ACROSS CHILDHOOD USING KINEMATIC ANALYSES

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The candidate confirms that the work submitted is their own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

Sensorimotor control is pivotal in children's development, allowing them to learn, explore and play. There are many factors within the external environment influencing children's sensorimotor development. The present thesis aimed to study the impact of ethnicity and socioeconomic position on sensorimotor control in childhood, using kinematic analyses, and how to improve the measurement of such constructs. Chapter 2 derived a latent measure of socioeconomic circumstances which was sensitive to ethnic differences to use in subsequent analyses. Chapters 3 and 4 used Principal Components Analysis and Confirmatory Factor Analysis, respectively, to reduce the plethora of kinematic indices produced by the Clinical-Kinematic Assessment Tool and determine the theoretical constructs that best underpin sensorimotor control. These analyses found that the many hundreds of individual kinematic data points could be reduced to a substantially smaller number of sensorimotor components. Chapter 5 is a two-part study exploring the relationship between ethnicity, socioeconomic circumstances and sensorimotor control in early childhood and how these relationships compare when using conventional variables versus the more novel latent measures derived in Chapters 2-4. Overall, the analyses demonstrate that White British children's performance was superior to their British-born Pakistani peers even after controlling for socioeconomic factors. Additionally, latent measures of sensorimotor control were better predictors compared to conventional variables, suggesting these measures offer a more accurate reflection of performance and circumstances. Lastly, Chapter 6 explored whether the ethnic differences found in Chapter 5 persisted into mid-childhood and studied how children's sensorimotor control developed across these two timepoints.

Results demonstrated that early ethnic differences in sensorimotor control reduced by mid-childhood. In summary, this thesis adds to the sparse literature on how a child's ethnicity and their resulting environment can influence sensorimotor control, and also how this relationship changes over time. It also highlights that empirically derived latent measures may be more accurate and appropriate.

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Abbreviations

ADHD – Attention Deficit-Hyperactivity Disorder

ALSPAC – Avon Longitudinal Study of Parents and Children

ASC – Autistic Spectrum Condition

BiB – Born in Bradford

CFA – Confirmatory Factor Analysis

CKAT – Clinical-Kinematic Assessment Tool

CNS – Central Nervous System

DCD – Developmental Coordination Disorder

DDST – Denver Developmental Screening Test

EF – Executive Function

EPC – Expected Parameter Change

IMD – Index of Multiple Deprivation

LCA – Latent Class Analysis

MABC-2 – Movement Assessment Battery for Children-2

MI – Modification Indices

MTB – Means-Tested Benefits

PCA – Principal Component Analysis

pPA – penalised Path Accuracy

PLT – Path Length Time

RMSE – Root Mean Squared Error

SEP – Socioeconomic Position

SES – Socioeconomic Status

TGMD-2 – Test for Gross Motor Development-2

Chapter 1 General Introduction

Early Piagetian theory suggests that competent motor control is vital for one's ability to interact with, and understand the environment through "purposeful, coordinated movements" (Latash, 2012, p. 1; Piaget, 1952). This occurs even prior to birth, as the unborn infant interacts with their environment by responding through movement whilst in the womb (Dusing, 2016). Indeed, motor development has been described as "enabling", suggesting that movement provides a plethora of new opportunities to further develop knowledge about objects, surfaces, people and events in the surrounding environment (Adolph & Hoch, 2019; Adolph & Robinson, 2015; Campos et al., 2000; Gibson, 1988; Thelen, 2000; Thelen et al., 1994). Thus, it is pivotal to understand how these interactions are facilitated and equally, impeded.

This chapter begins by introducing the concept of sensorimotor control including its theoretical underpinnings and the various aspects of health and development that it can impact across the lifespan. Next, the role of sociodemographic factors in sensorimotor control and other aspects of health and development is briefly discussed, alongside highlighting gaps that remain in the literature. Finally, the context of the current thesis and an overview of each chapter is described.

1.1 Sensorimotor control

The nomenclature describing the ability to move and control the body efficiently is highly varied and terms are often used interchangeably, causing inconsistencies across the literature. Sensorimotor control is often referred to as *"fine motor skills"* (e.g., Grissmer et al., 2010); *"manual coordination"* (e.g., Hill et al., 2016); *“pen skills”* (e.g., Shire et al., 2016); or *“manual dexterity”* (e.g., Stöckel & Hughes, 2016). However, such terminology is frequently used to also describe more complex motor skills which generally require practice, feedback and instruction, and are often context-specific, such as copying shapes using pen and paper or using scissors (J. E. Clark & Metcalfe, 2002; Gallahue & Ozmun, 2006; Lubans et al., 2010). Therefore, the use of these broad definitions can refer to movements of varying complexity.

Narrower, more precise definitions of sensorimotor control, however, have been provided. Tresilian (2012) argues that a key premise of sensorimotor control is that it involves a fundamental component which can then be combined to perform more complex actions. In addition, competent sensorimotor control includes applying the appropriate levels of force, using anticipatory visual information, prospective control, and producing a smooth trajectory (Snapp-Childs, Mon-Williams, et al., 2013). For example, in prehension movements, such as reaching to pick up a cup of tea, there are generally two key phases: the “reach” phase which involves transportation of the hand to the target object and the “grasp” phase which allows the appropriate aperture to grasp the object and avoid knocking it over (Ingram & Wolpert, 2011; Jeannerod, 1984; Mon-Williams & Tresilian, 2001; Rand et al., 2006). Each of these components require the use of key sensorimotor processes. Franklin and Wolpert (2011) argue that to ensure accurate and skilful action, the sensorimotor control system must encounter and overcome several problems including: non-linearity, non-stationarity, delays, redundancy, uncertainty, and noise. This demonstrates the complexity involved in performing such actions. Thus, the study of sensorimotor control at this fundamental level is a prerequisite for deeper exploration of more complex actions.

Despite the inconsistencies within the literature, throughout the present thesis, sensorimotor control is defined as the capacity to skilfully execute specific sensory-guided movements with a single goal-directed action (Edwards et al., 2019; Franklin & Wolpert, 2011; Tresilian, 2012). As such, the term specifically refers to the general processing abilities of the sensorimotor system to produce core movements at a basic level (i.e., aiming a limb towards a target).

1.1.1 Theoretical underpinnings of sensorimotor control

To produce such core movements, the human sensorimotor control system uses two main internal models to guide goal-directed action, forward and inverse (Atkeson, 1989; R. P. Cooper, 2010; Flanagan et al., 2006; Gritsenko et al., 2009; Hyde & Wilson, 2011; Waterman et al., 2017; Wolpert et al., 1995; Wolpert & Kawato, 1998).

Forward models provide the nervous system with a means of accurately predicting the state of the body and how it will interact with the world around us; it is essential for the perception of our environment (Waterman et al., 2017; Wolpert et al., 1995; Wolpert & Kawato, 1998). It does this by using the available sensory information regarding the current state of the body (i.e., velocity and position of the limb) and a copy of the motor command (efference copy) to predict the sensory consequences of movement (Miall & Wolpert, 1996; Wolpert et al., 2011; Wolpert & Kawato, 1998). The Bayesian Brain Hypothesis (Knill & Pouget, 2004) is one view which suggests that the forward model uses sensory information probabilistically, based on prior experience (priors) and a likelihood to generate predictions (Friston, 2010). Sensory samples are then tested to update the prior beliefs about how the body interacts with the world (Friston, 2010).

In contrast, inverse models act as controllers and are required in order to change the state of the body by specifying the necessary motor commands (R. P. Cooper, 2010; Flanagan & Wing, 1997; Wolpert et al., 1995, 1998; Wolpert & Kawato, 1998). Previous research suggests that inverse models are implicitly produced by feedback control strategies which compare the actual motor response to the desired response via error signals (Wolpert & Kawato, 1998). When the discrepancy between the actual and expected motor response is large, the temporal lag in response is much greater (Miall et al., 2001). Thus, the sensorimotor system corrects only errors that directly impair the task goal, and those errors which are not task-relevant are ignored. This prevents redundancy whilst minimising the chances of further task-relevant errors being generated due to over-correction of task irrelevant errors (Wolpert et al., 2011). This phenomenon is known as the minimum intervention strategy (Todorov & Jordan, 2002).

Despite distinctions between the roles of the forward and inverse models, there is an intimate relationship between the two in order to make efficient goal-directed movements (Flanagan et al., 2006). Indeed, Wolpert and Kawato (1998) suggest that each forward model has a paired inverse model which acts as a control strategy to guide optimal movement. Due to temporal delays as a result of neural conduction, muscle activation and receptor transduction, sensory feedback loops within inverse models are not enough for efficient sensorimotor control (Desmurget & Grafton, 2000; Wolpert et al., 2011). By making prior predictions and bypassing the sensory feedback loops, forward models allow the sensorimotor system to respond much more quickly (Wolpert et al., 1998). Thus, the two systems must work synergistically to elicit the appropriate motor response (Wolpert et al., 1998; Wolpert & Kawato, 1998).

1.1.2 Wider implications of sensorimotor control

In addition to the more obvious benefits that arise from developing adequate sensorimotor control (i.e., the ability to perform various activities of daily living or perform more complex movements accurately and with ease), there are wider-reaching effects of proficient motor competence, and repercussions for a lack thereof. Competent perception and action (i.e., sensorimotor control) are thought to underlie more complex cognitive functions, a view which stands in contrast to the traditional view of these being separate entities from cognition (Leonard, 2016; L. B. Smith & Sheya, 2010; von Hofsten, 2004). This view that higher-order cognition occurs within the context of the physical world, through interactions with the environment is often referred to as the Embodied Cognition perspective (Barsalou, 1999; Foglia & Wilson, 2013; Gibbs, 2005; Jirak et al., 2010; M. Wilson, 2002; R. A. Wilson & Foglia, 2017). Indeed, this perspective suggests that there is no distinction between sensorimotor control (traditionally considered a “lower-order” skill) and “higher-order” cognitive functions, such as language abilities, as both are regulated by the body (Foglia & Wilson, 2013; Jirak et al., 2010). The subsequent sections will discuss the wider implications of competent sensorimotor control in various aspects of health and development, including cognition, handwriting, academic achievement, and mental and physical health.

1.1.2.1 Cognition

Firstly, findings from the neuroscience literature have demonstrated the close association between cognition and motor skills during childhood. In their review, Diamond (2000) refers to cognitive and motor development being “fundamentally intertwined” (p.44). They elaborate further, suggesting that the cerebellum and dorsolateral prefrontal cortex (dPFC) are tightly coupled; brain areas which have been traditionally thought to underpin motor and cognitive tasks, respectively (Diamond, 2000). Indeed, additional evidence has found patients with cerebellar lesions often fail a range of cognitive tasks involving verbal fluency (Appollonio et al., 1993; Schmahmann & Sherman, 1998), planning (Botez et al., 1989; Grafman et al., 1992; Leiner et al., 1986; Schmahmann & Sherman, 1998), and working memory (Schmahmann & Sherman, 1998; Strick et al., 2009). In a meta-analysis, Jirak et al. (2010) also demonstrated a strong association between language and sensorimotor control. The authors concluded that during language processing, brain areas primarily related to sensorimotor tasks (e.g., the primary motor, supplementary motor and premotor cortices) are also active.

Furthermore, numerous behavioural studies have explored the relationship between performance on cognitive and motor tasks. Executive function (EF) is a construct responsible for the control and organisation of behaviour, generally associated with three higher-order cognitive processes: working memory; inhibition; and attention shifting (Anderson et al., 2010; Diamond, 2013; Houwen et al., 2019; Miyake et al., 2000; M. Schmidt et al., 2017; Zelazo & Carlson, 2012). EF has been previously linked to improved social skills and academic attainment and it is thought to contribute towards increased “school readiness” (Blair & Raver, 2015; Hudson et al., 2020). Previous correlational studies have found significant positive associations between fine motor skills and executive functioning (Cameron et al., 2016; Leonard & Hill, 2015; McClelland & Cameron, 2019). Furthermore, children identified as experiencing motor difficulties have been found to perform poorly compared to typically developing controls on a range of EF tasks, including those that assess working memory; fluency; inhibition; and planning (Leonard et al., 2015; Michel et al., 2018). Interestingly, Leonard et al. (2015) found significant differences only on non-verbal assessments of EF such as the “odd-one-out” task (a visuospatial task) but not listening recall. However, given the correlational nature of these studies, causal inference cannot be determined.

Using structural equation modelling to investigate the mediating role of EF in the relationship between motor control and academic attainment, Schmidt et al. (2017) found a significant indirect relationship between coordination abilities and EF collected at two distinct timepoints. This was not the case when focusing on the relationship between strength or endurance and EF, suggesting that sensorimotor control specifically is linked with these abilities. Furthermore, Hudson and colleagues (Hudson et al., 2020) investigated the impact of a motor skill intervention on executive function, including inhibitory control, attention shifting and working memory. The findings indicated a significant improvement in inhibitory control and attention shifting compared to wait-list controls, demonstrating the important role competent motor control may play in relation to supporting wider developmental outcomes.

Other evidence supporting the association between cognitive and motor function comes from research into non-motor developmental disorders. For example, more than 50% of children with Attention-Hyperactive Deficit Disorder (ADHD) experience motor difficulties reaching clinical diagnosis (Kadesjö & Gillberg, 1999; Watemberg et al., 2007). These findings are further supported by neuropsychological research which has also found that the cerebellum of boys with ADHD is smaller compared to controls (Berquin et al., 1998; Castellanos et al., 1996; Mostofsky et al., 1998, 2002), which, as discussed, is an important part of the sensorimotor system. Similarly, movement difficulties are common in other neurodevelopmental disorders such as dyslexia (Geuze & Kalverboer, 1994; P.

H. Wolff et al., 1990); specific language disorder (SLI; Hill et al., 1998) and Autistic Spectrum Disorder (ASD; Leary & Hill, 1996; Manjiviona & Prior, 1995; Slavoff & Bonvillian, 1997). This evidence stresses the importance of competent sensorimotor control for cognitive function.

1.1.2.2 Handwriting

There are, of course, tasks that require a combination of motor and cognitive skills. Handwriting, for example, is a complex skill which is underpinned by several key sensorimotor processes as well as cognitive and language-related processes, such as the translation of internal to orthographic representations (Berninger, 2000; Berninger et al., 2002). Even with the rise of technology in the classroom (Mangen & Balsvik, 2016; Marquardt et al., 2016), handwriting is often required for learning activities across most school contexts (Caçola, 2014; Feder & Majnemer, 2007; Shire et al., 2016). It relies on key sensorimotor control mechanisms including visuomotor integration, the application of appropriate force through the writing utensil, postural control, motor planning, and using both feedforward and feedback control, amongst others (Denton et al., 2006; Feder & Majnemer, 2007; Rosenblum et al., 2010; Shire et al., 2016; Smits-Engelsman et al., 2001; Snapp-Childs, Casserly, et al., 2013). These movements then require integration with the mental imagery of letters (Meulenbroek & van Galen, 1988). The complexity of handwriting as a skill is also increased due to the need to consider and plan the syntax and spelling of the words, convert phonemes into graphemes, and maintain attentional control (Planton et al., 2013; Rosenblum et al., 2010). Because of these reasons, children can often struggle with handwriting, leading to many repercussions within the classroom. For example, the academic work of children with poor handwriting is often marked disproportionally lower compared to “neater” work, regardless of the content (Amundson, 2001; V. Connelly et al., 2005; Markham, 1976). Additionally, handwriting difficulties also impact a child’s ability to communicate and express their ideas easily (Francis et al., 2016), thus, increasing the likelihood of under-achievement.

However with greater sensorimotor control, handwriting becomes more automated and permits greater cognitive resources, such as attention, to be placed on other higher order processes (Berninger et al., 1992; Medwell & Wray, 2007; Tucha et al., 2008). For example, when copying from the whiteboard, children can place increased amounts of “freed-up” cognitive resources on understanding and retaining the information, rather than on supervising the sensorimotor processes needed to execute production of each letter. Indeed, Prunty and colleagues (Prunty et al., 2014), found that children with diagnosed motor difficulties, such as Developmental Coordination Disorder (DCD), took longer pauses during a handwriting task. The authors attributed this to a lack of ability to produce automatic movement and process motoric and higher-order components of writing (e.g., planning) concurrently. Greater pauses likely increase the time taken to complete schoolwork, leading to incomplete tasks in the time allocated and falling behind academically. Furthermore, taking longer than their peers to complete writing tasks and experiencing more difficulties also decreases children’s self-esteem in their academic abilities and discourages writing (Berninger et al., 1997; Feder & Majnemer, 2007; Lange et al., 2007; Racine et al., 2008). Thus, within the context of handwriting, increased sensorimotor control facilitates engagement and motivation to perform an activity that is integral to learning, particularly within traditional, mainstream academic settings.

1.1.2.3 Academic achievement

Beyond handwriting specifically, previous research has found significant relationships between children’s motor proficiency and direct measures of academic achievement. Fine motor skills are often embedded in many classroom activities such as drawing and colouring, using scissors and grouping objects for counting. Such activities facilitate learning via the association of visual representations with theoretical concepts (Cameron et al., 2016).

A wealth of research has investigated the association between motor skills (specifically fine motor) and mathematic achievement (Carlson et al., 2013; Dinehart & Manfra, 2013; Grissmer et al., 2010; Hudson et al., 2020; Luo et al., 2007; Macdonald et al., 2020; Pagani et al., 2010). Sensorimotor interactions with the environment appear to encourage the development of abstract concepts such as shape, number and time (Piaget & Garcia, 1989; Sheridan et al., 2017). Walsh (2003) elaborates, suggesting that concepts of time and space are associated with representations of number via a similar representation of magnitude. In addition, early years mathematics teaching often emphasises the manipulation of objects to facilitate learning, such as counting with objects (Guarino et al., 2013). For example, Bayesian analyses demonstrated non-zero relationships between two out of three computerised sensorimotor tasks (Aiming and Steering but not Tracking) and scores in standardised assessments of mathematics in primary-school aged children (Giles et al., 2018).

Previous research has also explored numerical processing using a mental number line task and how this relates to sensorimotor control in adults (Sheridan et al., 2017). The mental number line requires spatial representation of number (de Hevia, 2016; Mix & Cheng, 2012; Sheridan et al., 2017). When the numerical processing task was more difficult (reversed number line), both the reaction time (i.e., time taken to process the task and initiate movement) and movement time (i.e., time to complete the movement from start to finish) was slower. In addition, for these conditions, there was a significant positive relationship between performance on the numerical processing task and sensorimotor control. Similarly, Simms et al. (2016) found the relationship between performance on a number line task and mathematics achievement was at least partly explained by visuomotor integration (measured via a pencil-and-paper copying task) and visuospatial skill. Execution of visuomotor tasks requires a coupling of fine motor coordination and attentional control to coordinate visual- and motor-related brain areas (Kim et al., 2017; Shin et al., 2008). Kim et al. (2017) used structural equation models to explore the relationship between fine motor control and mathematic achievement via visuomotor integration, finding a tight coupling between spatial processing in numerical tasks and sensorimotor control.

In addition to mathematics, significant relationships have also been found between fine motor skills and reading achievement in children (Dinehart & Manfra, 2013; Giles et al., 2018; Macdonald et al., 2020; Pitchford et al., 2016). Macdonald et al. (2020) suggested that approximately 25% of the variance associated with reading can be accounted for by fine motor skills, although to a lesser extent than mathematics (where it accounted for 33% of variance). This is important, as the literature consistently argues for the importance of reading in determining children’s levels of academic success, intelligence, and general cognition (A. Cunningham & Stanovich, 2003; Mol & Bus, 2011; West et al., 1993). Furthermore, even after controlling for EF, visuomotor integration significantly predicted phonological awareness and letter-word identification, skills necessary for children’s ability to read text (Cameron et al., 2012).

Several mechanisms have been proposed to explain this specific relationship, as well as the links with academic achievement more generally. In a similar vein to the arguments proposed in the previous section, related to handwriting, one view suggests that this is due to neurological associations between cognitive and motor skills (Dinehart & Manfra, 2013; Grissmer et al., 2010). Adequately automated levels of sensorimotor control subsequently permit greater amounts of cognitive resources to be distributed to the integration of conceptual information, rather than to perceptual or motoric information (Cameron et al., 2016).

An alternative explanation relates to the compensatory effect of fine motor skills to facilitate learning, when other key classroom skills may be sub-optimal (Cameron et al., 2016). For example, when inhibitory control was poor, academic achievement did not falter if children had strong visuomotor skills (Cameron et al., 2015). Cameron et al. (2016) argued that this was because fine motor skills supported children’s self-regulation abilities. Previous research has demonstrated the impact of adequate self-regulation on academic attainment outcomes (McClelland & Cameron, 2011). Thus, for children’s academic achievement, the development of sensorimotor control is likely essential.

1.1.2.4 Mental and physical health

In addition to learning and cognition, sensorimotor control has a role in both mental and physical health. For example, previous research has demonstrated that children and adults experiencing clinically significant levels of motor difficulties often face further challenges with their mental health (Cairney et al., 2010; Crane et al., 2017; Harrowell et al., 2018; E. L. Hill & Brown, 2013; Lingam et al., 2012; Rigoli et al., 2017). Importantly, longitudinal studies have provided evidence for the direction of this relationship, such that early motor difficulties during childhood predict psychopathology in later childhood and adolescence (Lingam et al., 2012; Sigurdsson et al., 2002).

The Elaborated Environmental Stress Hypothesis (Cairney et al., 2013; Mancini et al., 2016) suggests that motor difficulties provide children with a “primary stressor” which lead to a range of “secondary stressors” such as peer conflict (e.g., getting picked last for sport teams due to poor motor skill), low self-esteem and self-competence. It is these secondary stressors which are believed to increase the risk of mental health issues, such as anxiety.

Similarly, this relationship has also been found in non-clinical, community-based, samples. Hill and colleagues (Hill et al., 2016) explored the relationship between sensorimotor control and children’s mental health using the Strengths and Difficulties Questionnaire (SDQ). The authors found that children’s Total Difficulties Score (related to the hyperactivity, peer problems, conduct problems and emotional problems subscales of the SDQ) was predicted by performance on a sensorimotor task. Thus, understanding sensorimotor control may provide insights into mental health.

However, although previous research has consistently demonstrated the importance of sensorimotor control and the widespread impact it can have on health and development, it is still relatively under-studied. After conducting a review of social science journal articles published between 1986 and 2004, Rosenbaum (2005) found papers focused more on attention, memory, cognition, language, perception and decision making, with motor control less commonly studied. This led Rosenbaum to describe research into motor control as “the Cinderella of Psychology” (2005, p. 308).

1.1.2.4.1 Developmental Coordination Disorder

Sensorimotor control below the expected norm for the child's age can have far-reaching implications, such as those already discussed, even if the child is otherwise viewed as "typically-developing" (Gaul & Issartel, 2016). However, there can be particularly serious repercussions if sensorimotor difficulties surpass the clinical threshold. Developmental Coordination Disorder (DCD) is a relatively common neurodevelopmental disorder, affecting approximately 2-6% of school-aged children (Lingam et al., 2009b). Children with DCD present motor deficits which cause disruption to activities of daily living and delays in the achievement of key motor milestones (A. L. Barnett, 2008; A. L. Barnett & Prunty, 2020; Dewey & Wilson, 2001; Zwicker et al., 2012). These deficits, however, are not due to an underlying intellectual disability, as can be the case with cerebral palsy. It frequently presents as a co-morbid disorder, with individuals commonly also experiencing attention difficulties such as Attention-Deficit Hyperactivty Disorder (ADHD) (A. L. Barnett & Prunty, 2020). Kadesjö & Gillberg (1999) found 47% of children with moderate-to-severe DCD exhibited at least five symptoms of ADHD and 19% meeting all the diagnostic criteria.

While there is no "gold-standard" clinical assessment for the diagnosis of DCD (Dewey et al., 2002), a child's performance below the 5th percentile on a norm-reference test of motor competence is included in the criteria of substantial motor deficits (Sugden et al., 2006). Thus, the EACD recommends the use of tests such as the Movement Assessment Battery for Children-2 (MABC-2) (Henderson et al., 2007) or BOT-2 (Bruininks & Bruininks, 2005) for this assessment (Blank et al., 2019). Other criteria for the diagnosis of DCD includes substantial deficits to activities of daily living, motor problems not better explained by co-morbidities, and the onset of symptoms occurring in childhood (Blank et al., 2019).

1.1.3 Sociodemographic and contextual influences of sensorimotor control

With such far-reaching consequences of inadequate sensorimotor control, it is important to understand which factors put children at an increased risk. Sociodemographic factors (sometimes referred to as socio-structural factors) refer to the context of one's environment and include a range of variables including socioeconomic circumstances, education levels, ethnicity, place of birth, residing neighbourhood and language (Honjo, 2004). Such factors have a great influence on many outcomes related to physical, mental and social health and wellbeing, including sensorimotor control and more broader definitions of motor control. The two sociodemographic factors focused on within the present thesis are socioeconomic circumstances and ethnicity.

1.1.3.1 Ethnicity

Previous research has suggested that an individual's ethnicity can influence their health and development, in both children and adults. For example, individuals from ethnic minority or non-White British populations in the UK are routinely found to exhibit poorer health outcomes and quality of life (Aspinall & Jacobson, 2004; Garcia et al., 2020; Karlsen & Nazroo, 2010; Wohland et al., 2015). Within the COVID-19 pandemic, widening inequalities were found for ethnic minority groups. For example, research found that members of ethnic minority groups were twice as likely to require more hours of clinical care after contracting the virus, compared to their White majority counterparts (Topriceanu et al., 2021). Additionally, the sleep of individuals from ethnic minorities was disproportionately impacted as a result of lockdown (Bann et al., 2021). Within the UK, it is

Bangladeshi and Pakistani individuals who often show the greatest levels of disadvantage across a variety of health outcomes (Nazroo, 2003). Research often defines these groups collectively, alongside other ethnicities originating from the Indian subcontinent, as being individuals of “South Asian” heritage.

Ethnic differences within child samples have been found for a range of outcomes such as academic achievement (F. C. Curran & Kellogg, 2016; Frederickson & Petrides, 2008; J.-S. Lee & Bowen, 2006; Sonnenschein & Sun, 2017; Strand, 2007), physical activity levels (Marshall et al., 2007), and increased adiposity (Saxena et al., 2004; Shaw et al., 2007). Furthermore, in both US (F. C. Curran & Kellogg, 2016; J.-S. Lee & Bowen, 2006; Sammons, 1995; Sonnenschein & Sun, 2017) and British (Frederickson & Petrides, 2008; Strand, 2007) samples, children from some ethnic minority groups have been found to fare worse on educational outcomes.

Ethnic differences have been also found in studies exploring children’s motor skills (Adeyemi-Walker et al., 2018; L. M. Barnett et al., 2019; Cintas, 1995; Eyre et al., 2018; Kelly et al., 2006; Mayson et al., 2007; Venetsanou & Kambas, 2009). For example, research has suggested that White British and Black students out-perform their South Asian peers on assessments measuring Fundamental Movement Skills (Adeyemi-Walker et al., 2018; Eyre et al., 2018). Chow et al. (2001) also found ethnic differences in fine motor tasks, suggesting this was likely due to differences in culturally specific norms and the appropriateness of such norms across different populations. There is currently little research which explores the role of ethnicity in objectively measured sensorimotor control. However, ethnicity is a complex term and must first be defined accordingly, within the context of this thesis, before exploring ethnic differences further.

The term ethnicity is relatively recent, appearing in the Oxford English Dictionary in 1953, and not measured within the British Census until 1991 (Davey Smith et al., 2000; Hutchinson & Smith, 1996). However, there is a lack of consensus regarding its definition and measurement (R. Connelly et al., 2016). Most commonly, ethnicity is described as a social construct which relates to group identity based on shared attributes such as religion, culture, history and ancestry (Baumann, 2004; Bulmer, 1996; R. Connelly et al., 2016; Hutchinson & Smith, 1996; S. Jones, 1997; Platt, 2007, 2011; Rex, 1991). Johnson (2000) has combined these different aspects into a single definition: “a concept referring to a shared culture and way of life, especially as reflected in language, folkways, religious and other institutional forms, material cultures such as clothing and food, and cultural products such as music, literature and art” (p. 109). Importantly, Nazroo (1998) argued that ethnicity is not fixed over the lifespan and while one’s culture is bound within history, it can change depending on the context. Within the UK’s Office for National Statistics, ethnicity commonly refers to a combination of nationality and skin colour when used in the UK Census (R. Connelly et al., 2016).

The United Kingdom has an increasingly diverse and multicultural society (Jivraj, 2012), yet a large proportion of social inequalities are proposed to be partly explained by ethnic differences (A. F. Heath et al., 2008; A. F. Heath & Cheung, 2007; Platt, 2007; Tomlinson, 1991). There are several proposed pathways for how one’s ethnicity may influence their health and development. Balarajan proposed these may include: “biological, cultural, religious, socio-economic or other environmental factors” (Balarajan, 1996, p. 119). Karlsen adds to this by suggesting racism may also play a large role in explaining poorer health outcomes within ethnic minority groups (Karlsen, 2007).

Whilst advances in technology and innovation have provided evidence that genetic differences can be apparent between ethnic groups (Huang et al., 2015), previous research has suggested that there may be greater genetic differences *within* ethnic groups than *across* groups (J. B. Kaplan & Bennett, 2003; Nazroo & Williams, 2006; Rosenberg et al., 2002). Instead, some researchers have stressed the importance of socialisation and the environmental context for explaining ethnic differences. Sonnenschein and Sun (2017) used mediation analyses to explore the potential mechanisms within ethnic differences as they relate to influencing academic achievement. The authors suggested these differences were due to differences in parental knowledge of child development and provision of enrichment activities. Others have suggested that ethnic differences in academic skills can be influenced by whether English is spoken in the home or not (e.g., Reardon & Galindo, 2014). With regard to motor control, which is less likely to be affected by language, differences in parenting practices across ethnic groups have been proposed as an explanation for ethnic differences, such as the type and quality of stimulation provided in the home (Cintas, 1995; van Schaik et al., 2018; WHO Multicentre Growth Reference Study Group, 2006). Thus, various mechanisms underpinning ethnic differences in sensorimotor control may exist, which are likely be complex and intertwined.

1.1.3.2 Socioeconomic circumstances

Importantly, ethnicity cannot exist as an independent contributor to one’s health and development. It is commonly argued that associations with ethnicity are confounded by other characteristics, such as socioeconomic position (SEP). Cheng et al. (2015) suggest that ethnicity is linked with SEP and the two interact. These interactions are, in part, due to larger socioeconomic inequalities often experienced by individuals from ethnic minority groups, sometimes referred to as a "double disadvantage" (K. Clark & Drinkwater, 2007; Garner & Bhattacharyya, 2011; Jivraj & Khan, 2013).

As early as 1916, differences in mortality rates between Black and White people were explained by differences in socioeconomic circumstances rather than genetic or cultural differences (Trask, 1916). Williams (2002) stated that ethnic differences in health are much smaller than differences between socioeconomic groups, with most ethnic differences being a result of socioeconomic inequalities (Navarro, 1990; Sheldon & Parker, 1992; Nazroo & Williams, 2006). More recent support for this claim comes from work demonstrating that ethnic differences in health and lifestyle are still apparent, but drastically reduced, when accounting for SEP (Erens et al., 2001; Marshall et al., 2007; Nazroo, 2003; Williams, 1999).

These interactions are unsurprising considering the large body of research suggesting that one's socioeconomic context is consistently associated with various health outcomes across the lifespan. One US study suggests that around 70% of the length and quality of life can be attributed to social determinants of health, 40% of which were socioeconomic factors such as education, employment and community safety (County of Los Angeles Public Health, 2013). Acknowledgement of the link between health and deprivation is not new, with accounts dating back to ancient China, Egypt, and Greece highlighting the existence of such relationships (Krieger et al., 1997; Liberatos et al., 1988; Lynch et al., 1996). Indeed, research conducted by Oakes and Rossi (2003) almost two decades ago demonstrated the large rise in published articles exploring the relationship between SEP and health. A review of the relationship between income inequality and health also demonstrated that in societies in which there are larger discrepancies between the “rich” and the “poor” overall health is typically poorer (Pickett & Wilkinson, 2015). This review demonstrated that countries such as Japan, where income inequality (ratio of income between the richest compared to poorest) was deemed the lowest out of 21 countries, had overall better health and social outcomes. In contrast, the most unequal society in terms of income, the USA, was found to have the worst health.

A comprehensive body of research has consistently found that more deprived individuals, in general, tend to face an increased risk of several health issues including: maternal mental health (Uphoff et al., 2015); self-rated overall health (Präg et al., 2016); oral health (Delgado-Angulo et al., 2019) and mortality (Claussen, 2015). Concerningly, SEP can start to have these detrimental impacts on health and development from a very early age (Bradley & Corwyn, 2001). A large meta-analysis of 58 studies published over a ten-year period between 1990 and 2000 found medium-to-large associations between academic attainment and SEP measured at both the pupil- and school-level (Sirin, 2005). Similar findings have been replicated more recently, indicating that this is very much still the case today (Coetzee et al., 2020; F. Zhang et al., 2020). Children from less affluent families have also been found to be at increased risk of stunted growth (Wagstaff & Watanabe, 2003), and face issues with literacy and verbal skills (Jednoróg et al., 2012); socioemotional wellbeing (Bøe et al., 2012); and general cognitive abilities, from as early as infancy (Roberts et al., 1999).

Even at a neurological level, differences have been found between children according to parental SEP (Betancourt et al., 2016; Hanson et al., 2013; Raizada & Kishiyama, 2010). Previous research has found the volume of children’s grey matter was significantly associated with parental SEP when measured by education and current occupation (Jednoróg et al., 2012) or household income (Hanson et al., 2011). Even prior to birth, MRI studies have found reduced SEP was associated with slower foetal brain development (Lu et al., 2021). Thus, there are catastrophic and widespread impacts of deprivation across the lifespan.

As will be discussed further in Chapter 5, there is some research suggesting that those from more deprived backgrounds are consistently more likely to show reduced performance on gross motor skill or fundamental movement skill assessments, compared to their more affluent peers (Adkins et al., 2017; L. M. Barnett et al., 2016; Niemistö et al., 2020; Peralta et al., 2019; Zeng et al., 2019). Indeed, children from more deprived backgrounds are also at greater risk of being diagnosed with movement disorders such as DCD (Lingam et al., 2009b). However, there is currently relatively little research which explores the role of socioeconomic factors on sensorimotor control or fine motor skill using appropriate methodology (see Chapter 5's introduction for an expanded discussion of this point and critique of previous research).

1.1.3.2.1 Definitions and measures of socioeconomic circumstances

Before the relationships between socioeconomic factors and sensorimotor control is explored further, the terminology describing socioeconomic context needs to be defined. Terms frequently used interchangeably across the literature include *socioeconomic status (SES); socioeconomic position (SEP), social class;* and *social stratification* (Darin-Mattsson et al., 2017; Galobardes et al., 2007; Wohlfarth, 1997). Whilst the term "socioeconomic" dates back as early as the 1800's, there is no universal definition used consistently across the literature (F. L. Jones & McMillan, 2001; Oakes & Rossi, 2003).

The work of early social theorists such as Weber & Marx have influenced the understanding of SEP today (Galobardes et al., 2007; Manstead, 2018). Marx's views suggests that SEP is related to one's hierarchy in society; contrasting those who work on the production line (i.e., factory workers or farmers) with those who own those businesses. Indeed, Marx's view was that an individual's social class in society was outside of the individual's own control. In contrast, Weber suggested that individuals had more agency in determining their place in society. Individuals were grouped such that the members shared common circumstances in which Weber proposed were "life chances". For example, a better education provides social advantage through increased career prospects and prestige. Like sensorimotor control, conflicting definitions lead to inconsistent measurement of SEP and therefore inconsistent conclusions drawn.

Whist varying terminology is used, there is a consensus that SEP is a complex, multi-dimensional construct which places individuals on a hierarchy within society based on resource- (e.g., household income, or ownership of material goods) and prestige-based (e.g., occupation, or education) based attributes (Braveman et al., 2001, 2005; Fairley et al., 2014; Galobardes et al., 2006; Howe et al., 2012; Jednoróg et al., 2012). SEP has been previously described to summarise "complex information about a person's life" (Blane, 1995, p. 904). The multifaceted nature of SEP adds further complexity to the measurement of SEP, increasing discrepancies from study to study even further.

The measurement of one's socioeconomic circumstances has been described as one of the most controversial conversations within social research (Oakes & Rossi, 2003). For example, an individual's SEP can be determined using a single indicator as a proxy measure, either on its own or alongside additional predictors.

One common example is level of education; for child samples, this is often their parent's level of education (e.g., Bøe et al., 2012; De Craemer et al., 2018). If using a prestige-based indicator such as education, a significant association with a health outcome may lead to the conclusion that the most effective way to reduce inequalities would be to invest in interventions that target learning and support for expecting parents, thus raising their level of education. Yet, if the proxy used is more resource-based, it may lead to the conclusion that the health outcome will be improved via increased accessibility to resources such as books, stimulating toys and technology. In other words, both knowledge and resources are necessary but, on their own, neither may be sufficient to promote healthy child development. Thus, inconsistencies arise as a result of the choice of measure used.

Alternatively, composite measures take into account several indicators related to socioeconomic circumstances (e.g., de Waal & Pienaar, 2020; Oakes & Rossi, 2003). Such composite measures are sometimes determined empirically by computing a latent variable (e.g., Fairley et al., 2014; Goodwin et al., 2018). Other times, a simple aggregate is created by combining scores from a range of different SEP indicators (e.g., Mcphillips & Jordan-Black, 2007; Stamatakis et al., 2014). Composite measures are arguably more accurate than various, potentially conflicting, individual proxies of SEP (Braveman et al., 2005; Fairley et al., 2014; Sherar et al., 2016). Further complexities are added when considering whether the measure of SEP is based on an individual- or group-based (e.g., school) level (e.g., Adkins et al., 2017). National-level indicators often use a postcode or wards to determine the social class of an area of residence or school as a whole (e.g., de Waal & Pienaar, 2020; Zylbersztejn, 2019). Due to the wide range of proxy measures used, and differences in how these are measured, interpretation of the associations with SEP and health and development outcomes can be difficult. Further discussion of the various ways that SEP can be measured, and their respective advantages and disadvantages, is presented in Chapter 2.

Although often used interchangeably, both SES and SEP will be used throughout the current thesis with each referring to a distinct definition. Socioeconomic *status* (SES) will refer to individual predictors used to describe one's circumstances, such as maternal education level. Meanwhile socioeconomic *position (SEP)* will be used to describe the multifaceted latent measures that considers multiple predictors simultaneously. In Chapter 2, the latter is discussed in more depth and its derivation is described.

1.2 Context, primary outcome measures and aims of the thesis

1.2.1 Context

As discussed, previous research has begun to demonstrate how social inequalities can arise as result of one's ethnic or socioeconomic background, yet few studies have studied the effect of these factors on the fundamental mechanisms of movement: sensorimotor control. Thus, further research is needed to understand how two important sociodemographic factors, socioeconomic background and ethnicity, influence sensorimotor control. Such research has the potential to provide insights into improving developmental outcomes from a young age. The associations between both SES and SEP with sensorimotor control are explored in Chapter 5. Of course, to use a composite measure of SEP requires the measurement of several indicators of the various aspects of an individual's socioeconomic circumstances which is not always possible or viable. Consequently, this research took advantage of an ongoing partnership with a large birth cohort study, which has invested heavily in measuring such factors.

The Born in Bradford (BiB) longitudinal birth cohort study collected, and continues to collect, a wide range of detailed predictors of child health, including those relating to an individual's sociodemographic circumstances. This provides the opportunity to produce a multifaceted measure of SEP to investigate the associations with children's sensorimotor control. Data collected as part of the Born in Bradford study was used throughout the current thesis.

BiB was established to understand how children's health, education, and wider development is impacted by various social, behavioural, environmental, and genetic factors (Raynor et al., 2008; J. Wright et al., 2013). Recruitment for the study began in March 2007 when pregnant mothers were approached at 26-28 weeks gestation and invited to participate. This occurred during their attendance at a routine oral glucose tolerance test at Bradford Royal Infirmary, West Yorkshire (Raynor et al., 2008; J. Wright et al., 2013). The initial recruitment process continued until December 2010 and involved a total of 13,776 pregnancies.

The city of Bradford is a unique location to study ethnic differences because of its largely bi-ethnic population, with 20% of the population having a South Asian background (Pakistani, Indian, or Bangladeshi); primarily Pakistani (Raynor et al., 2008). In one ward of the city, Little Horton, 37.8% of the population self-identified as Pakistani (Valentine, 2005). This compares to only 2.0% within England and Wales (Office for National Statistics, 2018a). This large proportion of Pakistani individuals is primarily a result of mass migration occurring from the region of Mirpur in the 1960s (Lothers & Lothers, 2012). At least 75% of all Pakistani immigrants to Bradford are reported to originate from this region of the country (Imran & Smith, 1997). During the 1960s, the Pakistani government built the Mangla Dam in Mirpur to generate hydroelectric power which resulted in large flooding around the dam and surrounding villages, forcing thousands of people out of their homes (Ballard, 1991; Lothers & Lothers, 2012). In search of a new life and employment, a large proportion of these people (mostly the men of the households) migrated to the UK, particularly within Yorkshire, to work in the factories that were at that time suffering a shortage of labour. Bradford, in particular, was deemed “a centre of textile excellence” (Valentine, 2005, p. 3) during the Industrial Revolution due to the large number of mills. Over the next few years, it was common for the rest of the family to migrate from Mirpur and settle in the UK to join the men who had found work (Ballard, 2002). Since then, Bradford has been known as “the Mirpuri capital city in the UK” (Lothers & Lothers, 2012, p. 5). Thus, this diverse and unique population offers a fascinating opportunity to study ethnic differences in children’s health and development using adequately powered and robust analyses.

In addition, the city of Bradford is also a suitable location for the study of the effects of socioeconomic deprivation on ill-health and adverse developmental outcomes. It is considered the 5th most income-deprived city in England (City of Bradford Metropolitan District Council, 2020a). As well as income-based measures, each town and city in the country is also ranked in terms of its relative level of deprivation based on the English Indices of Multiple Deprivation (IMD; Department for Communities and Local Government, 2015). This is a tool which measures the relative rates of deprivation across the country based on 37 individual indicators (e.g., homelessness; theft rates; post-16 education) across seven domains[1] which are weighted appropriately. For Bradford, 32.6% of the population resides in the top 10% most deprived areas of the UK, according to the IMD, reflecting high and widespread levels of disadvantage (Department for Communities and Local Government, 2015).

This has resulted in the city being ranked the 11th most deprived in the country, based on the number of deprived neighbourhoods. The high levels of deprivation are further demonstrated by the large proportion of families eligible for, and claiming, benefits. For example, within the UK population, 14.7% of children receive free school meals, yet this figure rises to 17.2% of children within Bradford (Department for Education, 2017). Thus, a deeper understanding of the numerous public-health issues that arise due to deprived socioeconomic circumstances can be obtained from studying these relationships within the BiB cohort (Raynor et al., 2008). Using data from BiB also counteracts the common bias for participants in research to be disproportionately recruited from high SEP populations (Baucom et al., 2017; Heinrichs et al., 2005).

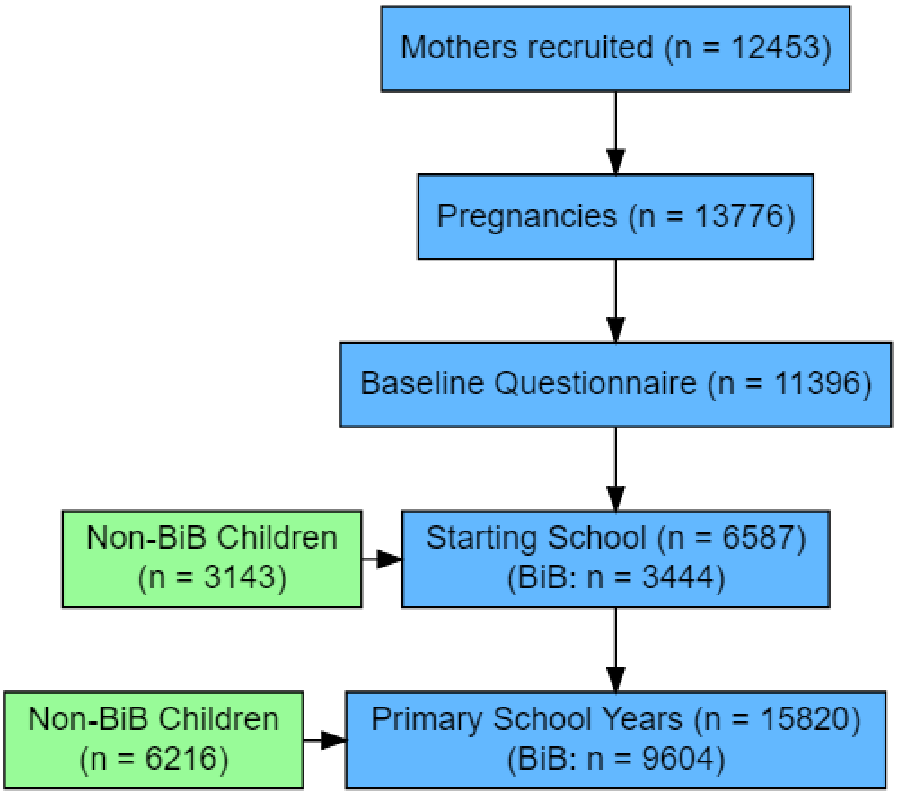
Since initial recruitment, several additional nested data collection sweeps and projects have been conducted which include children within the “original” BiB cohort (i.e., mothers recruited during pregnancy), as well as children from the wider Bradford population. These sweeps include: BiB1000 (Bryant et al., 2013); Starting School (Shire et al., 2020); Primary School Years (Bird et al., 2019; L. J. B. Hill et al., 2021); and Born in Bradford’s Better Start (Dickerson et al., 2016), amongst others. This thesis primarily focuses on analysis of sensorimotor data collected as part of the Starting School and Primary School Years sweeps, and

[1] Income; Employment; Education, Skills & Training; Health & Disability; Crime; Barriers to Housing & Services; Living Environment

demographic information collected during the Baseline Questionnaire. Each of these sweeps and their corresponding datasets are described in more detail in the following sections. All data collected from the Baseline Questionnaire or Starting School sweep was requested from the BiB Executive Board using the BiB Data Dictionary, an online database of all data available within BiB. See Figure 1 for an infographic of how each of the data collection sweeps is nested within the original BiB cohort.

Figure 1

Timeline of the BiB data sweeps



1.2.1.1 Baseline Questionnaire

During initial recruitment to BiB, mothers completed a Baseline Questionnaire which included numerous questions about their family background, lifestyle factors, health and wellbeing, and sociodemographic circumstances (Raynor et al., 2008; J. Wright et al., 2013). Anthropometric measurements were also taken. Due to the high proportion of Pakistani mothers; a large proportion of the sample spoke Urdu or Mirpuri. However, since the Mirpuri language does not have a written script, the questionnaire and information sheets were either transliterated or translated into Urdu. Bilingual researchers assisted non-English speaking mothers with the completion of the questionnaires. In total, 11396 mothers completed the Baseline Questionnaire. The BiB cohort of mothers and children who completed the Baseline Questionnaire contained an approximately equal proportion of South Asian and non-South Asian participants (J. Wright et al., 2013).

1.2.1.2 Starting School

Nested within BiB, the Starting School data collection sweep aimed to follow up BiB children and their peers during their first year of formal education (Reception class), during the 2012-13 and 2013-14 academic years. Three key areas of development were assessed: fine motor skills; literacy and communication; and social and emotional health, measured via the Clinical-Kinematic Assessment Tool (CKAT; Culmer et al., 2009), British Picture Vocabulary Scale – Second Edition (BVPS II; Dunn et al., 1997), and the Strengths and Difficulties Questionnaire (SDQ; Goodman & Goodman, 2009), respectively. These were all considered important indicators of school readiness (Shire et al., 2020). Testing was conducted in 77 schools in the Bradford district which were eligible if the Reception year included at least 10 children from the original BiB cohort (Shire et al., 2020). In total, 3444 BiB children consented to participate, although all children in Reception class aged 4-5 years old were eligible. Additional detail on the Starting School cohort is reported within Shire et al. (2020). All raw data were accessed via the BiB Data Dictionary.

1.2.1.3 Primary School Years

In 2017, a second, large-scale data sweep was conducted which aimed to collect follow-up data as the BiB children reached 7-11 years of age (Bird et al., 2019; L. J. B. Hill et al., 2021). Within this data sweep, rather than only testing children included in the original BiB cohort, testing was conducted on a whole class basis, including both BiB children (*n* = ~6000) and their classmates who were not part of the original cohort (*n* = ~9000). In total, 15820 children were tested from 86 Bradford schools over two years (L. J. B. Hill et al., 2021). It was intended that all children were tested as close to their eighth birthday as possible, however there was some deviation due to the very large sample size and logistics of school testing. I (Megan Wood), was involved in the data collection for this sweep during an internship affiliated with BiB during a year-long placement as part of the BSc Psychology (Industrial) degree. During testing, the Clinical-Kinematic Assessment Tool (CKAT) was administered to measure sensorimotor control, alongside a digitised assessment of cognitive skills. Within the cognitive battery, there were assessments of working memory (forward digit recall; backward digit recall; Corsi), inhibition (Flanker), and processing speed. Data from the cognitive battery were not used within the current thesis and were studied by a colleague within the ESRC White Rose Doctoral Training Network.

Pre-processed sensorimotor data from the Primary School Years sweep was not available via the BiB Data Dictionary. Therefore, under the supervision of my primary supervisor (Dr Liam Hill) and lead of the Born in Bradford data management team (Dr Dan Mason), I (Megan Wood) was responsible for reviewing the sensorimotor data from the Primary School Years sweep, cleaning it and pre-processing it for quality control purposes, prior to it being made publicly available via the BiB Data Dictionary. Cases were omitted from further analyses primarily for one or more of the following reasons: incompleteness; duplication or issues occurring during testing that were recorded in an accompanying field note. Data were reviewed on a task-by-task basis, and thus sample sizes varied across tasks. Further detail of how the quality control was conducted is included in Appendix A.

1.2.1.4 Additional Data

As well as data collected within BiB cohort sweeps, this thesis includes analysis of additional data collated from five previously published theses and manuscripts within the author’s research group (Berry, 2017; Flatters, Hill, et al., 2014; L. J. B. Hill et al., 2016; Sheridan, 2015; Shire, 2016). These data were collected from eight Bradford primary schools and included a total of 1740 children aged 4-12 years. Children from these datasets may or may not have been participants of the larger BiB cohort. Because these data were not linked with the BiB sweeps, only basic demographic information was available for these participants (e.g., age, handedness, sex). Ethical consent for the re-analysis of these data was obtained from the University of Leeds ethics committee (Ethics reference: PSC-826).

1.2.2 Primary outcome measures

As discussed, sensorimotor control was objectively measured in both the Starting School and Primary School Years data sweeps, as well as in previous data collections within the research group, using CKAT. These data are noteworthy because, in a similar regard to the difficulties of accurately capturing children’s family socioeconomics, the measurement of sensorimotor control can often be challenging – making the data used in this thesis rare, in terms of both its quantity and the quality of its measurement.

Several longitudinal cohort studies measure children's motor development, yet the methods used are not always appropriate for large, community-based settings. The methods employed by BiB have substantial advantages over those used in similar, earlier cohort studies. For example, the Avon-Longitudinal Study of Parents and Children (ALSPAC) (Golding et al., 2001), the Western Australian Pregnancy (Raine) Study (Straker et al., 2017), and the EDEN mother-child cohort (Heude et al., 2016) are all cohort studies which measure children's motor control in some capacity. However, there are several limitations to the methods used. For example, ALSPAC have data available at only one timepoint (age 7), therefore longitudinal or repeated-measures analysis is not possible. Whilst the Raine and EDEN studies both have data collected at multiple timepoints, the nature of the data collected is prone to bias. For example, parental questionnaires are used within EDEN, which, as discussed further in Chapter 3, are prone to subjective responses from parents (Kohler et al., 2013; Lemler, 2012; Stone et al., 2010). In addition, the Raine study uses an assessment battery which compares performance to a US normative sample from the 1970s. As a result, these norms may be outdated and no longer accurately reflect children's motor development due to differences in leisure time activities such as increased used of touch-screen devices and videogames (Bedford et al., 2016; Borecki et al., 2012; Lin et al., 2017; Neumann & Neumann, 2014; Ribner & McHarg, 2021).

In contrast, BiB offers an invaluable opportunity to study children's sensorimotor control at scale. First and foremost, with thousands of children enrolled within the cohort and the additional children tested during data sweeps, studies can be conducted with very large sample sizes. At this scale, participants can be grouped by demographics of interest (e.g., academic year groups; SEN status etc.) and still retain large enough samples to conduct robust analyses. Outside of cohort studies, independent research teams would struggle to obtain such large samples from a relatively homogenous population. These large samples are only possible through the close engagement and large investments that such cohort studies make into building ongoing relationships with the local authority and local schools, where testing takes place. For example, within the Primary School Years cohort, 86 of a total 142 Bradford primary schools were involved in data collection (L. J. B. Hill et al., 2021). In addition, because data collection was conducted within schools, the amount of time children spent out of the classroom was limited; minimising disruption to learning compared to testing within a controlled laboratory setting.

Furthermore, unlike ALSPAC, BiB collected sensorimotor data at multiple timepoints across development. For example, there is currently sensorimotor data available for a large sample of children at 4-5 years old (Starting School), with a substantial proportion of these children retested at 7-10 years (Primary School Years). Thus, it permits investigation into children's developmental trajectory over time on an individual basis. Compared to cross-sectional analysis, longitudinal data permits the researcher to measure the stability of particular phenomena over time (Farrington, 1991; Miller, 1998). Furthermore, compared to cross-sectional studies, increased confidence in causality can be placed on longitudinal data (Farrington, 1991; Rajulton, 2001). Robinson et al. (2006) provide an example of the benefits of longitudinal research by investigating children's reading development between first and third graders. Biases would be introduced if, for example, a new reading curriculum was introduced for first graders that the older cohort had not been exposed to, were the design to be cross-sectional. Measuring performance of the same cohort of children minimises the introduction of such biases.

Lastly, measuring sensorimotor control within a large cohort study such as BiB, with many areas of interest, permits data linkage with various aspects of children's development (e.g., academic achievement; mental health; sociodemographic factors). This permits the exploration of the factors which influence sensorimotor control and how this relates to various aspects of wider development.

1.2.2.1 The Clinical-Kinematic Assessment Tool (CKAT)

Within Born in Bradford, sensorimotor control is assessed using a computerised assessment called the Clinical Kinematic Assessment Tool (CKAT). As the name suggests, CKAT is a kinematic assessment of sensorimotor control, providing an objective and precise alternative to parental questionnaires or observational measures conducted by researchers (e.g., Blanchard et al., 2017; Blank et al., 2012; Culmer et al., 2009; L. J. B. Hill et al., 2016; J. Schmidt et al., 2009; Zwicker et al., 2012). Kinematics can be defined as the quality of movement, taking into account the velocity, acceleration and form of one or more body parts in synergy, relative to time (A. C. Cunningham et al., 2019; Hall, 2018; Singer et al., 2016). As discussed further in Chapter 3, the use of kinematic measures of sensorimotor control is advantageous in that it provides the additional precise, kinematic detail that traditional observational assessment batteries cannot.

CKAT is a tablet-based device which measures sensorimotor processes via uni-manual interactions with a hand-held manipulandum and consists of three tasks:

Tracking, Aiming, and Steering (Culmer et al., 2009; Flatters, Mushtaq, et al., 2014). CKAT, and each of the three tasks, are described in further detail in Chapter 3. For now, a brief justification of each task's value in understanding sensorimotor control is detailed below.

Tracking tasks are frequently used to measure sensorimotor function (Kim et al., 2017; I.-C. Lee et al., 2013; Röijezon et al., 2017; van Roon et al., 2008). Performance on such tasks can provide an indication of a child's ability to use forward models to make anticipatory predictions of the target's trajectory and move accordingly to reduce the frequency of error (Miall et al., 2001; Miall & Wolpert, 1996). Alternatively, children can complete tracking tasks by making a series of small, corrective movements as the target moves which increases both temporal and spatial error (Culmer et al., 2009). It is generally preferred to take the former approach, as this produces much smoother movement (Culmer et al., 2009). The latter is typical of children with DCD, who have previously exhibited deficits in predictive control on similar tracking tasks (Ferguson et al., 2015).

Aiming tasks are commonplace in assessments of manual control, used as early as the 19th century (Woodworth, 1899). The aiming movement itself is considered to consist of two distinct phases; often referred to as the "Two-Component Model" (Woodworth, 1899). This includes an initial "ballistic" phase of acceleration followed by a deceleration or "homing" phase. These phases are related to feedforward and feedback control, respectively (M. Heath et al., 1998; Plumb et al., 2008; Woodworth, 1899). In addition, the use of "jump" events (sometimes referred to as the "step-perturbation paradigm") are incorporated into the later stages of this task. This paradigm has been previously used in several aiming tasks (e.g., Heath et al., 1998; Pélisson et al., 1986; Plumb et al., 2008; Wilmut et al., 2006) to study one's online control of movement trajectory (Culmer et al., 2009; Latash, 2012; Plumb et al., 2008). Lastly, unlike the other tasks, Aiming is entirely self-paced and carries no time constraints. This provides the opportunity to assess whether performance deviates from the bell-shaped speed profile typically found in human hand movements and understand the spatio-temporal structure of participants' aiming movements (Culmer et al., 2009; Elliott et al., 2001; Jeannerod, 1988)

The Steering task requires participants to use both feedforward and feedback mechanisms in order to apply an appropriate load on the stylus at the right time (Culmer et al., 2009; Davidson & Wolpert, 2005). By providing the optimum trajectory, in addition to the optimum speed, participants receive continuous visual information, which the sensorimotor system can use to inform future movements (Gonzalez et al., 2011). Similar tasks, involving the tracing of various shapes, have been previously included in several computerised motor assessments (e.g., Lee et al., 2014; Röijezon et al., 2017). Additionally, a pencil and paper tracing task is also used within the manual dexterity component of the MABC-2 (Henderson et al., 2007).

1.2.2.2 Outstanding limitations of kinematics

CKAT is an appropriate tool to investigate the associations of sensorimotor control and sociodemographic indicators at scale as it provides an objective measure of precise kinematic data. However, while kinematic assessments in general are more optimal than observational or questionnaire-based alternatives due to the level of detail they provide, they still hold some limitations. For example, it can be difficult to draw meaningful conclusions from kinematic tools, such as CKAT, due to the sheer quantity of data obtained from a large array of different kinematic variables. Therefore, a subset is often used, presenting the researcher with the necessity to form a logical selection process for the variables to analyse. This is an issue which the current thesis aims to resolve using empirical methods to drive the selection of the kinematic variables produced by CKAT to use in subsequent analyses (see Chapters 3 and 4).

1.2.3 Aims of the current thesis

The importance of developing competent sensorimotor control is well-established in the literature, impacting many aspects of health and development (Giles et al., 2018; L. J. B. Hill et al., 2016; Hudson et al., 2020; Jirak et al., 2010; Sheridan et al., 2017; Shire et al., 2016; Zelazo & Carlson, 2012). Previous research has found that there are associations with several sociodemographic indicators and children’s motor skills (e.g., Adeyemi-Walker et al., 2018; Eyre et al., 2018; Mcphillips & Jordan-Black, 2007; Morley et al., 2015), however little research has investigated these relationships using precise, unbiased methods with a focus specifically on sensorimotor control. In addition, there is currently no research which has explored the longitudinal impact of ethnicity on sensorimotor control.

The chapters contained within this thesis therefore aim to understand the sociodemographic influences impacting upon children’s sensorimotor control across the primary school years. Specific attention is given to studying whether ethnic differences exist, whilst controlling for any confounding influence of socioeconomic circumstances and then investigating interactions between these factors. It was apparent that the methodologies used in previous research were not optimal for such analyses and therefore, it was necessary to adapt existing measures of SES and sensorimotor control to limit biases which may have previously arisen.

Chapter 2 describes the derivation of a multi-faceted measure of SEP required for later chapters: an ethnic-specific latent measure of SEP. Accounting for ethnic differences in the measurement of SEP is not typical in the literature, but it has been argued that adjusting for ethnic differences may be necessary to accurately determine an individual's socioeconomic circumstances. Therefore, it was deemed necessary to understand how this affected the relationship with sensorimotor control. These latent classes have been previously derived by Fairley et al. (2014) within the BiB cohort, however the variables were not accessible from the Born in Bradford Data Dictionary, so Fairley et al.'s work was replicated within this chapter in order to derive these variables. Raw data from which the latent classes were derived were obtained from the Baseline Questionnaire.

Chapter 3 describes the creation of component scores describing sensorimotor performance via CKAT using Principal Components Analysis (PCA). Providing empirically driven scores of sensorimotor control from a larger range of kinematic indices than have been previously used is more likely to increase the accuracy of measurement, and limit the biases that often occur with traditional observational measures of motor control. Doing so ensured the largest amount of systematic variance in sensorimotor control was captured, whilst preventing the inclusion of redundant kinematic variables in the analysis. These measures of sensorimotor control were required for use in subsequent chapters. Data used within this chapter were previously collected by colleagues within the research group (see earlier Additional Data sub-section for more details).

Chapter 4 extended the work of Chapter 3 by refining the models produced by the PCA using Confirmatory Factor Analysis (CFA). These models were further revised with respect to existing theory of sensorimotor control. They were then tested on a new sample to ensure replication was possible, and that the models were valid and psychometrically sound. This new sample included kinematic data from both the Starting School and Primary School Years sweeps. As previously mentioned, data cleaning and quality control was conducted by the author on the Primary School Years data studied here, which is described in Appendix A. Description of these data is also included in the following paper: Hill et al. (2021), which I co-authored.

Having derived the appropriate measures during the preceding chapters, it was then possible to conduct the main research study. Chapter 5 therefore sought to investigate the influence of sociodemographic factors (ethnicity and SEP) on 4-5-year-old children’s sensorimotor control using objective measures, and further studied how ethnicity and SEP may interact. In addition, this chapter aimed to compare and contrast a set of “traditional” and “revised” measures (the latter derived in Chapters 2, 3 and 4) of sensorimotor control and SEP, to determine the effect of different measurement methods on the conclusions drawn. It was also possible to study how an ethnic-specific measure of SEP affected the relationship with sensorimotor control, compared to a cohort-wide measure. This chapter used kinematic data obtained during the Starting School sweep and sociodemographic information (ethnicity and SEP) from the Baseline Questionnaire.

Finally, Chapter 6 used repeated measures of children’s sensorimotor control at two timepoints (4-5 years and 7-10 years) to explore the developmental changes during the primary school years. It also aimed to investigate the impact of ethnicity on these developmental changes and whether any ethnic differences were invariant or changed over time. Through the derivation of more precise scoring of kinematics developed within Chapters 3 and 4, it was possible to understand and disentangle how specific components of sensorimotor control develop over this time period. Thus, detailed investigation of age-related differences was conducted for each of the sensorimotor components derived. Within this chapter, sensorimotor performance was determined using the kinematic data obtained during both the Starting School and Primary School Years, and ethnicity was obtained from the Baseline Questionnaire.

Chapter 2 Reproducing an ethnically sensitive measure of Socioeconomic Position using Latent Class Analysis

2.1 Introduction

Socioeconomic position (SEP) is a complex, multi-dimensional construct which places individuals on a hierarchy within society based on resource- (e.g., household income, or ownership of material goods) and prestige-based (e.g., occupation, or education) attributes (Braveman et al., 2001; Fairley et al., 2014; Galobardes et al., 2007; Howe et al., 2012). Chapter 1 described how the terms SES (Socioeconomic Status) and SEP are often, confusingly, used interchangeably in the previous literature (see Section 1.1.3.2). For clarity however, within this thesis SEP will be used when discussing multifaceted latent measures of socioeconomic circumstances, whilst SES will refer to individual predictors of one's circumstances.

Due to its multifaceted nature, SEP can be estimated from several directly observed measures (e.g., household income, qualifications, occupation), with different indicators accounting for distinct, but potentially overlapping pathways (Howe et al., 2012). Thus, the relationships found between one's socioeconomic circumstances and various health outcomes (e.g., motor control, cognition) can vary widely or be masked entirely when using imprecise, one-dimensional measures (e.g., maternal education only) to represent a multi-dimensional construct. As such, researchers should carefully consider the most appropriate measure of socioeconomic influences. Presently, authors do not always provide a rationale and justification for specific measurement methods and there are several limitations concerned with relying on any one of the traditional measures examples given above, which are commonly used across the literature as singular estimates of SES.

2.1.1 Use of unidimensional indicators

As discussed, SEP is multidimensional, with Krieger et al. (1997) referring to it as an aggregate concept which should be measured as such. However, it is commonplace in research that a single, univariate proxy is used to reflect an individual's SES, such as maternal education or household income. Indeed, Myer and colleagues argue that the socioeconomic position of developed societies is becoming increasingly more intricate and dynamic (Myer et al., 2008). Thus, it is evident that such a complex construct cannot be captured by a single indicator and so multiple indicators are recommended (Nazroo, 1998). This is supported by previous research which has found inconsistent relationships between various health outcomes across different unidimensional measures of SES (Braveman et al., 2005; Erola et al., 2016; Marks, 2011). These findings have been mirrored when investigating children's motor competence. Children with more educated parents tend to perform significantly better compared to their peers with less educated parents on various measures of motor competence (e.g., Cools et al., 2011; Lejarraga et al., 2002; Zeng et al., 2019). However, when SES was measured via other means (e.g., parental occupation), this relationship failed to be replicated (Cools et al., 2011). In addition, whilst both paternal occupation and maternal education significantly predicted children's fine motor performance in an Argentinian sample, this relationship was stronger for maternal education (Lejarraga et al., 2002). This provides evidence for the limitations of using univariate indicators of SES as different conclusions may be drawn as a result.

Furthermore, univariate indicators of SES fail to account for nuance in individual circumstances and may be skewed by extreme or unusual cases. For example, maternal education is commonly used in developmental research and epidemiology because it is thought to capture “knowledge-related assets” (Galobardes et al., 2007, p. 26). However, Braveman and colleagues (Braveman et al., 2005) warn against using level of education interchangeably with income or wealth as an indicator because the common assumption that more qualifications lead to a higher occupational class, in turn providing a greater income does not always prove to be the case (Davey Smith et al., 1998; Erola et al., 2016). Measures of education can become problematic, such as the introduction of biases when the wider context is not considered. For example, an individual who takes a more vocational route may not have obtained a high number of formal qualifications (e.g., postgraduate degrees, professional qualifications) yet they may still be in a highly paid career with a large disposable income (Sherar et al., 2016). Thus, it is inaccurate to categorise this individual as being in the same socioeconomic positon as an unemployed individual receiving multiple benefits and struggling to provide for their family. Using only employment status or occupation presents similar problems. A single measure related to employment (e.g., employed; unemployed; self-employed) cannot account for multiple jobs, temporary or seasonal work, overtime or bonuses (Elgar et al., 2016; Howe et al., 2012). All of which can have a substantial impact on income.

As with the measurement of any construct, there are inevitable imprecisions and biases. However, these biases are exacberated when only one proxy measure of the construct is relied upon. For example, in Cools et al.’s (2011) study of relationships between parental education and motor competence, discussed earlier, occupation was categorised as “active” versus “passive”, an arguably vague and coarse indicator that is unlikely to directly map onto high and low SES. The authors did not provide detail into how this was categorised and thus, it cannot be replicated by other researchers. Therefore, the reliance on a single, imprecise measure to reflect one's socioeconomic standing is contentious, at best.

Similarly, education can be measured in multiple ways such as the number of years in education or highest qualification obtained. As already discussed, highest qualification may not be the most accurate indicator of an individual's SEP due to context, but number of years in education is not an appropriate alternative. Individuals who have skipped or repeated academic years would therefore not be measured accurately. Whilst uncommon, this may become more problematic in larger samples or those collected across countries where length of time in education can vary (e.g., differences in the age which children start and finish compulsory education).

To counteract some of these issues around using single measures of education or occupation, subjective poverty and ownership of goods has been used to provide context. For example, an individual can indicate to what extent they feel they can afford several necessities and "luxuries" such as the means to keep the home suitability warm, take holidays or have a hobby (Fairley et al., 2014). A meta-analysis conducted by Quon & McGrath (2014) found subjective social status predicted several health outcomes in adolescents. Indeed, another recent study found that subjective social status is significantly associated with cardiometabolic risk (McClain et al., 2021). Other researchers agree, arguing that subjective poverty or social status may be more useful than objective measures (Singh-Manoux et al., 2006). Such measures can provide further nuance and account for differeces in circumstances between individuals who may have otherwise been viewed homogenously. For example, it is likely inappropiate to suggest a single mother of four children with a seconday school education is comparable to a single, self-employed male with mutliple businesses who also only attended secondary education. Thus, the addition of further indicators may more accurately reflect one's socioeconomic circumstances than a unidimensional measure of SES.

The final major issue with unidimensional measures of SES relates to systematic bias, which is particularly prevalent in marginalised groups. For example, household income is commonly used to determine an individual's socioeconomic circumstances (e.g., Akee et al., 2018; Lee et al., 2019; Zilanawala et al., 2016). However, household income may be particularly problematic for use in ethnic minority samples. For example, as many as 35% of women of a South Asian origin (e.g., Pakistani, Bangladeshi) were found to be unaware of or unwilling to provide their household income when asked for research purposes (Prady et al., 2013). Similarly, in multi-ethnic samples educational achievements and qualifications may not be equivalent and as easily comparable across participants because qualifications may have been achieved outside of the country that the research is taking place (Howe et al., 2012). Further issues regarding ethnicity and uni-demensional measures of SES are discussed in greater detail in later sections.

Thus, using a single measure as a proxy for SES can be prone to a number of biases, leading to an inaccurate representation of one's socioeconomic circumstances. The alternative approach of measuring SEP should therefore better reflect the multifaceted nature of socioeconomic circumstances.

2.1.2 Area-based measures of socioeconomic position

As an alternative to unidimensional indicators measured at an individual-level, previous research has used multidimensional indicators of SEP measured at an area-level. These are arguably less prone to some of the previously outlined biases. A commonly used indicator of area-based SEP is the Index of Multiple Deprivation (IMD) (Ministry of Housing Communities and Local Government, 2019) but others used in the UK include: the Townsend Deprivation Index (Townsend et al., 1988); Underprivileged Area Score (Jarman, 1983); Breadline Britain Index (Mack & Lansley, 1985) and the Northern Ireland Multiple Deprivation Measure (M. Noble et al., 2001). As the term “index” suggests, these measures take a range of area-based factors into consideration to produce a neighbourhood “rank” of deprivation. Often the household or school postcode is used as a determiner of this rank. Although useful for understanding the social environment of an individual, area-based measures are commonly used for convenience when it is not possible or feasible to measure on an individual level (Galobardes et al., 2007; Shavers, 2007). Taking IMD as an example, neighbourhoods are stratified into a hierarchy based on 37 indicators, distributed across seven domains: Income Deprivation; Employment Deprivation; Health Deprivation and Disability; Education, Skills and Training Deprivation; Crime; Barriers to Housing Services; and Living Environment Deprivation (Ministry of Housing Communities and Local Government, 2019).

In addition to convenience, such measures do have a place within research as they can provide contextual information regarding where an individual resides, which may be particularly important for some health outcomes. For example, the relationships between air quality and asthma prevalence (Khreis et al., 2018;

Shavers, 2007), access to green space and mental health (Mceachan et al., 2016; McEachan et al., 2018), availability of sports facilities and physical activity (Halonen et al., 2015) or proportion of fast-food eateries and childhood obesity levels (Fraser & Edwards, 2010). Area-based indicators have also been used in previous research when investigating the relationship between SEP and children’s motor skills, with children attending schools in more deprived areas exhibiting poorer motor skills than their peers in more affluent schools (Mcphillips & Jordan-Black, 2007; Morley et al., 2015). However, whilst it is commonplace to use such measures, as if they were univariate indicators, there are several limitations to this approach.

Firstly, although area-based measures are often an index of multiple indicators, sometimes the area is categorised using only a single measure. In this regard, these are no better than univariate measures and are subject to similar biases. This is illustrated by an earlier review by Pickett and Pearl (2001), concluding that some neighbourhood characteristics may be a better predictor of health outcomes than others. Similarly, Tomaz et al. (2019) used the average household income and geographical context to categorise areas as high income versus low income and rural versus urban before relating these to the gross motor skills of 3-6-year-old South African children from each of these groups. The authors did not find significant differences in the motor skills between children from urban low-income and urban high-income areas. However, significant differences were found between children from rural and urban areas, irrespective of income. This demonstrates how a single indicator of neighbourhood socioeconomic position may not be enough. Similar findings were reported by Birnbaum et al. (2019) who also used an area-based measure of household income to represent SES. Again, no significant association was found between SES and performance on two gross motor skill subtests (jumping from side to side and standing long jump). The findings from these studies would imply that there is no relationship between socioeconomic circumstances and motor skills in children, which contradicts some of the literature previously discussed. These inconsistencies may be a result of imprecise measurement of socioeconomic circumstance.

Furthermore, area-based measures of SEP are not always found to accurately reflect individual circumstances because they consider the *average* circumstances of individuals within the area (Ioannides, 2004). Indeed, research has found poor correlations between area- and individual-level measures (Geronimus & Bound, 1998; Southern et al., 2005). For example, Southern et al. (2005) compared area-based estimates of household income versus self-reported estimates at an individual-level and found poor agreement. The authors did, however, find that both measures, whilst not correlated, did significantly predict health-related quality of life, concluding that area- and individual-level measures may simply reflect different constructs. Several studies support this, concluding that area-based measures are poorer at identifying relationships with obesity levels (Bodea et al., 2009), walking behaviour (Hearst et al., 2013), and self-reported health (Geronimus & Bound, 1998) compared to individual-based measures.

Similarly, there are issues of heterogeneity when using area-based measures. For example, individuals entitled to benefits (a common individual-level indicator of SES) have been previously found to reside within areas categorised as both high and low SES (Hearst et al., 2013), suggesting that an area-level indicator can, in certain cases, be highly unrepresentative of individual circumstances. These issues are further exacerbated when researchers investigate school-aged populations and analyse the SEP of the *school*, rather than pupils' homes. Some have argued that we can assume children predominantly attend schools within their own catchment area (Department for Education, 2014; Morley et al., 2015), however this is not always the case. The geographical size of the areas represented by a single SEP classification may also add further issues to the representation of individuals' circumstances. For example, Hyndman et al. (1995) found that capturing SEP across larger areas (e.g., neighbourhood-level) was less accurate than when using smaller areas (e.g., street-level). Thus, using area-based measures to categorise individuals increases the risk of misclassification.

To summarise, while area-based measures are often more readily available from datasets such as the England and Wales Census, with some even offering more multi-faceted estimates of socioeconomic factors, it must be acknowledged that they are still subject to several biases: accuracy, heterogeneity, and lack of context. As a result, the conclusions drawn may not be accurate.

2.1.3 Ethnic sensitivity in SEP measures

As discussed, selecting multiple measures that accurately reflect the socioeconomic circumstances of an individual is necessary, yet it is also vital to ensure the measures selected are appropriate across various social demographics (e.g., sex, nationality, and age) within the sample (Braveman et al., 2005; Delgado-Angulo et al., 2019; Fairley et al., 2014; Uphoff et al., 2015). For example, the strength of the relationship between SEP and various health outcomes (e.g., low birth weight, Type-2 diabetes) has been found to vary across different ethnic groups (Bécares et al., 2012; Mallicoat et al., 2020; Nazroo, 1998; Thomas et al., 2012; Uphoff et al., 2015). One potential explanation for this is that the meaning or priority of various aspects of SEP may not be equal across different ethnic groups (Kelaher et al., 2009; Shavers, 2007). For example, applying the terminology used in their original paper, Kelaher et al. (2009) found that individuals in the “Pakistani and Indian” group were less likely to own their own car if university educated, yet the opposite was true for the “White” group. This highlights potential ethnic differences in behaviour relating to socioeconomic circumstances, despite similar levels of education (a proxy measure of SES).

In addition, using area-based measures of SEP may not be appropriate in some communities because the decisions to live in a particular area may be driven by factors *other* than socioeconomic circumstances. For example, the decision to live in a particular neighbourhood may be more influenced by ethnic density than an area’s level of deprivation or affluence (Bhugra, 2004; Dorsett, 1998). In the UK, for example, Pakistani individuals were generally found to live in areas where the Pakistani population exceeded 50% of the total ethnic minority population for that area (Dorsett, 1998). In West Yorkshire (including Bradford), this finding was even more stark, with Pakistani people tending to live in areas where the largest proportion of all ethnic minority groups was also Pakistani (Dorsett, 1998). Therefore, while ethnic minority groups do tend to show lower levels of SEP, it is plausible that families moving to Bradford, a city of high deprivation, may be driven to do so, in part, by a motivation to be around people from a similar cultural, ethnic and religious background, rather than out of necessity. As such, it would be inappropriate to assume that all families within a neighbourhood or ward share similar socioeconomic circumstances without accounting for individual differences.

Furthermore, research from the UK’s Fourth National Survey of Ethnic Minorities found that while British Indian and British Pakistani individuals were more likely to own their homes (often an indicator of high SEP), although this was often lower quality housing compared to their white counterparts (Kelaher et al., 2009; Nazroo, 2003). In addition, Pakistani individuals were categorised as the poorest ethnicity, based on income. Thus, without context, indicators such as “home ownership” may be misleading in multi-ethnic samples as they do not reflect comparative circumstances across ethnic groups. Thus, it is necessary to consider measures of SEP which are sensitive to ethnic differences or take wider context into account.

2.1.4 A latent class approach

Latent Class Analysis (LCA) is a method of statistical analysis proposed by Lazarsfeld (1950) which is used as a means of grouping observations or individuals by measures which cannot be directly observed, such as depression, socioeconomic position, or personality (Dean & Raftery, 2010; Linzer & Lewis, 2011; Porcu & Giambona, 2017). It has been used as an alternative means of producing a multidimensional measure of SEP that includes a wide range of socioeconomic indicators (Fairley et al., 2014; Mallicoat et al., 2020; Moonansingh et al., 2019).

In LCA, numerous measurable (manifest) variables are used as proxies to estimate underlying constructs (latent variables). Cases or observations which behave similarly on a number of these manifest variables commonly cluster together within the same latent classes and are considered mutually exclusive (Lanza & Rhoades, 2013; Linzer & Lewis, 2011; Sartipi et al., 2016). As a result, LCA has been previously used to group individuals on various commonalities such as symptoms of eating disorders (Pinhas et al., 2017), indicators of intellectual disability (Nouwens et al., 2017), and even political behaviours

(Alvarez et al., 2017). Taking Pinhas and colleagues' (2017) study as an example of how the process works, the authors took common symptoms of eating disorders and ran an LCA in a sample of UK, Canadian, and Australian children. Eating disorders cannot be measured directly, but the symptoms can, making it ideal for LCA. Analyses revealed two distinct clusters of children: those with body dissatisfaction and a preoccupation with food and exercise, which are symptoms consistent with Anorexia Nervosa, and a second cluster of children who did not have these preoccupations with their body and food. Children in the second cluster were instead more likely to experience somatic symptoms and have a comorbid psychiatric disorder, aligning with Avoidant/Restrictive Food Intake Disorder (ARFID). The authors concluded that the analysis lent support to there being two distinct latent classes of eating disorder diagnoses.

Importantly, LCA is considered a "person-centred analysis" as it finds a model to fit and classify observations at an individual level, distinguishing it from methods such as Item Response Theory, which measures how well data fits an idealised model, or Factor Analysis, which is concerned with the relationships amongst variables (Bartholomew et al., 2011; Porcu & Giambona, 2017; Sartipi et al., 2016). Another alternative technique, Principal Components Analysis (PCA), is better suited to continuous data, whereas LCA is favoured for categorical data (Kolenikov & Angeles, 2009). Whilst Non-Linear Principal Components Analysis (NLPCA) can be used with categorical data (Linting & Kooij, 2011; Michailidis & de Leeuw, 1998), NLPCA may not be appropriate for use in models comprising of more complex variables (Sartipi et al., 2016). In addition, NLPCA has several assumptions which must be met, such as normality (Sartipi et al., 2016). Therefore, for the classification of individuals into SEP latent classes, LCA is arguably the most appropriate statistical method.

2.1.5 The present study

Considering the discussed limitations with uni-dimensonal measures of SES and area-level measures of SEP, Fairley et al. (2014) developed latent classes of SEP using data collected from the Born in Bradford Baseline Questionnaire (see Chapter 1 for a description of these data). The latent models encompassed 19 individual-level indicators of SES and used them to produce a single measure, which represented the dynamic and multifaceted construct of SEP within a bi-ethnic population. Considering that Bradford was ranked the 13th most deprived local authority in the country in 2019, it may not be appropriate to use an area-based measure of SEP as there are widespread levels of area-level deprivation across the city (Ministry of Housing Communities and Local Government, 2019). Therefore, individual-level indicators should be preferred for use to accurately capture subtle differences and account for families who have migrated to the city due to its high ethnic density.

In total, Fairley and colleagues (2014) produced three latent models: a "cohort-wide" latent measure of SEP which had been constructed using the entire bi-ethnic sample, and two "ethnic-specific" latent measures of SEP. The latter two models were each developed specifically for a White British and Pakistani sample, respectively. These latent measures provide a means to make comparisons of SEP on health and development both across and within ethnic groups. The authors found that the cohort-wide model revealed five latent classes of SEP, concluding that it was an appropriate model to use as a global measure of SEP which could then be used in combination with information on ethnicity to study interactions between SEP and ethnic group. Meanwhile, both ethnic-specific models suggested that individuals were best categorised into four latent classes and that various measures of SEP aggregated differently across White British and Pakistani samples. The authors suggest that these models are suited for investigating the impact of SEP *within* ethnic groups, such as in split-group analyses. As a result, it was evident that there were subtle differences in the derived latent variables, depending on whether these were ethnically-specific, or ethnically-independent. The ethnic-specific latent model provides the opportunity to investigate the impact of SEP on health within ethnic groups in greater detail and with greater precision.

Mallicoat et al. (2020) used these measures to investigate social gradients in several health outcomes related to maternal and infant health (e.g., maternal mental health, low birth weight). However, these measure have yet to be used to explore potential social gradients regarding sensorimotor control.

A practical problem arose in preparing to conduct this analysis. Within BiB's Data Dictionary, only the cohort-wide latent classes of SEP had been retained for open-access use. The ethnic-specific classes had not. Therefore, to further explore social gradients in sensorimotor control using an ethnic-specific measure within each ethnic group, it was necessary to replicate Fairley and colleagues' (2014) analyses within this thesis, to reproduce the ethnic-specific latent classes for use in subsequent analyses[1]. The analytical steps taken to accomplish this, and a brief review of their findings, are described in the rest of this chapter.

2.2 Method

2.2.1 Data

[1] Although on a slightly different dataset, see Section 2.2.1 for details on the difference in inclusion and exclusion criteria between the samples used in this Chapter compared to the Fairley et al. (2014) paper.

The data from 9617 White British and Pakistani mothers, obtained from the BiB Baseline Questionnaire, were included in analysis. For the purpose of the thesis, only White British and Pakistani mothers were included whilst Fairley et al. (2014) also included “Mixed”, “Black or Black British”, “Asian” (including Bangladeshi and Indian), “Chinese” and “Other” ethnic groups. Data from these individuals included a range of SEP indicators (manifest variables) and other demographic information. Only individuals with complete socioeconomic and ethnicity data were included in analyses. In contrast, Fairley and colleague’s (2014) criteria only excluded cases where specific types of demographic information were missing (ethnicity, age, marital and cohabitation status).

2.2.2 Measures of SEP

In accordance with Fairley et al. (2014), 19 measures were entered into the latent class models. These variables encompassed both objective monetary and non-monetary measures, as well as subjective measures of poverty. These are summarised in Table 1.

The highest educational qualification and the country in which this was completed was recorded for both the mother and father. Qualifications obtained in countries other than the UK were to allow comparison. In cases where the qualification had been obtained from outside of the UK and sufficient information was not provided, education was coded as “foreign unknown”. As shown in Table 1, as per Fairley et al.’s (2014) original study, education level was categorised into seven groups based on the UK ENIC classifications (formerly known as the “UK National Academic Recognition Information Centre” prior to Brexit).

Employment status was measured differently between the mothers and fathers. Father’s employment was loosely based on the National Statistics Socio-

Economic Classification (NS-SEC) (Rose & Pevalin, 2003). Such categorisation was not considered appropriate with the mothers as over a quarter stated that they had never been in employment. Instead, as shown in Table 1, a simpler description of employment status was applied: currently employed, previously employed, and never employed.

Although a typical indicator of SEP, household income was not used in the present study due to the sample containing a high proportion of Pakistani individuals (for reasons explained earlier in Section 2.2.1). Instead, three alternative questions were asked to obtain a picture of the mothers' financial situation: subjective poverty, receipt of means-tested benefits (e.g., income support), and whether bill payments were up to date. As discussed in Section 2.1.1, such indicators have been used in previous research and provide some context concerning an individual's financial situation that cannot otherwise be captured using objective measures alone (E. Goodman et al., 2007; Singh-Manoux et al., 2006; L. S. Wolff et al., 2009). In addition, mothers were also asked 11 questions regarding the ability to afford various material items. Importantly, these questions were subjective in nature. This included providing mothers the option to indicate the item is not deemed necessary, regardless of if it could be afforded or not. These questions were based on the Households Below Average Income Survey (Adams et al., 2012).

Table 1

Summary of the 19 SEP manifest variables included in the LCA [continues on next page]

SEP Manifest Variable	Response Options
Mothers' level of employment *(Mother's LoEm)*	Currently employed; previously employed; never employed
Fathers' level of employment *(Father's LoEm)*	Non-manual; manual; self-employed; student; unemployed; don't know
Receipt of means-tested benefits *(MTB)*	No; yes
Housing tenure *(HT)*	Owns outright; mortgage; lives rent-free; private landlord; social housing; other; don't know
Mothers level of education *(Mother's LoEd)*	<5 GCSE equivalent; 5 GCSE equivalent; A-level equivalent; higher than A-level; other; don't know; foreign unknown
Fathers level of education *(Father's LoEd)*	<5 GCSE equivalent; 5 GCSE equivalent; A-level equivalent; higher than A-level; other; don't know; foreign unknown
Up to date with bills *(Bills)*	No; yes; don't know
Subjective poverty *(SubPov)*	Living comfortably; doing alright; just about getting by; quite difficult; very difficult
Able to afford…	
…two pairs of all-weather shoes *(Shoes)*	Have; don't want or need; can't afford
…money to replace any worn out furniture *(Furn)*	Have; don't want or need; can't afford
…family and friends for a drink/meal at least once a month *(FF)*	Have; don't want or need; can't afford

[Continued]

Table 1 [continued]

Summary of the 19 SEP manifest variables included in the LCA

SEP Manifest Variable	Response Options
…a hobby or leisure activity *(Hob)*	Have; don't want or need; can't afford
…a small amount of money to spend on yourself each week *(Self)*	Have; don't want or need; can't afford
…a holiday from home for at least one week once a year *(Hol)*	Have; don't want or need; can't afford
…to keep home warm enough during winter *(Warm)*	Have; don't want or need; can't afford
…money to replace or repair major electrical goods *(Elec)*	Have; don't want or need; can't afford
…household contents insurance *(Ins)*	Have; don't want or need; can't afford
…to keep home in decent state of decoration *(Dec)*	Have; don't want or need; can't afford
…to make regular savings of £10 a month *(Save)*	Have; don't want or need; can't afford

2.2.3 Ethnicity

The present analyses were conducted on individuals who self-reported as White British or Pakistani during the baseline questionnaire. These ethnicities represent 47% and 53% of the sample in this study respectively. Only these two ethnic groups were included due to the relatively small sample size of the “Other” ethnic group within the BiB cohort and its heterogeneous nature (Fairley et al., 2014).

2.2.4 Statistical Analysis

All latent class analyses were conducted using the `poLCA` package (Linzer & Lewis, 2011) in R (R Development Core Team, 2020). It was not necessary to conduct the Full Information Maximum Likelihood (FIML) approach manually as missing values are not included in analyses by default within the `poLCA` package. This is in contrast to Fairley et al. (2014) who used FIML to deal with missing data. Instead, as advised by Linzer and Lewis (2011), the present study derived each model by multiple re-estimations to increase the confidence that the global maximum, rather than local maximum of the log-likelihood function was found. Unlike global maxima, the local maximum of a latent model can vary depending on starting values which is not ideal for accurate estimation of latent models (Vermunt & Magidson, 2004). Both methods are commonly used to perform LCA, and this was the only deviation from the analytical approach taken within the original analysis reported by Fairley et al. (2014).

Two independent latent class analyses were conducted, one for the White British and another for the Pakistani group, to identify and compare differences in the latent structure of SEP across ethnic groups. To determine how many classes were to be retained in each model, log-likelihood, Bayesian Information Criterion (BIC; Schwarz, 1978) and entropy were examined. A larger log-likelihood is suggestive of better fit, with the maximum log-likelihood being desired. The maximum log-likelihood is reached when the log-likelihood “ceases to increment beyond some arbitrarily small value” (Linzer & Lewis, 2011, p. 4). BIC is a model fit statistic whereby a lower value is indicative of more preferred model fit, and has been found to be the most appropriate criterion to use (Nylund et al., 2007). Entropy is a measure of uncertainty or randomness, with lower values suggesting there is less variability between each latent class (Larose et al., 2016). Thus, a value closer to one indicates better fit as each class is considered more distinct.

Individuals were then classified into their most likely SEP class using posterior membership probability. This refers to the probability of an individual belonging to a latent class based on item responses from each manifest variable (Vermunt & Magidson, 2004). This probability is calculated by the package using Bayes' formula (Linzer & Lewis, 2011).

2.3 Results

Two independent latent class analyses were conducted, one for the White British and one for the Pakistani sample. The entropy, BIC and log-likelihood values used to determine the most suitable model are reported in Table 2 and Table 4.

2.3.1 Pakistani sample

Based on the model fit statistics (see Table 2), a four-class model was selected as being most appropriate fit for the data as the entropy value; which should be as close to one as possible; was higher for the four-class model, compared to a three- or five-class model.

When compared to Fairley et al. (2014), the latent structure was generally replicated, albeit with slightly different proportions and minor differences, likely due to due to the small difference in sample sizes (explained in Section 2.2.1). Amongst the minor differences were whether mothers were likely to be behind with bill payments and housing tenure in the Most Deprived group. Fairley et al. (2014) suggested that it was most likely that women in this latent class were in social housing, yet the present analysis suggested it was most likely that the women had a mortgage. For the “behind on bills” variable, the original manuscript suggested that women *were* behind with their bills, yet the present analysis found that all mothers were up to date, regardless of their latent class membership. However, while there were minor differences for some of the items, as expected, generally the interpretations were similar.

Table 2

Model fit statistics for Latent Class analysis models for the Pakistani sample

Model	Entropy	BIC	Log-Likelihood
1	1	174160.1	-86746.90
2	0.83	165304.7	-81981.77
3	0.76	163776.3	-80880.12
4	0.78	162698.6	-80003.84
5	0.74	162599.1	-79616.67
6	0.76	162582.3	-79270.84

See Table 3 for a breakdown of how each SEP manifest variable contributed towards each latent class for the Pakistani sample, noting that the corresponding descriptions of each of these manifest variables (and the abbreviations used here) can be found by referring back to Table 1.

Table 3

Description of each latent class from a 4-class model (Pakistani sample) [continues on next page]

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Class Size (%)	2107 (23%)	1367 (9%)	1170 (41%)	484 (27%)
Class Characteristics *(based on posterior probability)*				
Manifest Variable				
Mother's LoEm	Currently employed	Never employed	Never or previously employed	Never employed
Father's LoEm	Non-manual employment	Manual and non-manual employment	Manual employment	Manual employment
MTB	Not receiving means-tested benefits	Moderate receipt of means-tested benefits	Moderate receipt of means-tested benefits	High receipt of means-tested benefits
HT	Mortgage	Mortgage or living rent-free	Mortgage or owns outright	Mortgage
Mother's LoEd	Highly educated	Medium level of education	Low level of education	Low level of education
Father's LoEd	Highly educated	Medium level of education	Low level of education & high don't know response	Mixed responses

[Continued]

Table 3 [continued]

Description of each latent class from a 4-class model (Pakistani sample)

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Bills	Up to date with bills	Up to date with bills	Up to date with bills	Up to date with bills
SubPov	“Living comfortably” or ”doing alright”	“Doing alright”	“Doing alright”	“Just about getting by”
Shoes	Can afford two pairs all-weather shoes	Can afford two pairs all-weather shoes	Can afford two pairs all-weather shoes	Can afford two pairs all-weather shoes
Furn	Can afford to replace worn out furniture	Don’t want/need to keep furniture in good repair	Can afford to keep furniture in good repair	Cannot afford to keep furniture in good repair
FF	Can afford family/friends over for a drink/meal at least once a month	Can afford to have family/friends round once a month	Can afford to have family/friends round once a month	Can afford to have family/friends round once a month
Hob	Can afford to have a hobby or leisure activity	Can afford/don’t want to have a hobby	Can afford/don’t want to have a hobby	Can afford/don’t want to have a hobby

[Continued]

Table 3 [continued]

Description of each latent class from a 4-class model (Pakistani sample)

	Class 1 (Least Deprived)	Class 2	Class 3	Class 4 (Most Deprived)
Self	Can afford a small amount of money to spend on self each week	Can afford a small amount of money to spend on self	Can afford a small amount of money to spend on self	Mixed response for affording small amount of money to spend on self
Hol	Can afford a holiday from home	Cannot afford/don't want a holiday	Cannot afford/don't want a holiday	Cannot afford a holiday
Warm	Can afford to keep home warm during winter	Can afford to keep home warm	Can afford to keep home warm	Can afford to keep home warm
Elec	Can afford to replace/repair major electrical goods	Don't want/need to keep electrical items in good repair	Can afford to keep electrical items in good repair	Cannot afford to keep electrical items in good repair
Ins	Can afford home contents insurance	Mixed response for affording home contents insurance	Can afford home contents insurance	Mixed response for affording home contents insurance

[Continued]

Table 3 [continued]

Description of each latent class from a 4-class model (Pakistani sample)

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Dec	Can afford to keep home in good decoration	Can afford to keep home in good decoration	Can afford to keep home in good decoration	Mixed response for affording to keep home in good decoration
Save	Can afford to make regular savings	Can afford to make regular savings	Can afford to make regular savings	Mixed response for affording to make regular savings

2.3.2 White British sample

The same process was repeated for the analysis of the White British sample. Again, a four-class model was selected based on the model fit statistics (see Table 4). Although the BIC was smaller with the addition of a fifth class, this was very slight. In addition, the percentage change of the log-likelihood was less than 1%, in comparison to a 1.49% difference between a three- and four-class model and a 2.3% difference between a two- and three-class model. Where there are only arbitrary differences with the inclusion of an additional class, it is generally considered good practice to select the model with fewer classes (L. M. Collins & Lanza, 2009; Fairley et al., 2014). Therefore, the four-class model was deemed most appropriate. Only one minor difference was found between the current results and those from Fairley et al. (2014): the current analysis suggested a moderate proportion of White British women receiving means-tested benefits in Class 3, the second most deprived category. Meanwhile, Fairley et al. (2014) suggested this was a high proportion. The distribution of all other indicators was identical.

Table 4

Model fit statistics for Latent Class analysis models for the White British sample

Model	Entropy	BIC	Log-Likelihood
1	1	150230.4	-74787.23
2	0.90	134495.9	-66587.80
3	0.85	132084.4	-65049.91
4	0.85	130804.8	-64077.92
5	0.86	130297.9	-63492.32
6	0.85	130079.6	-63050.97

See Table 5 for a breakdown of how each SEP manifest variable contributed towards each latent class for the White British sample, noting that the corresponding descriptions of each of these manifest variables (and the abbreviations used here) can be found by referring back to Table 1.

Table 5

Description of each latent class from a 4-class model (White British sample) [Continued over next pages]

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Class Size (%)	1935 (42%)	723 (16%)	977 (22%)	854 (19%)
Class Characteristics *(based on posterior probability)*				
Manifest Variable				
Mother's LoEm	Currently employed	Currently employed	Currently or previously employed	Previously employed
Father's LoEm	Non-manual employment	Non-manual employment	Manual or non-manual employment	Manual employment or unemployed
MTB	Not in receipt of means-tested benefits	Not in receipt of means-tested benefits	Moderate level of receipt of means-tested benefits	High receipt of means-tested benefits
HT	Mortgage	Mortgage	Private renting or social housing	Private renting or social housing
Mother's LoEd	Highly educated	Moderately educated	Low levels of education	Low levels of education

[Continued]

Table 5 [continued]

Description of each latent class from a 4-class model (White British sample)

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Father's LoEd	Highly educated	Moderately educated	Low levels of education with high don't know response	Low levels of education with high don't know response
Bills	Up to date with bills	Up to date with bills	Up to date with bills	Some behind on bills
SubPov	"Living comfortably" or "doing alright"	"Doing alright" or "just about getting by"	"Doing alright"	"Just about getting by"
Shoes	Can afford two pairs of all-weather shoes	Can afford two pairs of all-weather shoes	Can afford two pairs of all-weather shoes	Can afford two pairs of all-weather shoes
Furn	Can afford to keep furniture in good repair	Cannot afford to keep furniture in good repair	Can afford to keep furniture in good repair	Cannot afford to keep furniture in good repair

[Continued]

Table 5 [continued]

Description of each latent class from a 4-class model (White British sample)

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
FF	Can afford to have family/friends round once a month	Can afford to have family/friends round once a month	Can afford to have family/friends round once a month	Can afford to have family/friends round once a month
Hob	Can afford to have a hobby	Can afford or don't want to have a hobby	Don't want to have a hobby	Mixed response for affording to have a hobby
Self	Can afford a small amount of money to spend on self	Can afford a small amount of money to spend on self	Can afford a small amount of money to spend on self	Cannot afford a small amount of money to spend on self
Hol	Can afford a holiday	Mixed response for affording a holiday	Mixed response for affording a holiday	Cannot afford a holiday
Warm	Can afford to keep home warm	Can afford to keep home warm	Can afford to keep home warm	Can afford to keep home warm

[Continued]

Table 5 [continued]

Description of each latent class from a 4-class model (White British sample)

	Class 1 (Least Deprived)	**Class 2**	**Class 3**	**Class 4 (Most Deprived)**
Elec	Can afford to keep electrical items in good repair	Cannot afford to keep electrical items in good repair	Can afford to keep electrical items in good repair	Cannot afford to keep electrical items in good repair
Ins	Can afford home contents insurance	Can afford home contents insurance	Can afford or don’t want home contents insurance	Cannot afford or don’t want home contents insurance
Dec	Can afford to keep home in good decoration	Can afford to keep home in good decoration	Can afford to keep home in good decoration	Cannot afford to keep home in good decoration
Save	Can afford to make regular savings	Mixed response for affording to make regular savings	Can afford to make regular savings	Cannot afford to make regular savings

2.3.3 Comparing latent structures across ethnic groups

As Table 3 and Table 5 indicate, there are several differences in the latent structures for Pakistani and White British women. Firstly, a larger proportion of Pakistani women were classified in the “Most Deprived” latent class (27%), compared to their White British counterparts (19%). This difference was even more marked when comparing those in the Least Deprived group; 23% and 43% for Pakistani and White British, respectively. The following sections contrast the derivation of each class between the two ethnic groups and demonstrate how the measurement of SEP should consider ethnicity. It also illustrates how belonging to the “Most Deprived” group as a Pakistani individual does not subject one to the same socioeconomic circumstances as a White British individual in their respective “Most Deprived” latent class. Thus, these classes should only be used in split-group analysis to investigate within-ethnic group differences.

2.3.3.1 Employment

Pakistani mothers tended to be “never employed” in the Most Deprived class, in contrast to White British mothers, who were more likely to have been “previously employed”. Meanwhile, within this class, Pakistani fathers were more likely to be in manual employment. White British fathers were equally as likely to be in manual employment or unemployed. This implies that Pakistani fathers may be more likely to be in employment, albeit in lower-paid, lower-skilled occupations than their White British counterparts. Meanwhile, in the Least Deprived latent class, mothers were most likely to be currently employed and fathers in non-manual employment which was the case for both the White British and Pakistani samples. In summary, it was apparent that Pakistani mothers were generally less likely to be in current employment, regardless of their broader socioeconomic circumstances, suggesting that employment status alone would not be an accurate proxy measure of SEP.

2.3.3.2 Means-tested benefits

It was evident that both White British and Pakistani mothers had a higher chance of being in receipt of benefits in each respective “Most Deprived” class. However, there was still a moderate likelihood of Pakistani individuals being in receipt of benefits if in Class 2 (the second least deprived). In contrast, White British individuals classified into Class 2 were unlikely to be receiving benefits. This indicates that a larger proportion of Pakistani families are likely to be in receipt of means-tested benefits, whereas only the two most deprived classes of White British individuals are likely to be receiving such benefits.

2.3.3.3 Housing tenure

There were clear ethnic differences in the latent models regarding housing tenure. The analyses revealed that Pakistani individuals were more likely to own their home, either with a mortgage, or outright, irrespective of class. In contrast, there was a dichotomy in the White British sample. The two least deprived classes were most likely to have a mortgage and the most deprived groups in social housing or private rental property. These differences align with previous literature (Kelaher et al., 2009; Nazroo, 2003) and illustrate the limitations of using housing tenure as a single indicator of socioeconomic position.

2.3.3.4 Education

There were many more similarities between the two ethnic groups regarding education. It was evident that the least deprived groups showed the highest levels of education, with this reducing with increasing deprivation. Interestingly, for both ethnic groups, the two most deprived latent classes indicated that the education level of the father was commonly unknown. These findings suggest that parental education levels may be an appropriate indicator of SEP in a bi-ethnic sample as this is comparable across the two groups. It also supports the use of parental education as an indicator when limited socioeconomic data are available, lending support to its use in future research. However, it is unclear to what extent this would apply to a multi-ethnic, as opposed to bi-ethnic, sample and it does not imply that this is suitable for use as a single indicator.

2.3.3.5 Bills

There was only one difference between ethnic groups on whether individuals were up to date with bills. It was apparent that all individuals were most likely to be up to date with their bills except for the most deprived class of the White British sample. This could be due to spending patterns or the increased number of White British individuals in rented housing. For example, recent research has suggested that "Asian" ethnic groups are less likely to hold "high-cost credit" products (e.g., car finance, payday loans or store credit) compared to "White" ethnicities (Financial Conduct Authority, 2021).

2.3.3.6 Subjective poverty

Regarding subjective poverty, there were few differences between the two ethnic-specific models. It was evident that for both groups, individuals from the Least Deprived class were most likely to state they were "living comfortably" or "doing alright" and the Most Deprived "just about getting by". Interestingly, within the second least deprived class for White British women, it was approximately as likely for individuals to respond, "just about getting by" or "doing alright". In contrast, the second least deprived class in the Pakistani group were most likely to be “doing alright”. Although arguably paradoxical, this does align with previous research using a multi-ethnic sample in the United States, in which Wolff et al. (2009) found that Black participants had higher perceived social status compared to their White counterparts, even when objective measures of social class showed no differences.

2.3.3.7 Material deprivation

Lastly, some ethnic differences were found with how items related to material deprivation fit in each of the latent classes. For example, there were more mixed responses across these 11 questions in the Pakistani group in the Most Deprived class, whereas in the White British model, mothers more consistently reported not feeling they could afford the item or activity (e.g., making regular savings, purchasing home contents insurance). Within Class 3 of both models (the second most deprived), White British individuals were more likely to spend money on a holiday, whereas there was a largely mixed response in the Pakistani sample. Otherwise, there were many similarities across the two groups. For example, in the Most Deprived group, neither ethnic groups felt they could afford to replace electrical items or furniture, or keep them in good repair. At the other end of the deprivation scale, ethnicities were also more similar, with none of the individuals classified into the Least Deprived group reporting being materially deprived, regardless of their ethnic group. Individuals in these groups were most likely to report that they were able to afford various “luxury” items such as holidays or having hobbies.

2.4 Discussion

The aim of the present study was to replicate the work of Fairley et al. (2014) to produce a multi-dimensional measure of socioeconomic position that is sensitive to ethnic differences. It was necessary to derive these measures for use in subsequent analysis within this thesis (see Chapter 5) because they were not available from the Born in Bradford Data Dictionary. For both White British and Pakistani groups, a four-class model was selected as the most appropriate structure, and the classes largely reflected those reported by Fairley and colleagues (2014), justifying these models. These analyses made it possible to assign a large sample of mothers to their most likely group membership based on their socioeconomic circumstances.

Whilst this was a replication study, there are some methodological limitations that should be noted. Firstly, there was a slight discrepancy in the proportions of each latent class reported here, compared to the original study. Although the same sample was used, a potential explanation for this could be the way in which missing data were treated. As previously mentioned, the `poLCA` package within the open-source statistical software R was used in the present study which treats missing values differently to the method used by Fairley et al. (2014). In the present sample, only cases with complete data were included, whereas Fairley et al. (2014) used a Full Information Maximum Likelihood (FIML) approach which uses estimations for missing data. Although slightly reducing the sample size, the current method estimates latent class membership on directly-observed variables only. This also explains why there are more discrepancies in the Pakistani proportions, as there are fewer fully-observed cases. A potential explanation is that cultural differences in reporting biases may mean Pakistani women were less willing, less likely to know, or less able to provide answers to all questions, particularly those related to finances - such as home insurance or savings (Prady et al., 2013).

Thus, whilst the results do not offer an exact replication, by conducting this analysis in open-source software, the code can be distributed for the use within further analysis and applications by other researchers. How these derived SEP latent classes impact upon children’s sensorimotor control will be explored in subsequent chapters.

Chapter 3 Improving interpretability and reducing noise of kinematic data: A Principal Components Analysis

3.1 Introduction

3.1.1 Movement kinematics

Movement kinematics have been measured as early as the 19th century when the Edison pen was used to measure speed of hand movement (Binet & Courtier, 1893). Measuring *how* a movement is performed; referred to as "process-oriented" assessment (Eddy et al., 2020; Logan et al., 2018) offers a deeper level of description of children's sensorimotor control. Such measures have a number of advantages over more traditional measures of assessment known as "product-oriented" measures. Product-oriented measures focus on the achievement or outcome of specific skills, such as successfully catching a ball or the time it takes to run a set distance (Eddy et al., 2020; Logan et al., 2018).

3.1.2 Benefits of kinematic assessment

3.1.2.1 Dimensionality

Traditional standardised assessments of motor skills generally measure motor performance in terms of "product-oriented" outcomes, such as the widely used Movement ABC-2 (MABC-2; Henderson et al., 2007) and BOT-2 (Bruininks & Bruininks, 2005). Whilst these measures; particularly the MABC-2, are recommended for use as diagnostic tools for the identification of disability (e.g., Developmental Coordination Disorder), they are limited in the level of detail they provide (R. Blank et al., 2012; Culmer et al., 2009; L. J. B. Hill et al., 2016). For example, such assessments only provide a simple dichotomous outcome which determines whether a task has been completed successfully, or not (Logan et al., 2018). They also tend not to measure motor control along a continuum.

Once scores are produced for each child, they are compared against “norms”, collated from a normative sample. Normative samples represent what is “typical” for a given population (e.g., children of a particular age range) and are used as a reference group (O’Connor, 1990; Ware & Keller, 1996). Taking the MABC-2 as an example, thresholds at the bottom 5^{th} and 15^{th} percentiles are suggested as representing “impairment” and “at-risk” of impairment, respectively (Venetsanou et al., 2011). For diagnostic purposes, this relatively sparse level of detail is often sufficient to open access to additional treatment and support, such as physiotherapy (Croft et al., 2015; Jutel, 2014). However, greater detail regarding *how* movement is executed across a range of abilities is not readily or easily obtainable using such methods.

An additional problem with normative data lies with the standardisation of these norms. The original MABC-2 norms were based on a sample of typically developing British children, however many studies have found cross-cultural differences, ceiling effects or differences in the factor structure when comparing to children from other countries. This has been demonstrated when comparing British or American norms to performance of children from: Israel (Engel-Yeger et al., 2010), Greece (Ellinoudis et al., 2008), Japan (Hirata et al., 2018; Miyahara et al., 1998), and Spain (Ruiz et al., 2003).

Ceiling effects lead to inaccurate assumptions of children’s abilities and limit the usefulness of such measures (Chow et al., 2006; French et al., 2018; Van Waelvelde et al., 2004). For example, when children are performing at ceiling level on a particular task, it is not possible to determine when a child’s limits have been reached. In addition, the MABC-2 has “stopping rules” in tasks that allow multiple attempts. Therefore, children who achieve maximum performance on their first attempt are less likely to experience, potentially confounding, mental or muscular fatigue compared to peers who require several attempts (French et al., 2018). As a result, subsequent tasks can be performed more optimally. For this reason, French et al. (2018) suggested that measures such as the MABC-2 are only useful for identifying *impairment* and have little utility in discriminating between children performing at the higher end of the spectrum of abilities. For example, Japanese children demonstrated ceiling effects in five out of eight test items of the MABC (Miyahara et al., 1998), with Chow et al. (2006) finding 92% of children reaching ceiling in a balance task (walking along a line with heels raised). Therefore, without sufficient modification of test items or the creation of culture-specific reference norms, the application of such measures to other, particularly non-clinical, populations may be limited.

Furthermore, subsequent refinement of scores obtained from such batteries may be inadequate and oversimplified. Whilst tasks in a battery may reflect various aspects of sensorimotor control and their various mechanisms, the scores derived from the number of successfully completed tasks are often averaged to produce an overall test-battery score. For example, the BOT-2 (Bruininks & Bruininks, 2005) consists of a range of subtests, yet performance is often reduced to a simple “Total Motor Composite” (e.g., Martinez Hernandez & Caçola, 2015). Thus, more detailed information regarding which aspects of sensorimotor control a child is having the most difficulty with, or on which particular tasks, is lost.

On the contrary, kinematic measures offer the scope for measuring motor control dimensionally, providing a more nuanced insight of children’s abilities which reflect its heterogeneous nature (Zwicker et al., 2012). By measuring the fundamentals of sensorimotor control along a continuum, the need to produce numerous normative samples for various cultures and/or regions is no longer necessary.

Furthermore, many neurodevelopmental disorders are now viewed and measured along a spectrum, such as Autistic Spectrum Disorder (Ousley & Cermak, 2014) and other forms of child psychopathology (A. Goodman & Goodman, 2009; R. Goodman, 1997). Kaplan and colleagues extend this view to DCD, suggesting this disorder too exists on a “continuum of severity” (B. Kaplan et al., 2006, p. 723). Thus, kinematic tools supporting the dimensional measurement of sensorimotor control may be more suitable and reflective of this condition’s dimensional nature.

3.1.2.2 Objectivity

In addition to supporting dimensional measurement, computer-recorded kinematic measurements are arguably more objective, minimising the influence of researcher bias. One method of recording movement kinematics is through computerised motion-capture devices. Such devices often use optoelectronic systems which rely on cameras picking up signals from multiple sensors (e.g., infra-red emitting diodes) placed on the body. Examples include the NDI Optotrak, Vicon MX (Vicon Motion Systems), and SMART-D system (Bioengineering Technology and Systems). These do not require subjective experimenter judgements and previous research has commended such devices for their high levels of accuracy, precision, and repeatability (Richards, 1999; J. Schmidt et al., 2009).

In contrast, children's motor ability is often assessed via parental reports such as the Denver Developmental Screening Test (DDST; Frankenburg & Dodds, 1967) or DCDQ'07 (B. N. Wilson et al., 2007). While parents offer a good overall insight of their child's development, they may not provide the most accurate indication of their child's motoric abilities when compared to performance-based motor assessments (Kennedy et al., 2011; Zysset et al., 2018). In support of this hypothesis, Blanchard et al. (2017) found that a reaching and grasping task was able to predict scores on the MABC-2, but not the DCDQ'07, suggesting parents' evaluations of their child's motor skills should be interpreted with caution.

Meanwhile, Kelly and colleagues administered a parent-informed questionnaire based on items from the DDST (Kelly et al., 2006). This measure classified children as presenting developmental delay based on parental perception of whether a series of motor milestones have been attained. Research suggests that the DDST has poor sensitivity, with limited concurrent and predictive validity (Cadman et al., 1984; Meisels, 1989). This, alongside the level of imprecision, subjectivity and potential bias that comes with parental reports of this nature suggest it may not be an appropriate measure of motor ability.

Other motor assessments use observation by trained researchers or clinicians to measure children's motor competence. However, such measures (e.g., the TGMD-2, MABC-2, and BOT-2) still depend on subjective human judgement. Even when conducted by trained clinicians or researchers, observational methods have been found to result in discrepancies between observers in up to 15% of cases (Smits-Engelsman et al., 2008). When combined with the previously discussed issues of dichotomous measurement, such discrepancies in judgement can lead to an increased chance of misclassification; potentially preventing access to therapeutic services, or incorrectly labelling a child as “impaired”. In addition, previous research has found differences in judgements of the same child using different observational motor assessments, with some findings showing more than 20% disagreement between the MABC-2, DCDQ’07, and BOT-2 (Crawford et al., 2001; van Hartingsveldt et al., 2005). Instead, kinematic assessments rely on objective metrics describing the characteristics of simple movement (e.g., acceleration, velocity), which are required in the execution of more complex actions (Cook et al., 2013). Thus, they cannot be influenced by an observer’s experience or expertise, or parental biases.

3.1.2.3 Specificity

As noted, kinematic assessment focuses on recording distinct components of movement which form the “building blocks” for more complex action. For example, Zoia et al. (2006) use 17 different kinematic parameters to fully describe a simple reach-to-grasp movement; breaking this fundamental sensorimotor task down into various phases (i.e., “reaching” component, “grasping” component). Thus, it was possible to identify participants’ abilities in each aspect of sensorimotor control required for such tasks.

Consequently, while product-oriented assessments are useful for the identification and diagnosis of children with a coordination disability (e.g., DCD), determining and analysing the entire *process* of movement offers additional value within the context of therapeutic intervention. To intervene appropriately and effectively, it is necessary to understand the specific aspects of sensorimotor control that are causing difficulty and preventing tasks being completed successfully (K. C. Collins et al., 2018; Raw et al., 2017). For example, a child may face difficulties with producing a smooth movement yet retain optimum temporal accuracy, or struggle with acceleration but exhibit excellent spatial accuracy. However, if the desired outcome is achieved, product-oriented tools would not detect impairment. Furthermore, if knowledge is obtained about *how* movement is sub-optimal, targeted interventions can focus on addressing these specific underpinning dimensions of sensorimotor control rather than generically focusing on training all components of the task as a whole.

Lastly, traditional product-oriented assessments often include tasks which are misrepresented as relatively simple. For example, the MABC-2 includes a ball-catching task where children are required to throw a ball against a wall and catch it. However, successfully catching the ball is also dependent on a successful throw, making it difficult to determine where the difficulties lie (Van Waelvelde et al., 2004). Because kinematic measures generally focus on recording very simple movements, they are less likely to be confounded by such complexities. Therefore, one could argue that to fully understand a child's sensorimotor control abilities and then to intervene appropriately, the capacity to break movement down into the specific kinematic parameters is essential.

3.1.3 Large-scale kinematic assessment

As discussed in Chapter 1, large cohort studies (e.g., BiB, ALSPAC) are incredibly useful tools for gaining broad insights into various aspects of health and the complex relationships that exist between them (Golding et al., 2001; J. Wright et al., 2013). The large samples in these studies make for incredibly powerful analyses, which may be difficult to acquire under standard experimental investigations due to limited resources and time. However, precise measurement of children's movement abilities at scale presents a plethora of challenges for researchers, which are discussed in the following sections.

3.1.3.1 Laboratory-based measures

Whilst the previously mentioned motion-capture devices offer an objective kinematic assessment of movement, they are not always the most feasible for large scale measurement. For example, devices such as the Optotrak are large, static devices, often needing dedicated or purpose-built laboratory space (Culmer et al., 2009). Schools are often used as a base for testing to take place in cohort studies, such as BiB, because they provide easy access to participants in a familiar environment. It is of course often impractical to transport large devices into community settings. In addition, motion-capture devices often rely on the placement of multiple sensors and/or cameras, requiring extensively trained researchers and technical support (Culmer et al., 2009). As a result, this also increases both the overheads and time taken to test each participant. Thus, with a finite number of resources, space, time and money in large cohort studies, such specialised technology is not practical.

3.1.3.2 Truncated measures

To overcome these issues, previous cohort studies, such as ALSPAC, have used truncated measures like the ALSPAC Coordination Test (ALSPAC-CT) to assess children’s motor skills at scale (Taylor et al., 2018). This is an adapted version of the aforementioned MABC, including only a handful of the original subtests: heel to toe walking, beanbag throw, placing pegs, and lace threading (Taylor et al., 2018). Several ALSPAC studies have used this version of the tool (Lingam et al., 2009a; Schoemaker et al., 2013; Taylor et al., 2018). Whilst using a shortened version of the task reduces administration time and can be conducted in community settings, additional methodological issues arise.

The main issues relate to how adaptation affects the tool's psychometric properties. Whilst the literature suggests that MABC and MABC-2 have high levels of validity and reliability (Ellinoudis et al., 2011; Schulz et al., 2011; Smits-Engelsman et al., 2008), these studies were conducted using the complete form. The development of the ALSPAC-CT was based on a principal components analysis, extracting the highest loading subtests for each of the three motor domains (balance, ball skills, and manual dexterity; Lingam et al., 2009). This suggests the included tasks are most representative of each domain. However, there were a number of subtests that also loaded highly yet were not included. Thus, it cannot be automatically assumed that the psychometric properties of the full MABC apply to a truncated version, such as the ALSPAC-CT.

Other truncated assessments have also been criticised for their inability to accurately represent the same domain as their long-form equivalent (Brahler et al., 2012; Carmosino et al., 2014; Jírovec et al., 2019; Mancini et al., 2020). For example, more than 30% of children identified with motor difficulties using the long-form BOT-2 were not recognised by the short form (Mancini et al., 2020).

Thus, whilst the ALSPAC-CT has a reduced administration time and is portable, there are questions regarding its validity, in comparison to the longer-form standardised assessments it was inspired by. Consequently, results arising from its use in large cohort studies should be interpreted with caution. In contrast, there are alternative assessments that could be used in large-scale community settings that address many of these limitations.

3.1.3.3 End-point kinematics

Motion-capture devices receive a large quantity of three-dimensional information from multiple electromagnetic or infra-red sensors across the body, up to 500 individual markers in some devices (Northern Digital Inc., 2020). As a result of the high level of precision and accuracy obtained, they are arguably the “gold-standard” in movement research (Ozkaya et al., 2018). However, as previously discussed, such devices are often impractical and expensive, particularly in large-scale studies (Culmer et al., 2009; Ozkaya et al., 2018). Therefore, more practical alternatives may be better suited for use within large, community-based samples such as cohort studies, even if this comes at the cost of comparatively reduced fidelity.

Digitised, tablet-based end-point kinematic measures have been used to provide objective measurement of motor control for over two decades (Smits-Engelsman & Van Galen, 1997). Rather than their three-dimensional counterparts, end-point kinematic measures record time-stamped two-dimensional Cartesian X-Y coordinates of hand movement which are then used to calculate an array of common kinematic metrics. This, as the name suggests, is achieved via a single “end-point” (i.e., a finger or hand-held stylus) to infer function of the entire upper limb and sensorimotor control system.

Although focused on hand movement, rather than the entire body, Culmer et al. (2009) argued that upper limb function influences hand movement, and that the hand is used as a reference in motor planning. This is supported by several commonly used kinematic assessments which are underpinned by more general sensorimotor control of the upper limbs. For example, efficient movement takes the least taxing route for the body which is usually the shortest movement trajectory (Nordin et al., 2014). Similarly, producing smooth movements requires appropriate muscle tone and joint torque (Nordin et al., 2014). Therefore, recording smoothness of end-point movement can indirectly measure general sensorimotor control and upper limb function. Thus, whilst tablet-based end-point kinematic measures do not *directly* capture movement of the entire limb to the same extent as their motion-capture counterparts, they still provide a useful indicator of sensorimotor control.

Similarly, as humans we naturally navigate through a three-dimensional world, and thus valuable spatial information of complex and dynamic movement cannot be obtained when using tablet-based two dimensional measures (Maykut et al., 2015). However, by removing the third dimension, the reliance on stereopsis (ability to perceive depth), is eliminated, thus focusing entirely on motoric ability. More applied tasks executed in three dimensions such as bead-threading in the MABC-2 risk placing children with lack of stereopsis or who have issues like amblyopia at a disadvantage (O'Connor et al., 2010; Suttle et al., 2011). Thus, whilst the depth of information regarding movement is reduced, there are some merits of reducing sensorimotor assessment to two dimensions due to the reduced risk of confounding factors exerting influence on results.

Furthermore, there are a number of practical benefits in using tablet-based kinematic devices. For example, tablet devices are highly portable and can be administered within classroom settings easily (Flatters, Mushtaq, et al., 2014). By "taking the lab to the school", researchers gain access to a larger pool of participants whilst causing minimal disruption to learning by negating the need to take children off-site (Alibali & Nathan, 2010). Using such devices, a number of studies have obtained sensorimotor data from larger samples (n >100) than would likely be possible with motion-capture devices (Accardo et al., 2013; L. J. B. Hill et al., 2014; Rosenblum et al., 2006).

On a similar note, administration times should be kept to a minimum, even when conducted in school settings to prevent additional disruption to learning. Traditional clinical measures of motor skills (e.g., MABC-2) can take up to an hour per assessment and can only be conducted on one child at a time. Likewise, the set-up of motion-capture devices is often lengthy, to ensure correct positioning of the sensors and cameras. In contrast, due to the vast quantity of sensorimotor data recorded and the ease of administration, tablet-based kinematic assessments can require as little as 12-15 minutes to obtain a detailed description of children's unimanual movements (Flatters, Hill, et al., 2014). Additionally, certain assessment tools require little specialist training to administer, and so can be deployed by research assistants, undergraduate students, or teachers. This contrasts with more clinical or laboratory-based measures, which often require administrators to undergo extensive training to gain sufficient technical expertise and/or accurately judge "acceptable" motor competence through observation. Consequently, tablet-based kinematic measures are more feasible in school-settings at a large scale.

While feasibility is important, the accuracy of end-point kinematic devices is arguably even more crucial. Previous literature has found that the temporal and spatial accuracy can be "on-par" with more sophisticated laboratory-based systems (Culmer et al., 2009). The Slurp Tool (previously named the Lee-Ryan Eye-Hand Coordination Test) uses an Apple iPad application to measure tracing ability (Junghans & Khuu, 2019; K. Lee et al., 2014). It has been found to have high temporal accuracy, with precision to 1000th of a second (Junghans & Khuu, 2019). Similarly, CKAT (Culmer et al., 2009) is sensitive enough to detect the small differences across kinematic outcomes that exist between males and females (Flatters, Hill, et al., 2014).

In conclusion, tablet-based end-point kinematic devices offer portable, process-oriented assessment of sensorimotor control with adequate accuracy that can be administered quickly and cheaply within community-settings. Thus, they are an appropriate choice for use within large-scale cohort studies.

3.1.4 Selecting the most appropriate kinematic variables

As discussed, end-point kinematic assessments record a series of time-stamped X-Y coordinates, producing hundreds, if not thousands, of individual data points for a single trial. Using these data, an array of kinematic variables can be derived which such measures have been praised for. However, a dilemma faced by researchers is determining which aspects of movement to focus on, and how to quantify (sensori)motor control using the wealth of data available. Thus, whilst there is some overlap across studies, there is no universal agreement on the metrics used or the names to describe them, creating inconsistencies within the motor control literature (Tran et al., 2018). In addition, the likelihood of "cherry-picking" metrics increases when such a large choice of kinematic measures is available (Murphy & Aguinis, 2019). For example, reviews have identified up to 49 kinematic variables of upper limb function, with another finding 17 commonly used specifically in end-point kinematic assessments (De Los Reyes-Guzmán et al., 2014; Tran et al., 2018).

In addition, even amongst similar aiming tasks, the metrics selected can vary widely. These can include: jerk; acceleration; movement time; peak velocity; reaction time, among others in various combinations (A. C. Cunningham et al., 2019; Flatters, Hill, et al., 2014; M. Heath et al., 1998; Hussain et al., 2018; Hyde & Wilson, 2011). As there are so many possibilities to describe movement, discrepancies sometimes occur even using the same measurement tool (e.g., Cunningham et al., 2019; Flatters, Hill, et al., 2014; Hill et al., 2016). Taking a simple reach-to-grasp task as an example, the upper-limb movements involved can be described in a plethora of ways. Movement Time could account for the time taken from the initial onset of movement through to coming to a complete stop, or it can be broken down further into phases within it (e.g., reaction time; time to peak speed; deceleration etc.).

Researchers select the variables considered most appropriate in describing performance on a task, however a large amount of variance reflecting sensorimotor control is likely not captured by any single variable (Hussain et al., 2019). The alternative, however, is equally unpalatable; to include tens of various kinematic metrics to describe performance on a single task, is usually not meaningful or practical. Striking the right balance between too few and too many metrics is particularly pertinent for clinicians and teachers, who need to understand where children's difficulties lie but may not possess the skills to interpret complex kinematic analyses (Rosenblum et al., 2006). Thus, a more nuanced, empirically driven approach in selecting the most suitable kinematic metrics to describe performance on sensorimotor tasks is necessary.

3.1.4.1 Principal Components Analysis

Principal Components Analysis (PCA) is a data reduction technique which aims to determine which variables or metrics within a large dataset explain the largest amount of variance of an attribute or variable (Jolliffe, 2002; Ringnér, 2008). Previous work has used PCA to identify the most valuable metrics collected by the KINARM (a robotic tool to study upper-limb motor control) to explain sensorimotor functioning in stroke survivors (Wood et al., 2018). It was found that up to 20 items per task could be reduced to three to five independent components; reducing the amount of data described by 67-79% (Wood et al., 2018). Consequently, it became clearer which elements of the task should be retained for use in subsequent analyses, and which were redundant, adding unnecessary noise to the data. Similar studies have been conducted using PCA on a range of movement assessments, finding many kinematic variables can be reduced to a smaller number of independent components (Hinkel-Lipsker & Hahn, 2018; Matsuura et al., 2019; Sandlund et al., 2017). Using such methods reduces the ambiguity surrounding selection of kinematic metrics to analyse.

PCA is one of the most common methods of unsupervised dimensionality reduction which aims to reduce a large number of correlated variables into new, uncorrelated principal components (Jolliffe, 2002; Ringnér, 2008; Van Der Maaten et al., 2009). Principal components are "linear combinations of the original variables" (Ringnér, 2008, p. 303) containing a large amount of the variance in the original dataset (Jolliffe, 2002). PCA is favoured over other methods such as Exploratory Factor Analysis (EFA) when the variables are thought to be "causal or formative indicators of the over-arching construct rather than reflective effects of it" (Wood et al., 2018, p. 2). EFA is typically employed when the underlying constructs cannot be measured or observed directly so rely on the derivation of hypothetical constructs (Cattell, 1973; Yong & Pearce, 2013). For example, screening tools for mental health diagnoses use directly observable symptoms to describe and categorise diagnoses like depression and anxiety (Timothy A. Brown et al., 1997). In contrast, items within PCA *are* directly measured but are reduced into a simpler form. Although alternative, non-linear techniques have been developed to address some limitations of existing methods, comparisons of dimensionality reduction techniques have shown PCA is superior to competitor methods across various datasets (Van Der Maaten et al., 2009).

3.1.5 The present study

Within the present thesis, sensorimotor control was assessed using CKAT. As described in Chapter 1, this is a tablet-based device which aims to measure sensorimotor processing via uni-manual interactions with a hand-held stylus (Culmer et al., 2009; A. C. Cunningham et al., 2019; Flatters, Hill, et al., 2014). Despite being subject to similar limitations of end-point kinematic measures already discussed, CKAT was deemed an appropriate choice due to its applicability for use in large-scale community-based settings. CKAT shares several strengths common to kinematic assessment batteries (particularly its portability, accuracy, quick administration, and minimal need for specialist training).

Like all kinematic assessments, CKAT generates an array of kinematic metrics, and it is currently not clear which are most appropriate and/or necessary in quantifying children's sensorimotor control. Across the three tasks, there are 13 different metrics obtained (see Table 7), equating to a plethora of data made available to researchers. For example, the Aiming task, records eight metrics for each of the 75 aiming movements produced. One full CKAT assessment battery produces a dataset of over 600 metrics per participant. This is an unrealistic number of independent measures to analyse on a trial by trial basis, and not useful for interpretation and dissemination. Currently, researchers select a handful of metrics *a priori*, which are argued, on theoretical grounds, to be the most appropriate measures of children's sensorimotor control within the given sub-tasks (e.g., Cunningham et al., 2019; Flatters, Hill, et al., 2014; Flatters, Mushtaq, et al., 2014; Giles et al., 2018; Raw et al., 2017). However, these metrics are not always consistent across studies and justification for these selections has, until now, not been motivated directly by empirical evidence.

Furthermore, the metrics selected are sometimes then simplified further by averaging performance across the three tasks to produce a single "overall" measure (e.g., Hill et al., 2016). Similar to the issues discussed earlier in truncating measures (see section 3.1.3.2), this may mask subtleties within the underlying mechanisms of sensorimotor control. For example, previous research has found significant relationships between sensorimotor control and various cognitive and academic outcomes (Giles et al., 2018; Simmatis et al., 2020). However, these relationships were task-specific; academic achievement was only consistently related to performance on a Steering task, but not with Aiming or Tracking tasks. If performance across independent tasks was compiled into a single measure, such relationships may have not emerged.

Consequently, the present study aims to use PCA to investigate how performance on CKAT can be most suitably used to conceptualise sensorimotor control. It aims to strike an appropriate balance between accounting for a large amount of variability in sensorimotor control from the many kinematic metrics the tool records, whilst limiting noise and redundant information.

3.2 Methods

3.2.1 Participants

The present study is a secondary data analysis of a dataset compiled from five previously published studies and dissertations (Berry, 2017; Flatters, Hill, et al., 2014; L. J. B. Hill et al., 2016; Sheridan, 2015; Shire, 2016). These data are described in more detail in Chapter 1. In total, 1740 participants were included in these analyses, with an age range of 4-12 years (M = 7 years, 10 months, SD = 2 years, 0 months). Participant demographics are displayed in

Table **6**. Participants were excluded from analysis for a particular task if more than one data point on any metric was missing. As such, the sample size for each task varied: Tracking (*n* = 1730), Aiming (*n* = 1323), and Steering (*n* = 1727). Ethical approval for the re-analysis of these data was granted by the University of Leeds ethics committee (Ethics reference: PSC-826).

Table 6

Sample demographics for the training dataset

Handedness	**Sex**		
	Male	Female	**Total**
Left	111	88	199
Right	749	786	1535
Unknown	2	4	6
Total	862	878	1740

3.2.2 Procedure

All data were collected between 2012 and 2014 from eight primary schools within Bradford. Detail of these data are described in Section 1.2.1.4.

3.2.3 Materials

CKAT was used to measure children's sensorimotor control via three tasks: Tracking, Aiming, and Steering which are described in detail below. It uses time-stamped X-Y coordinates of the stylus location which are recorded at a rate of 120 Hz to derive a range of task-relevant kinematic variables. During data collection, the preferred hand was used to complete the battery, with the device placed in front of the child, horizontally orientated and approximately 10 centimetres from the edge of the table. In total, CKAT takes 12-15 minutes to complete. Testing was conducted on a Toshiba tablet PC (Portege M700-13P). A description of each of the kinematic variables recorded by CKAT and the task which captures them is included in Table 7.

Table 7

Description of each kinematic variable automatically calculated by the Clinical-Kinematic Assessment Tool [continues on next page]

	Metric	Metric Category	Description
All Tasks	Normalised Jerk	Dynamic	Movement smoothness. A time-derivative of acceleration
	Path Length Time	Temporal	Time taken to create path length
	Path Length	Spatial	Distance travelled from start to end of movement
Task-Specific			
Tracking & Steering	Path Accuracy	Spatial	Measure of spatial errors against a reference trajectory

[continued]

Table 7 [continued]

Description of each kinematic variable automatically calculated by the Clinical-Kinematic Assessment Tool [continues on next page]

	Metric	Metric Category	Description
Aiming Only	Peak Speed	Temporal	Fastest speed reached within the movement (mm/s)
	Time to Peak Speed	Temporal	Time taken to reach peak speed (secs)
	Deceleration Time	Temporal	Amount of time from peak speed to end of movement (secs)
	Reaction Time	Temporal	Time between presentation of the stimulus & reaching a threshold of specified speed[1]
	Movement Time	Temporal	Time taken between movement first exceeding the velocity threshold then falling back below[1]

[continued]

[1] Velocity threshold is set at 50 mm/s.

Table 7 [continued]

Description of each kinematic variable automatically calculated by the Clinical-Kinematic Assessment Tool

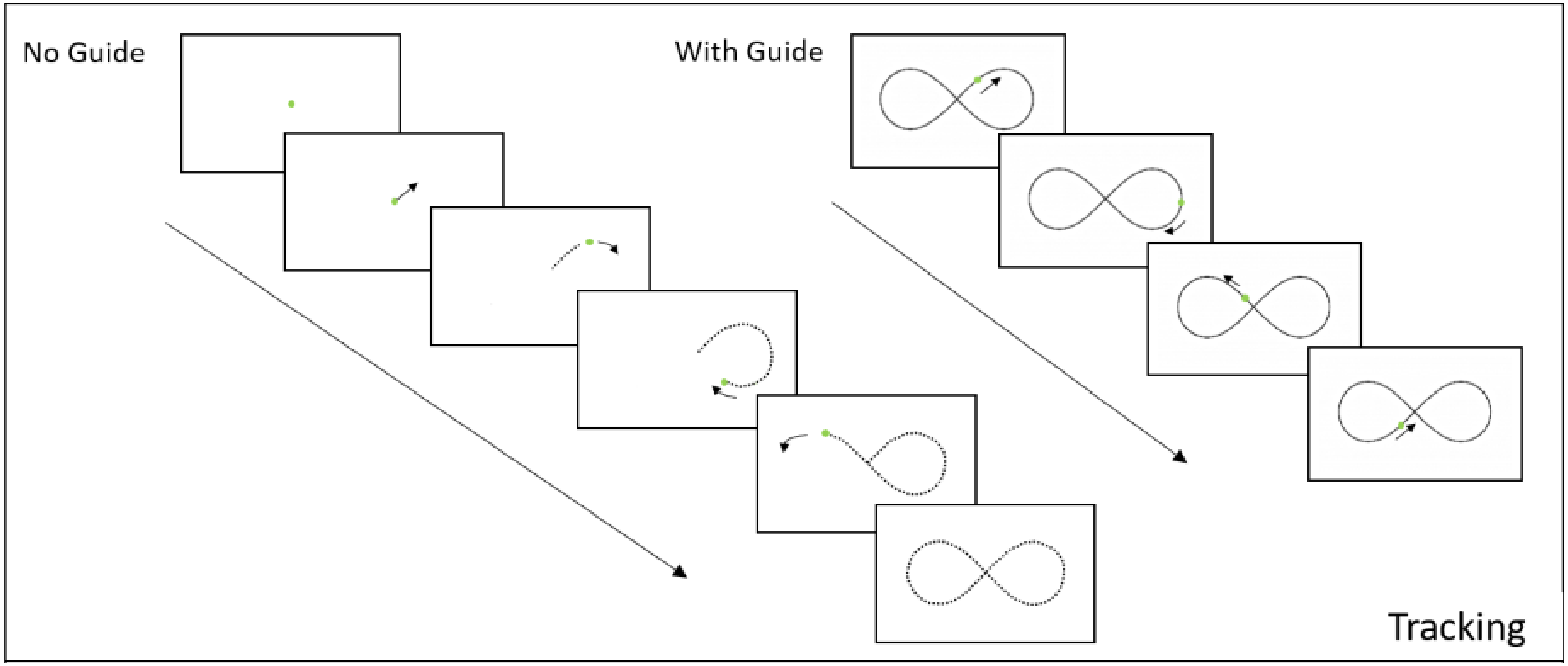
	Metric	Metric Category	Description
Tracking Only	X Gain	Dynamic	“Degree to which the movement corresponds to the target sine wave” on X axis (Culmer et al., 2009, p. 187).
	Y Gain	Dynamic	“Degree to which the movement corresponds to the target sine wave” on Y axis (Culmer et al., 2009, p. 187).
	Mean RMSE	Dynamic	Amount of error related to both temporal & spatial accuracy in comparison to reference trajectory
	Standard Deviation of RMSE	Dynamic	The SD of all RMSE measurements across conditions (i.e., amount of variability in tracking errors)

3.2.3.1 Tracking

The first sub-task is Tracking which requires participants to use the stylus to track a moving red dot around the screen in a series of sinusoidal waves. It consists of two conditions; related to the presence or otherwise of a visual guide that indicates the target's trajectory (shown in Figure 2). The "No Guide" condition is completed first, with three revolutions completed at three variable speeds: slow, medium, and fast (nine trials in total). These speeds of the target are 42, 84, and 168 mm/s, respectively and it takes 84 seconds in total to complete the nine revolutions. The same procedure is then repeated for the "With Guide" condition but this time with the assistance of the visual guide. This provides additional spatial information to predict target trajectory and facilitate performance. However, the ability to take advantage of this additional spatial information has been previously found to be dependent on participant age and target speed (Ferguson et al., 2015; Flatters, Hill, et al., 2014). At slower target speeds, this information can be used more effectively, and it is of greater benefit to older children, who generally possess a greater degree of sensorimotor control (Flatters, Hill, et al., 2014).

Figure 2

Infographic of the Tracking task on the Clinical-Kinematic Assessment Tool

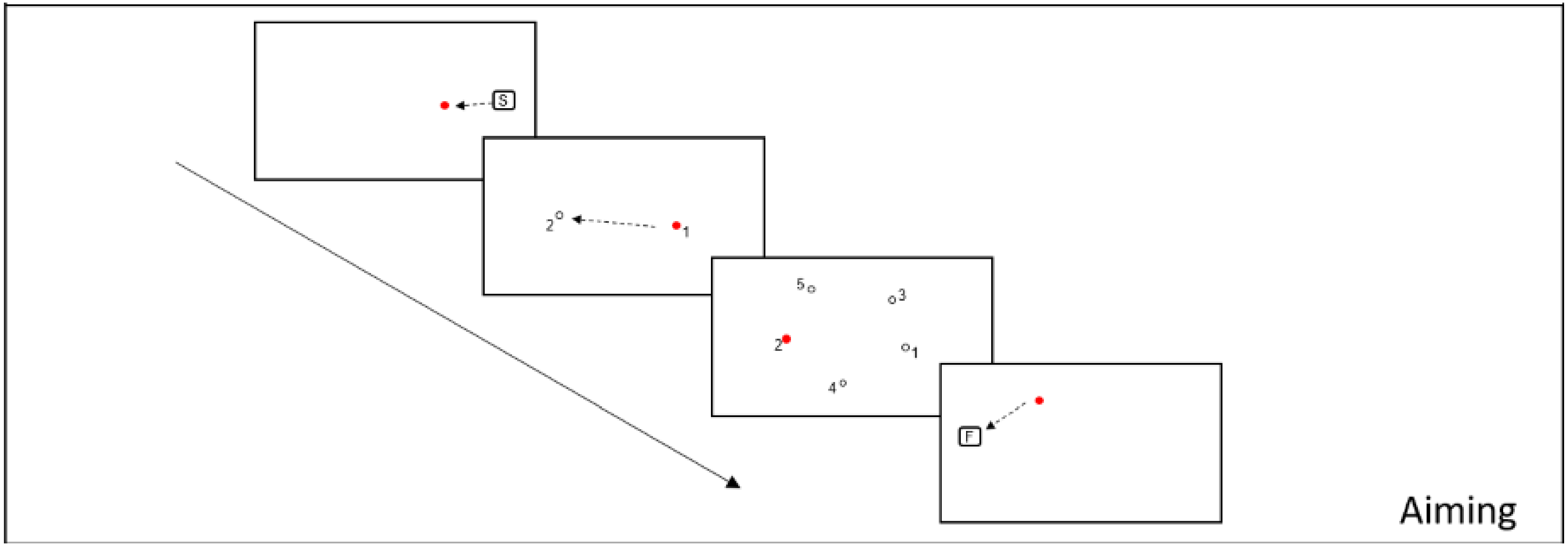


3.2.3.2 Aiming

The second task in the battery, Aiming, requires participants to make a series of 75 aiming movements, as quickly and accurately as possible, towards individually presented targets that appear sequentially in a pseudo-randomised order. As shown in Figure 3, these aiming movements take the form of a pentagram but, unlike the With Guide condition of the Tracking task, no visual guide is provided. Upon arrival at each target, the target disappears and is immediately presented in a new target-location. Participants are required to keep the stylus in contact with the screen throughout the task. The first 50 of these movements are constant, totalling ten repetitions of the pentagram shape. The final 25 movements incorporate a “Jump” condition. Six trials within this condition were included where the target location changes to the next in sequence as the participant reached 40mm from the target (accounting for 12 aiming movements). This required the execution of an online corrective movement (Flatters, Hill, et al., 2014). These trials were included to reduce the predictability of the sequence and ensure participants treat each trial as an independent movement. These “Jump” trials were pseudo-randomly interspersed between 13 standard aiming movements, referred to hereafter as “Embedded-Baseline” trials. These were identical to those within the Baseline condition (i.e., the target did not change location), thus negating the need to make an additional online correction. Thus, the Aiming task comprised three target presentation types, which were included as independent conditions within the present analyses: Baseline, Jump, and Embedded-Baseline.

Figure 3

Infographic of the Aiming task on the Clinical-Kinematic Assessment Tool

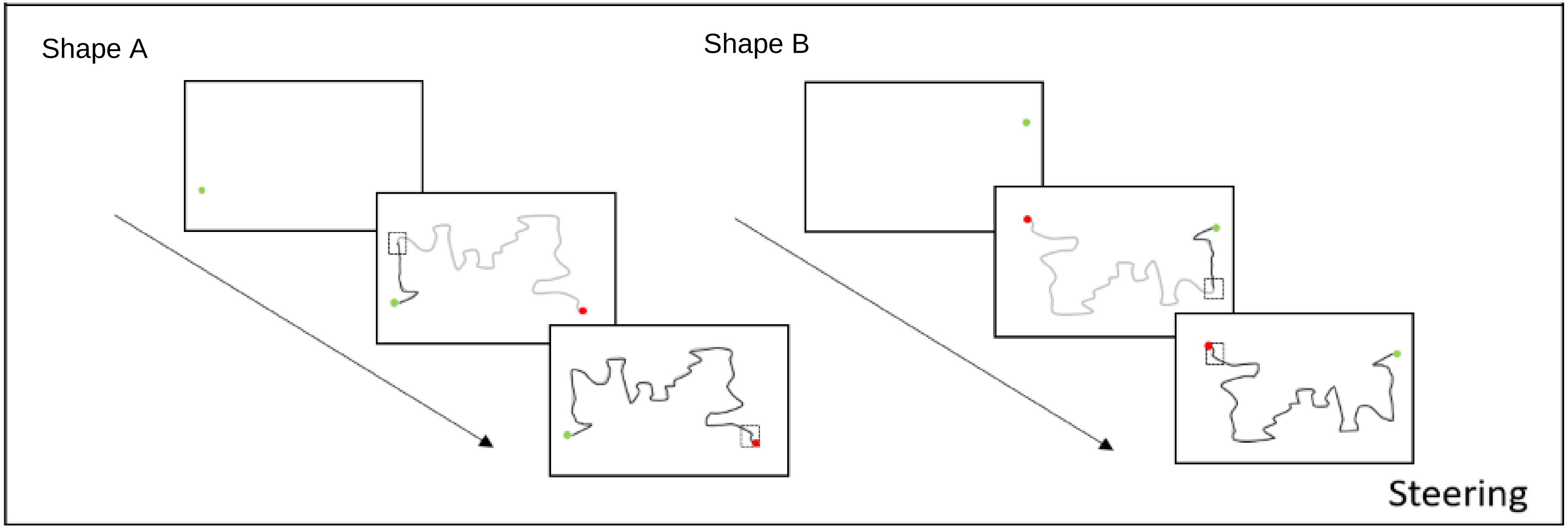


3.2.3.3 Steering

The final task, Steering (previously referred to as "Tracing"; see Flatters, Hill et al., 2014) requires participants to accurately trace an abstract path (5mm wide) from the left to right side of the screen (see Figure 4). During this task, participants are also required to keep within a box which moves sequentially along the path every five seconds to constrain movement speed. This was included with the intention to prevent a speed-accuracy trade-off (Flatters, Hill, et al., 2014). Within this task, there are two conditions: "Shape A" and "Shape B" which are identical in shape but are mirrored vertically (see Figure 4). In the original version of the CKAT battery (Flatters, Hill, et al., 2014), each shape is presented three times in alternate order (i.e., A, B, A, B, A, B); six trials in total. However, to limit the duration of testing within the Starting School and Primary School Years sweeps, this was truncated to contain just one trial from each condition within these versions of CKAT (Shape A and B).

Figure 4

Infographic of the Steering task (Shape A and Shape B conditions) on the Clinical-Kinematic Assessment Tool



3.2.4 Statistical Analysis

3.2.4.1 Data Cleaning

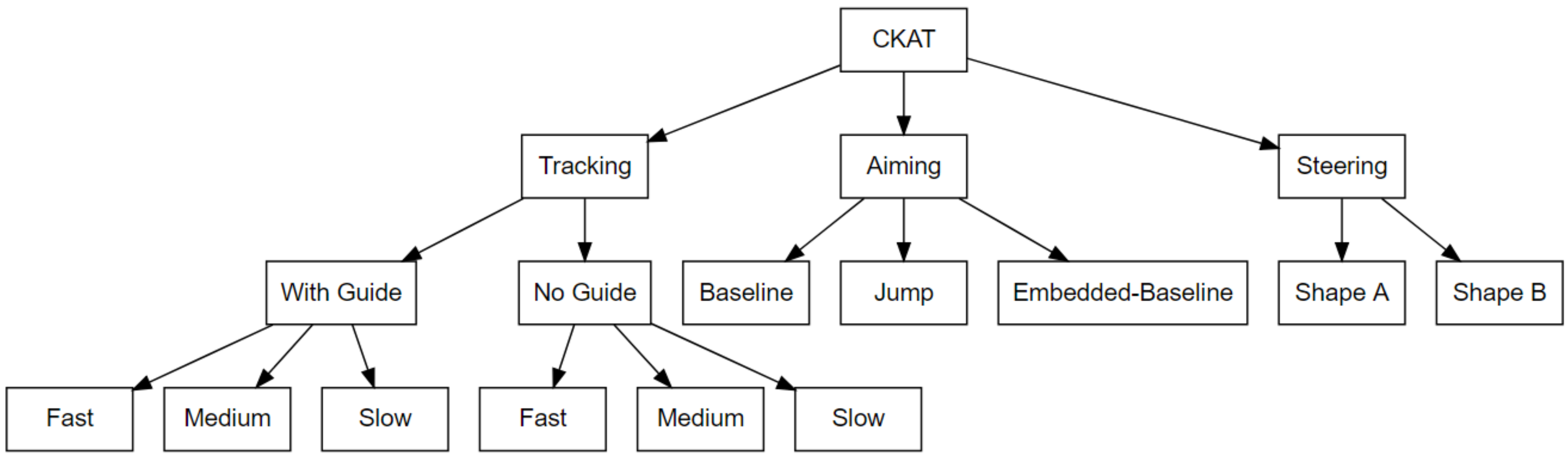
Prior to analysis, a mean value was calculated for each metric within each task, and within each condition within a task (e.g., a mean value for Peak Speed of the Jump trials within the Aiming task). The justification for this was to minimise the measurement error associated with random trial-to-trial variability. Therefore, the analysis would be more representative of children's general sensorimotor performance and not influenced by random or outlying data points (potentially arising due to temporary fluctuations in the equipment's sampling rate).

In addition, as previously described, the Steering task originally contained three trials of each condition (Shape A and Shape B). However, in subsequent data collection within the Born in Bradford project, due to time limitations, this task was truncated to just one trial per condition: reducing the number of trials from six to two. The present analyses aimed to build models that would be applied to the BiB data which used the truncated version of CKAT. Therefore, to ensure uniformity across the data and allow direct comparison, only the first trial from each condition with this task was analysed within the present study (two Steering trials in total).

Figure 5 breaks down the battery into each respective task and condition. Consequently, there were 42, 24, and 8 individual data points entered into the PCA for Tracking, Aiming, and Steering, respectively. To allow comparison across each metric, data were scaled and standardised. Throughout this chapter, note that "metrics" refer to the variable names (i.e., "Peak Speed" or "Movement Time") and "items" refer to individual data points from a specified condition (i.e., "Fast + No Guide: Path Length").

Figure 5

Flow diagram of the conditions included within each task of the CKAT battery



3.2.4.2 Principal Components Analysis

Prior to conducting the PCA, assumptions were checked. The Kaiser-Meyer-Olkin (KMO) test was used to verify the sampling adequacy for the analysis. Values for this statistic will lie between 0 and 1, with values below 0.6 are deemed "unacceptable" and those above 0.8 described as "meritorious" (Kaiser, 1974). In addition, KMO values for individual items are required to be greater than the acceptable limit of 0.5 (Kaiser, 1974). Bartlett's test of sphericity indicated whether the correlations between items were sufficiently large to conduct PCA.

PCA was conducted in R (Version 3.6.1; R Development Core Team, 2020) using the `psych` package (Version 1.9.12, Revelle, 2019). As discussed in Chapter 1, sensorimotor control encompasses a range of more specific behaviours, and each of the three CKAT tasks was designed to assess one of these more distinct fundamental behaviours within the domain of sensorimotor control. Thus, independent analyses were conducted for each task. This approach addresses previously discussed issues around reducing sensorimotor control, and wider motor skills assessment, which arise when performance gets collapsed into a single measure of "general motor skill", as has been used in previous assessments. Additionally, by not inputting all data points into a single analysis, it provides scope for investigating specific relationships between various developmental outcomes, distinct aspects of sensorimotor control, and underlying mechanisms.

3.2.4.2.1 Selecting the number of components to retain

To determine the number of components to retain, several criteria were assessed and contrasted: eigenvalues, scree plots, and cumulative variance explained. Component eigenvalues represent the relative share of total variance accounted for by that component (Finch et al., 2017). Kaiser's criterion suggests that eigenvalues greater than one are considered acceptable (Kaiser, 1974). However, Zwick and Velicer (1986) suggest that Kaiser's criterion should not be used in isolation and may lead researchers to inaccurately describe the underlying structure of data. Therefore, scree plots (Cattell, 1966) and cumulative variance were also examined. Scree plots (Figure 6, Figure 7, and Figure 8) demonstrate the eigenvalues visually on a line graph. Where the line begins to plateau, it suggests that including an additional component does not explain a substantial amount of additional variance. Lastly, the amount of cumulative variance a model explains was also examined. Jolliffe (2002) suggests a sensible threshold for cumulative variance is between 70 and 90%, although this can vary depending on the dataset in question. Cattell (1966) suggested that a "true number of factors to extract" does not exist (p.273), and thus interpretation of these three methods collectively is necessary to select the most appropriate number of components to retain. Where a consensus is not reached using the three criteria, multiple potential models may be tested and interpreted.

3.2.4.2.2 Interpretation of components

Once the number of components to be retained was selected, interpreting how each metric contributed to each component was determined via a two-stage process. The first stage involved examining component loadings. Metrics with component loadings greater than or equal to .50 were deemed to contribute a substantial amount of the variance of that component. Recommendations on what threshold to use varies across the literature, but Comrey & Lee (1992) suggest that loadings of 0.45 and above are "relevant", 0.55 are "good", and 0.63 "very good".

The second stage of interpretation involved reviewing these component loadings further alongside current theory. For example, in rare instances an item would load highly onto a component but a clear theoretical explanation for it doing so was not apparent. In other words, its loading appeared inconsistent with existing theory. The relevance of such items was investigated further in subsequent analyses. Considering component loadings are built upon mathematical models, Kellow does caution that the analyst is required to apply some “logical interpretation” in their analyses, rather than following strict and arbitrary criterion (Kellow, 2006).

3.2.4.2.3 Application of rotations

In addition, rotations were used to aid interpretability by transforming the coordinates of the component solution. This alters the loadings on each solution and often makes the loading patterns more distinct (Finch et al., 2017; Kellow, 2006; Yaremko et al., 1986). However, rotation does not adjust the amount of variance a component explains, it simply changes the dimensional space of the data (Kellow, 2006). There are two methods of rotation: Oblique and Orthogonal. The most appropriate to apply depends on the correlation between items (Tabachnick & Fidell, 2019). If the correlation between items is .32 or above (implying at least 10% shared variance), it is recommended that an oblique rotation should be applied (Tabachnick & Fidell, 2019). Conversely, in models where items are not considered to be sufficiently correlated, it is recommended that an orthogonal rotation is applied. For the two types of rotations, there are multiple options available (e.g., Oblimin, Varimax, Promax, Quartimax). Within the present analyses, Oblimin and Varimax were used for oblique and orthogonal rotations, respectively. Although Gorsuch (1983) suggests that the choice of rotation to be applied should not dramatically influence a clear structure, these respective methods were selected as they are among the most commonly used in the literature and most often recommended (Stevens, 1992; Tabachnick & Fidell, 2019).

3.3 Results

3.3.1 Tracking

As outlined in Section 3.2.3.1 (see also Figure 2), the Tracking task consists of two conditions: “With Guide” and “No Guide” referring to the presence of the visual guide. These two conditions are then each performed at three different speeds: “Slow”, “Medium” and “Fast”; resulting in a total of six conditions for the task. In addition, seven metrics (see Table 7) are captured for each of these conditions. As such, 42 items were entered into the PCA.

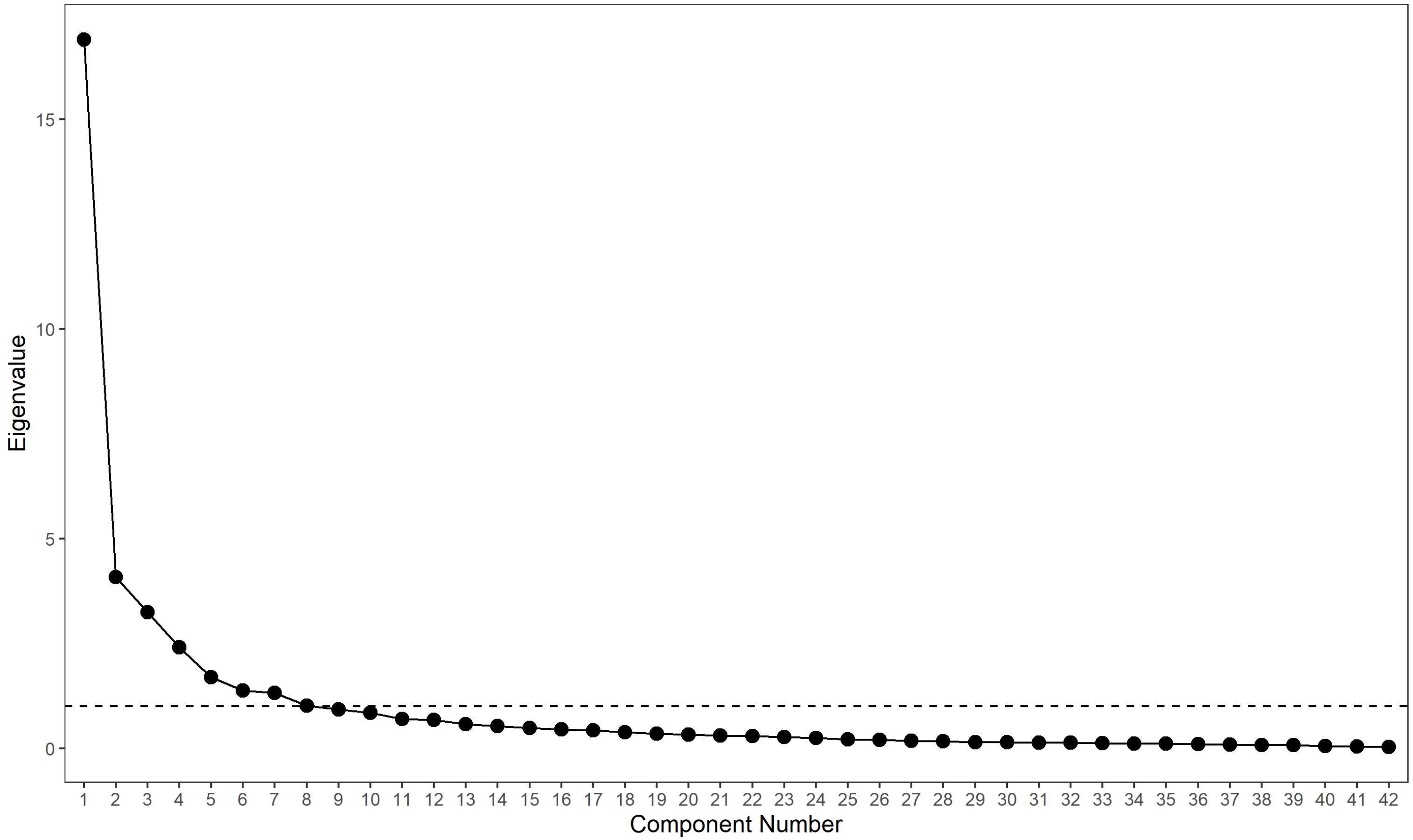
The KMO test verified the sampling adequacy, KMO = .93 (“marvellous” according to Kaiser, 1974). Bartlett’s test of sphericity indicated that the correlation between items was sufficiently high χ^2 (861) = 78216.3, p< .001.

3.3.1.1 Selecting components to retain

From the 42 items entered into the model, analyses revealed eight components that had eigenvalues above Kaiser’s criterion of one, explaining a total variance of 71%. The scree plot (Figure 6) was slightly ambiguous, showing inflexions that would justify retaining both seven and nine components. Given the large sample size, the convergence of the scree plot, proportion of variance explained, and Kaiser’s criterion, nine components were initially retained to be interpreted further.

Figure 6

Scree plot showing the number of components to be retained for the Tracking task



Note: Dashed line represents an eigenvalue of 1 on the Y axis.

3.3.1.2 Description of component loadings

Correlations between items indicated that an oblique rotation should be applied to aid interpretability of the component loadings. Refer to Table 8 for a breakdown of the component loadings following this rotation. Two of the eight components reflected performance on specific metrics across most of the six conditions: Path Length (Component 5), Normalised Jerk (Component 6). With the exception of one item (Fast + With Guide: Path Accuracy) inconsistently loading onto Component 5, these components consisted of only items related to each of these metrics. However, only on the Normalised Jerk component did items from all six conditions load sufficiently. The six remaining components were reflective of the six specific conditions within this task, with the same four metrics loading consistently on each: X Gain, Y Gain, Mean RMSE and SD of RMSE. One metric, Path Accuracy was not well accounted for in any of the components because it did not consistently load onto an independent component across all conditions, nor cluster with other metrics within one of the condition-specific components. This suggests that Path Accuracy does not appear to explain unique variance in kinematic performance within this specific CKAT task. The fit based upon diagonal values was .99, indicating a good model fit (Field et al., 2012).

Table 8

Component loadings on an eight-component model for the Tracking task following oblique rotation (N = 1730). [Continues on next pages].

	Component							
Item	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Slow + With Guide: Y Gain	**-.92**	-.01	.01	-.04	.07	.05	.03	-.03
Slow + With Guide: SD of RMSE	**.90**	.01	.03	.04	.02	.04	.04	-.01
Slow + With Guide: X Gain	**-.87**	-.05	-.01	-.08	.01	.01	.01	-.04
Slow + With Guide: Mean RMSE	**.85**	.06	.06	.09	-.08	-.02	.04	.03
Slow + With Guide: Path Length	.49	.00	-.02	-.01	.44	.18	-.03	.01
Slow + No Guide: SD of RMSE	.03	**.90**	.02	.00	.10	.11	-.02	.00
Slow + No Guide: X Gain	.06	**-.90**	-.01	-.01	.16	-.04	-.04	.04
Slow + No Guide: Y Gain	-.12	**-.86**	.01	.10	.03	.13	-.06	-.01
Slow + No Guide: Mean RMSE	.06	**.74**	.11	.09	.00	-.01	.14	.03
Slow + No Guide: Path Accuracy	.20	**.50**	.04	.04	.23	-.10	.12	.13

[continued]

Table 8 [continued]

Component loadings on an eight-component model for the Tracking task following oblique rotation (N = 1730).

	Component							
Item	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Fast + With Guide: SD of RMSE	.07	.01	**.80**	.02	.09	.01	.11	.00
Fast + With Guide: Path Length	.09	-.06	**-.79**	-.05	.33	-.03	.11	-.01
Fast + With Guide: Mean RMSE	.03	.06	**.78**	.08	.00	-.06	.07	.07
Fast + With Guide: X Gain	-.08	-.05	**-.77**	-.10	-.10	.04	-.01	-.08
Fast + With Guide: Y Gain	-.06	-.01	**-.75**	-.08	-.15	.01	-.05	-.06
Medium + With Guide: SD of RMSE	.05	-.04	.02	**.92**	.00	.08	.03	-.03
Medium + With Guide: Mean RMSE	.06	-.02	.11	**.85**	-.13	-.01	.06	-.01
Medium + With Guide: X Gain	-.09	-.03	-.03	**-.84**	-.05	.01	-.01	-.01
Medium + With Guide: Y Gain	-.11	-.01	.00	**-.80**	-.07	.03	-.03	.01

[continued]

Table 8 [continued]

Component loadings on an eight-component model for the Tracking task following oblique rotation (N = 1730).

	Component							
Item	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Medium + No Guide: Path Length	.07	-.02	.07	.06	**.78**	.06	-.13	-.07
Medium + With Guide: Path Length	.01	-.08	-.13	.02	**.66**	.09	.18	-.07
Slow + No Guide: Path Length	.12	.03	.01	.05	**.61**	.21	-.02	.13
Fast + No Guide: Path Length	.11	-.09	-.07	-.08	**.60**	-.05	.08	**-.58**
Fast + With Guide: Path Accuracy	-.05	.17	.24	.17	**.57**	-.05	.01	.19
Medium + With Guide: Path Accuracy	-.04	.14	.00	.45	.49	-.03	.04	.17
Slow + With Guide: Path Accuracy	.14	.16	.00	.26	.47	.00	.00	.15
Medium + No Guide: Normalised Jerk	-.05	.04	-.02	.01	.00	**.80**	.19	.02
Fast + No Guide: Normalised Jerk	-.05	-.04	-.05	.02	-.03	**.78**	-.04	.23
Medium + With Guide: Normalised Jerk	-.05	.04	-.03	.16	.03	**.74**	.05	-.04
Slow + With Guide: Normalised Jerk	.29	.09	-.07	-.01	.06	**.64**	-.02	-.01
Fast + With Guide: Normalised Jerk	.08	-.11	.45	-.24	.02	**.61**	.03	-.10
Slow + No Guide: Normalised Jerk	-.04	.48	-.05	.09	.11	**.54**	-.13	-.01

[continued]

Table 8 [continued]

Component loadings on an eight-component model for the Tracking task following oblique rotation (N = 1730).

	Component							
Item	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Medium + No Guide: Y Gain	-.06	-.06	.03	.02	.04	.06	**-.87**	-.01
Medium + No Guide: X Gain	.10	-.08	.02	-.04	.21	-.04	**-.80**	-.10
Medium + No Guide: SD of RMSE	.05	.02	.08	.11	.16	.21	**.73**	-.02
Medium + No Guide: Mean RMSE	.04	.11	.17	.18	.04	.04	**.63**	.08
Medium + No Guide: Path Accuracy	.16	.07	.10	.11	.32	-.13	.42	.13
Fast + No Guide: Y Gain	-.16	.01	.01	.05	-.05	.03	-.16	**-.79**
Fast + No Guide: X Gain	-.01	-.04	-.12	-.10	.17	-.05	-.08	**-.73**
Fast + No Guide: SD of RMSE	.14	.01	.08	-.03	.14	.23	.08	**.68**
Fast + No Guide: Mean RMSE	.08	.09	.22	.14	.07	.02	.11	**.55**
Fast + No Guide: Path Accuracy	.10	.09	.14	.11	.38	-.18	.02	.47
Eigenvalues	4.73	4.26	4.23	4.58	3.89	3.31	3.47	3.57
% Total Variance	11	10	10	11	9	8	8	9

Note: Component loadings over .50 appear in bold and red typeface.

3.3.1.3 Interpretation of component loadings

The loading of Normalised Jerk and Path Length on two performance-specific components suggest they both explain unique variance in sensorimotor control. Considering previous literature, it is perhaps not surprising that these elements surfaced as independent components. As previously noted, the nature of the Tracking task permits participants to make a series of corrective *ad-hoc* movements which can produce a less smooth trajectory. Alternatively, the participant can use forward models to predict target trajectory and apply anticipatory corrections to their own movement accordingly, producing smoother, less jerky, movement (Culmer et al., 2009). Additionally, as suggested by Nordin et al. (2014), efficient movement takes the shortest path to minimise a limb's exerted effort. Thus, it is again unsurprising that a distinct component relating to Path Length emerged.

For the six condition-specific components (i.e., Slow + With Guide), it was found that metrics related to both temporal and spatial accuracy loaded together (Mean RMSE, SD of RMSE, X Gain, and Y Gain), reflecting a dynamic aspect of sensorimotor control, whereby speed and accuracy interacted. This also reflects the nature of the task as participants are required to maintain spatial accuracy, by keeping the stylus on the target, at the same time as they exhibit temporal accuracy, in order to keep up with the increasing speed. From here on in, this is referred to as reflecting “Dynamic Accuracy”.

There were, however, several theoretical inconsistencies, namely:

- Slow + No Guide: Path Accuracy loaded onto Component 2. (related to “dynamic accuracy” of the Slow + No Guide condition)

- Fast + With Guide: Path Length condition loaded onto Component 8 (related to Dynamic Accuracy of the same condition)
- Fast + With Guide: Path Accuracy from the Fast + With Guide condition loaded onto Component 5 (related to overall Path Length).

It is perhaps reassuring to note that for the first two of these inconsistencies, the additional item loaded onto condition-specific components of the same condition. With so few of these theoretical inconsistencies, it is arguably appropriate to apply some logical discretion and omit these items from further analyses. Lastly, only one instance of cross-loading was found. This was for Fast + No Guide: Path Length, which loaded onto both Component 5 (related to overall Path Length) and Component 8 (related to Dynamic Accuracy of the Fast + No Guide condition). The loading onto Component 8 could be considered theoretically inconsistent as it diverges from the general pattern of results found. Subsequent analyses will determine its importance in explaining performance within this task.

A number of cases emerged where items did not load sufficiently onto any of the eight components. Four of these were items related to Path Accuracy. Interestingly, the two remaining Path Accuracy metrics which did reach the threshold of .5, did so only marginally (.50 and .57 for the Slow + No Guide and Fast + With Guide conditions, respectively). This suggests that for Tracking, metrics related to simple spatial accuracy do not capture unique variance well. Instead, more dynamic spatial metrics that also take temporal accuracy into account (e.g., Mean RMSE) appear more relevant. The only remaining item not loading sufficiently onto any of the eight components was Slow + With Guide: Path Length.

3.3.1.4 Summary

Within the current literature, the metric most commonly used to quantify performance on the Tracking task is the mean RMSE (Flatters, Hill, et al., 2014; Flatters, Mushtaq, et al., 2014; L. J. B. Hill et al., 2016; Raw et al., 2012). It is therefore reassuring that the present findings support the importance of this metric in explaining variance in sensorimotor control, as it consistently loads onto all six of the condition-specific components. It also suggests that prior reliance on this metric alone in studies using CKAT is not without merit. However, this metric on its own explains a smaller amount of overall variance compared to the current model.

For several reasons, it is also interesting that the component with the largest eigenvalue (therefore explaining the largest proportion of variance) is Slow + With Guide: Dynamic Accuracy. Firstly, at the slowest speed, and with the assistance of a visual guide, this condition could be considered the easiest to complete. This corroborates previous research finding that, with increasing speed, tracking performance significantly decreases (Ferguson et al., 2015; Flatters, Hill, et al., 2014; Raw et al., 2012). Therefore, as the task becomes more difficult, children may place a larger emphasis on their temporal accuracy, in order to keep up with the target. As a result, the level of spatial accuracy is compromised. Thus, within conditions at the slower speeds, a more accurate representation of children's sensorimotor control may be captured, suggesting why this condition explains the largest amount of variance. Further support of this claim comes from previous research, which finds this condition is most sensitive to detecting subtle sex differences in performance (Flatters, Hill, et al., 2014).

Furthermore, previous evidence suggests a shift in the internal sensorimotor mechanisms when the target speed increases. With increasing speed, less reliance is placed on feedback systems as it becomes more difficult to use online information provided by previous performance. This is due to a delay caused by visual processing (Wolpert et al., 1998). Instead, greater emphasis is placed on feedforward control mechanisms which predict and anticipate future target movement with minimal delay (Ferguson et al., 2015; van Roon et al., 2008; Wolpert et al., 1998). Thus, including condition-specific components enables researchers to pinpoint the specific mechanisms that may be sub-optimal in participants' performance.

3.3.2 Aiming

The aiming task comprises three types of target presentation: "Baseline", "Jump", and "Embedded-Baseline" which refer to how the target moves between each trial (see Section 3.2.3.2 for a more detailed description). As detailed in Table 1 eight metrics are captured during this task and thus, 24 items were included in the PCA.

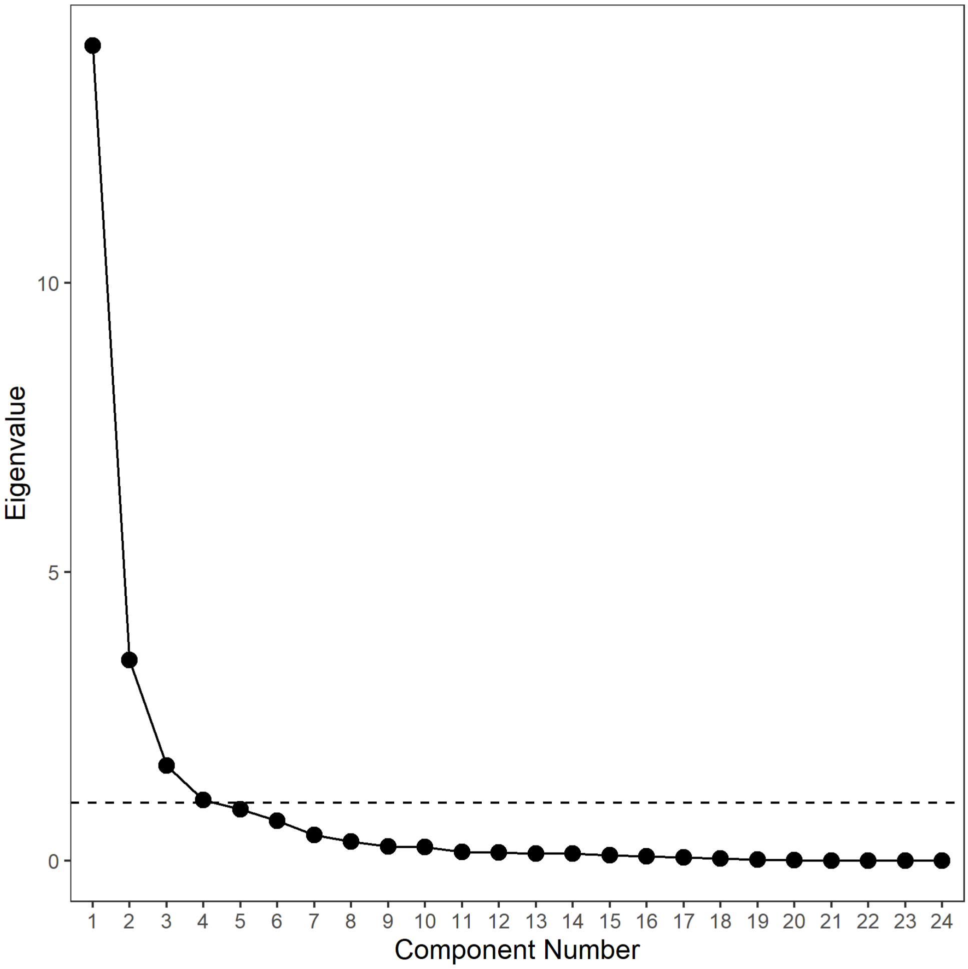
The KMO test verified the sampling adequacy; KMO = .83 ("meritorious" according to Kaiser, 1974), and all KMO values for the individual items were acceptable at >.67. Bartlett's test of sphericity indicated that correlations between items were sufficiently large for PCA, χ^2 (276) = 73242.02, p< .001.

3.3.2.1 Selecting components to retain

Four components had eigenvalues exceeding one, which explained a total variance of 85%. Upon also assessing the scree plot (Figure 7), four components were retained in the subsequent analyses.

Figure 7

Scree plot showing the number of components to be retained for the Aiming task



Note: Dashed line represents an eigenvalue of 1 on the Y axis.

3.3.2.2 Description and interpretation of component loadings

Correlations between items were sufficiently high to apply oblique rotation to improve interpretability. Although a four-component model was retained based on the above criteria, the fourth component did not contain any items reaching the loading threshold of .5 (see Table 9). Thus, a three-component model was also subsequently extracted and interpreted after oblique rotation (see Table 10). These models will be discussed each in turn. Although counter-intuitive, loadings above one are possible when using an oblique rotation as the loadings represent regression coefficients rather than correlations (Jöreskog, 1999).

3.3.2.2.1 Four-component model

Within the four-component model (see Table 9), the first component explained a large proportion of variance (41%). It consistently accounted for Reaction Time, Time to Peak Speed, and Path Length Time across all three conditions. In addition, Movement Time from the Jump and Baseline conditions also loaded highly, as well as Normalised Jerk from the Baseline condition. These metrics would suggest that this component is indicative of a participant's "General Speed of Movement", and will henceforth referred to as such. This interpretation is made on the basis that all the metrics loading here relate to how quickly the participant performs each trial. Furthermore, although not explicitly obvious, Normalised Jerk could also be considered a measure of speed as it is reflective of when there is a change in force such as during acceleration (Eager et al., 2016). It makes intuitive sense that a large proportion of unique variance within this task was related to speed compared to other tasks, as participants were instructed to perform "as quickly and accurately as possible" under no time constraints. Therefore, a larger emphasis may have been placed on speed rather than spatial accuracy.

The second component explained 25% of the total variance. It contained the Path Length items from all three conditions, as well as two items related to the Deceleration Time metric, and one item of Movement Time. Therefore, this component could be interpreted as representing "Movement Efficiency" because, as previously described, efficient movement takes the shortest trajectory (Nordin et al., 2014) which is captured by Path Length. At first glance, the remaining items may be deemed inconsistent, however when considering the mechanics of movement, rational explanations can be proposed. For example, although only one item of Normalised Jerk loaded onto this component, it could be argued that it is related to this component, as decreased path length is likely to represent smoother movement. It is also conceivable that with a decreased Path Length, movements may be quicker, producing quicker deceleration, and thus shorter Movement Time. Subsequent analyses will determine the importance of these items within this component (see Chapter 4).

Component three was relatively simple, consisting only of items related to the Peak Speed metric across all three conditions (14% variance explained). This is interesting, especially considering previous research using CKAT has thus far not considered this metric within their analyses. However, previous research using other kinematic assessments has found individuals within clinical samples, such as Stroke patients (Hussain et al., 2018), children with DCD (Elders et al., 2010; Gonsalves et al., 2015), and ataxia (Ramos et al., 1997), have slower Peak Speed compared to healthy controls. This provides grounds for including it as an additional component of sensorimotor control to consider. Furthermore, Peak Speed is widely accepted as reflecting feedforward control, and it is this aspect of sensorimotor control which children with DCD show the greatest difficulty with (Elders et al., 2010; Plumb et al., 2008). Thus, including Peak Speed as an independent metric within the CKAT battery may be indicative of one of the key mechanisms underpinning proficient sensorimotor control.

As previously stated, the fourth component did not contain any items which reached the threshold value. It also only contributed 5% of total variance, and thus excluding it from subsequent analyses still captures 80% of total variance of the model.

Lastly, within this model, several items did not load sufficiently onto any component, suggesting that they do not explain unique variance within this task. These items were: Normalised Jerk from the Embedded-Baseline and Jump conditions, as well as Deceleration Time from the Jump condition.

Table 9

Component loadings on a four-component model for the Aiming task following oblique rotation (N = 1323)

	Component Loadings			
Item	**1**	**2**	**3**	**4**
Embedded: Reaction Time	**1.02**	-.11	.04	-.12
Jump: Reaction Time	**1.01**	-.17	.02	-.11
Baseline: Reaction Time	**1.00**	-.11	.03	.12
Baseline: Time to Peak Speed	**.92**	.02	-.02	.17
Embedded: Time to Peak Speed	**.88**	.12	.01	-.13
Baseline: Path Length Time	**.79**	.20	-.11	.23
Jump: Path Length Time	**.77**	.30	-.10	-.09
Jump: Time to Peak Speed	**.71**	.12	-.13	.04
Embedded: Path Length Time	**.69**	.40	-.10	-.10
Baseline: Normalised Jerk	**.68**	.03	.44	.35
Jump: Movement Time	**.68**	.40	-.11	-.09
Baseline: Movement Time	**.51**	.44	-.20	.32
Jump: Deceleration Time	.38	.37	.02	-.21
Embedded: Path Length	-.12	**.96**	.19	-.03
Jump: Path Length	-.04	**.88**	.20	.03
Embedded: Deceleration Time	.10	**.84**	-.23	-.04
Embedded: Movement Time	.28	**.76**	-.17	-.08
Baseline: Path Length	.18	**.64**	.27	.41
Baseline: Deceleration Time	.39	**.50**	-.22	.36
Embedded: Normalised Jerk	.35	.46	.33	-.39
Embedded: Peak Speed	-.11	.06	**.91**	-.04
Baseline: Peak Speed	-.02	-.10	**.89**	.16
Jump: Peak Speed	.03	.13	**.86**	-.13
Jump: Normalised Jerk	.41	.24	.46	-.41
Eigenvalues	9.92	5.93	3.29	1.14
% of Total Variance	41	25	14	5

Note: Component loadings over .50 appear in bold and red typeface.

3.3.2.2.2 Three-component model

After applying an oblique rotation (Oblimin), the clustering of items suggested a similar pattern to the four-component model, with only a few minor differences (see Table 10).

Component 1 was identical to its equivalent in the four-component model, accounting for 42% variance and thus will not be interpreted further.

Component 2 explained only 1% less variance than in the four-component model, differing only by replacing Deceleration Time from the Baseline condition with Normalised Jerk from the Embedded-Baseline condition. Interestingly, Baseline Deceleration Time was one of only two metrics that did not sufficiently load onto any component within this model (the other being Deceleration Time from the Jump condition). As two of three of the Deceleration Time metrics were not included in the model, it may suggest it has minimal relevance in explaining unique variance of sensorimotor control on this task, after accounting for other metrics. Deceleration Time is commonly understood as reflecting feedback control (Elders et al., 2010; Plumb et al., 2008). However, previous research has found group differences in the Movement Time of aiming movements in children with DCD are best explained by differences in Deceleration Time (Plumb et al., 2008). Thus, as the (total) Movement Time metric within the CKAT battery encompasses both the time to peak speed and deceleration time, the feedback control mechanisms relating to deceleration may be already captured in weightings of Movement Time within this model’s components. As such, it is possible that including both metrics in the model is redundant and omitting Deceleration Time will not decrease the amount of variance explained.

Lastly, Component 3 again explained 14% of variance and only differed by one metric: the addition of Normalised Jerk from the Jump condition. This is arguably a theoretical inconsistency, given all other items relate to Peak Speed. In addition, the three Peak Speed items all loaded highly on this component (>.8) whilst Normalised Jerk had a comparatively weak loading (.6).

Table 10

Component loadings on a three-component model for the Aiming task following oblique rotation (N = 1323)

	Component Loadings		
Item	**1**	**2**	**3**
Baseline: Reaction Time	**1.03**	-.14	.02
Embedded: Reaction Time	**1.00**	-.10	.07
Jump: Reaction Time	**.99**	-.16	.05
Baseline: Time to Peak Speed	**.96**	-.01	-.04
Embedded: Time to Peak Speed	**.86**	.13	.04
Baseline: Path Length Time	**.84**	.16	-.14
Baseline: Normalised Jerk	**.77**	-.02	.38
Jump: Path Length Time	**.76**	.30	-.07
Jump: Time to Peak Speed	**.72**	.11	-.13
Embedded: Path Length Time	**.67**	.40	-.08
Jump: Movement Time	**.66**	.40	-.08
Baseline: Movement Time	**.59**	.39	-.24
Baseline: Deceleration Time	.47	.45	-.27
Embedded: Path Length	-.11	**.95**	.20
Jump: Path Length	-.02	**.87**	.19
Embedded: Deceleration Time	.10	**.83**	-.21
Embedded: Movement Time	.27	**.76**	-.15
Baseline: Path Length	.28	**.58**	.20
Embedded: Normalised Jerk	.28	**.50**	.40
Jump: Deceleration Time	.35	.39	.06
Embedded: Peak Speed	-.10	.07	**.91**
Jump: Peak Speed	.02	.14	**.88**
Baseline: Peak Speed	.02	.14	**.88**
Jump: Normalised Jerk	.34	.28	**.61**
Eigenvalues	10.12	5.77	3.34
% Total Variance	42	24	14

Note: Component loadings over .50 appear in bold and red type-face.

3.3.2.3 Aiming: Summary

The model fit, based upon off-diagonal values was .99 for both the 3- and 4-component models, indicating good fit (Field et al., 2012). In contrast to the Tracking task, it is interesting that components were not condition-specific (i.e., Peak Speed from all three conditions loaded onto a single component). This raises questions of the importance of all three conditions within the assessment battery if they are not explaining additional unique variance. However, movements made within the Jump condition can be thought of as “double-step” target movements, frequently used across the literature for assessing online control (Blanchard et al., 2017; Culmer et al., 2009; Hyde & Wilson, 2011). Thus, it may be sufficient and justifiable to truncate the Aiming task by only analysing the Baseline and Jump conditions and omitting redundant data from the Embedded-Baseline. The Embedded-Baseline trials were interspersed pseudo-randomly around the Jump movements and were included only to ensure that the presentation of the target was not predictable when switching into and out of Jump movements (i.e., not every movement within the last 25 aiming movements was a ‘Jump’ trial). In additional confirmatory analyses (see later chapters), the relative appropriateness of both a 3- and 4-component model will be explored further.

3.3.3 Steering

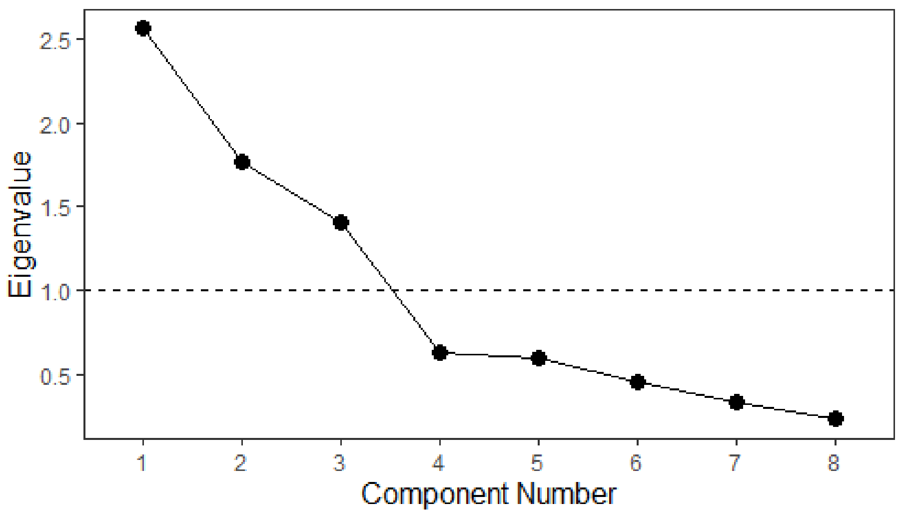
The Steering task has only two conditions, each requiring the participant to steer along a differently shaped trajectory (Shape A and Shape B). Four metrics were captured within this task (see Table 7) and thus eight items were entered into the PCA. The KMO test verified the sampling adequacy for the analysis KMO = .60 (“mediocre” according to Kaiser, 1974). Correlations between items were deemed sufficient according to Bartlett's test of sphericity, χ^2 (28) = 4183.94, $p <$ .001.

3.3.3.1 Selecting components to retain

Three components had eigenvalues greater than one and in combination explained 72% of the variance which is within Jolliffe's (2002) recommendation of 70-90%. The scree plot's inflexions justified the retention of three components (see Figure 8). Therefore, a three-component model was selected as the most appropriate for this task.

Figure 8

Scree plot showing the number of components to be retained for the Steering task



Note: Dashed line represents an eigenvalue of 1 on the Y axis

3.3.3.2 Description and interpretation of component loadings

An oblique rotation (Oblimin) was applied to improve interpretability of the model. The model fit based upon off-diagonal values was good (.9). As Table 11 shows, three metrics loaded onto Component 1; Path Length (B); Normalised Jerk (B); and Path Length Time (B), explaining 34% variance. As previously discussed, more efficient movement takes a shorter trajectory, reflecting greater control of the arm muscle and joints (Nordin et al., 2014). Additionally, less smooth movement (potentially due to making a series of *ad-hoc*, corrective movements) would likely produce a longer path length. Thus, on this task, it is not surprising that these items have loaded together. Thus, this component could be interpreted as representing “Movement Efficiency” of Shape B.

Component 2 (explaining 33% variance), indicates a similar pattern but for Shape A: Path Length (A); Normalised Jerk (A); and Path Length Time (A). Like the Tracking task, it is interesting that the analysis indicates that the two conditions describe unique variance and should be interpreted independently. Likewise, Component 2 could be interpreted as signifying “Movement Efficiency” of Shape A.

Lastly, Component 3 consists of Path Accuracy from both Shape A and Shape B as well as Path Length Time (B) which had a negative loading. Whilst it is conceivable that a less accurate trajectory perhaps takes longer to execute, it could be argued that Path Length Time (B) is theoretically inconsistent on this component. It also contributes a much smaller amount than the other two items in this component; only just reaching the threshold of .50. This item additionally shows evidence of cross-loading as it also sufficiently loads onto Component 1, justifying further investigation of its importance in explaining unique variance on this task. As Path Length Time for one or both conditions load across all three components, it is worth speculating that it may not be contributing unique variance in explaining performance on the Steering task. If Path Length Time is included in Component 3, it may be interpreted as reflecting general spatio-temporal accuracy. A more intuitive interpretation though, may be to only include the Path Accuracy metrics, which would be suggestive of this component likely representing solely “Path Accuracy”. Further analyses (see Chapter 4) will determine whether Path Length Time should be considered a redundant metric within this model, omitted from future analyses.

Table 11

Component loadings on a three-component model for the Steering task following oblique rotation (N = 1727)

	Component loadings		
Item (Condition)	**1**	**2**	**3**
Normalised Jerk (B)	**.88**	.01	.01
Path Length (B)	**.84**	-.03	.20
Path Length Time (B)	**.64**	.07	**-.53**
Normalised Jerk (A)	-.10	**.86**	.05
Path Length Time (A)	.07	**.77**	-.32
Path Length (A)	.08	**.73**	.32
Path Accuracy (B)	.10	.08	**.85**
Path Accuracy (A)	.01	-.07	**.79**
Eigenvalues	1.95	1.90	1.89
% of Total Variance	24	24	24

Note: Component loadings over .50 appear in bold & red typeface.

3.3.3.3 Summary

A three-component model was deemed the most suitable for describing performance on the Steering task, explaining 72% of the variance. All eight items loaded sufficiently onto at least one component. There was however, one instance of cross-loading found (Path Length Time (B)) which was speculated as being theoretically inconsistent.

In previous CKAT literature, Steering is quantified by the metric: *penalised* *path accuracy (pPA);* a measure which amalgamates temporal and spatial accuracy, combining Path Length Time and Path Accuracy into a single measure. However, the current analyses emphasise the importance of Path Length as an additional measure of spatial accuracy in explaining variance associated with children's sensorimotor control. Although not included in previous CKAT literature, other kinematic measures have previously used this metric as an outcome (e.g., Accardo et al., 2013; Naish et al., 2013; Rosenblum et al., 2013). Similarly, the present analyses demonstrate the importance of movement smoothness, which again has not been commonly considered for this CKAT task. Thus, these analyses suggest that the inclusion of additional spatial metrics, such as Path Length and Normalised Jerk would be beneficial for gaining a more detailed and accurate understanding of children's sensorimotor control.

Further investigation will determine whether Path Length Time is a necessary item for describing performance and how it relates to other items within the model. The model will also be validated using novel data with subsequent confirmatory analyses to assess its appropriateness for describing sensorimotor control on a kinematic steering task, in Chapter 4.

3.4 Discussion

The aim of this study was to employ a data reduction technique (Principal Components Analysis) to explore which of the numerous metrics that can be derived from an end-point kinematic assessment contribute in a systematic way towards describing children's sensorimotor control. The present analyses were specific to the Clinical-Kinematic Assessment Tool (CKAT) and demonstrated its potential to capture more detailed summaries of children's sensorimotor control than previous studies using this measure have (Flatters, Hill, et al., 2014; Giles et al., 2018; L. J. B. Hill et al., 2016; Shire et al., 2016). It was found that the large variety of metrics available via CKAT could also be combined through analyses into a smaller number of theoretically meaningful dimensions, for all three tasks.

For the Tracking task, analyses indicated that it was meaningful to differentiate across conditions for some of the more dynamic kinematic metrics (capturing both spatial and temporal accuracy). In addition, two more general (non-condition specific) dimensions emerged, each explaining variance associated with a specific aspect of sensorimotor control (i.e., Normalised Jerk and Path Length).

For both Aiming and Steering, the same metrics were observed to load together on single components, irrespective of the task condition (Baseline versus Jump and Shape A versus Shape B, respectively). The variance within these two tasks was found to be sufficiently explained by three or four components for Aiming, and three components for Steering. Further investigation will determine which of the two potential models for the Aiming task is most appropriate, using unseen data.

It is critical to note that these analyses demonstrate distinct dimensions existing within the over-arching construct of sensorimotor control, suggesting these nuances are masked when research condenses the description of motor control into a single "overall" battery measure (French et al., 2018). As previously discussed, this more reductive approach has been practiced in both kinematic (e.g., Hill et al., 2016) and traditional measures of motor ability (e.g., Henderson et al., 2007).

This chapter also provides additional support for the use of kinematic measures in research, as it demonstrates the large level of detail that can be acquired in *how* movement is executed, rather than whether the "end-goal" is achieved, or not. As discussed, from an applied perspective, this approach enables a clinician or teacher to identify which specific aspect of sensorimotor control a child is facing difficulties with (i.e., speed or spatial accuracy) and can thus intervene accordingly.

From a research perspective, this study provides a platform for future work to investigate group differences in how movement is executed. For example, previous research has investigated sex differences in various aspects of children's movement and motor control (Bolger et al., 2018; Flatters, Hill, et al., 2014; Morley et al., 2015). This research has often demonstrated that boys' and girls' competencies differ as a result of *task.* For example, by determining performance using only one kinematic metric per task, it is difficult to determine exactly *how* movement varies across the sexes. The increased speed found in male performance on the Aiming task in Flatters et al. (2014) may be a result of a quicker response time, faster deceleration or shorter Path Length, or perhaps a combination of all of these. However, without using a more expansive method to record and describe kinematic performance, the ability to drill down into various aspects of sensorimotor control and identify which aspects are most informative and influential is not possible.

With the increased level of detail of sensorimotor control that is demonstrated within the present study, a deeper understanding of potential group differences in the underpinning mechanisms is also possible. The example above describes sex differences; however, this can be applied to a wide number of demographic groups including ethnicity, age or clinical samples.

3.4.1 Strengths and Limitations

A strength of this work is the large sample size, a vital prerequisite of PCA, as models built on smaller samples are much more susceptible to being influenced by outliers (Jolliffe, 2002). The smallest number of participants in the present analyses was in the Aiming task (n = 1323) which is still substantially larger than previous similar research, where the largest sample was 208 (Wood et al., 2018). In addition, the sample employed a wide age range (4-12 years), supporting its applicability for children across the primary school years.

A potential limitation is that the sample included only typically developing children. Although not originally intended for diagnostic use, it may be beneficial to investigate further how the models compare to those built using clinical samples, such as children with DCD. This could indicate future applications of CKAT to more clinical settings. However, building models on “typical” children is first necessary, to better enable comparisons to then be made with children who are displaying “atypical” movement patterns.

Furthermore, the analyses did not differentiate by handedness. Previous literature has found left-handers to perform more poorly on motor tasks, compared to their right-handed peers (C. Freitas et al., 2014). Whilst the literature may benefit from an investigation in the loading of kinematic metrics according to preferred hand, this was not possible in the present study. Although the sample size was large, there were not enough left-handed participants to achieve sufficient power for such sub-group analysis. However, the analyses were repeated after excluding left-handed participants producing models which replicated those produced on the whole sample.

3.4.2 Conclusions

The aim of this work was to reduce the dimensionality of a large body of sensorimotor data collected via the Clinical-Kinematic Assessment Tool. This was achieved by conducting Principal Component Analysis to produce an empirically guided structure of new metrics to be used in subsequent analyses. It was found that for each of the three CKAT tasks, a reduced number of components was able to capture a large amount of variance underlying sensorimotor control. In addition, it is encouraging to learn that the results found here do align with the present use of CKAT, albeit with an additional level of detail captured. The present study also has wider applications. It demonstrates that dimension reduction techniques offer an alternative to cherry-picking kinematic variables to maximise the amount of variance explained. In addition, such techniques should be considered by researchers interested in limiting the amount of noise present in their sensorimotor data and/or if they wish to simplify the interpretation of their data, to optimise the level of detail captured whilst also not making it overly complicated for a less expert audience to also make good use of (e.g., informing clinicians and/or teachers in their respective practices).

Further confirmatory analyses and interpretation with a new, unseen sample will confirm the model structures proposed in the present study (see Chapter 4). Necessary further adjustments can then be made before applying this revised scoring of CKAT to future experimental investigation of sensorimotor control (see Chapter 5 onwards).

Chapter 4 Further refinement of scoring kinematic assessments using Confirmatory Factor Analysis

4.1 Introduction

Before investigating potential relationships between sensorimotor control and other aspects of children's lives, psychometrically sound measures are required. The development and refinement of such measures requires rigorous and robust statistical modelling across multiple contexts and samples (T. A. Brown, 2015; Schmitt & Kuljanin, 2008; Suhr, 2006).

As discussed in Chapter 3, Principal Components Analysis (PCA) is a data reduction technique used to condense a large number of observed variables into a smaller array of components reflecting the underlying latent structure (Jolliffe, 2002). Although widely used and suitable for this purpose, it is largely exploratory with no pre-determined hypotheses regarding the latent structure with items free to load across any component (Finch et al., 2017; Jolliffe, 2002). In addition, PCA has been described as "insufficient" as a standalone method, with one study finding discrepancies in component loadings across samples (Björklund, 2019; Finch et al., 2017). Thus, additional statistical techniques are required to complement PCA to produce robust model estimations.

4.1.1 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA), like PCA, is a technique used to reduce a set of variables to a fewer number of factors representing latent constructs, based on shared variance (Babyak & Green, 2010; D. L. Jackson et al., 2009). However, it differs from more exploratory approaches such as PCA or Exploratory Factor

Analysis (EFA) in that it is hypothesis driven, with all aspects of the model specified by the researcher *a priori* based on existing research or theory such as imposing constraints (Babyak & Green, 2010; T. A. Brown, 2015; D. L. Jackson et al., 2009; Matsunaga, 2010). When used following PCA, CFA is often conducted on an “unseen” or novel sample, independent of that used to build the initial models with PCA. Thus, while PCA provides insight to the general shape of the latent structure, a larger amount of confidence can be placed in models that can be reproduced on data from new samples using CFA (Bandalos, 1996; Maccallum et al., 1999). This aids researchers in selecting the most suitable model from a number of plausible options suggested by the PCA.

Furthermore, as PCA permits items to load freely, there may be numerous cases which do not align with theory. Thus, CFA can drive model re-specification which is guided by existing theory such as the omission of indicators which do not load highly onto any factor. Brown (2006) refers to these as “poorly behaved indicators” (p. 106). This produces models which are both mathematically and theoretically plausible. The shift in approach from exploratory to confirmatory is also reflected in the terminology used. For example, PCA refers to “items” which load onto “components”. In contrast, the CFA literature refers to these as “directly observed variables” loading onto “latent variables”.

In summary, CFA offers the capacity to subject the models produced by PCA to further rigorous testing while accounting for existing theory. Thus, it is considered an appropriate method of analysis for the present study.

4.1.2 The present study

As previously described, the CKAT battery produces a large array of individual data points reflecting multiple kinematic metrics across different conditions for the

Tracking, Aiming, and Steering tasks. However, the prior PCA (Chapter 3) suggested systematic variation in performance on these three tasks could best be described by considering a smaller number of underlying latent variables. Each of these models had compelling justification as to why they were the most appropriate.

For example, analyses suggested Tracking may be best described with eight components. For Aiming, while the criteria suggested a four-component model was the most appropriate, none of the items met the threshold, justifying the testing of the three-component model. Lastly, Steering analyses proposed that a three-component model may be suitable.

Whilst these models derived from the PCA are the most mathematically parsimonious, some item loadings did not always align with theory. With further refinement guided by existing theory, it was predicted that a number of these theoretical inconsistencies would be eliminated. The present study tested the reproducibility of these models on a novel sample of 4-11 year old children and sought to determine which of the proposed plausible models was the most appropriate for each task. Ultimately, this process aimed to determine the single, best fitting model for each task that will be used to describe sensorimotor control data collected by CKAT throughout this thesis.

4.2 Methods

4.2.1 Participants

The present study included sensorimotor data collected previously as part of two sub-cohorts within the Born in Bradford project; “Starting School” and “Primary School Years”. Detail of these two cohorts is described in Chapter 1. Relevant demographic information for the participating children is presented in Table 12, including a breakdown from each cohort. In total, 22406 children were included in the present analyses, with an age range of 4-11 years (M = 7 years, 10 months; SD = 16.34 months). Similarly to the analysis in Chapter 3 (PCA), participant data were analysed on a task by task basis, with participants excluded from an individual task if more than one data point on any metric was missing. Therefore, the total sample size for each task was: Tracking (*n* = 22139); Aiming (*n* = 20030); Steering (*n* = 22266). Prior approval was granted from the BiB Executive Board for the analysis of these data.

There is a slight discrepancy between the sample in the present study and that from which the models were trained with PCA (see Chapter 3). The Starting School and Primary School Years cohorts include 4-5-year-old and 7-10-year-old children, respectively (with the exception of two 6 year olds and one 11 year old child). Thus, there are no data for children aged 6 years.

Table 12

Sample demographics for the test dataset

	Starting School	**Primary School Years**	**Full Cohort**
n	6586	15820	22406
Sex (%)			
Males	1329 (20.2%)	8068 (51.0%)	9042 (40.3%)
Females	1290 (19.6%)	7752 (49.0%)	9397 (41.9%)
Not Specified	3967 (60.2%)	0	3967 (17.7%)
Mean Age [Range]	4 yrs, 11m [4 yrs, 0 m-5 yrs, 10m]	8 yrs, 4 m [6 yrs, 9 m-11yrs, 9m]	7 yrs, 10 m [4 yrs, 0 m-11yrs, 9m]
Handedness (%)			
Left	592 (9.0%)	1626 (10.3%)	2218 (9.9%)
Right	5968 (90.6%)	14175 (89.6%)	20143 (89.9%)
Not Specified	26 (0.4%)	19 (0.1%)	45 (0.2%)

4.2.2 Materials/Procedure

Kinematic data were again obtained via CKAT, thus the materials and procedure are identical to that already described in Chapter 3.

4.2.3 Statistical Analysis

The data were prepared in the same way as previously reported to ensure uniformity (averaging across trials, centring and scaling). The models proposed by the PCA in the previous chapter were tested on these unseen data using Confirmatory Factor Analysis; via the `lavaan` package (Version 0.6.5; Rosseel, 2012) for R (Version 4.0.0; R Development Core Team, 2020).

Whilst the chi-square statistic is generally always reported, it is sensitive to sample size and nearly always significant when sample sizes are large (T. A. Brown, 2015; Byrne, 2013; Kenny, 2016). Thus, a selection of alternative goodness of fit indices were also included to determine model fit. Fit indices generally fall into three categories: absolute fit; parsimony correction; and comparative fit. Brown (2015) recommends one from each category should be inspected. Thus, the robustness of the proposed models was tested using Standardised Root Mean Square Residual (SRMR); Root Mean Square Error of Approximation (RMSEA); and Comparative Fit Index (CFI) based on recommendations from Brown (2015) and Kline (2005). Bayesian Information Criterion (BIC) was also inspected when conducting additional model modifications, with a smaller BIC being preferred.

There is debate across the literature regarding the thresholds which should be used for each of these indices to determine a good-fitting model. For example, Browne & Cudeck (1992) reported that RMSEA <.08, SRMR <.08, and CFI > .90

suggests good model fit. Models with RMSEA values between .08 and .10 have also been reported as indicating “mediocre” model fit (MacCallum et al., 1996). More conservative fit indices have also been suggested in the literature, such as RMSEA <.06 and CFI > .95 (Hu & Bentler, 1999). However, as indicated by the lack of agreement across academics, such fit metrics should be considered guidelines rather than being overly rigid in applying arbitrary thresholds to interpret them (Hermida, 2015; Hooper et al., 2008). Although there are no universal guidelines regarding which should be used, the present study aimed towards: RMSEA <.10, SRMR <.08 and CFI >.90.

Firstly, a one-factor model was tested where all items were loaded onto a single latent variable. This was to refute the hypothesis that individual task metrics do not differentiate into unique underlying dimensions.

The original, unmodified models determined by the PCA were next applied to the new sample. These models were the most mathematically parsimonious and blind to theoretical consideration. Thus, items were free to load on whichever component maximised the amount of variation explained. For example, this model would allow a Path Accuracy item to load onto a component where all other items were related to Path Length. From here on in, these models will be referred to as the “Statistical Model” for each of the three tasks. For each task, findings from the testing of two competing statistical models are reported.

Next, hypothesis-driven amendments were made to the Statistical Models to increase the interpretability. This involved making alterations that principally sought to reduce theoretical inconsistencies in the relationships between the observed variables and the latent variables. For example, omitting items which were not theoretically consistent (i.e., removing Path Accuracy from the previous example). Doing so aimed to determine a model fit which accounted for both a statistical and theoretical perspective. Such models are referred to as the "*A Priori* Theoretical Model".

Lastly, some additional refinement was conducted on some models to produce a "Posterior Theoretical Model". This, however, was not always necessary. To arrive at these models, Modification Indices (MI) were examined in parallel to the Estimated Parameter Change (EPC) value to identify metrics with high shared covariance (T. A. Brown, 2015; Jöreskog, 1993; D. Kaplan, 1990). Re-specifying the model in this way by correlating error terms between variables can produce better fitting models but it is only recommended to do so if sound theoretical justification can be provided (T. A. Brown, 2015; Byrne, 2013; Jöreskog, 1993). For example, it would be difficult to justify items to correlate which did not have common characteristics (i.e., Slow + With Guide: Normalised Jerk with Fast + No Guide: X Gain). In contrast, greater rationale may be provided for allowing two items derived from the same condition such as Baseline Reaction Time and Baseline Path Length Time to correlate as they are derived from the same condition.

4.3 Results

Findings are reported for each of the three tasks in turn, This includes the one-factor model, Statistical Model(s), A Priori Theoretical Model, and Posterior Theoretical Model.

4.3.1 Tracking

As noted, the prior PCA suggested an Eight-Component model was most plausible. Results for the One-factor, Statistical, *A Priori* Theoretical, and Posterior Theoretical Models are reported.

4.3.1.1 One-factor model

As expected, the unidimensional, one-factor model indicated poor fit across all fit metrics: χ^2 (819, N = 22139) = 561860.49, p <.001, CFI = .44, SRMR = .12, RMSEA = .18. Thus, it was evident that data from this task should be structured across multiple dimensions. The fit statistics for this model (and all subsequent models) are shown in Table 13.

Table 13

Fit statistics for the proposed models of the Tracking task

Model	χ^2	Df	CFI	SRMR	RMSEA	BIC
One-Factor Model	561860.49*	819	.44	.12	.18	2197310.98
Eight-Factor Statistical Model	145821.45*	600	.83	.08	.11	1607285.72
Eight-Factor A Priori Theoretical Model	133031.31*	499	.83	.11	.11	1473011.10
Eight-Factor Posterior Theoretical Model	115659.98*	498	.86	.07	.10	1455649.77

* Statistically significant at $p<.001$

4.3.1.2 Eight-factor statistical model

The eight-factor statistical model was only approaching acceptable fit. As detailed in Chapter 3, this model included items deemed to be related to a form of "dynamic accuracy" for each condition, as well as independent components for items related to Normalised Jerk and Path Length. It did also include one cross-loading item; Fast + No Guide: Path Length. The CFA showed mixed results with SRMR reflecting adequate model fit, RMSEA approaching acceptable, and CFI further from acceptable (χ^2(600, *N* = 22139) = 145821.45, *p* <.001, CFI = .83, SRMR = .08, RMSEA = .11).

4.3.1.3 A priori theoretical model

It was evident that the removal of some theoretical inconsistencies was required to improve both the model fit and interpretability. The following items were omitted from the model:

- Slow + No Guide: Path Accuracy from Component 2
- Fast + With Guide: Path Length from Component 3
- Fast + With Guide: Path Accuracy from Component 5
- Fast + No Guide: Path Length from Component 8

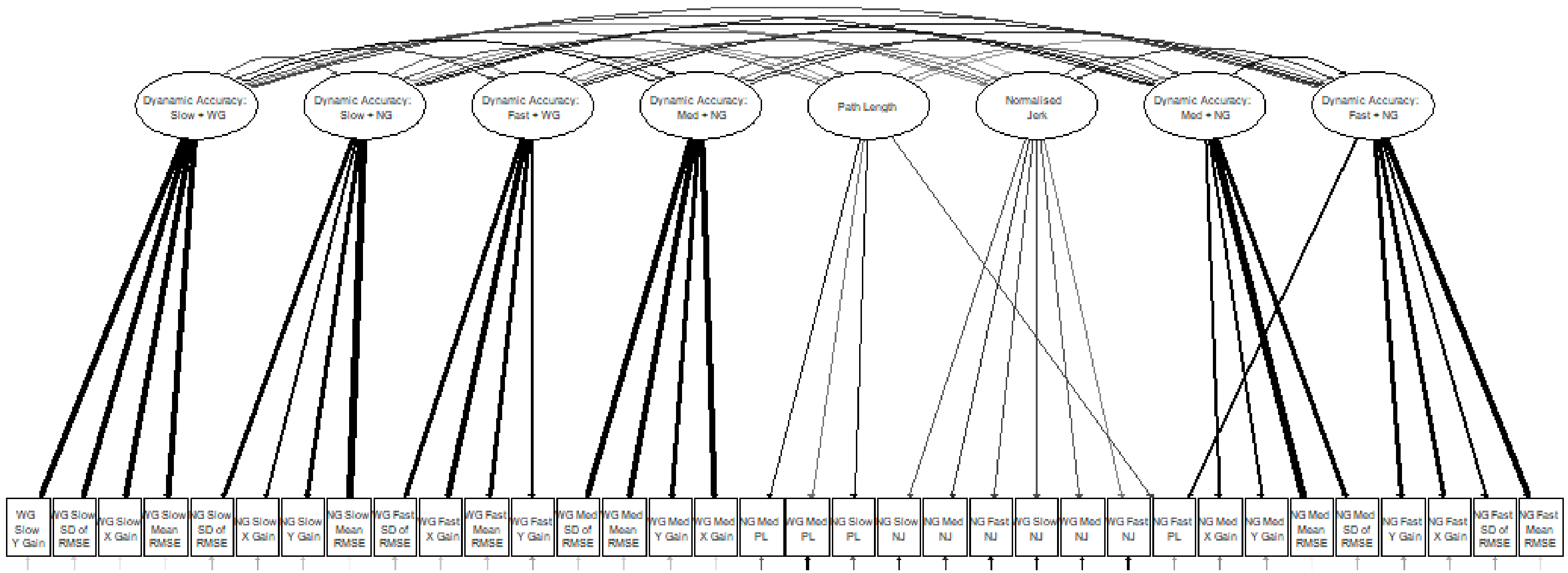
The removal of these items did not improve model fit as much as expected, with some fit indices actually worsening (χ^2(499, *N* = 22139) = 133031.31, *p* <.001, CFI = .83, SRMR = . 11, RMSEA = .11). Thus, it was necessary to inspect the modification indices to understand how the model could be improved.

4.3.1.4 Posterior theoretical model

Upon inspecting the modification indices of the *A Priori* Theoretical Model, it was evident that Fast + No Guide: Path Length explained a large amount of variance in both Components 5 and 8 (Overall Path Length and Fast + No Guide Dynamic Accuracy, respectively). Interestingly, it was not necessary for Fast + With Guide: Path Length to follow the same pattern and be included in Component 3 (Fast + With Guide Dynamic Accuracy). Goodness-of-fit indices demonstrated that although the threshold for CFI was not quite reached, this model was the most appropriate in explaining the underlying structure of the Tracking task from both a theoretical and statistical viewpoint $\chi^2(498, N = 22139) = 115659.98$, $p <.001$, CFI = .86, SRMR = . 07, RMSEA = .10). See Figure 9 for the path diagram of the final model. The model was interpreted as comprising six condition-specific “Dynamic Accuracy” components, plus components representing “Path Length” and “Normalised Jerk”.

Figure 9

Path diagram of final model for Tracking task (Eight-Component Posterior Theoretical Model)



Note: Rectangle boxes represent manifest (observed) variables. Double-headed curved arrows represent correlation. Ellipses represent latent (unobserved) variables. Single headed arrows from latent to manifest variables represent factor loadings – thickness of these arrows represent the size of the loadings. Single-headed arrows towards manifest variables represent residual error

4.3.2 Aiming

As described in the previous chapter, although similar, both the three- and four-Factor models were tested on the unseen sample to assess the most appropriate fit. Thus, the results from the One-Factor, Three-Factor Statistical, Four-Factor Statistical, and *A Priori* and Posterior Theoretical Models are reported. Table 14 displays the fit statistics for all Aiming task models reported.

4.3.2.1 One-factor model

The unidimensional model did not converge due to a not positive-definite matrix, therefore results for this model are not reported.

Table 14

Fit statistics for the proposed models of the Aiming task

Model	χ^2	**Df**	**CFI**	**SRMR**	**RMSEA**	**BIC**
One-factor model	Not positive-definite matrix					
Three-factor statistical model	948449.71*	206	.28	.10	.48	880642.79
Four-factor statistical model	Not positive-definite matrix					
A priori theoretical model	52913.47*	32	.72	.07	.29	434024.22
Posterior theoretical model	18202.54*	30	.90	.06	.17	399333.10

** Statistically significant at p<.001*

4.3.2.2 Three-factor statistical model

Although containing a number of items deemed theoretically inconsistent, this model included factors interpreted as General Speed; Peak Speed, and Movement Efficiency. Prior to further modifications, this model demonstrated very poor fit (χ^2 (206, N = 20030) = 948449.710, p <.001, CFI = .28, SRMR = .10, RMSEA = .48.

4.3.2.3 Four-factor statistical model

This model only differed from the three-factor model by the omission of Normalised Jerk from the Jump and Embedded conditions, and the addition of Deceleration Time from Baseline. Although similar, without further re-specification, the statistical four-factor model did not converge due to a not positive-definite matrix so is not reported.

4.3.2.4 A priori theoretical model

The three-factor statistical model contained a number of theoretical inconsistencies, many of which from the Embedded condition. Following the hypothesis proposed in Chapter 3 that this condition may be redundant and add additional noise rather than meaningful theoretical value, models excluding this condition were explored. In addition, Movement Time is defined as the time between the first movement exceeding 50mm/s and then falling back below it. Therefore, it could be argued that this item is predominantly captured by Path Length Time. In addition, this item just reached above the loading threshold for both the three- and four-factor models. Thus, it was considered justifiable to omit this item for both the Baseline and Jump conditions. Lastly, the Normalised Jerk metrics were omitted from the model as these did not load consistently on any one component. After the omission of the items not aligning with prior theory, the model still had poor fit (χ^2 (32, N = 20030) = 52913.47, p <.001, CFI = .72, SRMR = .07, RMSEA = .29.

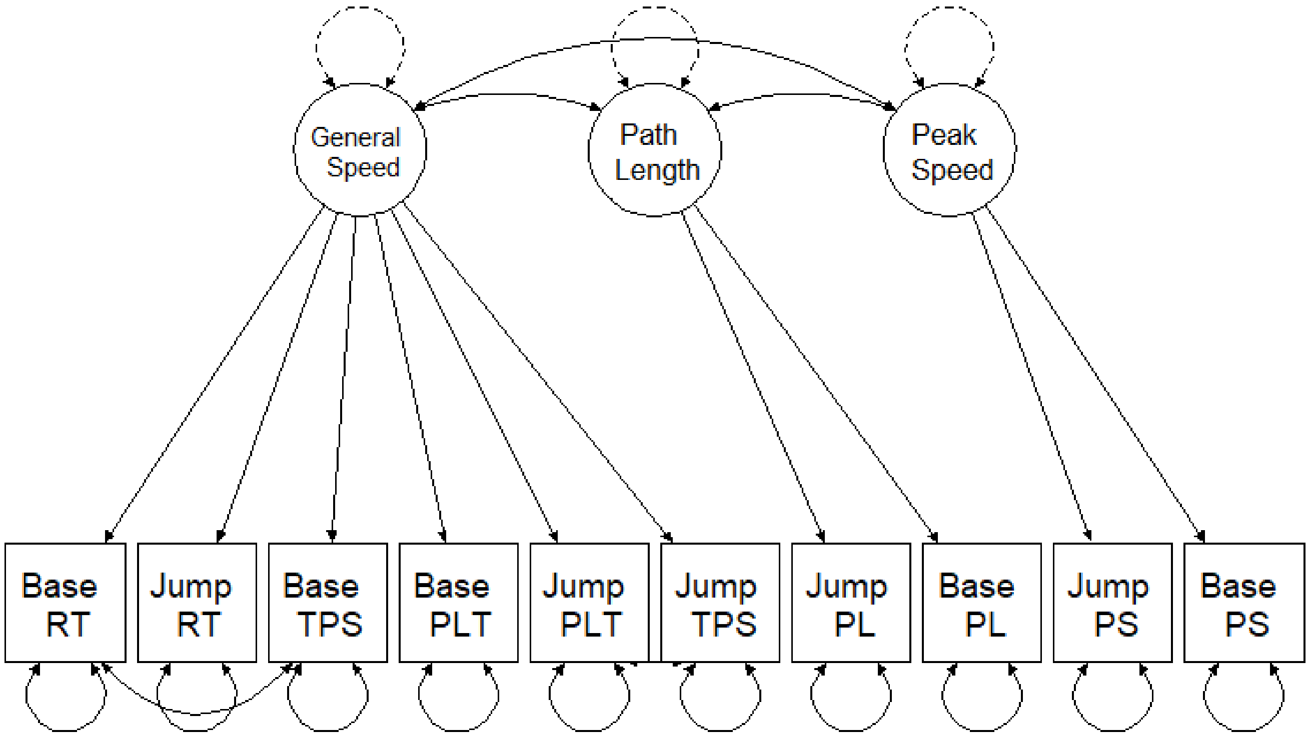
4.3.2.5 Posterior theoretical model

Following inspection of the modification indices (MI), it was suggested that the model should allow Baseline: Reaction Time and Baseline: Time to Peak Speed (MI = 26565.43, EPC = .30), plus Jump: Path Length Time and Jump: Time to Peak Speed (MI = 5883.75, EPC = .19) to co-vary. Justification for modifying the model in this way is that these variables come from the same condition. In addition, one could argue that Time to Peak Speed and Reaction Time capture the ability to make initial movement at speed. Culmer et al. (2009) provided a visualisation to argue that Time to Peak Speed encompasses Reaction Time, therefore it is unsurprising that these variables share unique variance. Furthermore, the correlation between Path Length Time and Time to Peak Speed may be justified as it is likely to take less time to complete the task if the participant has a “head start” by reaching peak speed quickly. This is evidenced by previous research finding that when elements of an aiming task are modified via the inclusion of a distractor, movement takes both longer to execute (i.e. Path Length Time) and longer to reach peak speed (Mcintosh & Buonocore, 2012).

After this relatively substantial re-specification, the model approached good fit (χ^2 (30, N = 20030) = 18202.54, p <.001, CFI = .90, SRMR = .06, RMSEA = .17) and aligned more with existing sensorimotor control theory. When compared to the three-Component Statistical Model, the Posterior Theoretical Model which removed justifiably redundant or inconsistent items was vastly improved, χ^2 difference (176, N = 20030) = 930247, p <.001. Figure 10 shows the structure of the final model which was interpreted as representing “General Speed”; “Path Length”; and “Peak Speed”.

Figure 10

Path diagram of final model for Aiming task (Three-Component Posterior Theoretical Model)



Note: RT = Reaction Time; TPS = Time to Peak Speed; PLT = Path Length Time; PL = Path Length; PS = Peak Speed

Rectangle boxes represent manifest (observed) variables. Double-headed curved arrows represent correlation. Ellipses represent latent (unobserved) variables. Single headed arrows from latent to manifest variables represent factor loadings – thickness of these arrows represent the size of the loadings. Single-headed arrows towards manifest variables represent residual error

4.3.3 Steering

The PCA suggested a three-component model would be the most appropriate fit. Thus, the Statistical Model is reported alongside the *A Priori* and Posterior Theoretical Models. Fit statistics for all reported models can be found in Table 15.

4.3.3.1 One-factor model

Firstly, the one-factor model showed extremely poor fit, providing evidence that there are distinct sensorimotor dimensions underpinning this task (χ^2 (20, N = 22266) = 27282.64, p <.001, CFI = .53, SRMR = .14, RMSEA = .25).

Table 15

Fit statistics for the proposed models for the Steering task

Model	χ^2	Df	CFI	SRMR	RMSEA	BIC
One-Factor Model	27282.64*	20	.53	.14	.25	2574366.60
Three-Factor Statistical Model	10676.37*	16	.82	.09	.17	458021.45
A Priori Theoretical Model	1075.80*	6	.95	.03	.09	360521.40

** Statistically significant at p <.001*

4.3.3.2 Three-factor statistical model

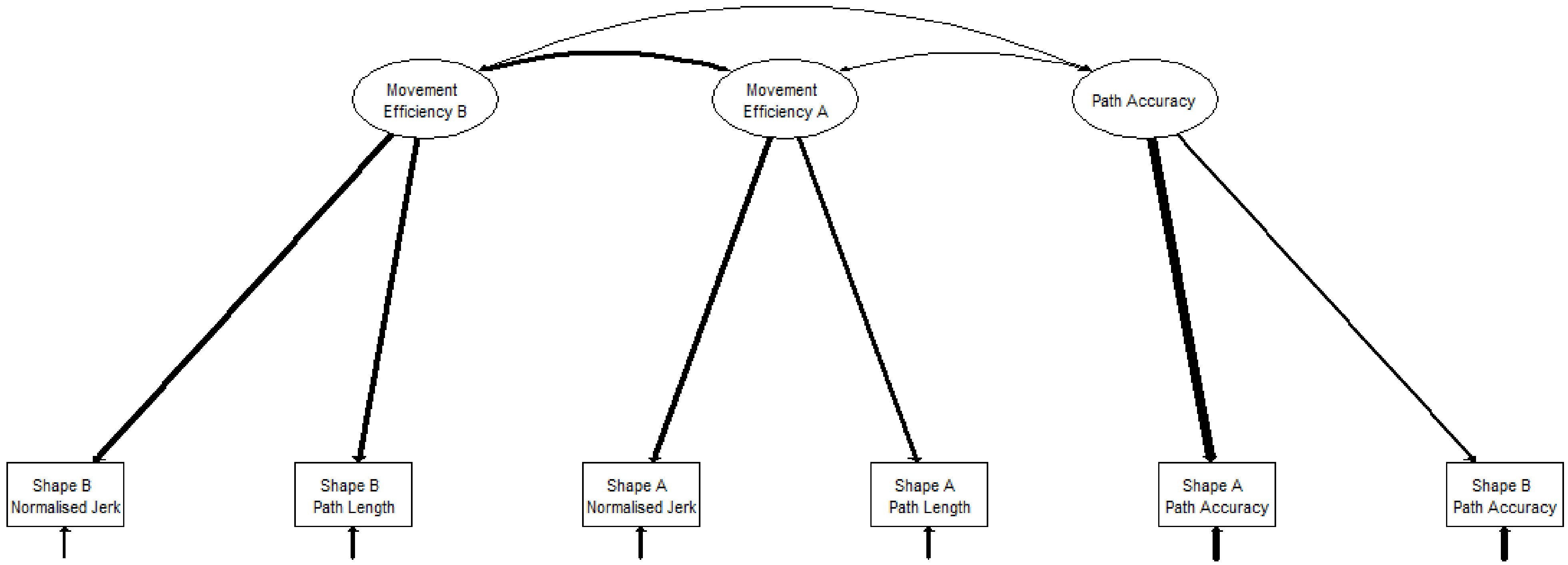
As reported in the previous chapter, the three-component model suggested Path Length Time from Shape B cross-loads across both Component 1 and Component 3. This was deemed theoretically inconsistent as the third component generally aligned with Path Accuracy. Although approaching acceptable model fit, further modification and re-specification was deemed necessary, (χ^2 (16, *N* = 22266) = 10676.37, *p* <.001, CFI = .82, SRMR = .09, RMSEA = .17).

4.3.3.3 A priori theoretical model

Some model re-specification was conducted to improve model fit and reduce the theoretical inconsistencies. Firstly, as suggested in Chapter 3, the Path Length Time metric (which had previously cross-loaded across Component 1 and 3) was omitted. This was for both Shape A and B. Justification for this decision was that one item related to Path Length Time loaded onto each of the three components, suggesting that as a whole, the metric adds little unique variance to the model. This is supported by no component consisting of solely items related to Path Length Time. In addition, the Steering task is somewhat temporally constrained with the inclusion of the timed box (see Section 1.2.2.1 for further detail) and thus, it may be less useful to include a temporal metric. The final model produced indicated good model fit, (χ^2 (8, *N* = 22266) = 1075.80, *p* <.001, CFI = .95, SRMR = .03, RMSEA = .09). No further modification indices were deemed necessary. As shown in Figure 11, the final model contained three components, interpreted as Movement Efficiency (Shape B); Movement Efficiency (Shape A); and Path Accuracy.

Figure 11

Path diagram of the final model for Steering task (three-component a priori theoretical model)



Note: Rectangle boxes represent manifest (observed) variables. Double-headed curved arrows represent correlation. Ellipses represent latent (unobserved) variables. Single headed arrows from latent to manifest variables represent factor loadings – thickness of these arrows represent the size of the loadings. Single-headed arrows towards manifest variables represent residual error

4.4 Discussion

4.4.1 Summary of findings

The aim of the present study was to use confirmatory factor analysis to determine the most interpretable and appropriate model fit for three tasks of CKAT to measure sensorimotor control. The models tested were proposed by a principal components analysis conducted previously (see Chapter 3). Subsequent exploration guided further refinement of these models to determine the most appropriate factor structure to be taken forward and applied for future studies investigating children's sensorimotor control. Findings suggested that sensorimotor control should be quantified via eight, three, and three dimensions, for the Tracking, Aiming, and Steering tasks, respectively. These factor structures had acceptable model fit when tested on a large, unseen dataset. Thus, we can place confidence in the ability of such model structures to account for performance on these sensorimotor tasks.

Quantifying movement in the proposed structure better captures the multi-faceted nature of sensorimotor control and various skills that this encompasses (e.g., different aspects of speed, spatial accuracy etc.). The findings from the present study align with previous research such as Wood et al. (2018). Using an alternative kinematic assessment, metrics such as movement smoothness (i.e., normalised jerk) and reaction time were better described across multiple independent components, each explaining unique variance within sensorimotor control.

4.4.2 Strengths and limitations

In comparison to other motor skill assessments and the previous use of CKAT, this refinement of the CKAT scoring provides a much more detailed description of how children execute movement. As previously discussed in Chapter 3, a large number of motor assessments are product-oriented (e.g., MABC-2), limiting the level of detail that can be captured. Even when process-oriented, kinematic assessments are used, the number of variables used to describe movement are often sparse. When compared to the Slurp Tool (K. Lee et al., 2014), which only quantified sensorimotor control via “time taken” and “number of errors” to account for spatial and temporal accuracy, the current analyses allow sensorimotor control to be described in a greater level of detail. Furthermore, alternative quantification of the CKAT subtests used in previous literature (e.g., Hill et al., 2016; Shire et al., 2016) were guided by theory, but were not grounded by specific empirical testing. Thus, the latent structures proposed in the present study are arguably more robust and justifiable descriptors of systematic variation in task performance, and thus sensorimotor control.

An additional strength of this study is the large datasets used to train and test the proposed models independently. PCA and CFA should not be conducted on the same samples, as this increases the risk of overfitting (Fokkema & Greiff, 2017). Thus, the current study benefits from using data collected from the Born in Bradford study, as this provides a large sample of sensorimotor data from a relatively homogenous sample of 4-11 year old children.

There are some limitations to be noted. Whilst the models tested were based on prior principal components analysis, the final models do reflect some *ad hoc* refinement such as allowing the error to co-vary across items or truncating the battery by omitting particular conditions. As discussed in Section 4.2.3 of this chapter, modifications should not be made to models without an adequate rationale, as this increases the risk of Type 1 error (Schreiber et al., 2006).

However, all decisions concerning model re-specification were driven by existing theory and no modifications were made without sound theoretical justification. In addition, any correlated error terms included in the final models were all within the same component which Hooper et al. (2008) argue is preferred than allowing items to correlate across latent factors. For this reason, it was more justifiable to allow two observed variables from the Movement Efficiency latent variable to co-vary rather than observed variables from different latent variables (e.g., co-varying an observed variable from Movement Efficiency with an observed variable from Path Accuracy). It was deemed necessary to refine the structure of the latent factors in this way in order to increase interpretation and meaningfulness on an applied level – making it more user-friendly for clinicians, teachers, and researchers alike.

Thus, the present analyses did encompass an element of exploratory analysis and so is not *strictly* confirmatory. However, the latent structures proposed in the present study are arguably more robust and justified than those in previous literature. Additional testing of these model structures can be conducted in future research across different populations when new data of a similar scale becomes available.

4.4.3 Conclusions

The present study aimed to inform future work on how to quantify sensorimotor control using CKAT. The factor structure proposed will be applied throughout subsequent studies within this thesis. It also provides evidence that sensorimotor control is a complex, multifaceted construct and thus measurement and analysis of sensorimotor data should reflect this. Whilst the present use of CKAT is not clinically diagnostic, it will provide indication of the specific aspects of movement a child is having the most difficulty with. As such, targeted interventions and/or support can be implemented to limit the consequences of poor sensorimotor control (e.g., poor academic attainment). More specific to this thesis, these findings can be used to provide additional information on how particular aspects of sensorimotor control develop throughout childhood and may be impacted by external factors, such as sociodemographic influences.

Chapter 5 Understanding the relationships between ethnicity, socioeconomic circumstances and sensorimotor control

5.1 Introduction

Sociodemographic factors can have a dramatic impact on a wide range of health and developmental outcomes (Altschul et al., 2019; Brodersen et al., 2005; Drozd et al., 2021; Gouge et al., 2019; Wickersham et al., 2021). As discussed in Chapter 1, ethnic and socioeconomic inequalities have been found in several areas of health and development (Aspinall & Jacobson, 2004; Bann et al., 2021; Claussen, 2015; Delgado-Angulo et al., 2019; Garcia et al., 2020; Karlsen & Nazroo, 2010; Kate E Pickett & Wilkinson, 2015; Präg et al., 2016; Uphoff et al., 2015; Wohland et al., 2015). Of particular concern is that these differences are found even in early childhood, likely contributing to further “domino effects”, through influencing the likelihood of additional adverse outcomes later in the life-course.

There are several proposed pathways in how one’s ethnicity may influence their health and development. Balarajan proposed these may include: “biological, cultural, religious, socio-economic or other environmental factors” (Balarajan, 1996, p. 119). Karlsen (2007) adds to this by suggesting racism experienced by some ethnic minority groups may also contribute towards ethnic differences in health outcomes. Understanding whether ethnic differences exist, and to what extent is first required, before these mechanisms can be explored further.

In terms of socioeconomic circumstances, research suggests increased disadvantage is associated with health and development inequalities at even a neurological level (Raizada & Kishiyama, 2010). Previous research has found that these relationships may be explained by a combination of individual (e.g., education, income, living arrangements) and area-based (e.g., access to services and amenities, infrastructure of local area, general attitudes towards health behaviours) mechanisms (Flensborg-Madsen et al., 2019; Macintyre et al., 1993; Niemistö et al., 2020). These sociodemographic factors (ethnicity and socioeconomics) have also been associated with children's motor abilities, with this research reviewed in the following sections.

5.1.1 Motor skills and ethnicity

Evidence to date has suggested ethnic differences within children's motor skills (Adeyemi-Walker et al., 2018; L. M. Barnett et al., 2019; Chow et al., 2001; E. Cohen et al., 1999; Eyre et al., 2018; Josman et al., 2006; Kelly et al., 2006; Tripathi et al., 2008; Ueda, 1978; Victora et al., 1990). Specifically, two studies have found UK primary-school-aged children from a South Asian background exhibited significantly poorer fundamental movement skills or fine motor skills compared to their White British and Black peers (Adeyemi-Walker et al., 2018; Eyre et al., 2018; Kelly et al., 2006). Fundamental Movement Skills were measured using the Test of Gross Motor Development-2 (TGMD-2; Ulrich, 2000) which categorises tasks into two domains: "Object Control" (i.e., catching, kicking) and "Locomotion" (i.e., running, jumping). Of note, the relationships between motor skill and ethnicity differed by domain within these three studies. Significant ethnic differences were found in the locomotor subtest of the TGMD-2 but not object control. Interestingly, the opposite was found in an Australian study which compared the fundamental movement skills of children from "Asian" and "European" backgrounds. Significantly poorer object control skills were found in the Asian group, but this was not the case for the locomotor domains (L. M.

Barnett et al., 2019). Thus, the cited evidence raises questions about the methodology used when investigating ethnic variation regarding children's motor skills.

As discussed in Chapter 1, ethnicity is an incredibly complex and multi-faceted construct so assuming homogeneity of such large groups as "Asian" versus "European" may be inappropriate and introduce biases. Rather than providing participants with the opportunity to self-report their ethnicity (or use parental-report), Barnett and colleagues (L. M. Barnett et al., 2019) split their sample into only two groups; based on the language spoken at home. A "cultural and linguistically diverse (CALD) classification hierarchy" then determined whether they should be grouped as "Asian" or "European". Grouping individuals in this way, however, does not necessarily determine a child's ethnic background accurately. For example, in some African countries such as Cameroon or Congo, the official language is French and thus regularly spoken in the home. Applying this classification in such a setting would erroneously assume children from these countries are more like their European peers although the culture (and genetics) are likely very different. Additionally, this method classifies children from a large range of different ethnicities (i.e., who speak a variety of different Asian languages) within the same category. Therefore, the subtle nuances of one's ethnic identity may not be accurately captured when using language spoken at home as a proxy measure for ethnicity. Thus, the findings should be interpreted with caution.

Similar limitations may be found within other studies which group participants as simply "Black", "White" or "Asian" (e.g., Adeyemi-Walker et al., 2018; Eyre et al., 2018). Instead, focus should be placed on a more specific ethnic group (e.g., White British) rather than more general groups (e.g., White) as large discrepancies across culture can still arise. Overgeneralisation of ethnicity increases the risk of assuming homogeneity within a large range of individuals which may otherwise vary largely (Bradby, 2003; Nazroo, 1998; Nazroo & Williams, 2006). For example, categorising an individual as “Asian” within the US encompasses people from approximately 28 different countries – each having their own unique religion, cultural practices and belief systems (Lin-Fu, 1993). Indeed, Bhopal et al. (1991) argue that the term “Asian” is rarely used as a self-descriptor by people around the South-East Asian continent. Rather, it is a term used by others outside of that community. Consequently, more specific, appropriate, and inclusive terminology is required when investigating ethnic differences.

Secondly, ethnic differences may be a result of methodological constraints in the measurement of motor skills, and biases that may arise due to these chosen methods. The TGMD-2 (used by (Adeyemi-Walker et al., 2018; L. M. Barnett et al., 2019; Eyre et al., 2018) is a standardised assessment battery widely used in the literature to assess children’s fundamental movement skills, but it has several limitations specific to this line of research. For example, batteries such as the TGMD-2 (Ulrich, 2000), as well as the BOT-2 (Bruininks & Bruininks, 2005), are assumed to be an accurate representation of general motor competence but are largely sport-specific (Larsson & Quennerstedt, 2012; Ng & Button, 2018). Subsets include kicking, striking a stationary ball, throwing a ball at a target, and catching a tossed ball. Some researchers have suggested that such skills are based on norms often biased by sex, race and social status (Larsson & Quennerstedt, 2012; Jan Wright & Burrows, 2006). Furthermore, some skills within assessment batteries may be more akin to sports played more frequently within some groups than others (Bardid et al., 2015). Thus, disadvantaged or minority groups (e.g., ethnic minorities, low-income households), who are less likely to engage in extra-curricular activities such as sports (Brockman et al., 2009; Casper et al., 2011; Somerset & Hoare, 2018) are likely disadvantaged in being able to develop their skills in a way which meets the requirements of the task (e.g., two-handed ball strike). As a result, they are deemed less competent than their peers because their motor skills are assessed in this biased context, even if their core sensorimotor mechanisms may be equally well-developed - just less adapted to the specific expectations of the dominant culture.

However, as discussed in Chapter 3, even if assessment batteries are not sport-specific, they are often subjective in nature; relying on observation methods by trained researchers or clinicians, such as the MABC-2 (Henderson et al., 2007) and DDST (Frankenburg & Dodds, 1967). The subjectivity of such assessment batteries may be exacerbated when investigating ethnic or socioeconomic differences due to potential unconscious biases or experimenter effects. For example, when assessing interventions, studies with non-blinded assessors are generally more likely to find significant effects compared to those blinded to the experimental objectives (Hróbjartsson et al., 2013). Previous research has also suggested that implicit biases towards various sociodemographic groups (e.g., defined by ethnicity, SES, sex) may impact perceptions of children’s abilities (Mason et al., 2014). The avoidance of such biases may therefore be difficult when using subjective assessments and thus previous findings may not reflect true ethnic differences but rather limitations with the method of assessment.

5.1.2 Accounting for SES

As briefly discussed in Chapter 1, when conducting such research, it is important to acknowledge that ethnicity cannot and should not be viewed in isolation. It has been argued that ethnicity is intertwined with SES; with the two interacting with, and confounding each other (Cheng et al., 2015). As early as 1916, differences in health (mortality rates) between Black and White people were explained by differences in socioeconomic circumstances rather than genetic or cultural differences (Trask, 1916). Williams (2002) stated that the ethnic differences in health are much smaller than differences between socioeconomic groups, with most ethnic differences being a result of socioeconomic inequality (Navarro, 1990; Sheldon & Parker, 1992). More recent support for this claim comes from work demonstrating that ethnic differences in health and lifestyle are still apparent, but drastically reduced when accounting for SES (Erens et al., 2001; Marshall et al., 2007; Nazroo, 2003; Williams, 1999).

There is evidence to suggest that the relationship between ethnicity and SES should also be taken into consideration when investigating ethnic differences in children's motor skills. Whilst Kelly et al. (2006) found Pakistani and Bangladeshi infants were significantly more likely to exhibit delay in gross and fine motor milestones, these ethnic differences disappeared when adjusting for SES. That is, the advantage originally exhibited by White British infants compared to Pakistani and Bangladeshi was explained by differences in their socioeconomic circumstances.

Indeed, individuals from ethnic minorities are generally over-represented in the most deprived groups based on income, particularly those from Pakistani or Bangladeshi backgrounds (Nazroo & Williams, 2005; Office for National Statistics, 2018). Previously cited evidence which found children of South Asian origin exhibit poorer motor skills (e.g. Adeyemi-Walker et al., 2018; Eyre et al., 2018) did not account for SES in analyses, only suggesting that participants all came from schools in “low-SES areas” of England. Individual socioeconomic circumstances, and the nuances of SES were not appropriately acknowledged or controlled for. Thus, it is conceivable that any ethnic differences previously found may be a result of the inequalities associated with social disadvantage in wealth within the sample, rather than genetic or cultural differences. If this is the case, a different approach would be necessary for addressing differences through prevention or intervention strategies, as a result of social disadvantage compared to differences related to genetics or culture.

5.1.3 Motor skills and SES

The idea that ethnic differences in motor skills are the result of associated differences in SES is entirely plausible considering the large body of evidence which demonstrates how children’s motor abilities are strongly associated with their family’s socioeconomic situation. Research shows that children from lower SES backgrounds (based on indicators such as education, employment status, household income), are at an increased risk of poor motor ability compared to their less-deprived peers (Adkins et al., 2018; Comuk-Balci et al., 2016; Cools, De Martelaer, Samaey, & Andries, 2011; Ferreira, Godinez, Gabbard, Vieira, & Caçola, 2018; Ghosh, Ghosh, Dutta Chowdhury, Wrotniak, & Chandra, 2016; Mcphillips & Jordan-Black, 2007; Mülazımoğlu-Ballı, 2016; Verheijen et al., 2020; Zeng, Johnson, Boles, & Bellows, 2019). For example, Morley and colleagues (Morley et al., 2015), used the Index of Multiple Deprivation (IMD; Ministry of Housing Communities and Local Government, 2007) and the BOT-2 (Bruininks-Oseretsky Test of Motor Proficiency; Bruininks, 1978) to investigate the impact of

SES on both fine- and gross-motor skills in 4-7 year olds. It was found that 40% of the children in the low SES group scored below average on the BOT-2, compared to only 22% of the children in the high SES, and 19.4% of children from the medium SES groups. Using maternal education as a measure of SES, research has found it to significantly predict fine motor (Comuk-Balci et al., 2016; Verheijen et al., 2020) and locomotor (Zeng et al., 2019) skills in early childhood. However, the relationship between SES and motor ability is somewhat dependent on how SES is conceptualised, and which indicators are used. For example, significant associations have been found for parental education, but not parental occupation within the same sample (Cools et al., 2011). Therefore, differences in which indicators of SES are used may account for some inconsistencies across the literature as to how strongly SES may influence motor abilities.

5.1.4 Interaction between SES and ethnicity

Furthermore, the complexities of the relationship between ethnicity and socioeconomic inequalities have also been established in research investigating social gradients in multi-ethnic samples. The term "social gradient" refers to the phenomenon that inequalities in health are often related to inequalities in sociodemographics, whereby the poorest individuals are often the sickest (Cheng et al., 2015; World Health Organization, 2013). Previous research has shown steep social gradients for various health outcomes (e.g., preterm birth, mental health) for White British individuals which are not replicated to the same extent for Pakistanis (Aveyard et al., 2002; Bhopal et al., 2002; Chandola, 2001; Fischbacher et al., 2014; Mallicoat et al., 2020; Uphoff et al., 2015; Zilanawala et al., 2016). In other words, ethnicity appeared to moderate the relationship between SES and health. Thus, it is possible that the same trend applies to children’s motor skills, in that there may be larger discrepancies in motor skills between socioeconomic groups within White British, compared to Pakistani individuals.

5.1.4.1 The present study

Upon reviewing the current evidence, it was evident that studies exploring the association of one’s ethnicity and/or socioeconomic circumstances often use methodologies which are not optimal, leading to a lack of clarity and consistency of results when reviewing the current evidence. For example, the subjective and sport-specific nature of the assessments often used may confound findings. Instead, by focusing on the underpinning mechanisms of movement, a more detailed understanding of *how* movement is sub-optimal can be obtained. Kinematic assessment batteries offer this ability (discussed in detail in Chapter 3) and are arguably preferable to more subjective assessments, which are more prone to bias and human error. By measuring motor skills more accurately and objectively, greater confidence can also be placed in conclusions drawn from studies exploring its association with various sociodemographic factors.

In Chapter 3 and Chapter 4, PCA and CFA, respectively, were conducted to reduce the dimensionality of the kinematic output from CKAT. It was predicted that a measure which describes a greater amount of systematic variance, that is based upon both theoretical and empirical evidence would be better able to capture more subtle differences in sociodemographics, compared to conventional scoring methods of CKAT (i.e., *a priori* metric selection based on theoretical but not empirical justifications). In addition, using a data-driven approach of selecting kinematic variables criticism of potential “cherry-picking” of variables (Murphy & Aguinis, 2019). This is the first study to apply this revised scoring procedure to answer novel research questions. Thus, the analyses within Study 1 of this chapter used the “conventional” one-metric-per-task scoring system (e.g. L. J. B. Hill et al., 2016) and Study 2 used the novel, revised approach derived in Chapter 3 and Chapter 4.

Measurement choices in relation to SES may also explain some of the inconsistencies found across the literature thus far, as different relationships have been found depending on the way SES has been measured. By investigating multiple measures of SES, it is possible to pin-point which may be more accurate indicators of children requiring additional help. As previously discussed, a latent measure of SEP may better capture the multifaceted nature of the construct. Chapter 2 describes the method used to obtain latent classes of SEP from 19 individual indicators which were adjusted for individual ethnicity. Thus, as was the case for sensorimotor control, the analyses were conducted using both the “conventional” method of multiple, commonly used individual predictors of SES in Study 1 here and again with the latent class measure of SEP in Study 2.

Furthermore, rarely do studies explore the complex *interaction* between ethnicity and SES. Considering how sensorimotor control underpins a large aspect of children’s development and wellbeing (Augustijn et al., 2018; Harrowell et al., 2018; L. J. B. Hill et al., 2016; Kwan et al., 2016; Zwicker et al., 2013), this gap in the literature needs addressing. By understanding ethnic differences (or even whether they exist after appropriately controlling for SES), it is possible to address potential inequalities through targeted intervention, which may be specific to ethnic minority groups.

As such, the present chapter aimed to use an objective kinematic assessment tool to explore how ethnicity and socioeconomic circumstances influence sensorimotor control in school-aged children. It also aimed to investigate how these relationships are affected by the method of measuring these variables. To do so, the present chapter is divided into two distinct studies. The first study uses the “conventional” measures (CKAT scoring and SES) and the second uses the “revised” measures to explore the relationships between ethnicity, socioeconomic position and sensorimotor control. Specifically, the following predictions were made:

1. Ethnicity will significantly predict children’s sensorimotor control performance in both Study 1 and 2 after controlling for age, sex, and handedness
2. Conventional measures of SES and cohort-wide SEP will both significantly predict children’s sensorimotor control performance in their respective studies after controlling for age, sex, and handedness
3. The strength of the relationship between ethnicity and sensorimotor control performance will weaken or disappear when controlling for conventional SES or cohort-wide SEP, and age, sex, and handedness
4. If a relationship with ethnicity persists after controlling for conventional SES or cohort-wide SEP, it will be moderated by the relationship between sensorimotor control performance and conventional SES, or ethnic-wide SEP
5. The impact of SEP on sensorimotor control will differ by ethnic group when using an ethnic-specific measure in sub-group analyses

5.2 Study 1

5.2.1 Method

5.2.1.1 Study setting and participants

The present study is a secondary data analysis of data collected from the Starting School sweep within the Born in Bradford study (this cohort is described in detail in Chapter 1). A detailed analysis plan was pre-registered prior to accessing secondary data from BiB (see https://osf.io/jb5z3/). Although data from “non-BiB” children were also collected within this sweep, only those with both complete sensorimotor data and additional demographic information obtained during the Baseline Questionnaire were included in the present analyses (*n* = 2480). Due to the bi-ethnic nature of the sample, most participants identified as either White British (*n* = 806) or Pakistani (*n* = 1362), with 312 recorded as “Other”. As such, participants coded as “Other” were excluded from this analysis. The number of participants from the various ethnic groups within this category were too few to enable meaningful statistical analysis of them. In addition, only participants with complete sensorimotor and demographic data were retained in the final analysis (*n* = 2168).

Table 16 displays the demographic information for this sample and shows how this varied by ethnic group. As can be seen in the table, a larger proportion of the sample were of Pakistani origin and a larger proportion of Pakistani individuals were categorised into the lower SES groups compared to their White British peers. This is particularly evident for proportion of those in the most deprived IMD quintile. Similarly, an approximately even split between those receiving and not receiving means-tested benefits was also found with Pakistani mothers, whilst a larger proportion of White British mothers did *not* receive such benefits. The distribution of education levels were relatively similar across the two ethnicities.

Table 16

Demographic information for the whole sample and stratified by ethnicity

	Pakistani	White British	Whole Sample
Child Demographics			
N (%)	1362 (62.8)	806 (37.2)	2168 (100.0)
Sex			
Male (%)	687 (50.4)	412 (51.1)	1099 (50.7)
Female (%)	675 (49.6)	394 (48.9)	1069 (49.3)
Handedness			
Left (%)	103 (7.6)	98 (12.2)	201 (9.3)
Right (%)	1259 (92.4)	708 (87.8)	1967 (90.7)
Maternal Demographics			
Receipt of Means-Tested Benefits			
Yes (%)	647 (47.5)	307 (38.1)	954 (44.0)
No (%)	715 (52.5)	499 (61.9)	1214 (56.0)
IMD Quintile[1]			
1 (%)	1121 (82.3)	420 (52.1)	1541 (71.1)
2 (%)	175 (12.8)	161 (20.0)	336 (15.5)
3 (%)	62 (4.6)	170 (21.1)	232 (10.7)
4 (%)	2 (0.1)	33 (4.1)	35 (1.6)
5 (%)	2 (0.1)	22 (2.7)	24 (1.1)
Maternal Education			
< 5 GCSEs equiv. (%)	383 (28.1)	180 (22.3)	563 (26.0)
5 GCSEs equiv. (%)	472 (34.7)	291 (36.1)	763 (35.2)
A-Level equiv. (%)	157 (11.5)	119 (14.8)	276 (12.7)
> A-Level equiv. (%)	290 (21.3)	137 (17.0)	427 (19.7)
Don’t Know (%)	21 (1.5)	9 (1.1)	30 (1.4)
Foreign Unknown (%)	4 (0.3)	0 (0.0)	4 (0.2)
Other (%)	35 (2.6)	70 (8.7)	105 (4.8)

[1] Most Deprived = Quintile 1, Least Deprived = Quintile 5.

5.2.1.2 Materials

5.2.1.2.1 Socioeconomic Status (SES)

Information regarding mothers' socioeconomic circumstances was collected at recruitment within the BiB Baseline Questionnaire. Although a number of SES variables were recorded, the present analyses focused on three commonly used within studies from the Born in Bradford cohort and the wider literature: maternal education; IMD (Department of Communities and Local Government, 2011), and receipt of means-tested benefits. The subsequent sections describe each of these measures in turn.

5.2.1.2.1.1 Index of Multiple Deprivation (IMD)

IMD is used to classify English neighbourhoods into quintiles based on the relative level of deprivation, with lower quintiles indicating increased deprivation. These scores are derived from 37 indicators, distributed across seven domains: Income Deprivation; Employment Deprivation; Health Deprivation and Disability; Education, Skills and Training Deprivation; Crime; Barriers to Housing Services; and Living Environment Deprivation (Ministry of Housing Communities and Local Government, 2019). As noted in Chapter 1, the IMD ranks Bradford as the 11th most deprived city in England based on the number of deprived neighbourhoods in the city. This is a commonly used measure of SES in the literature (Stamatakis et al., 2014; Zilanawala et al., 2015), including in previous research using BiB data (Prady, Pickett, Croudace, et al., 2016).

5.2.1.2.1.2 Means-tested benefits

During the Baseline Questionnaire, mothers were additionally asked to specify whether they were in receipt of any means-tested benefits. Eligibility for such benefits (e.g., Jobseeker's Allowance, Housing Benefit) is dependent on household income and capital. This was coded dichotomously (Yes; No) and has been previously used as an indicator of SES within BiB studies (e.g., Kelly et al., 2017; Prady et al., 2016; Uphoff et al., 2015).

5.2.1.2.1.3 Maternal education

Lastly, maternal education was also used as an indicator of family SES. This measure is a widely used proxy of SES (e.g., Cools et al., 2011; Corsi et al., 2016; Lejarraga et al., 2002; Uphoff, Pickett, & Wright, 2016). Maternal education was coded as "<5 GCSE or equivalent", "5 GCSE equivalent"; "A-level equivalent"; "Higher than A-level"; "Don't Know"; "Foreign Unknown", and "Other". For the purposes of the present analyses, participants recorded as having responded with "Don't Know", "Foreign Unknown" or "Other" were omitted.

5.2.1.2.2 Additional demographic information

As described in Chapter 1, self-reported ethnicity was collected as part of the BiB Baseline Questionnaire administered at recruitment. This was coded into one of three categories: "White British"; "Pakistani"; or "Other". Although more nuanced descriptors of ethnicity were also collected (e.g., "Bangladeshi", "Mixed-White and South Asian"), the number of participants in these groups was much smaller and so these individuals were classified as "Other". Thus, ethnicity was stratified into only three groups (White British, Pakistani, and "Other").

Additional information was collected during testing to include as covariates. This included children's self-reported handedness, age in months (provided by the school), and sex.

5.2.1.2.3 Sensorimotor control

CKAT was used to measure children’s sensorimotor control (Culmer et al, 2009; Flatters et al., 2014). Consistent with previous literature, one kinematic metric was selected to quantify performance on each of the three tasks analysed as outcomes measured in Study 1. These metrics were the Root Mean Squared Error (RMSE), Path Length Time (PLT), and penalised Path Accuracy (pPA) for the Tracking, Aiming, and Steering tasks, respectively. These kinematic metrics have been routinely reported as outcomes in previous literature using CKAT (Flatters et al., 2014; Giles et al., 2018; Hill et al., 2021; Shire et al., 2016).

RMSE is the average distance (in millimetres) between the tip of the stylus and the target centre over the course of the Tracking task, with respect to each speed condition (i.e., Slow, Medium, Fast). This provides a measure of spatio-temporal accuracy. PLT is the average time taken to respond to and execute the aiming movement within the Aiming task, in seconds. For trials within the Jump condition, the PLT was calculated respective of the final target location. Lastly pPA takes path accuracy (i.e., a measure of all spatial errors) and multiplies it by the deviation from the “optimum” path length time of 36 seconds within the Steering task (see Equation 1). These tasks and the corresponding metrics provide insight on specific sensorimotor control mechanisms, namely, feed-forward and feedback mechanisms and the ability to make online corrections (Flatters, Hill, et al., 2014).

The median values of RMSE, PLT & pPA were computed before each was reciprocally transformed to normalise their distributions. Next, each transformed outcome was scaled and centred to allow comparisons across tasks. Lastly, an Overall CKAT score was computed by taking the mean of the three task scores.

This Overall CKAT score was used as the outcome variable within the present analyses. The use of an Overall Score has been used previously in the literature (e.g., Hill et al., 2016). A higher Overall CKAT score was indicative of better performance.

Equation 1

Formulaic expression of "Penalised Path Accuracy"

$$pPA = PA \times (1 + |(PLT/36) - 1|)$$

5.2.1.3 Procedure

The testing procedure for the collection of the sensorimotor data via CKAT was as detailed in Chapter 1.

5.2.1.4 Statistical analysis

A series of hierarchical linear regressions were used to investigate the proposed research questions using an alpha level of .05 to indicate statistical significance. All statistical analyses were conducted in R (version 4.0.0, R Development Core Team, 2020). Goodness of fit was compared between each additional step of the hierarchical model to indicate the explanatory power of each additional predictor variable. Step 1 of all models included the outcome variable (Overall CKAT Score) and the three baseline covariates (age, handedness, and sex).

Equation 2

Baseline model for the hierarchical linear regression for the effect of age, handedness and sex on sensorimotor control

$$Y = b_0 + b_1AGE + b_2HAND + b_3SEX + \varepsilon$$

where Y is children’s Overall CKAT score, AGE is the child’s age in months, HAND is handedness and SEX is the child’s biological sex.

Next, Model 1, which related to Research Question 1 (RQ1; the role of ethnicity on sensorimotor control) was divided into two steps. Step 1 was as above. Step 2 then added ethnicity as an additional predictor to the model.

Equation 3

Step 2 of the hierarchical linear regression (Model 1) for the effect of ethnicity on sensorimotor control (RQ1)

$$Y = b_0 + b_1 ETH + b_2 X + \varepsilon$$

where Y is children's Overall CKAT score, ETH is the participant's ethnic group (White British or Pakistani) and X is the covariates included (age, handedness and sex).

Models 2, 3 and 4 were associated with RQ2 (the role of SES). Each of these three models included one of the three indicators of SES as an additional predictor in Step 2 (maternal education, receipt of means-tested benefits, or IMD) and were run independently. For maternal education, the reference category was <5 GCSEs or equivalent. The reference category for IMD was Quintile 1 (Most Deprived).

Equation 4

Step 2 of the hierarchical linear regression (Models 2,3 & 4) for effect of SES on sensorimotor control (Research Question 2)

$$Y = b_0 + b_1 SES + b_2 X + \varepsilon$$

where *Y* is children's Overall CKAT score, SES is one of the three SES indicators (maternal education, receipt of means-tested benefits, or IMD), and X is the covariates included (age, handedness and sex).

Model 5 related to RQ3 (the role of ethnicity after controlling for SES). Within this model, Step 1 was as above. Step 2 included the covariates and all three SES indicators (maternal education, receipt of means-tested benefits, and IMD) entered simultaneously. Step 3 added ethnicity as an additional predictor to investigate whether ethnic differences were present after controlling for SES.

Equation 5

Step 3 of the hierarchical linear regression (Model 5) for effect of ethnicity on sensorimotor control after controlling for SES (Research Question 3)

$$Y = b_0 + b_1 SES + b_2 SES + b_3 SES + b_4 ETH + b_5 X + \varepsilon$$

where Y is children's Overall CKAT score, SES is one of the three SES indicators (maternal education, receipt of means-tested benefits, or IMD), ETH is the participant's ethnic group (White British or Pakistani) and X is the covariates included (age, handedness and sex). Note that in this model, all three SES indicators were added to the model simultaneously as additional covariates.

Lastly, moderation analyses were conducted to determine how the relationship between SES and sensorimotor control may be influenced by one's ethnicity (RQ4). These analyses are reflected in Models 6, 7, and 8. Step 2 of these models included the baseline covariates, SES (an independent model was conducted for each SES indicator, respectively), and ethnicity. Step 3 added in the interaction term between the respective SES indicator and ethnicity. Moderation analyses were conducted for each of the three SES indicators in independent models, irrespective of whether the SES indicator was previously found to significantly predict performance.

Equation 6

Step 3 of the hierarchical linear regression (Models 6, 7 & 8) for the moderating effect of SES and ethnicity on sensorimotor control (Research Question 4)

$$Y = b_0 + b_1 ETH + b_2 SES + b_3 ETH \cdot SES + b_4 X + \varepsilon$$

where *Y* is children's Overall CKAT score, ETH is the participant's ethnic group (White British or Pakistani), SES is one of the three SES indicators (maternal education, receipt of means-tested benefits, or IMD), X is the covariates included (age, handedness and sex), and ETH·SES refers to the moderation.

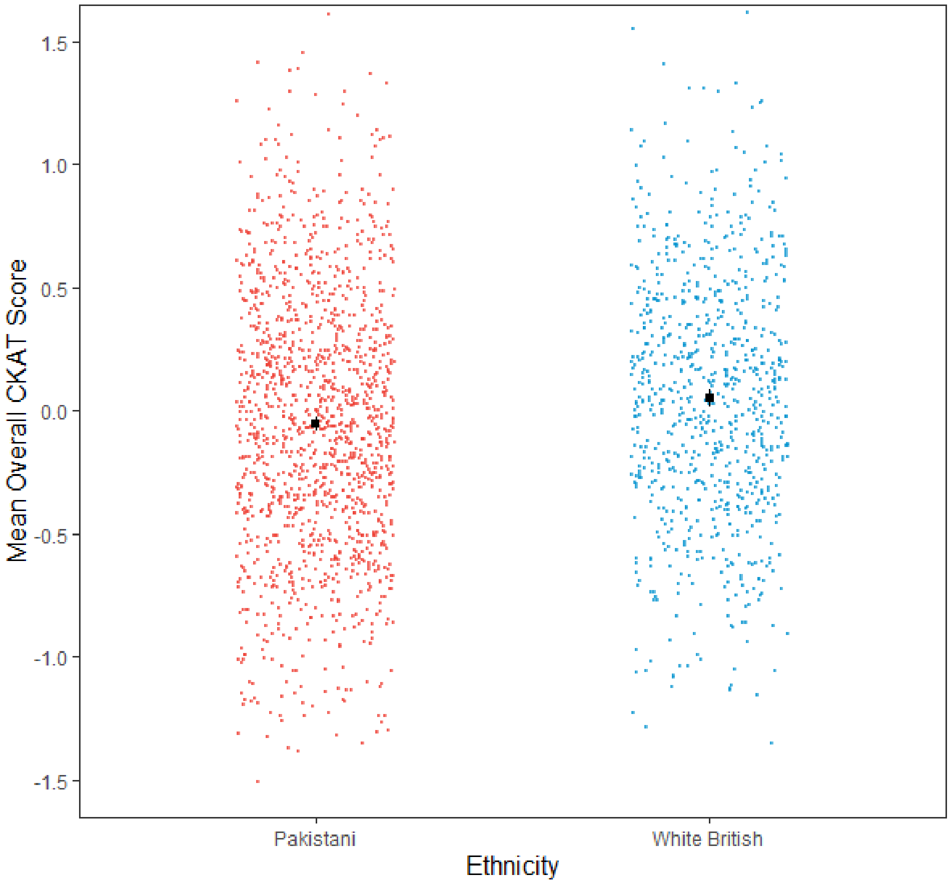
5.2.2 Results

5.2.2.1 RQ1: Does ethnicity predict Overall CKAT score when controlling for age, sex and handedness?

Overall CKAT score was contrasted between White British and Pakistani participants. As shown in Figure 12, on average, White British participants produced greater Overall CKAT scores (M = .05, SD = .50) compared to their Pakistani peers (M = -.05, SD = .53).

Figure 12

Mean values of Overall CKAT Score stratified by ethnicity



Note: Each dot represents an individual participant. Higher score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals- these are very small due to the large sample sizes.

Hierarchical linear regression was then conducted to determine the effect of ethnicity on Overall CKAT score when controlling for age, sex, and handedness. As shown in Table 17, ethnicity was a significant predictor of Overall CKAT Score, b = 0.113 [0.068, 0.157], p<.001. Including ethnicity as an additional predictor in the regression model explained 3.6% of the variance in Overall CKAT score (R^2= .036, F(4,2163) = 20.464, p<.001). This was an increase of 1% compared to Step 1 which was statistically significantly different from zero (ΔF(1, 2163) = 24.575, p<.001).

Table 17

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age and ethnicity (Model 1)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.026	
(Intercept)	-0.489** [-0.689, -0.288]	0.102			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.111** [0.036, 0.185]	0.038	.062		
Age (Years)	0.095** [0.053, 0.137]	0.021	.095		
Step 2				.036	.010**
(Intercept)	-0.544** [-0.745, -0.344]	0.102			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.125** [0.051, 0.199]	0.038	.070		
Age (Years)	0.095** [0.054, 0.137]	0.021	.095		
White British	0.113** [0.068, 0.157]	0.023	.105		

*Note: * indicates p< .05. ** indicates p< .01. Reference category for ethnicity is Pakistani. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient.* R^2 *= R-squared,* ΔR^2 *= change in R-squared.*

5.2.2.2 RQ2: Does SES predict Overall CKAT score when controlling for age, handedness?

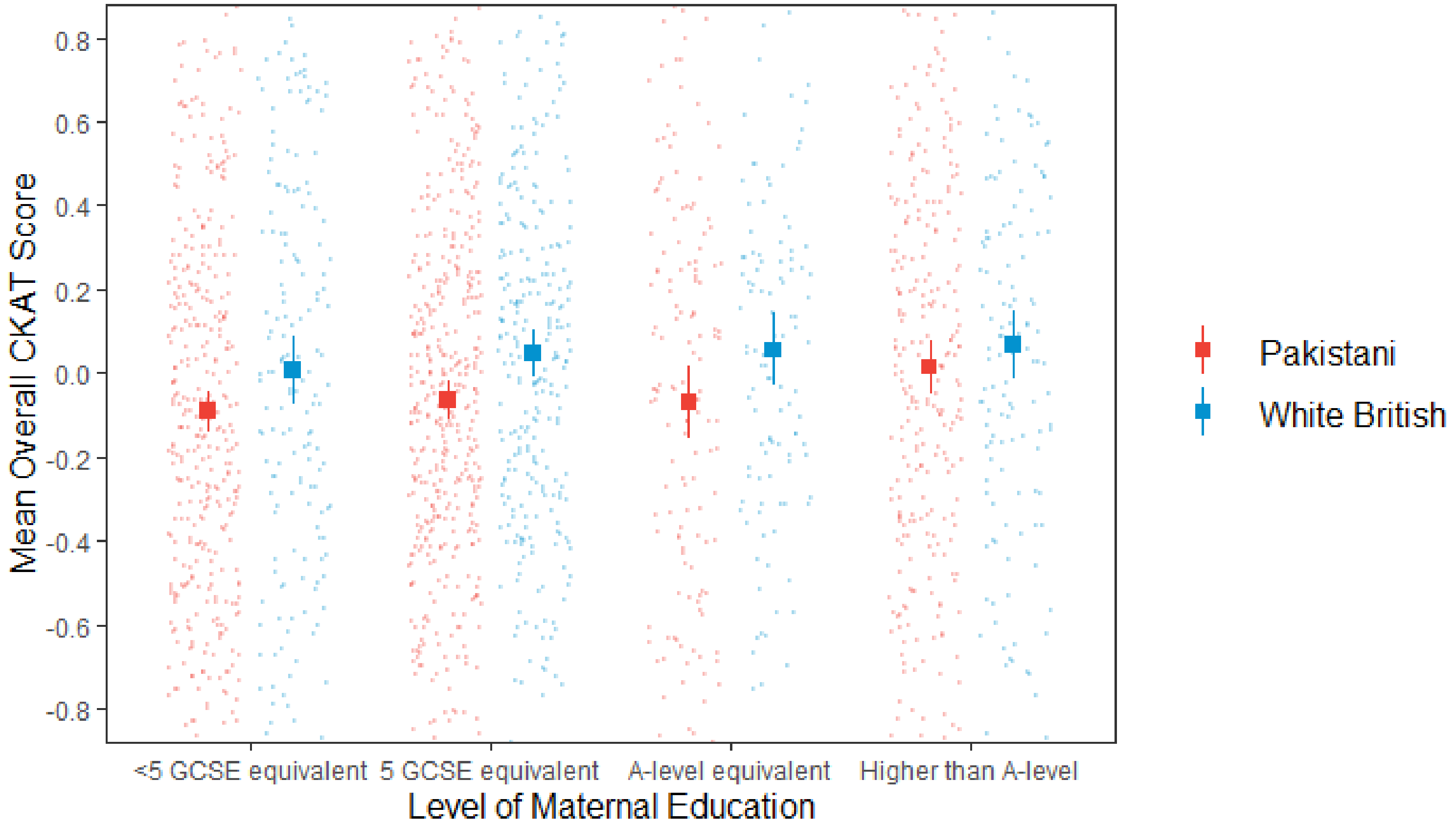
To understand the predictive value of SES on children's sensorimotor control, each of the three SES predictors (maternal education, receipt of means-tested benefits, IMD) were entered into Step 2 of three independent hierarchical linear regression models (Model 2, Model 3, and Model 4).

5.2.2.2.1 Maternal education

On average, children with mothers with the highest level of education (above A-level or equivalent) had greater Overall CKAT scores compared to those with less educated mothers for both ethnic groups (see Figure 13).

Figure 13

Overall CKAT score across level of maternal education, stratified by ethnicity



Note: Each dot represents an individual participant. Higher score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals.

Step 1 of Model 2 explained 2.4% of the variance (R^2 = .024, $F(3,2025)$ = 16.600, p<.001). As shown in Table 18, the inclusion of maternal education as an additional predictor of Overall CKAT Score alongside age, sex, and handedness at Step 2 explained 2.9% of the variance (R^2 = .029, $F(6,2022)$ = 9.889, p<.001). This increased the total amount of variance explained by 0.5% compared to Step 1, which was an increase that was significantly different from zero $\Delta F(3, 2022)$ = 3.125, p =.025). Compared to children of mothers with fewer than five GCSEs (the reference category), only those whose mothers had the highest qualification level (above A-level or equivalent) were predicted to score significantly higher Overall CKAT scores (b = 0.100, p=.002). None of the lower levels of education showed statistically significant increases over the lower (reference) level in this model (i.e., <5 GCSEs). In addition, age, sex, and handedness were all found to be significant predictors of Overall CKAT score (see Table 18), with right-handed children outperforming left-handers, females outperforming males, and older children outperforming their younger peers.

Table 18

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age, and maternal education (Model 2)

Predictor	***B* [95% CI]**	**SE**	**β**	**R^2**	**ΔR^2**
Step 1				.024	
(Intercept)	-0.458** [-0.664, -0.252]	0.105			
Male	-0.112** [-0.156, -0.067]	0.023	-.108		
Right-handed	-0.103* [0.024, 0.181]	0.040	.056		
Age (Years)	0.089** [0.046, 0.132]	0.022	.089		
Step 2				.029	.005*
(Intercept)	-0.515** [-0.73, -0.30]	0.108			
Male	-0.113** [-0.16, -0.07]	0.023	-.110		
Right-handed	0.100* [0.02, 0.18	0.040	.055		
Age (Years)	0.092** [0.05, 0.13]	0.022	.093		
5 GCSEs equiv.	0.045 [-0.01, 0.10]	0.028	.043		
A-Level equiv.	0.052 [-0.02, 0.13]	0.038	.035		
Above A-Level equiv.	0.100** [0.04, 0.16]	0.033	.079		

*Note: * indicates p< .05. ** indicates p< .01. Reference category for maternal education is <5 GCSEs or equivalent. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient. R^2 = R-squared, ΔR^2 = change in R-squared.*

5.2.2.2.2 Means-tested benefits

On average, there was little difference in the performance of children from families who were not in receipt of means-tested benefits (M = -0.01, SD = 0.51) compared to children whose families did receive such benefits (M = -0.02, SD = 0.53; see Figure 14).

Figure 14

Mean Overall CKAT Score between recipients of Means-Tested Benefits, stratified by ethnicity

Note: Each dot represents an individual participant. Higher score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals.

Table 19 shows that a model including means-tested benefits alongside the covariates (Model 3) explained 2.6% of the variance of Overall CKAT Score (R^2 = .026, F(4,2163) = 14.244, p <.001. However, in comparison to Step 1, this addition of receipt of means-tested benefits did not significantly increase the unique variance explained by the model (ΔF(1, 2163) = 0.330, p = .566). Again, sex, age, and handedness were all found to significantly predict Overall CKAT score. The direction of these effects was identical to those for maternal education (Model 2).

Table 19

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age, and receipt of means-tested benefits (Model 3)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.026	
(Intercept)	-0.489** [-0.689, -0.288]	0.102			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.111** [0.036, 0.185]	0.038	.062		
Age (Years)	0.095** [0.053, 0.137]	0.021	.095		
Step 2					
(Intercept)	-0.483** [-0.684, -0.281]	0.103		.026	<.001
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.111** [0.036, 0.186]	0.038	.062		
Age (Years)	0.095** [0.053, 0.136]	0.021	.095		
Receipt of MTB: Yes	-0.013 [-0.056, 0.031]	0.022	-.012		

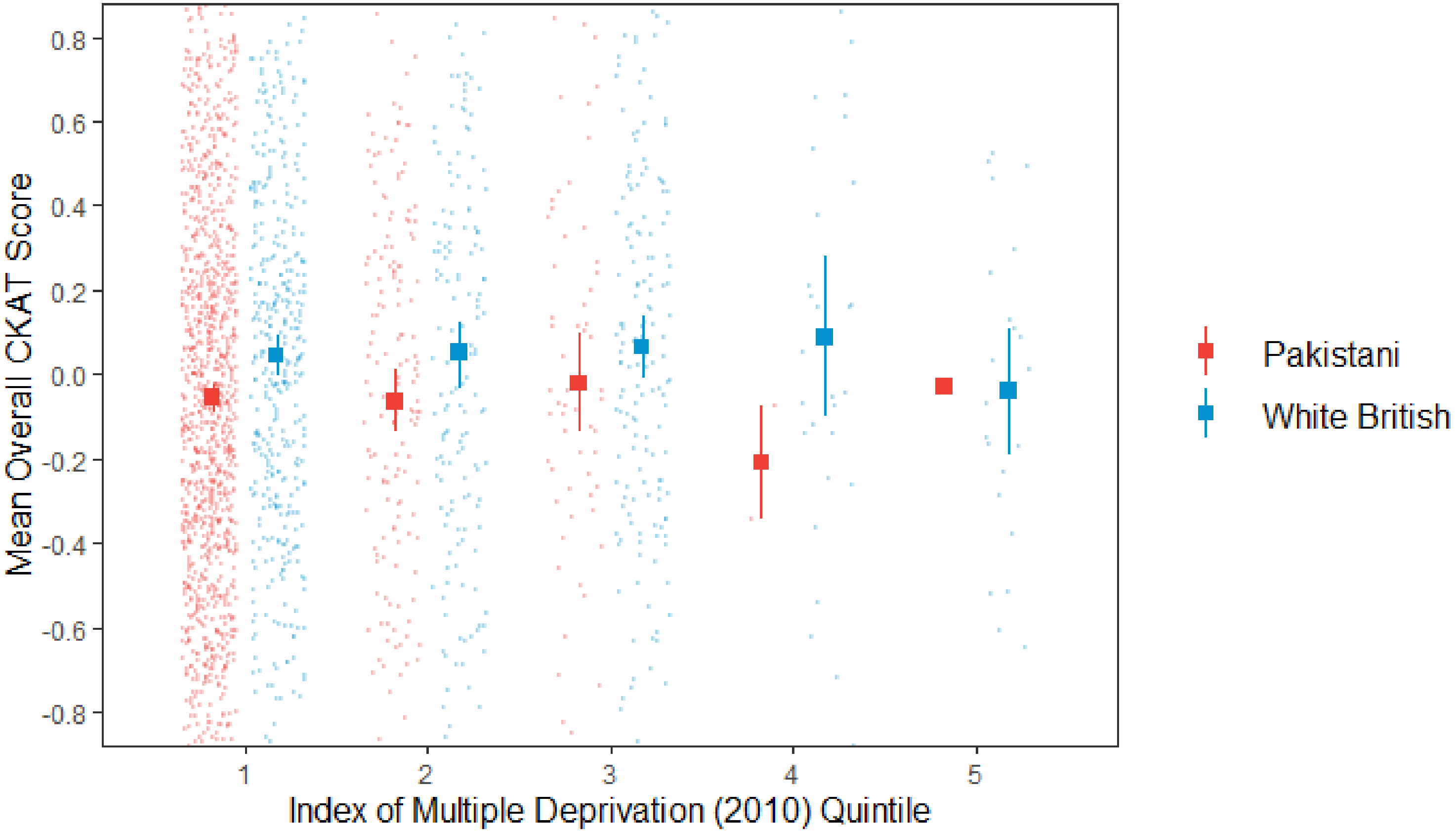
*Note: * indicates p< .05. ** indicates p< .01. Reference category for receipt of means-tested benefits is "No". SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient. R^2 = R-squared, ΔR^2 = change in R-squared.*

5.2.2.2.3 Index of Multiple Deprivation

As Figure 15, shows, there was a general trend of increasing Overall CKAT Score with increasing affluence, as determined by IMD, up to Quintile 3 within both ethnic groups. After this point, White British children in Quintile 4 tended to demonstrate further benefit but this was not mirrored in the Pakistani sample. Children in Quintile 5 performed similarly across ethnic groups. However, findings in relation to Quintiles 4 and 5 should be interpreted with caution as they may be a result of the particularly small sample sizes in these higher IMD quintiles. For example, only two Pakistani children were designated as falling within Quintile 5 (see Table 16). As there were too few participants within Quintiles 4 and 5 to run regression analyses and draw meaningful conclusions, participants from these groups were omitted from further analysis.

Figure 15

Mean Overall CKAT score across IMD (2010) quintile, stratified by ethnicity



Note: Each dot represents an individual participant. Higher score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals- these are very small due to the large sample sizes.

IMD group was entered into the regression model (Model 4) with the most deprived group (Quintile 1) as the reference category (see Table 20). It was found that the model including this predictor alongside the covariates explained 2.8% of the total variance in Overall CKAT Score (R^2 = .028, F(5,2103) = 12.076, p < .001). This inclusion of IMD as a predictor variable at Step 2 did not significantly improve the amount of variance explained by the model compared Step 1 (ΔF(2, 2103) = 2.975, p = .051). Sex, handedness, and age remained significant predictors of Overall CKAT score (see Table 20). It is important to note that performance was significantly different between Quintile 1: Most Deprived (the reference category) and only one of the two dummy variables of IMD (Quintile 3).

Table 20

Hierarchical linear regression table for Overall CKAT Score as predicted by sex, handedness, age, and Index of Multiple Deprivation (Model 4)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.025	
(Intercept)	-0.486** [-0.689, -0.283]	0.104			
Male	-0.109** [-0.153, -0.065]	0.022	-.105		
Right-handed	0.118** [0.042, 0.194]	0.039	.066		
Age (Years)	0.092** [0.050, 0.135]	0.022	.092		
Step 2				.028	.003
(Intercept)	-0.506** [-0.710, -0.302]	0.104			
Male	-0.111** [-0.155, -0.067]	0.022	-.107		
Right-handed	0.123** [0.047, 0.199]	0.039	.068		
Age (Years)	0.093** [0.051, 0.135]	0.022	.093		
IMD Quintile 2	0.025 [-0.036, 0.085]	0.031	.017		
IMD Quintile 3	0.087* [0.016, 0.158]	0.036	.052		

*Note: * indicates p< .05. ** indicates p< .01. Reference category for IMD = Quintile 1 (Most Deprived). SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient.* R^2 *= R-squared,* ΔR^2 *= change in R-squared.*

5.2.2.3 RQ3: Does ethnicity still predict Overall CKAT score even after controlling for measures of SES?

To examine how much variance in Overall CKAT Score could be explained by ethnicity after controlling for all three measures of SES (maternal education, IMD, and receipt of means-tested benefits), variables were entered into the regression model in three steps (see Table 21). As before, age, sex, and handedness were entered in Step 1; Step 2 added the three SES measures, and Step 3 added ethnicity as a predictor. Step 2 of the model accounted for 3.0% of the total variance explaining Overall CKAT score (R^2 = .030, $F(9,1964)$ = 6.705, p<.001). After including ethnicity as an additional predictor into Step 3 of the regression model, the total amount of variance explained was 3.8% (R^2 = 0.038, $F(10,1963)$ = 7.822, p<.001). Adding ethnicity as an additional predictor in Step 3 significantly improved model fit compared to Step 2, $\Delta F(1,1963)$ = 17.366, p <.001). As can be seen in Table 21, in the final step of the regression model, both ethnicity (b = .107, p<.001) and having above A-level or equivalent maternal education compared to fewer than 5 GCSEs (b. = .105, p=.002) were still significant predictors of Overall CKAT Score. The direction of the effect was as expected, with White British children outperforming Pakistani children.

Table 21

Hierarchical linear regression table for Overall CKAT Score as predicted by sex, handedness, age, Index of Multiple Deprivation, receipt of means-tested benefits, maternal education, and ethnicity (Model 5) [continues on next page]

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.023	
(Intercept)	-0.450** [-0.659, -0.241]	0.107			
Male	-0.110** [-0.155, -0.065]	0.023	-.106		
Right-handed	0.109** [0.029, 0.188]	0.041	.060		
Age (Years)	0.085** [0.042, 0.129]	0.022	.096		
Step 2				.030	.007*
(Intercept)	-0.517** [-0.733, -0.300]	0.110			
Male	-0.113** [-0.158, -0.068]	0.023	-.109		
Right-handed	0.110** [0.030, 0.190]	0.041	.060		
Age (Years)	0.089** [0.046, 0.133]	0.022	.090		
IMD Quintile 2	0.011 [-0.052, 0.073]	0.032	.008		
IMD Quintile 3	0.067 [-0.010, 0.143]	0.039	.040		
5 GCSEs	0.045 [-0.011, 0.101]	0.029	.042		
A-level equiv.	0.054 [-0.021, 0.129]	0.038	.036		
Above A-Level equiv.	0.094** [0.027, 0.162]	0.034	.073		
Receipt of Means-Tested Benefits: Yes	-0.007 [-0.054, 0.040]	0.024	-.007		

[continued]

Table 21 [continued]

Hierarchical linear regression table for Overall CKAT Score as predicted by sex, handedness, age, Index of Multiple Deprivation, receipt of means-tested benefits, maternal education, and ethnicity (Model 5)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 3				.033	.003**
(Intercept)	-0.554** [-0.771, -0.338]	0.110			
Male	-0.113** [-0.158, -0.068]	0.023	-.109		
Right-handed	0.118** [0.039, 0.198]	0.041	.065		
Age (Years)	0.089** [0.046, 0.133]	0.022	.090		
IMD Quintile 2	-0.011 [-0.074, 0.052]	0.032	-.008		
IMD Quintile 3	0.018 [-0.061, 0.097]	0.040	.011		
5 GCSEs	0.042 [-0.014, 0.099]	0.029	.040		
A-level equiv.	0.049 [-0.026, 0.123]	0.038	.032		
Above A-Level equiv.	0.105** [0.038, 0.173]	0.034	.082		
Receipt of Means-Tested Benefits: Yes	-0.004 [-0.050, 0.043]	0.024	.003		
White British	0.107** [0.056, 0.157]	0.026	.098		

*Note: * indicates p< .05. ** indicates p< .01 SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient.* R^2 *= R-squared,* ΔR^2 *= change in R-squared.*

5.2.2.4 RQ4: Does ethnicity moderate the relationship between SES and Overall CKAT score?

As illustrated in Table 22, Table 23, and Table 24, ethnicity did not appear to moderate the relationship between any of the three SES measures (maternal education, IMD quintile, receipt of means-tested benefits) and sensorimotor control. Thus, the influence of SES on Overall CKAT performance did not differ according to one's ethnic group. As shown in Table 22 and Figure 13, there did appear to be a relationship between maternal education and CKAT performance whereby children of mothers with the highest level of qualifications appear to perform superior to children of mothers with fewer than five GCSEs. However, as analyses show, this relationship did not differ by ethnicity.

Table 22

Hierarchical linear regression model for the moderating effect of ethnicity and maternal education on Overall CKAT score (Model 6) [continues on next page]

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.024	
(Intercept)	-0.458** [-0.664, -0.252]	0.105			
Male	-0.112** [-0.156, -0.067]	0.023	-.108		
Right-handed	-0.103* [0.024, 0.181]	0.040	.056		
Age (Years)	0.089** [0.046, 0.132]	0.022	.089		
Step 2				.038	.015**
(Intercept)	-0.560** [-0.771, -0.349]	0.108			
Male	-0.114** [-0.159, -0.070]	0.023	-.111		
Right-handed	0.112** [0.033, 0.190]	0.040	.061		
Age (Years)	0.092** [0.050, 0.135]	0.022	.093		
5 GCSEs equiv.	0.039 [-0.016, 0.094]	0.028	.037		
A-level equiv.	0.041 [-0.033, 0.114]	0.037	.027		
Above A-level equiv.	0.100** [0.036, 0.164]	0.033	.079		
White British	0.105** [0.059, 0.151]	0.024	.098		

[continued]

Table 22 [continued]

Hierarchical linear regression model for the moderating effect of ethnicity and maternal education on Overall CKAT score (Model 6)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 3				.038	<.001
(Intercept)	-0.557** [-0.770, -0.344]	0.108			
Male	-0.115** [-0.159, -0.071]	0.023	-.111		
Right-handed	0.110** [0.032, 0.188]	0.040	.060		
Age (Years)	0.093** [0.050, 0.135]	0.022	.093		
5 GCSEs equiv.	0.032 [-0.037, 0.100]	0.035	.030		
A-level equiv.	0.027 [-0.068, 0.121]	0.048	.018		
Above A-level equiv.	0.113** [0.035, 0.190]	0.040	.089		
White British	0.100* [0.010, 0.190]	0.046	.093		
5 GCSEs equiv. x White British	0.020 [-0.097, 0.136]	0.060	.013		
A-level equiv. x White British	0.034 [-0.117, 0.185]	0.077	.015		
Above A-level equiv. x White British	-0.040 [-0.177, 0.]	0.070	-.019		

*Note: * indicates p< .05. ** indicates p< .01. Reference category for maternal education = < 5 GCSEs. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient.* R^2 *= R-squared,* ΔR^2 *= change in R-squared.*

5.2.3 Discussion

Study 1 aimed to investigate the impact of two common sociodemographic factors: ethnicity and SES, on children's sensorimotor control and how these factors interact. Within this study, conventional methods of measurement were used; SES was measured via three commonly used proxy measures (Index of Multiple Deprivation, receipt of means-tested benefits and maternal education) and the widely used one-metric-per-task CKAT scoring method was used to measure sensorimotor control, with these metrics collapsed into one overall CKAT score.

Analyses revealed several key findings. Firstly, when controlling for participants' age, handedness and sex, ethnicity was a significant predictor of sensorimotor control. These ethnic differences support previous literature which have also found that children categorised by the authors as "Asian" are outperformed by White British children on measures of fundamental movement skills (Adeyemi-Walker et al., 2018; Eyre et al., 2018). This relationship remained significant even after controlling for all three measures of SES, contradicting previous research which found that ethnic differences in the achievement of motor milestones in infants did not remain significant once measures of SES were accounted for in the model (Kelly et al., 2006).

Table 23

Hierarchical linear regression model for the moderating effect of ethnicity and receipt of means-tested benefits on Overall CKAT score (Model 7) [continues on next page]

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.026	
(Intercept)	-0.489** [-0.689, -0.288]	0.102			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.111** [0.036, 0.185]	0.038	.062		
Age (Years)	0.095** [0.053, 0.137]	0.021	.095		
Step 2				.036	.010**
(Intercept)	-0.543** [-0.745, -0.341]	0.103			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.125** [0.051, 0.199]	0.038	.070		
Age (Years)	0.095** [0.053, 0.137]	0.021	.095		
Receipt of means-tested benefits: Yes	-0.003 [-0.046, 0.041]	0.022	.003		
White British	.112** [0.068, 0.157]	0.023	.105		

[continued]

Table 23 ***[continued]***

Hierarchical linear regression model for the moderating effect of ethnicity and receipt of means-tested benefits on Overall CKAT score (Model 7)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 3				.037	.001
(Intercept)	-0.539** [-0.742, -0.336]	0.104			
Male	-0.110** [-0.153, -0.067]	0.022	-.106		
Right-handed	0.125** [0.050, 0.199]	0.038	.070		
Age (Years)	0.095** [0.053, 0.136]	0.021	.095		
Receipt of means-tested benefits: Yes	-0.009 [-0.063, 0.045]	0.028	-.009		
White British	0.105 [0.047, 0.164]	0.030	.098		
Receipt of means-tested benefits: Yes x White British	0.017 [-0.073, 0.108]	0.046	.012		

*Note: * indicates p < .05. ** indicates p < .01 Reference category for maternal education = < 5 GCSEs. Reference category for receipt of means-tested benefits = No.. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient.* R^2 *= R-squared,* ΔR^2 *= change in R-squared.*

Secondly, from the three indicators of SES, maternal education and IMD was found to significantly predict Overall CKAT Score, suggesting that those from more disadvantaged families have significantly poorer scores compared to their more affluent peers. However, note that the impact of IMD should be interpreted with caution. Although children from Quintile 3 significantly outperformed children from Quintile 1 (the reference category), the effect of adding IMD as an additional predictor was minimal (i.e., increasing the amount of variance explained by less than 1%). This supports a wealth of research finding a significant association between social deprivation and motor skills (Adkins et al., 2017; Comuk-Balci et al., 2016; Cools et al., 2011; Ferreira et al., 2018; Ghosh et al., 2016; Mcphillips & Jordan-Black, 2007; Mülazımoğlu-Ballı, 2016; Verheijen et al., 2020; Zeng et al., 2019), which will now be reviewed.

Table 24

Hierarchical linear regression model for the moderating effect of ethnicity and Index of Multiple Deprivation (2010) Quintile on Overall CKAT score (Model 8) [continues on next page]

Predictor	***B* [95% CI]**	**SE**	**β**	**R^2**	**ΔR^2**
Step 1				.025	
(Intercept)	-0.486** [-0.689, -0.283]	0.104			
Male	-0.109** [-0.153, -0.065]	0.022	-.105		
Right-handed	0.118** [0.042, 0.194]	0.039	.066		
Age (Years)	0.092** [0.050, 0.135]	0.022	.092		
Step 2				.037	.012**
(Intercept)	-0.544** [-0.748, -0.340]	0.104			
Male	-0.110** [-0.154, -0.067]	0.022	-.106		
Right-handed	0.133** [0.058, 0.209]	0.039	.074		
Age (Years)	0.093** [0.051, 0.135]	0.021	.093		
IMD: Quintile 2	0.003 [-0.058, 0.064]	0.031	.002		
IMD: Quintile 3	0.038 [-0.036, 0.112]	0.038	.023		
White British	0.107** [0.059, 0.155]	0.021	.099		

[Continued]

Table 24 *[continued]*

Hierarchical linear regression model for the moderating effect of ethnicity and Index of Multiple Deprivation (2010) Quintile on Overall CKAT score (Model 8)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 3				.037	<.001
(Intercept)	-0.544** [-0.748, -0.339]	0.104			
Male	-0.111** [-0.154, -0.067]	0.022	-.106		
Right-handed	0.133** [0.057, 0.209]	0.039	.074		
Age (Years)	0.093** [0.051, 0.135]	0.021	.093		
IMD: Quintile 2	-0.005 [-0.087, 0.076]	0.042	.004		
IMD: Quintile 3	0.054 [-0.077, 0.185]	0.067	.032		
White British	0.106** [0.049, 0.163]	0.029	.098		
IMD: Quintile 2 x White British	0.017 [-0.107, 0.140]	0.063	.009		
IMD: Quintile 3 x White British	-0.021 [-0.180, 0.138]	0.081	-.011		

*Note: * indicates p < .05. ** indicates p < .01. Reference category for maternal education = < 5 GCSEs. Reference category for IMD = Quintile 1. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient. R^2 = R-squared, ΔR^2 = change in R-squared.*

The relationship between maternal education and performance on CKAT was, however, only found to be significant for those with greater than A-Level equivalent education, compared to those with fewer than 5 GCSEs, and when comparing IMD Quintile 3 with Quintile 1. Receipt of means-tested benefits was not found to significantly predict performance. These inconsistencies in the relationships with regard to the measure used support previous research. Cools et al. (2011) also found that differences in children's fundamental movement skills across socioeconomic groups that depended on the proxy measure used. The authors found significant associations with maternal and paternal education and performance, but not occupation, workload or family situation.

The significant relationships found between performance and maternal education are supported by previous literature that has also found a significant relationship between maternal education and children's fine motor skills in both typically developing (Comuk-Balci et al., 2016) and preterm infants (Patra et al., 2016). It could be argued that education level is more indicative of parenting practices, such as effective scaffolding behaviours, rather than the wealth and amenities of the family which other proxy measures may better reflect such as income (Carr & Pike, 2012; Fox et al., 1995). Furthermore, Rowe and colleagues (Rowe et al., 2016) found that an increase in years of education was positively associated with KIDI scores (Knowledge of Child Development Inventory; MacPhee, 1981, 2002). This suggests that increased level of maternal education may encourage practices that are conducive to a more stimulating home environment, regardless of home affordances. Alternatively, Patra et al. (2016) suggest the positive influence of maternal education on fine/sensorimotor skills could be a result of increased intelligence, use of positive psychology, and increased income level. Indeed, using path modelling, Jackson et al. (2017) suggested that greater maternal education had a direct effect on increased income and reduced financial strain. Thus, there are several potential mechanisms underpinning the significant relationship between maternal education and children's sensorimotor control.

IMD was also found to be a significant predictor of Overall CKAT Score, even if its inclusion did only increase the amount of variance explained by less than 1%.

As discussed in Section 5.2.1.2.1.1, IMD is reflective of the area in which a family resides. The present study suggests that children from families living in the third (middle) quintile achieved significantly greater Overall CKAT scores compared to their peers from IMD Quintile 1 (the most deprived). This corroborates previous literature which has found poorer motor skills in more deprived children, quantified via the IMD, as well as by using equivalent Brazilian (Ferreira et al., 2018), and Irish (Mcphillips & Jordan-Black, 2007) measures of neighbourhood-level deprivation. IMD comprises several indicators reflecting domains such as average household income, access to services and education. As a result, children from more deprived areas according to the IMD may attend poorer-performing schools, that place less attention on the development of sensorimotor control and manual dexterity tasks. For example, previous research has suggested that children attending private school or pre-school had increased fine motor skills compared to their peers attending a state institution (Bobbio et al., 2007; Corsi et al., 2016; de Barros et al., 2003). There, of course, may also be an influence of the likely increased household income for the children attending private institutions, as families able to pay expensive education fees are also likely to be able to afford other resources to support their child's learning. For example, more affluent families are more likely to have funds available for educational toys or extra-curricular activities, and more stimulating activities with parents (Bobbio et al., 2007; T. C. B. Freitas et al., 2013; Hua et al., 2016; Miquelote et al., 2012). It is worth noting that participants from the least deprived quintiles (Quintiles 4 and 5) were excluded from analysis due to small sample sizes. Thus, comparisons between these quintiles and the most deprived group were not possible. It may, therefore, not be appropriate to use IMD as a proxy measure of SES when studying participants from a particularly disadvantaged area, such as Bradford which is the 11th most deprived city in the UK (Department for Communities and Local Government, 2015). Furthermore, IMD can be determined relative to the whole country, as was done here, or a city-specific measure can be used which is determined relative to deprivation level of other neighbourhoods within the city. Therefore, different relationships may have been revealed if alternative IMD quintiles were used, which were specific to Bradford.

Lastly, receipt of means-tested benefits was not found to significantly predict Overall CKAT performance. One could argue that means-tested benefits are indicative of household income, with the advantage that it does not require the mothers surveyed to know the precise amount of household income. As previously discussed this is something which is often not known amongst Pakistani populations.

Families not on benefits may be more likely to have increased access to extra-curricular sports clubs or sports equipment (i.e., tennis balls, hockey sticks etc.). The attendance of sports clubs has been previously found to positively correlate with gross motor skills (Roth et al., 2010). Therefore, access to such activities could encourage and develop Fundamental Movement Skills (such as running and jumping) or gross motor skills, both of which are largely measured via sport-specific assessments. In contrast, the underpinning sensorimotor mechanisms as captured by assessment batteries such as CKAT, are less likely to be as strongly influenced by gross-motor sports participation. This offers a potential explanation as to why significant differences were not found between children from families who were and were not in receipt of such benefits. Equally, the lack of a significant relationship found for receipt of means-tested benefits as opposed to the other proxy measures of SES here, may be due its dichotomous nature.

As such, more subtle nuances across different socioeconomic circumstances are not captured. This is supported by previous work which has found SES to be a significant predictor of maternal mental health when measured via cohort-wide latent classes of SEP, ethnic-specific latent classes of SEP, employment status, and subjective poverty, but not when using receipt of means-tested benefits (Mallicoat et al., 2020). In addition, there are several circumstances which permit eligibility for the receipt of such benefits which may have obscured potential relationships more than if household income was asked for explicitly.

Lastly, no significant moderation was found between ethnicity, SES and Overall CKAT Score, suggesting there is limited evidence to suggest a different impact of SES upon sensorimotor control between White British and Pakistani children. This is somewhat contradictory to previous literature that finds few, or very weak social gradients for Pakistani individuals for other health- and development-related outcomes, whilst these were much stronger in the White British individuals (Uphoff et al., 2015).

5.2.3.1 Strengths and limitations of Study 1

A potential limitation of Study 1 is the sub-optimal measurement of SES. As discussed, a multifaceted measure could be more appropriate. This will be addressed in Study 2. In addition, while the use of kinematic measures offers increased precision and objectivity (Culmer et al., 2009; Ozkaya et al., 2018), only one metric per task was included in scoring (RMSE, PLT, and pPA). These were then also collapsed into a single overall battery score to replicate the approach taken to summarise performance in previously published research (e.g., Hill et al., 2016). As discussed in Chapter 3, including a greater number of metrics in the scoring of CKAT increases the amount of systematic variance explained which cannot be captured by any one variable (Hussain et al., 2019). Therefore, more consistent and/or stronger relationships may be revealed with a more objective and empirically justifiable approach being taken to selecting measures of sensorimotor control, as demonstrated in Chapters 3 and 4.

To summarise, significant ethnic differences in CKAT performance were found when using the conventional “one-metric-per-task” scoring system, even after three common measures of SES were controlled for. The impact of SES was somewhat inconsistent though, with significant relationships only between the most and least deprived groups when using maternal education and IMD as socioeconomic indicators. Using a measure of SES that is more inclusive and multifaceted may reveal more consistent relationships with sensorimotor control.

5.3 Study 2

Study 2 aimed to repeat the previous analyses using measures that may better represent the multidimensional nature of both sensorimotor control and socioeconomic circumstances as constructs. It aimed to understand how using such measures would affect the relationships and the conclusions drawn.

5.3.1 Methods

5.3.1.1 Study setting and participants

The data used within these analyses were also obtained from the Starting School sweep of the Born in Bradford cohort. Only children with complete data were included in analyses. Note that although this sample is taken from the same BiB sweep as was used in Study 1 (Starting School), due to the more detailed measures of both sensorimotor control and socioeconomic position requiring a larger number of datapoints, fewer participants had complete data, compared to that reported in Study 1. Thus, 1796 children were included in the present sample. The demographic information of these participants is reported in Table 25. It is evident that regardless of whether the “cohort-wide” or “ethnic-specific” measure was used to quantify SEP, that a larger proportion of Pakistani children come from more deprived families compared to White British. This indicates that even with more precise and sensitive measurement, there are still large discrepancies between ethnicities relating to their socioeconomic circumstances, with those from Pakistani backgrounds still more likely to be disadvantaged.

Table 25

Demographic information of the sample, stratified by ethnicity

	Pakistani	White British	Whole Sample
Child Demographics			
N (%)	1121 (62.7)	668 (37.3)	1789 (100)
Mean Age (SD)	4y11mo (4mo)	4y11mo (4mo)	4y11mo (4mo)
Sex			
Male (%)	540 (48.2)	330 (49.4)	870 (48.6)
Female (%)	581 (51.8)	338 (50.6)	919 (51.4)
Handedness			
Left (%)	81 (7.2)	83 (12.4)	164 (9.2)
Right (%)	1040 (92.8)	585 (87.6)	1625 (90.8)
Maternal Demographics			
Ethnic-Wide SEP Class[1]			
1 (%)	160 (14.3)	104 (15.6)	264 (14.8)
2 (%)	121 (10.8)	216 (32.3)	337 (18.8)
3 (%)	159 (14.2)	98 (14.7)	257 (14.4)
4 (%)	513 (45.8)	117 (17.5)	630 (35.2)
5 (%)	168 (15.0)	133 (19.9)	301 (16.8)
Ethnic-Specific SEP Class[2]			
1 (%)	210 (18.7)	282 (42.2)	NA
2 (%)	80 (7.1)	105 (15.7)	NA
3 (%)	505 (45.0)	157 (23.5)	NA
4 (%)	326 (29.1)	124 (18.6)	NA

[1] = "Least deprived and most educated"; 2 = "Employed and not materially deprived"; 3 = "Employed and no access to money"; 4 = "On benefits and not materially deprived"; 5 = "Most economically deprived".

[2] *White British Classifications: 1 = "Employed, educated, not materially deprived"; 2 = "Employed, moderate education, materially deprived"; 3 = "Low education, benefits not materially deprived"; 4 = "Low education, benefits, subjectively poor and materially deprived".*

Pakistani Classifications: 1 = "Educated, low benefits, not materially deprived"; 2 = Employed, moderate education, benefits, not materially deprived"; 3 = "Not employed, low education, benefits, not materially deprived"; 4 = "Not employed, moderate education, benefits, subjectively poor and materially deprived".

5.3.1.2 Materials

5.3.1.2.1 Socioeconomic position

Two measures of socioeconomic position were used in the present analyses. Firstly, the cohort-wide latent measure of SEP developed by Fairley et al. (2014) was used. This measure included 19 independent indicators relating to SEP which latent class analysis found to be best fit by a five-class model. These measures were appropriate for comparisons across ethnic groups. See Chapter 2 and Fairley et al. (2014) for a more thorough description of these latent classes. Informative labels describing the general characteristics of each of these ethnic-wide latent classes can be found in the footnote of Table 25.

Secondly, the ethnic-specific latent classes which were derived in Chapter 2 were used when conducting the sub-group analyses. As previously discussed, these data were not available in the BiB Data Dictionary so needed to be derived by the author for this thesis. Both the ethnic-specific and the cohort-wide measures were used to highlight the impact of using these, more culturally appropriate, ethnic-specific measures of SEP on relationships with sensorimotor control. These methods of measuring SEP within ethnicity have been used previously by Mallicoat et al. (2020), when exploring social gradients in health-related outcomes such as low birth weight and maternal mental health. As Fairley et al (2014) highlight, when exploring ethnic differences in health, the cohort-wide measure would be most appropriate. However for within-group analyses, the ethnic-specific measure may be more informative, and thus useful in planning subsequent intervention strategies.

Briefly, the ethnic-specific measure included four latent classes which were specific to Pakistani and White British individuals, respectively. They were derived using the same 19 predictors related to SEP. For both ethnic groups, increasing latent class was indicative of an increased level of deprivation (i.e., 1 = "Least Deprived", 4 = "Most Deprived"). The characteristics of each of these classes is described in further detail in Chapter 2. Informative labels describing the general circumstances of each of these ethnic-specific latent classes can be found in the footnote of Table 25.

5.3.1.2.2 Sensorimotor measures

As per Study 1, sensorimotor control was measured using CKAT (Culmer et al., 2009; Flatters, Hill, et al., 2014). However, rather than using a "one metric per task" approach and summarising this into a single Overall CKAT score, performance was quantified via the factor scores obtained from the PCAs and CFAs in Chapter 3 and Chapter 4. These analyses found that performance on the three CKAT tasks (Tracking, Aiming, and Steering) would be most appropriately scored via eight, three, and three components, for each task respectively. Factor scores were extracted for each component using the `lavaan` package (Rosseel, 2012). Except for Peak Speed, a lower score was indicative of better performance (i.e., less error) on all items. Therefore, the Peak Speed component was reverse scored to ensure uniformity in comparisons.

Whilst these components were extracted from the most parsimonious and theoretically sound models (referred to as the "final" model in Chapter 4), to increase practical interpretation, they were then summarised as a weighted mean of these factor scores, to produce a single score for each of the three tasks. Weighted means better reflect the amount of variance related to sensorimotor control that each component explains compared to a standard, equally weighted mean average. For example, the General Speed factor accounted for a larger proportion of the Aiming Overall Score, compared to the Peak Speed factor as it explained a larger proportion of the variance within the CFA (see Chapter 4). These weighted means were then averaged to produce an Overall CKAT Score to indicate general performance. Because each of the items contained within each factor most commonly represent the amount of error or time elapsed, a high score was indicative of poorer performance.

5.3.1.2.3 Additional demographics

Additional demographics were obtained and coded identically to those within Study 1. Similarly, the co-variates included sex, handedness and age.

5.3.1.3 Procedure

Although the measures were scored differently, the data within the present study were collected in the same way as reported in Section 5.2.1.

5.3.1.4 Statistical analysis

For study 2, hierarchical linear regressions were used to investigate the proposed research questions, using an alpha level of .05 to indicate statistical significance. All statistical analyses were conducted in R (version 4.0.0, R Development Core Team, 2020). Again, goodness of fit was compared between each additional step of the hierarchical model to indicate the explanatory power of each additional predictor variable. Step 1 of all models included the outcome variable (Overall

CKAT Score) and the three baseline covariates (age, handedness, and sex). See Equation 2 for the baseline model.

To explore the role of ethnicity on sensorimotor control (RQ1), Model 1 from Study 1 was replicated with the novel, latent Overall CKAT Score to produce Model 9 (see Equation 3). The reference category for ethnicity was Pakistani.

Model 10 was conducted to investigate the impact of cohort-wide SEP on sensorimotor control (RQ2) with cohort-wide included as an additional predictor in Step 2. The reference category for cohort-wide SEP was Class 5 (Most Deprived).

Equation 7

Step 2 of the hierarchical linear regression for effect of cohort-wide SEP on sensorimotor control (Research Question 2)

$$Y = b_0 + b_1 SEP + b_2 X + \varepsilon$$

where *Y* is children's Overall CKAT score, SEP is the vector of dummy variables for the 5-class cohort-wide measure of SEP, and X is the covariates included (age, handedness and sex).

To investigate RQ3, Model 11 was conducted to study the role of ethnicity after controlling for cohort-wide SEP, similarly to in Study 1. Step 2 of the model included the covariates and cohort-wide SEP, with Class 5 (Most Deprived) as the reference category. Step 3 added ethnicity as an additional predictor to investigate whether ethnic differences were present after controlling for SEP.

Equation 8

Step 3 of the hierarchical linear regression (Model 11) for effect of ethnicity on sensorimotor control after controlling for SEP (Research Question 3)

$$Y = b_0 + b_1 SEP + b_2 ETH + b_3 X + \varepsilon$$

where Y is children's Overall CKAT score, SEP is the vector of dummy variables for the 5-class measure of cohort-wide SEP, ETH is the participant's ethnic group (White British or Pakistani) and X is the covariates included (age, handedness and sex).

Lastly, a moderation analysis was conducted in Model 12 to explore how the influence of cohort-wide SEP on CKAT performance differed by ethnic group:

Equation 9

Step 4 of the hierarchical linear regression model for the moderating effect of cohort-wide SEP and ethnicity on sensorimotor control (Research Question 4)

$$Y = b_0 + b_1 ETH + b_2 SEP + b_3 ETH \cdot SEP + b_4 X + \varepsilon$$

where *Y* is children's Overall CKAT score, ETH is the participant's ethnic group (White British or Pakistani), SEP is the vector of dummy variables for the 5-class measure of cohort-wide SEP, X is the covariates included (age, handedness and sex), and ETH·SEP refers to the moderation.

In addition, to further explore the effect of an ethnic-specific measure of SEP compared to the cohort-wide measure (RQ5), sub-group analyses were conducted on the White British and Pakistani children. The analyses to investigate the effect of SEP on Overall CKAT Score were repeated using both the cohort-wide and ethnic-specific variables.

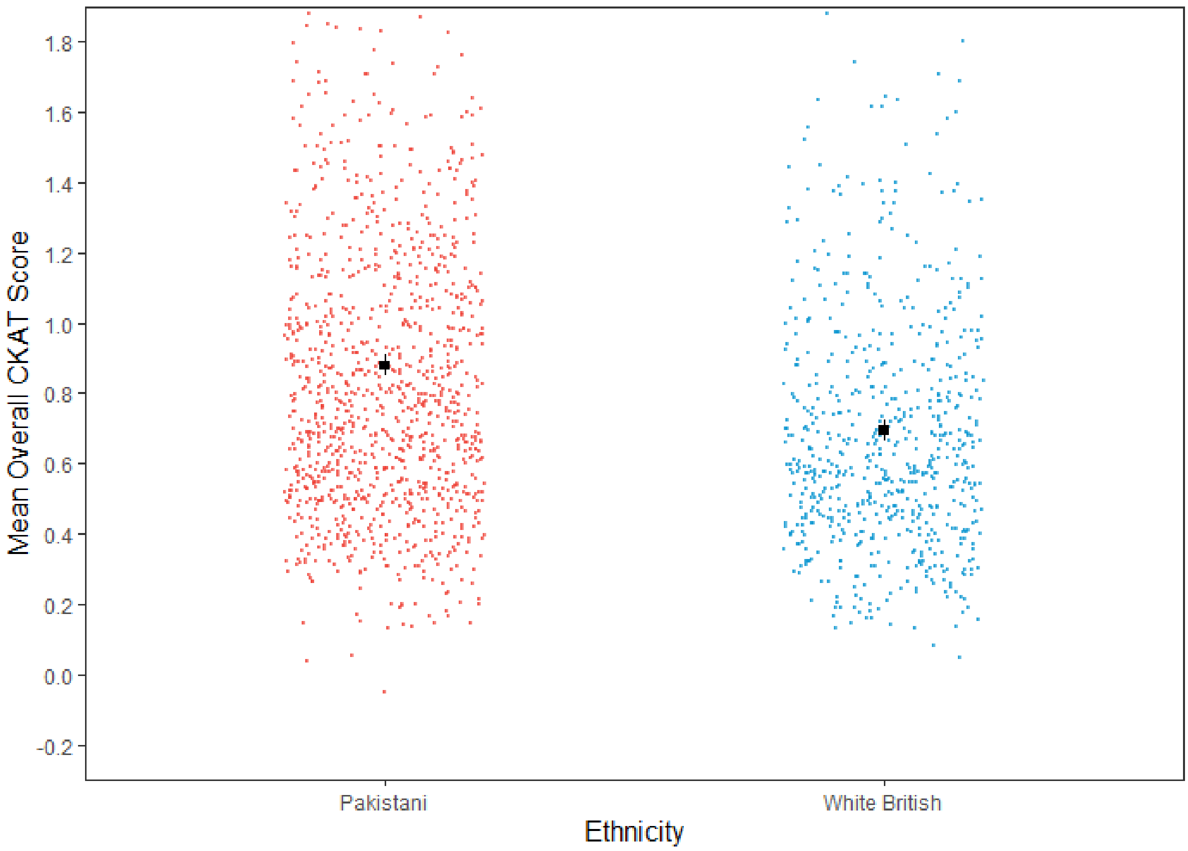
5.3.2 Results

5.3.2.1 RQ1: Does ethnicity predict Overall CKAT score after controlling for age, sex, and handedness?

As Figure 16 illustrates, White British participants (M = 0.69, SD = 0.38) performed significantly better (indicated by lower scores) compared to their Pakistani peers (M = 0.88, SD = 0.51).

Figure 16

Mean Overall CKAT score across White British and Pakistani samples



Note: Each dot represents an individual participant. Lower score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals- these are very small due to the large sample sizes.

A two-step hierarchical linear regression model was then conducted (Model 9), as presented in Table 26. Step 1 of the model (including handedness, age and sex as covariates) explained 7.6% of the variance (R^2= .076, F(3, 1785) = 49.215, p<.001). Both age (b_{Age} = -0.024 [-0.029, -0.020], p<.001) and sex (b_{Sex} = 0.150 [0.108, 0.193], p<.001), were significant predictors of performance at Step 1. At Step 2, after including ethnicity as an additional predictor, the model explained 11.2% of the total variance (R^2= .112, F(4, 1784) = 56.132, p< .001). Sex (b_{Sex} = 0.152 [0.111, 0.194], p<.001), age (b_{Age} = -0.024 [-0.029, -0.020], p<.001) and ethnicity ($b_{Ethnicity}$ = -0.186 [-0.229, -0.142], p<.001) were significant predictors of performance. White British children significantly outperformed Pakistani children, females outperformed males, and older children outperformed younger children. An ANOVA was conducted to compare Step 1 and Step 2 of the model and found significant improvement after the addition of ethnicity, ΔF(1, 1784) = 71.087, p<.001. Adding ethnicity to the model increased the amount of variance explained by 3.6%.

Table 26

Hierarchical linear regression table for Overall CKAT Score, predicted by sex, handedness, age and ethnicity (Model 9)

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.076**	
(Intercept)	2.198** [1.904, 2.491]	.150			
Age (Months)	-0.024* [-0.029, -0.020]	.002	-.227		
Right-handed	0.001 [-0.072, 0.075]	.038	.001		
Male	0.150** [0.108, 0.193]	.022	.158		
Step 2				.112**	.036
(Intercept)	2.279** [1.990, 2.567]	.147			
Age (Months)	-0.024** [-0.029, -0.020]	.002	-.225		
Right-handed	-0.026 [-0.098, 0.047]	.037	-.016		
Male	0.152** [0.111, 0.194]	.021	.160		
White British	-0.186** [-0.229, -0.142]	.022	-.189		

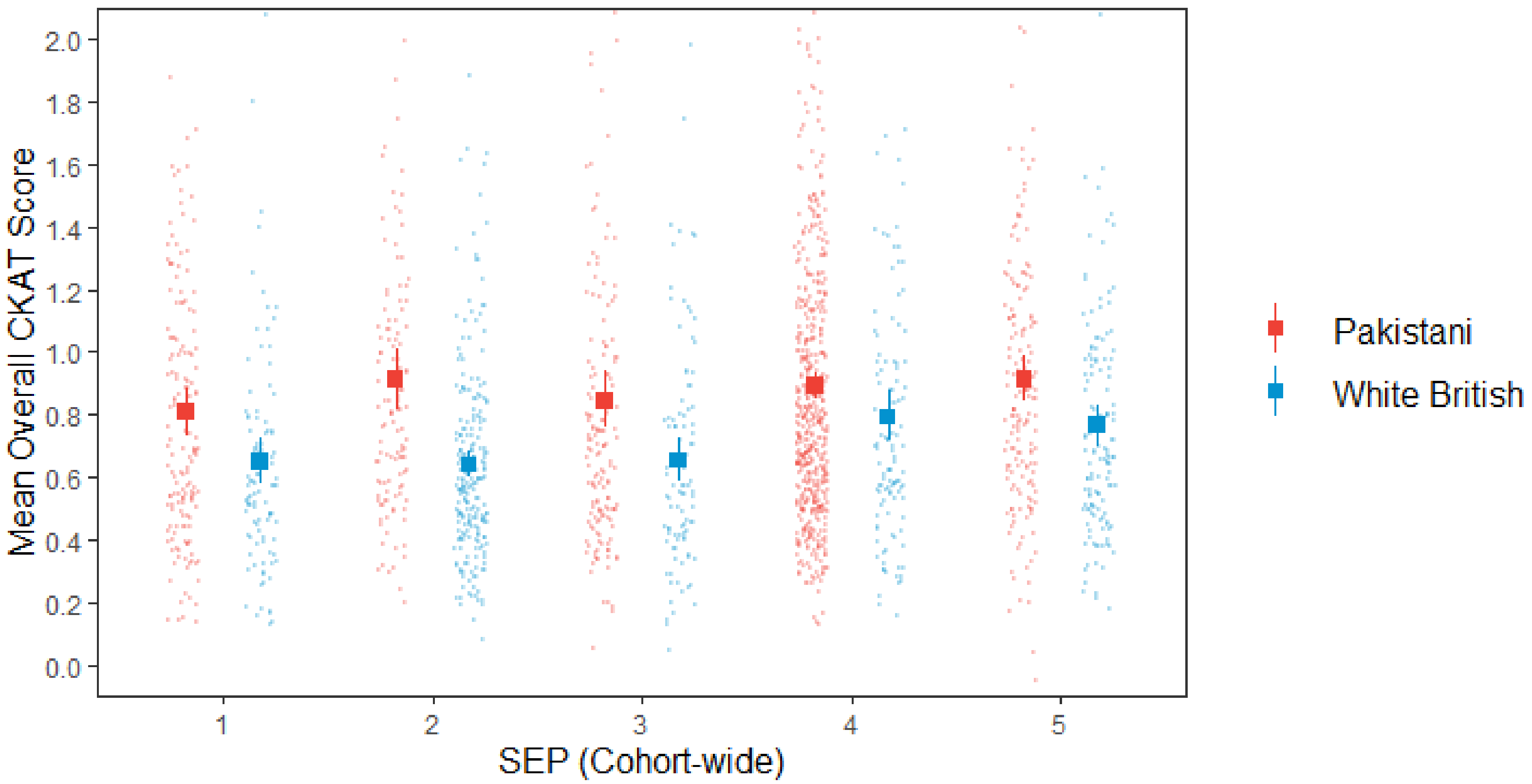
*Note: * indicates p < .05. ** indicates p < .01. Reference category for ethnicity = Pakistani. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient. R^2 = R-squared, ΔR^2 = change in R-squared.*

5.3.2.2 RQ2: Does a latent measure of SEP predict Overall CKAT score when controlling for age, handedness, and sex?

The second research question sought to understand the influence of one's socioeconomic position on sensorimotor control but this time using a measure of SEP which reflects its multifaceted nature. As can be found in Figure 17, there was a general trend of less deprived SEP classes showing better performance across both ethnic groups. However, as the figure shows, this trend does appear to differ between the Pakistani and White British samples.

Figure 17

Mean Overall CKAT score across IMD (2010) quintile, stratified by ethnicity



Note: Each dot represents an individual participant. Higher score is indicative of better performance. Error bars indicate 95% bootstrapped confidence intervals- these are very small due to the large sample sizes.

Step 1 of the model was identical to that reported within Section 5.3.2.1 and thus its results will not be repeated here. Step 2 of Model 10 (see Table 27) included the additional cohort-wide latent measure of SEP with Class 5 (Most Deprived) as the reference category, explaining 9.4% of the total variance, R^2= .094, $F(7,1781) = 26.510$, $p<.001$. SEP class was a significant predictor of Overall CKAT score for those in Class 1 ($b_{SEPClass1}$ = -0.100 [-0.175, -0.025], p =.009) and Class 2 ($b_{SEPClass2}$ = -0.118 [-0.189, -0.048], p =.001), compared to Class 5 (Most Deprived). In addition, both age (b_{Age} = -0.025 [-0.029, -0.020], p<.001) and sex (b_{Sex} = 0.158 [0.116, 0.200], p<.001), were found to significantly predict performance. In comparison to Step 1, the inclusion of SEP as an additional predictor significantly improved the model, $\Delta F(4, 1781) = 8.833$, p <.001. The addition of SEP to the model increased the amount of variance explained by 1.8%.

Table 27

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age, ethnicity and SEP, plus the interaction effect between SEP and ethnicity [continues on next pages]

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 1				.076**	
(Intercept)	2.198** [1.904, 2.491]	.150			
Age (Months)	-0.024* [-0.029, -0.020]	.002	-.227		
Right-handed	0.001 [-0.072, 0.075]	.038	.001		
Male	0.150** [0.108, 0.193]	.022	.158		
Step 2 (Model 10)				.094**	.018
(Intercept)	2.236** [1.942, 2.530]	.150			
Age (Months)	-0.025** [-0.029, -0.020]	.002	-.227		
Right-handed	-0.006 [-0.079, 0.067]	.037	-.004		
Male	0.158** [0.116, 0.200]	.022	.166		
SEP Class 1	-0.100** [-0.175, -0.025]	.038	-.075		
SEP Class 2	-0.118** [-0.189, -0.048]	.036	-.097		
SEP Class 3	-0.065 [-0.141, 0.010]	.039	-.048		
SEP Class 4	0.037 [-0.026, 0.099]	.032	.037		

[Continued]

Table 27 [continued]

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age, ethnicity and SEP, plus the interaction effect between SEP and ethnicity

Predictor	***B* [95% CI]**	**SE**	**β**	**R^2**	**ΔR^2**
Step 3 (Model 11)				.120**	.026
(Intercept)	2.316** [2.026, 2.607]	.145			
Age (Months)	-0.024** [-0.029, -0.020]	.002	-.225		
Right-handed	-0.029 [-0.101, 0.044]	.037	-.017		
Male	0.156** [0.114, 0.197]	.021	.164		
SEP Class 1	-0.109** [-0.183, -0.035]	.038	-.081		
SEP Class 2	-0.086* [-0.156, -0.016]	.036	-.071		
SEP Class 3	-0.076* [-0.150, -0.001]	.038	-.056		
SEP Class 4	-0.007 [-0.069, 0.056]	.032	-.007		
White British	-0.167** [-0.213, -0.122]	.023	-.170		

[Continued]

Table 27 [continued]

Hierarchical linear regression table for Overall CKAT Score predicted by sex, handedness, age, ethnicity and SEP, plus the interaction effect between SEP and ethnicity

Predictor	*B* [95% CI]	SE	β	R^2	ΔR^2
Step 4 (Model 12)				.123**	.003
(Intercept)	2.310** [2.017, 2.603]	.149			
Age (Months)	-0.024** [-0.029, -0.020]	.002	-.226		
Right-handed	-0.029 [-0.101, 0.044]	.037	-.017		
Male	0.155** [0.113, 0.196]	.021	.163		
SEP Class 1	-0.099* [-0.196, -0.003]	.049	-.074		
SEP Class 2	-0.001 [-0.105, 0.104]	.053	<.001		
SEP Class 3	-0.057 [-0.154, 0.040]	.049	-.042		
SEP Class 4	-0.005 [-0.083, 0.073]	.040	.005		
White British	0.135** [-0.237, -0.034]	.052	-.138		
SEP Class 1 x White British	-0.020 [-0.170, 0.130]	.077	-.010		
SEP Class 2 x White British	-0.143* [-0.285, -0.001]	.073	-.098		
SEP Class 3 x White British	-0.044 [-0.195, 0.108]	.077	-.021		
SEP Class 4 x White British	0.033 [-0.103, 0.169]	.069	.017		

*Note: * indicates p < .05. ** indicates p < .01. Reference category for SEP Class = Class 5 (Most Deprived). Reference category for ethnicity = Pakistani. SE = Standard Error. B = Unstandardized coefficient. CI = Confidence Interval. β = Standardised coefficient. R^2 = R-squared, ΔR^2 = change in R-squared.*

5.3.2.3 RQ3: Does ethnicity still predict CKAT performance even after controlling for SEP?

Grouping participants using the latent classes of SEP produced a more even distribution of participants, with no classes needing to be excluded from analysis due to small sample sizes (as was the case in Study 1). Step 1 of the model contained the three same covariates (age, handedness, and sex). Step 2 included these plus the cohort-wide latent SEP measure. This is identical to Step 2 of the model in the previous section and therefore results are not repeated here. Refer to Section 5.3.2.2 for detail of these model statistics for Step 2. Thus, only Step 3 of each model is reported in this section, which includes both cohort-wide SEP and ethnicity as predictors (see Table 27).

Including ethnicity as an additional predictor in Step 3 explained 12.0% of the total variance, R^2 = .120, F(8,1780) = 30.303, p <.001. In this model, ethnicity was still found to significantly predict performance, even after controlling for cohort-wide SEP, handedness, age and sex ($b_{Ethnicity}$ = -0.167 [-0.213, -0.122], p<.001). In addition, SEP class was a significant predictor for Class 1 ($b_{SEPClass1}$ = -0.109 [-0.183, -0.035], p = .004), Class 2 ($b_{SEPClass2}$ = -0.086 [-0.156, -0.016], p =.016), and Class 3 ($b_{SEPClass3}$ = -0.076 [-0.150, -0.001], p = .047), compared to Class 5 (Most Deprived). Lastly, both age (b_{Age} = -0.024 [-0.029, -0.020], p<.001) and sex (b_{Sex} = 0.156 [0.114, 0.197], p<.001) significantly predicted performance. As before, older children significantly outperformed their younger peers and females significantly outperformed males. Step 3 was found to be a significantly better model fit compared to Step 2, ΔF(1, 1780) = 51.581, p <.001). Adding ethnicity to the model in Step 3 increased the amount of variance explained by 2.6%.

5.3.2.4 RQ4: Does ethnicity moderate the relationship between SES and Overall CKAT score?

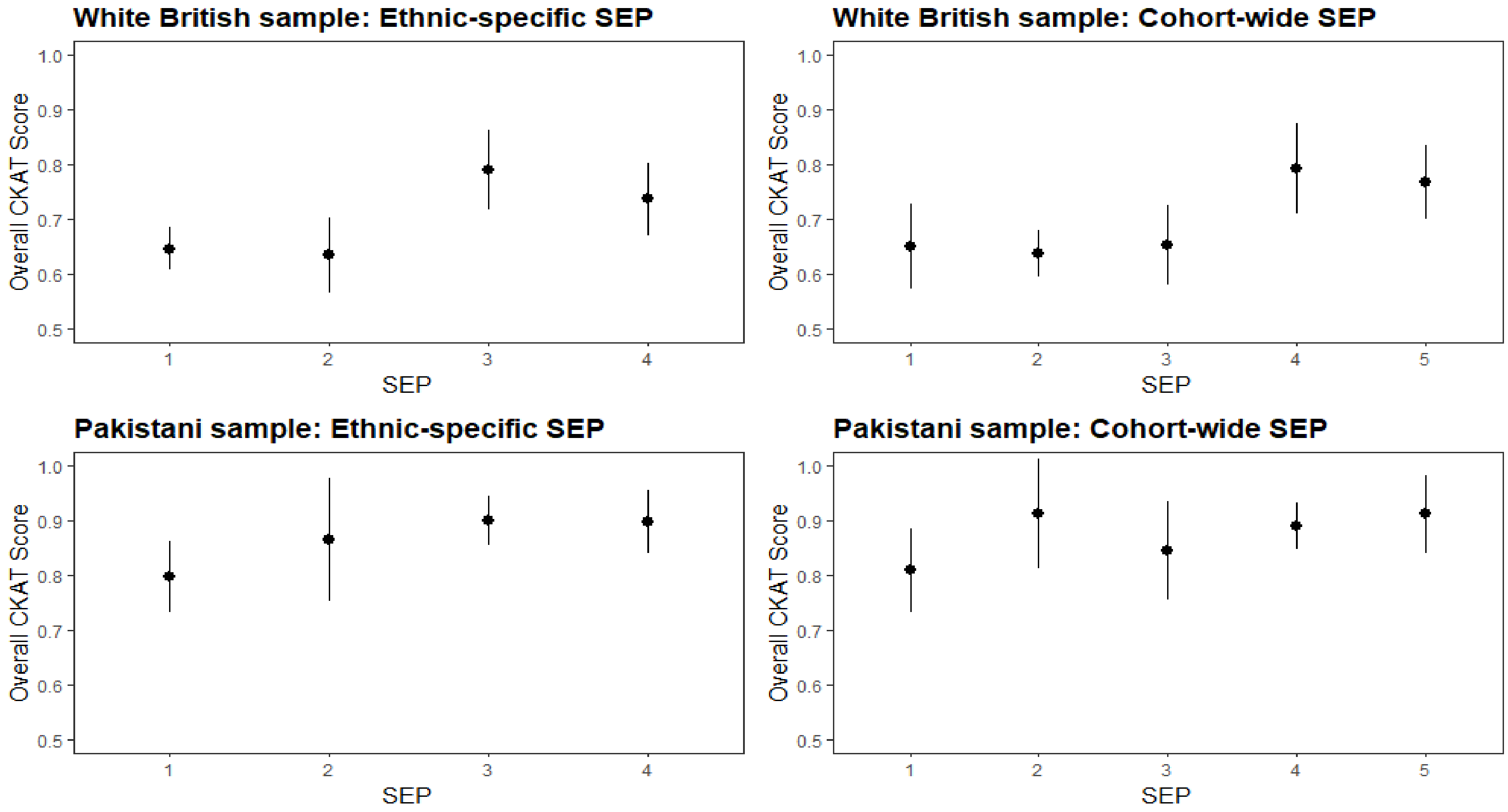
When investigating the moderating effect of ethnicity and cohort-wide SEP on Overall CKAT score, a significant moderation was only found at SEP Class 2, relative to SEP Class 1, for ethnicity, b = -0.14 [-0.29, -0.00], p = .05. No other moderation effects were found. This provides some indication that there may be a difference in the effect of SEP across ethnic groups. Additional split-group analyses investigated this further.

5.3.2.5 RQ5: Does the impact of SEP on sensorimotor control differ by ethnic group when using an ethnic-specific measure of SEP?

Split group analyses were conducted to investigate the role of SEP using both the cohort-wide latent SEP measure as well as the ethnic-specific latent SEP measure for both the Pakistani and White British samples. For the Pakistani sample, ethnic-specific SEP class was a significant predictor for Class 1 ($b_{SEPClass1}$ = -0.095 [-0.180, -0.010], p = .029) compared to Class 4 (Most Deprived). Using the ethnic-specific SEP latent classes in the model explained 8.7% of the total variance (R^2 = .087, F(6, 1114) = 17.595, p <.001). In contrast, when using the cohort-wide SEP classes with the Pakistani sample, no significant differences were found between Class 1, 2, 3 or 4 compared to Class 5 (Most Deprived), all p>.05. This model explained 8.5% of the total variance (R^2 = .085, F(7, 1113) = 14.724, p <.001). For the White British sample, however, using the ethnic-specific SEP latent class, there were significant differences between Class 1 ($b_{SEPClass1}$ = -0.106 [-0.182, -0.029], p = .007), and Class 2 ($b_{SEPClass2}$ = -0.099 [-0.193, -0.005], p = .040) when compared to Class 4 (Most Deprived). This model explained 11.6% of the total variance (R^2 = .116, F(6, 661) = 14.514, p <.001). When using the cohort-wide SEP classes, significant differences were found between Class 1 ($b_{SEPClass1}$ = -0.121 [-0.214, -0.028], *p* =.011), Class 2 ($b_{SEPClass2}$ = -0.143 [-0.221, -0.065], *p* < .001), and Class 3 ($b_{SEPClass3}$ = -0.104 [-0.198, -0.009], *p* =.031), compared to Class 5, explaining 11.7% of the total variance (R^2 = .117, $F(7, 660)$ = 12.500, *p* <.001). How the type of SEP measure affected each ethnic group's mean Overall CKAT Score is presented in Figure 18. This suggests that the ethnic-specific measure of SEP may be more appropriate for the Pakistani sample when investigating the effect of SEP on sensorimotor control.

Figure 18

The effect of SEP on Overall CKAT score by ethnicity and SEP measure



Note: Error bars represent 95% confidence intervals

5.3.3 Discussion

The second study within this chapter was a replication of Study 1 using more multidimensional, empirically validated measures of SEP and sensorimotor control. It aimed to investigate how the use of these measures would impact the relationships between SEP, sensorimotor control, and ethnicity. As expected, it was found that White British children performed significantly better compared to their Pakistani peers. This difference remained significant even after controlling for the cohort-wide latent measure of SEP. In line with the hypotheses and findings from Study 1, ethnicity was a significant predictor of sensorimotor control; White British children outperformed their Pakistani peers. This supports previous research which also suggests that White British children outperform their peers from other ethnic minority groups (Adeyemi-Walker et al., 2018; L. M. Barnett et al., 2019; Eyre et al., 2018).

Within the present study, the impact of a child's SEP on their sensorimotor control was studied using a latent measure of SEP, derived using 19 individual indicators of objective and subjective wealth and prestige. Investigation of the effect of cohort-wide SEP on CKAT performance indicated children from families in the two least deprived groups (Class 1 and Class 2) performed significantly better compared to the Most Deprived group. The findings support previous literature which shows that less deprived children outperform their most deprived peers (Adkins et al., 2017; Comuk-Balci et al., 2016; Cools et al., 2011; Ferreira et al., 2018; Ghosh et al., 2016; Mcphillips & Jordan-Black, 2007; Mülazımoğlu-Ballı, 2016; Verheijen et al., 2020; Zeng et al., 2019). These differences, however, only occurred between the first and second least deprived groups when compared with the most deprived group. No significant differences were found between

Class 3 and Class 4, compared with Class 5 (Most Deprived). Similar results were found when using this measure of SEP in regard to maternal mental health; those from less deprived SEP classes experienced fewer mental health problems in comparison to the most deprived group (Mallicoat et al., 2020). This is the first study of its kind to apply such multifaceted latent measures when exploring the impact of SEP on (sensori)motor control.

Lastly, moderation and split-group analyses suggested that there were differences between a larger number of SEP classes compared to the Most Deprived group within the White British sample compared to the Pakistani children. In addition, social gradients for the Pakistani sample were only evident when using the ethnic-specific latent measure of SEP. This, alongside evidence suggesting that there were differences between a larger number of SEP classes compared to the Most Deprived group suggests that the social gradients were different between the White British and Pakistani children. For example, larger differences were seen between SEP Class 1 and SEP Class 2 for the Pakistani group, whereas performance was relatively similar between these two classes for the White British sample. These differences, in part, align with previous research by Uphoff et al. (2015) who also found differences in social gradients for the Pakistani sample compared to White British for a range of health outcomes (including maternal mental health and low birth weight). In their case though, there were fewer and/or weaker social gradients in the Pakistani group compared to White British counterparts.

In addition, previous research has suggested that an ethnic-specific measure of SEP may also better capture subtle differences compared to a more general, cohort-wide measure. For example, when studying a Pakistani sample from the

Born in Bradford cohort, Mallicoat et al. (2020) also found significant differences between a greater number of classes in comparison to the reference category when using the ethnic-specific measure compared to the cohort-wide measure of SEP. These socioeconomic differences were found with both pre-term birth and smoking during pregnancy as the outcome variables. This supports previous research that claims ethnic differences should be accounted for in the measurement of socioeconomic circumstances (Braveman et al., 2001, 2005; Fairley et al., 2014). It also suggests that standard measures of SEP may not be suitable across all participants, particularly those from ethnic minority groups.

5.3.3.1 Strengths and limitations of Study 2

The present study investigated the influence of SEP on children's sensorimotor control using a latent measure of SEP. To allow comparisons to be drawn across ethnicities, the cohort-wide measure of SEP was used. It was only appropriate to use the ethnic-specific measure of SEP in a split-group analysis of Pakistani and White British participants, respectively. However, Goodwin et al. (2018) extended the work of Fairley et al. (2014) to include a latent class of SEP, which also took ethnicity and migrant status into account, investigating the role of SEP on psychological distress. Including these additional indicators in the model allowed comparisons to be made across ethnic groups whilst still accounting for ethnic differences in SEP. However, this method may not be appropriate for use in a largely bi-ethnic sample due to the homogeneity of the ethnic groups.

A strength of Study 2 was that by using a more multifaceted, latent measure of SEP, individuals were more evenly dispersed across the classes. In contrast, when using IMD as a proxy measure for SES (i.e., in Study 1), there was a much larger proportion of individuals classified in the more deprived IMD quintiles, leaving too few participants in the less deprived groups to conduct analysis with satisfactory statistical power. Thus, these participants needed to be omitted from analysis. In addition, the wider range of indicators used in the latent measure of SEP permits a more detailed understanding of a family's circumstances with the inclusion of spending priorities and subjective poverty. For example, it may be the case that a family is not receiving benefits, living in a relatively good neighbourhood and good education background. Using the traditional measures of SES would categorise this family as relatively privileged. However, it may be the case that the family is struggling to make ends meet and all income is put towards food and bills. Thus, there are no additional funds available for supporting motor development and physical education, such as purchasing motor-specific toys and extra-curricular activities. In addition, parents may work multiple jobs and therefore one-to-one time with the child to support and develop these skills is limited. Using the latent measure of SEP is more likely to capture these more subtle nuances.

A potential limitation of the present study is that it uses an Overall Score. In Chapter 3, some limitations of using composite motor scores are discussed. To account for this, analyses conducted in Chapter 3 and Chapter 4 derived a more interpretable scoring system for the CKAT assessment battery using a wider range of kinematic variables and thus capturing more systematic variance. Whilst this reduced over 600 individual data points to a smaller selection of meaningful dimensions, it was still not considered practical to investigate the sociodemographic influences for each independent dimension (there were twelve in total across the three sub-tasks). Therefore, a weighted mean was produced for each task which was then average to get an Overall Score. This prevented individual analysis of how sub-tasks and specific latent variables within each task were impacted upon. Using an Overall Score which was weighted appropriately with each of the kinematic dimensions and captured more systematic variance in this chapter, whilst a compromise, was still considered an improvement to using the conventional “one metric per task” approach as used in previous research (e.g., Flatters et al., 2014; Hill et al., 2016; Shire et al., 2016).

To summarise, this study aimed to use more multidimensional methods to investigate the ethnic and socioeconomic impact on children’s sensorimotor control, that were both more empirically and theoretically justifiable. How these findings differ from those using more “conventional” methods are discussed in relation to the current literature in the subsequent section. What these two studies can tell us collectively and how these relate to the current literature is discussed in the subsequent General Discussion section (both Study 1 and Study 2).

5.4 General discussion of Study 1 and Study 2

The primary aim of the present chapter was to investigate the impact of socioeconomic circumstances and ethnicity on children’s sensorimotor control. Additionally, it aimed to explore how using more multidimensional measures of these variables influenced the conclusions drawn.

5.4.1 Explanations of ethnic differences in sensorimotor control

In both studies, ethnicity was a significant predictor of Overall CKAT performance, regardless of the scoring system used. This was indeed the case even after controlling for all measures of SES (IMD, maternal education and receipt of means-tested benefits) or the latent measure of SEP, findings which contradict earlier findings by Kelly et al. (2006). In addition, within the work of Kelly et al.

(2006), parent-reported achievement of motor milestones was the method used to quantify motor skill. As reported in the Introduction and Chapter 3, the DDST was used to measure these milestones which is prone to bias with poor sensitivity and limited concurrent and predictive validity (Cadman et al., 1984; Meisels, 1989). Thus, it may not be an appropriate measure to explore sociodemographic effects of movement abilities. This does, however, support the work of Eyre et al. (2018) and Adeyemi-Walker et al. (2018), who also found White British children outperformed their South Asian peers. It is, of course, important to note the practical implications of such ethnic differences regarding the amount of variance explained. In both studies, a significant effect of ethnicity was found, yet the addition of ethnicity to Step 3 of Models 5 and 11 provided an R^2 change of only 0.01 and 0.03 when using the “traditional” and “revised” CKAT scoring methods, respectively. Similarly, Adeyemi-Walker et al. (2018) found significant but only small-to-moderate effect sizes between White British and Asian children.

Resultantly, whilst it is evident that there are some ethnic differences in sensorimotor control (Adeyemi-Walker et al., 2018; Eyre et al., 2018; Josman et al., 2006; Kelly et al., 2006; Victora et al., 1990), it is vital to consider the practical implications of such differences. Although the differences were significant, the effect of adding these predictors to the covariates was minimal. Thus, this brings into question whether Pakistani children would experience any wider repercussions on their development (e.g., academic attainment or physical activity) as a result of slightly reduced performance on the CKAT battery and warrants further investigation.

As discussed in Section 1.2.2.1, CKAT focuses largely on the underpinning mechanisms of movement (i.e., sensorimotor control), rather than more complex motor coordination which are often measured by sport-related motor assessments (e.g., the TGMD-2). Thus, the current findings are unlikely to be confounded by the assessment type and culture-biased norms (Larsson & Quennerstedt, 2012; Ng & Button, 2018; Jan Wright & Burrows, 2006). Furthermore, CKAT is a process-oriented assessment which aims to measure the various mechanisms of sensorimotor (e.g., feedforward control) rather than product-oriented goals such as catching ability. Therefore, the ethnic differences found are less likely to be confounded by cultural differences in physical activity levels or sports participation (Casper et al., 2011; Eyre & Duncan, 2013; Love et al., 2019).

Considering previous research, it was predicted any ethnic differences found would be largely accounted for by differences in socioeconomic circumstances (e.g., Kelly et al., 2006). However, neither studies were found to support this, as ethnicity was still found to significantly predict sensorimotor control, even after controlling for all three measures of SES, or the cohort-wide latent measure of SEP. This implies that there are some systematic differences of sensorimotor control between Pakistani and White British children that cannot be explained by differences in levels of social disadvantage between these ethnic groups. However, upon inspecting the standardised beta values, it was evident that ethnicity did have a slightly reduced impact on Overall CKAT performance when accounting for the cohort-wide latent measure of SEP. Kelly et al. (2006) found that all systematic variance explained by ethnicity was accounted for after controlling for simple, conventional measures of SES (i.e., household income, maternal education). Whilst the current findings suggest that some ethnic differences do persist, the hypothesis was supported in that the effect of ethnicity was reduced somewhat when using the cohort-wide latent measure of SEP. This was not the case in Study 1.

The ethnic differences found in the present chapter may be explained by several potential mechanisms. Currently, there is little evidence to suggest that ethnic differences in motor skills are a result of genetic disparities, and it is instead a consequence of the environment (Cooper et al., 2003; WHO Multicentre Growth Reference Study Group, 2006). One suggestion is that across ethnicities, there are differences in parenting practices. For example, previous research has found that there is a tendency to encourage and stimulate children's development (e.g., the achievement of motor milestones) in some cultures, whilst others are more inclined to allow the natural developmental trajectory to occur without interference (van Schaik et al., 2018; WHO Multicentre Growth Reference Study Group, 2006). Indeed, research has suggested that providing a more stimulating environment is associated with greater neonatal motor responsivity (Cintas, 1995). Additionally, Cintas (1995) found cultural differences in the specific skills which are encouraged by parents and how much parents allow the infant to interact freely with the environment. For example, in European and North American cultures, the infant is more likely to be encouraged to crawl freely to explore their surroundings, whereas African cultures generally prefer infants to remain in close proximity in the early years (Cintas, 1995). Therefore, it is plausible that ethnic differences likely result in differences in motor development due to variation in social context across these groups; such contexts are arguably modifiable risk factors which can be targeted with intervention.

5.4.2 Explanations of socioeconomic differences in sensorimotor control

Within the present chapter, the role of socioeconomic circumstances was first studied using three independent and widely used measures, namely IMD, receipt of means-tested benefits, and maternal education. Next, the role of socioeconomics was studied using a latent measure of SEP, derived using 19 individual indicators of objective and subjective wealth and prestige. Comparison of findings from the two studies suggests that it may be more useful and more appropriate to use a latent measure of SEP rather than more traditional, independent measures of SES. However, regardless of the measure used, there is evidence to suggest that those from more deprived backgrounds perform more poorly on a kinematic task of sensorimotor control. These conclusions align with previous research which has found similar relationships with more general movement coordination and fine motor skills (Ghosh et al., 2016; Mcphillips & Jordan-Black, 2007; Morley et al., 2015; Potter et al., 2013).

However, by focusing on sensorimotor control specifically and using a kinematic measure which is not biased by sport-related assessment (e.g., the TGMD-2), the current findings also suggest that differences found are not simply due to reduced sports participation and physical activity levels in lower socioeconomic environments.

Instead, potential explanations may include increased affordances to improve the quality of the home environment (T. C. B. Freitas et al., 2013). Previous research has found that homes of higher SES families are more likely to focus on building skills to prepare children for formal education through educational activities and positive parenting practices (Dumais, 2006; Duncan et al., 1994; Farkas, 2003; Heckman, 2006; Sui-Chu & Willms, 1996). In turn, these stimulating home environments build a range of skills, such as fine motor and sensorimotor control, prior to starting school, placing children at an advantage compared to their less-affluent peers (Potter et al., 2013).

To demonstrate, Potter et al. (2013) found that after controlling for the family environment (such as child activities and parental expectation), the effect of SES on fine motor skills alone was reduced. Similarly, Ferreira et al. (2018) found the home environment mediated the relationship between SES and performance on the BOT-2 (including fine motor performance). More specifically, increased SEP permits the capacity to purchase fine motor toys which encourages the use of the hands and coordinative abilities (T. C. B. Freitas et al., 2013). Together, this suggests that a more stimulating home environment, including resources and parenting behaviours, may encourage development of sensorimotor control in early childhood, explaining a substantial proportion of the effect of SEP in the present analyses.

Another possible explanation, particularly important in early school starters, is how frequently children attend preschool or formal childcare. Previous research has suggested that preschool environments are conducive to daily practice of fine motor activities (e.g., crafts, writing, colouring), and are thus likely to increase fine motor skills more quickly (de Barros et al., 2003; Poresky & Henderson, 1982; Stein et al., 2001; Vazir et al., 1998). In England, up to 30 hours of free childcare per week are provided by the Government for all families with 3-4 year-old children (Department for Education, 2018). Yet, with the increasing cost of childcare increasing the number of families falling below the poverty line (Hirsch & Valadez, 2015), it is unlikely that lower-SES families would have the means to purchase additional hours. Thus, children from higher SES families are likely to also have increased access to additional educational and stimulating toys, promoting motor skills outside of the home too.

As noted by Cools et al. (2011), the method used to measure SES can impact the relationships with motor skills. They found that children’s fundamental movement skills were significantly associated with maternal and paternal education levels, but not occupation, workload or family situation. This could explain the slightly different relationships found across different methods of assessment of SES. As discussed in Chapter 2, it also highlights the benefit of using a more multifaceted measure of SEP to account for subtle differences in circumstances and avoid inconsistencies.

5.4.3 Measuring sensorimotor control using kinematic measures

Generally, there are benefits of using a kinematic assessment of sensorimotor control, which have been discussed at length in Chapter 3. Such benefits include objectivity, precision, and dimensionality. Most notably, a process-oriented measure of sensorimotor control is also much less likely to be biased by sport-specific experience that can arise with measures that include kicking or catching such as the TGMD-2 (e.g., Larsson & Quennerstedt, 2012; Ng & Button, 2018). Instead, the core mechanisms underpinning sensorimotor control such as speed and jerk are captured. The current chapter highlights the benefits of using a more precise method of quantifying kinematic data which better represents its multidimensional nature. This is the first study to apply this new method to a novel research question and compare the findings when using the more conventional approach. In addition, although an Overall score was reported in Study 2, using this scoring method provides the opportunity to investigate more subtle differences in sensorimotor control across sociodemographic groups, such as differences in speed of movement, or dynamic accuracy.

5.4.4 Strengths and limitations

Taking both studies together, the present chapter highlights the impact of using more multidimensional measures that are both empirically and theoretically justifiable, providing evidence in favour of using these measures in subsequent research. However, although it was evident that the ethnic-specific latent SEP measure may be the most appropriate way of measuring a child's socioeconomic background, this cannot be applied when comparing performance across ethnic groups. Thus, when also exploring the additional influence of ethnicity, a more suitable measure which incorporates ethnic differences may need to be applied.

A potential limitation of this work is that it does only use a sample recruited from the Born in Bradford longitudinal cohort study. This provides access to a large sample of ethnic minority individuals and thus the sample is more evenly distributed across ethnic groups compared to previous research (e.g., Kelly et al., 2006). However, within Bradford, the population is ethnically dense (Uphoff et al., 2015). As a result, this high ethnic density may have had a potential preventative or “buffer” effect which has been previously found in studies assessing health (e.g., Gieling et al., 2010; Uphoff et al., 2016). Thus, the effect of ethnicity may be much larger in other areas of the UK which have a much smaller ethnic minority population.

5.4.5 Future research

The present chapter explored the sociodemographic impact on a typically developing sample. Whilst it is important to also measure motor control of typically developing children and acknowledge that difficulties can occur, albeit at a sub-clinical level (Gaul & Issartel, 2016), further research could build on this work by replicating with participants from a population with DCD. It would be interesting to explore whether the relationships found in the present study are replicated in a non-typically developing sample, and to what extent.

Previous research has suggested that children from lower socioeconomic strata are at increased risk of DCD or probable-DCD (Lingam et al., 2009b). It would also be useful to conduct this research using a wider range of ethnic minority groups to understand how ethnic differences may vary across multiple populations, other than just Pakistani and White British. Replicating this research in a less ethnically dense community would also be beneficial to increase generalisability beyond the niche area of Bradford.

5.4.6 Conclusions

The present chapter aimed to explore how sociodemographic factors, namely ethnicity and socioeconomic position related to sensorimotor control in 4-5 year old children. It found that even after controlling for SEP, ethnicity was still a significant predictor, even if only a relatively small proportion of variance was explained. As expected, SEP was also found to predict CKAT scores, and split group analyses revealed socioeconomic differences between the two ethnic groups, providing evidence that ethnic-specific SEP classes may be more appropriate when exploring the association between SEP and sensorimotor control. Thus, these analyses indicate that targeting interventions towards increasing education or motor skills for these groups may be beneficial. However, as the sample consisted of 4-5 year olds only, further research should investigate whether these differences persist with increasing age. This question is explored in Chapter 6.

Chapter 6 The development of sensorimotor control over the primary school years

6.1 Introduction

Akin to Piaget's (1952) description of the importance of sensorimotor control to facilitate interactions with the environment (see Chapter 1), Malina (2004) proposes that the development of motor behaviour enables children to "experience many dimensions of their environment" (p.50). The development of movement begins even prenatally and is essential for the appropriate growth of muscles and joints (Einspieler et al., 2008; Malina, 2004). Across the course of infancy, with increasing cerebral maturation, reflexive movements are replaced by voluntary action (Capute et al., 1978). Furthermore, during the first year of life, there is evidence to suggest children undergo vast visual and perceptual development, with improvements in motion perception, binocular vision, visual acuity, and contrast sensitivity (Braddick & Atkinson, 2011). Research and assessment of the development of motor behaviour and the sensorimotor system during infancy is largely based around the acquisition of key milestones related to postural, locomotor, and prehensile development (Malina, 2004).

Indeed, motor development research generally focuses on this period between infancy and early childhood (Golenia et al., 2017). Less research, however, focuses on motor development during mid-childhood, despite a "mid-growth spurt" occurring at around six-to-eight years of age and vast changes to the physical characteristics of the body (Golenia et al., 2017; King et al., 2012; Malina et al., 2004). However, the Dynamic Systems Approach would argue this change in the child's physical state would change how the child interacts with their environment and the movement tasks they face. Indeed, researchers have posited that there are ongoing complex interactions between the child, the task requirements, and the physical and social environment in relation to motor development, throughout childhood and beyond (Gallahue & Ozmun, 2006; Lewis, 2000; Malina, 2004; Newell, 1986; Thelen et al., 1994). For example, as the child adapts and changes, through morphological, physiological and neuromuscular development, interactions with the environment and task requirements also change (Malina, 2004). These interactions are dynamic, in that various components occur across multiple timescales (Spencer et al., 2011).

As previously discussed, competent sensorimotor control is necessary for the successful execution of fine motor tasks (Franklin & Wolpert, 2011; Snapp-Childs, Casserly, et al., 2013; Tresilian, 2012). Research has suggested that the development of optimal movement of the upper limbs and hands, for fine motor tasks, depends on: increased movement speed (Bard et al., 1990; Bourgeois & Hay, 2003), reduced movement variability (H Forssberg et al., 1991; Kuhtz-Buschbeck et al., 1998), and an increased ability to make online corrections in response to sensory feedback (Fuelscher et al., 2015; King et al., 2012). Thus, the use of kinematic analyses permit an in-depth and precise investigation of each of these elements over time. Traditional observational methods, particularly product-oriented, do not offer the same level of detail regarding how these aspects of sensorimotor control develop (De Los Reyes-Guzmán et al., 2014; L. J. B. Hill et al., 2016).

Intuitively, the literature suggests that with increasing age, there is an improvement in motor skills during childhood. Specifically, studies have suggested that over time, children show an increase in movement speed (R Blank et al., 1999; Kakebeeke et al., 2018; Rueckriegel et al., 2008; van Mier, 2006), improved fine motor proficiency on standardised tasks (Gaul & Issartel, 2016) and a refinement of reaching behaviours; becoming quicker and more accurate (Fuelscher et al., 2015; Golenia et al., 2017). Additionally, older children are better able to use online control to correct reaching movements (Fuelscher et al., 2015). Alramis and colleagues (Alramis et al., 2016) studied fine motor skills in children aged five to thirteen years using bead-threading and peg-board tasks. With increasing age, children’s performance on both tasks significantly improved, indicated by reduced time to complete the tasks. In addition, a task difficulty by age interaction was also found, where greater discrepancies between easy and difficult tasks were found for the younger children.

More recently, a bead-threading task has been used alongside a motion-tracking system to derive kinematic variables related to sensorimotor control to assess development of fine motor skills (Niechwiej-Szwedo et al., 2020). The authors found that performance increased across all kinematic measures on this task, concluding that performance reached a mature state at around eight-to-ten years. Importantly, it was noted that performance across different sensorimotor tasks may differ in their maturation rates and thus cannot necessarily be generalised, highlighting the importance of studying the developmental trajectories across multiple sensorimotor tasks and assessment batteries.

Returning to CKAT, Flatters et al. (2014) have previously used a cross-sectional design to investigate age-related changes in performance. Using a sample of 4-11 year olds, they found consistent improvements with increasing age across all three tasks (Tracking, Aiming, and Steering). In addition, there were age-related differences in how each condition impacted performance. For example, the additional benefit of the guide-line within the Tracking task was not evident in the youngest age group but grew with age across the later age group, whilst also interacting with task difficulty and being most pronounced on easier (slower) trials (Flatters, Hill, et al., 2014). This suggests that with increasing age and refined sensorimotor control, children are able to benefit from additional visual information. Thus far, there has not been longitudinal investigation on performance of CKAT using repeated-measures.

Explanations of motoric development have been proposed, however there are some conflicting perspectives. One school of thought is that development occurs as a function of changes within the sensorimotor mechanisms. Previous research has suggested that in younger children (approximately five to six years of age), feedforward mechanisms are most often adopted. This permits fast movement, as it does not require the use of online sensory feedback, however it does require an accurate internal model (Kawato, 1999; Seidler et al., 2004). Around the age of eight, there is believed to be a shift in the control mechanisms whereby children use more accurate proprioception feedback to execute movement. While this provides the capacity to make online corrections, feedback-based corrections are associated with slower movement (Pellizzer & Hauert, 1996). During this shift, it has been frequently documented that performance drops, particularly in relation to movement time (Bard et al., 1990; Chicoine et al., 1992; Fayt et al., 1992, 1993; Hay, 1979; Pellizzer & Hauert, 1996). This phenomenon is often referred to as a non-monotonic development trend. With further development, children begin to integrate these two control mechanisms, to produce more optimal movement and reach adult-like competency soon after (Desmurget & Grafton, 2000). It is important to note that both feedback and feedforward mechanisms continue to improve over time into late childhood, adolescence, and beyond, there is simply a shift in which mechanism is preferred.

Interestingly, a large proportion of studies which investigate age-related changes use samples of six-, eight-, and ten-year-old children and use cross-sectional designs rather than longitudinal measurement (Golenia et al., 2017, 2018). To the author's knowledge, little research has been conducted to investigate the development of sensorimotor control longitudinally across mid-childhood. In contrast to cross-sectional designs, longitudinal analyses provide the opportunity to study the individual rates of change and both inter- and intra-individual variability (Busey et al., 2010; Humes et al., 2012; Molenaar, 2004; Salthouse, 2014). Moreover, extant research that has used longitudinal designs tends to focus on the development of non-typically developing samples, such as those with Autistic Spectrum Conditions (ASC) (e.g., Travers et al., 2018), cerebral palsy (e.g., Smits et al., 2013; van Eck et al., 2009), and infants born pre-term or with low body weight (e.g., Goyen & Lui, 2002; Smyser et al., 2010).

As Gaul and Issrartel (2016) suggest, it is important to not only focus on children with clinically disordered movement patterns though, such as DCD, but also acknowledge that typically developing children can also experience difficulties. Thus, typically-developing populations also warrant investigation, for a variety of reasons. For example, in recent years children have become increasingly reliant on technology such as tablets and computers over traditional pen and paper in both education and leisure settings (Christakis, 2014; Common Sense Media, 2013; Cristia & Seidl, 2015). Therefore, it is necessary to investigate how children's sensorimotor control develops over childhood, as this may be changing in response to changes in modern society.

In Chapter 5, the role of ethnicity in children's sensorimotor control was explored, finding that it was a significant predictor at four-to-five years of age, even after controlling for SEP. In addition, although focused on Fundamental Movement Skills in a cross-sectional sample, Adeyemi-Walker and colleagues (2018) found ethnic differences in children in both early- (4-5 years) and middle-childhood (9-10 years). To date, however, no research has thus far investigated the role of ethnicity in the *development* of children's sensorimotor control over this time period. For example, whether differences are pervasive or diminish over time.

Whilst there is a paucity of research investigating ethnic differences in developmental trajectories of sensorimotor control, data from the Millennium Cohort Study (Dex & Joshi, 2004) has provided insight into longitudinal ethnic differences in cognitive and language development (N. R. Smith et al., 2016; Zilanawala et al., 2016). When comparing cognitive development amongst Bangladeshi, Black Caribbean, Black African, Indian, and Pakistani children, large ethnic inequalities were found at age three, compared to a White British reference group. Yet, when the children were tested again at age seven, these differences reduced, with the exception of Black Caribbean children. Indeed, for Indian, Bangladeshi, and Black African children, these differences were no longer significant at age seven. Similarly, Zilanawala et al. (2016) found, at age three, there was a significantly poorer performance on a vocabulary task within minority ethnic groups compared to the White British reference group. However, at age seven, only Black African children were still performing worse than the reference group, whilst Indian children were now surpassing their White British peers.

Similarly, looking at longitudinal ethnic differences in mental health between Hispanic and non-Hispanic children in the United States, Zhang and colleagues

(X. Zhang et al., 2020) found that at kindergarten, Hispanic children perceived their "physical functioning" levels significantly poorer compared to non-Hispanic children. The authors described physical functioning as being related to a child's perceived capabilities and energy levels. However, by third grade (approximately 8-9 years), no significant ethnic differences between Hispanic and non-Hispanic children were found. The authors proposed these changes were due to the effect of a structured and organised education, which encourages development and allows the Hispanic children to "catch-up". A final example includes early work by Sammons (1995), who studied various demographic influences upon educational attainment in a nine-year longitudinal study. In summary of their findings, Sammons suggested that "the patterns of ethnic differences evident amongst younger age groups are not stable over the longer term" (Sammons, 1995, p. 480). Together, these studies would suggest that the ethnic differences in sensorimotor control found in Reception may weaken, disappear entirely, or even reverse in direction by mid-childhood.

Chapter 3 and Chapter 4 produced more comprehensive factor scores of sensorimotor control which encompassed a larger number of kinematic metrics than has been used previously (e.g., Flatters et al., 2014; Hill et al., 2021). However, no research to date has investigated longitudinal development of motor skills using this with the revised, more empirically and theoretically justifiable scoring method for CKAT. In doing so, this chapter will provide a more detailed understanding of how various mechanisms of sensorimotor control develop over the course of childhood. For example, such analyses can be used to determine whether some aspects of sensorimotor control (e.g., peak speed) take longer to develop compared to others (e.g., movement smoothness). Formally testing age-related changes of the factor scores additionally serves as validation for the revised scoring method. For example, finding large deviations or limited age-related changes across components may reveal discrepancies in the developmental trajectories of these mechanisms of sensorimotor control which would otherwise remain undetected if using a one-metric-per-task approach. To illustrate this, it could be possible that one component is fully developed by age five, so shows few age-related changes after then, while another component has large developmental gains between the ages seven and nine.

The present chapter consists of two studies using distinct, but overlapping, samples of children. Study 1 uses an exploratory, cross-sectional design to investigate age-related differences in each of the individual sensorimotor components for each CKAT task. The aim of this study was to understand the developmental trajectory of sensorimotor control using a more multidimensional measure. Due to its exploratory nature, it was expected that there would be a general increase of performance with increasing age, but the rate of these improvements may differ across the different tasks and sensorimotor component.

To investigate further, Study 2 firstly used a repeated-measures design to understand the developmental change of sensorimotor control between two timepoints during early- and mid-childhood. Secondly, in an extension of the work in Chapter 5, ethnic differences in the development of sensorimotor control were also investigated. For this study, the following hypotheses were proposed:

1) There will be significant age-related changes in performance on all three CKAT tasks (Tracking, Aiming, and Steering) between Timepoint 1 (ages 4-5) and Timepoint 2 (ages 7-10).

2) Any ethnic differences found at Timepoint 1 (T1) will weaken or diminish by Timepoint 2 (T2).

6.2 Study 1: Cross-sectional analysis of sensorimotor control

A cross-sectional analysis was first conducted to determine the developmental trajectory of each of the sensorimotor dimensions derived in Chapter 3 and Chapter 4.

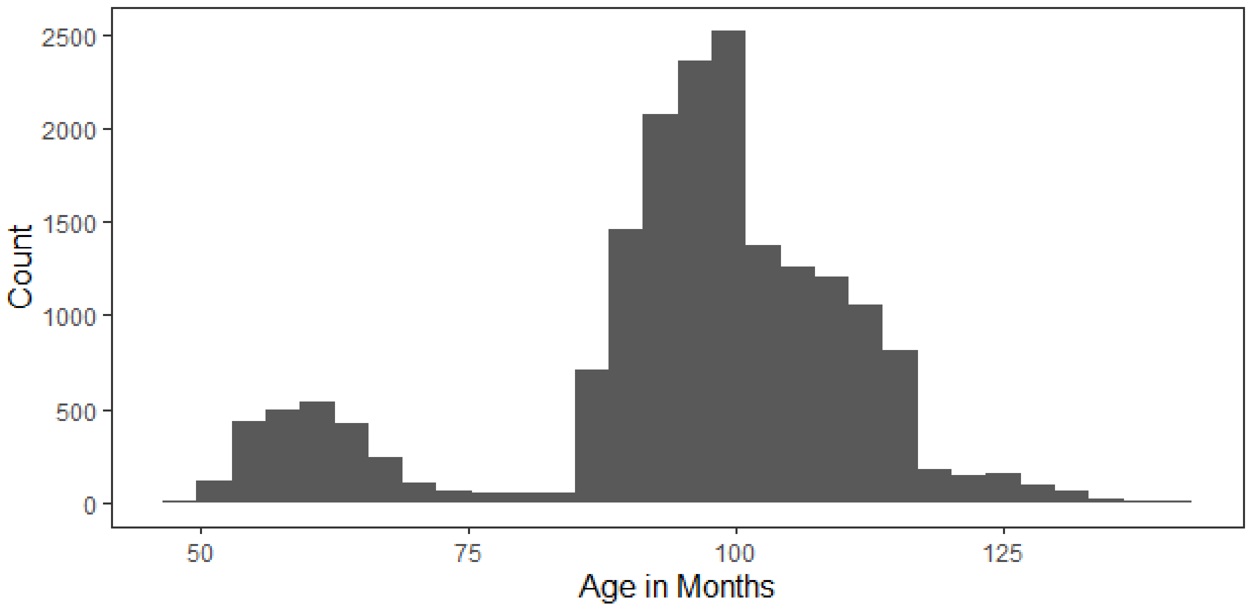
6.2.1 Study 1: Method

6.2.1.1 Participants

For this cross-sectional analysis, the sample included 18132 children aged 4-11 years (M = 7 years, 5 months, SD = 16 months). The data comprised of both participants in BiB's Starting School and Primary School Years cohorts, as well as additional data collected as part of previous theses and manuscripts (see Chapter 1 for additional detail). This additional non-BiB data was added to the sample for the cross-sectional analysis to include children aged six (this age group was not tested in either the Starting School or Primary School Years sweep). As shown in Figure 19, there were fewer children around age six and age eleven children compared to other age groups. However, over 200 six year old (72 to 83 months) and 62 eleven year old (132 to 143 months) children were included in analyses, enough to draw meaningful conclusions about age-related differences.

Figure 19

Distribution of ages included in sample by months (n = 18132)



6.2.1.2 Procedure and materials

Individual analyses were conducted for each factor score from the Tracking, Aiming, and Steering tasks within CKAT (see Section 5.3.1.2.2 for a more thorough explanation of how these scores were derived).

6.2.1.3 Statistical analysis

A series of one-way ANOVAs were conducted to investigate age-related differences amongst 4–11-year-olds for each factor score. This was followed by multiple comparisons with Tukey's HSD correction. All statistical analysis was conducted in R, version 4.0.2 (R Development Core Team, 2020).

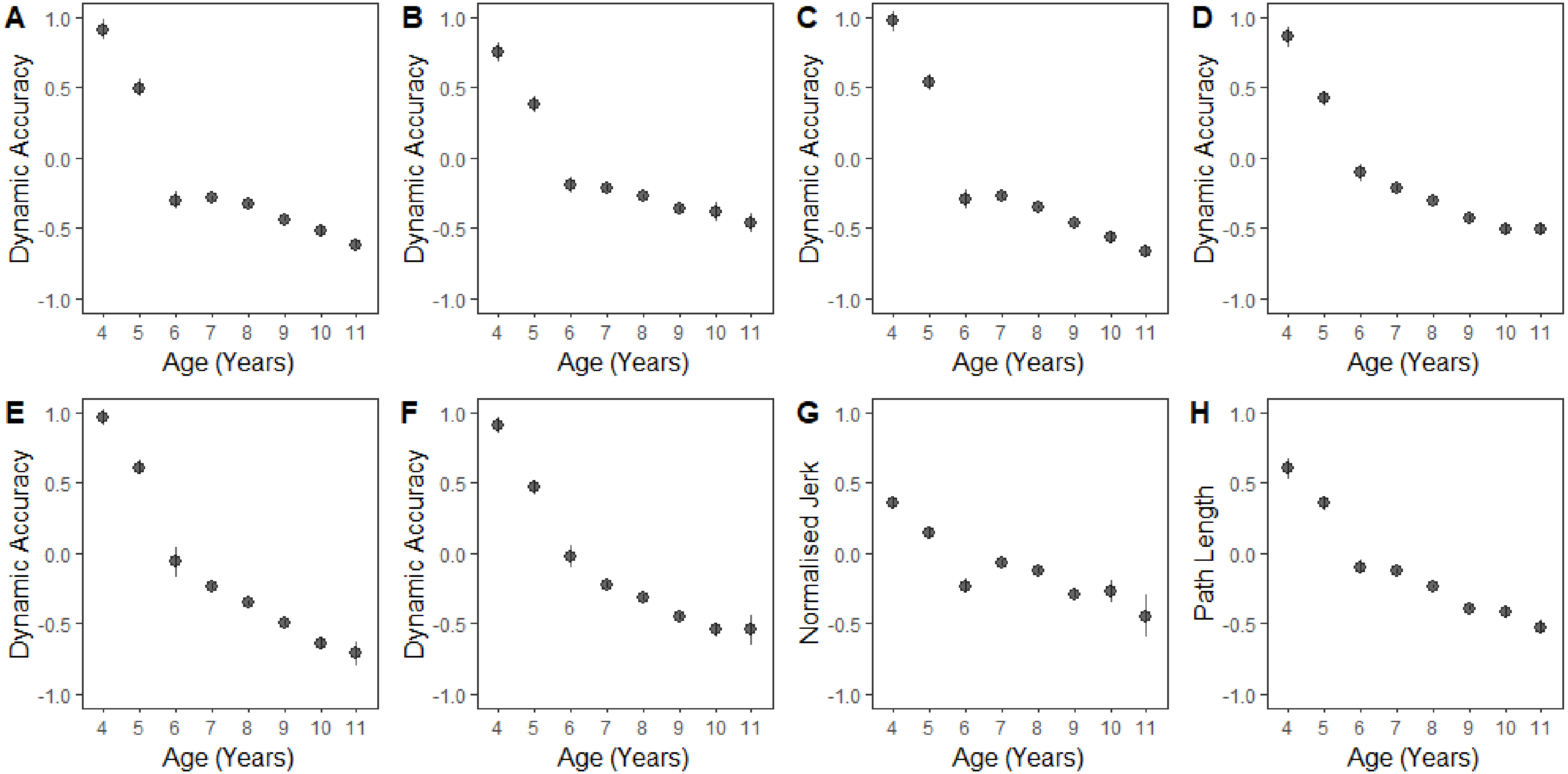
6.2.2 Study 1: Results

6.2.2.1 Tracking

A significant effect of age was found on all eight Tracking components (all p<.001). Multiple comparisons generally found that older children performed significantly better than their younger peers, however there were some exceptions. Tables detailing all multiple comparisons with Tukey's HSD correction can be found in Appendices B-O. No significant differences were found between children aged nine and eleven, or between ten and eleven year old children for any of the eight Tracking components (all p>.05). In addition, no significant differences were found between nine and ten year olds on Dynamic Accuracy: Slow + With Guide; Dynamic Accuracy: Slow + No Guide; Dynamic Accuracy: Medium + No Guide; Dynamic Accuracy: Fast + No Guide; Normalised Jerk; or Path Length (see Appendices B-I). This indicates that for the Tracking task, significant differences were most consistently found amongst the younger age groups or between the youngest and oldest age groups. This suggests that larger developmental changes were found in early childhood, with smaller incremental gains later which may begin to plateau. One exception is the lack of significant differences found between six and seven year olds on five of the eight components (Dynamic Accuracy: Slow + With Guide; Dynamic Accuracy: Slow + No Guide; Dynamic Accuracy: Medium + No Guide; Dynamic Accuracy: Medium + With Guide; and Path Length). Figure 20 shows the developmental trajectory for each component of the Tracking task.

Figure 20

Mean performance on each Tracking component by age



Note: ***A:*** *Dynamic Accuracy (Slow + With Guide);* ***B:*** *Dynamic Accuracy (Slow + No Guide);* ***C:*** *Dynamic Accuracy (Medium + With Guide);* ***D:*** *Dynamic Accuracy (Medium + No Guide);* ***E:*** *Dynamic Accuracy (Fast + With Guide);* ***F:*** *Dynamic Accuracy (Fast + No Guide);* ***G:*** *Normalised Jerk;* ***H:*** *Path Length.*

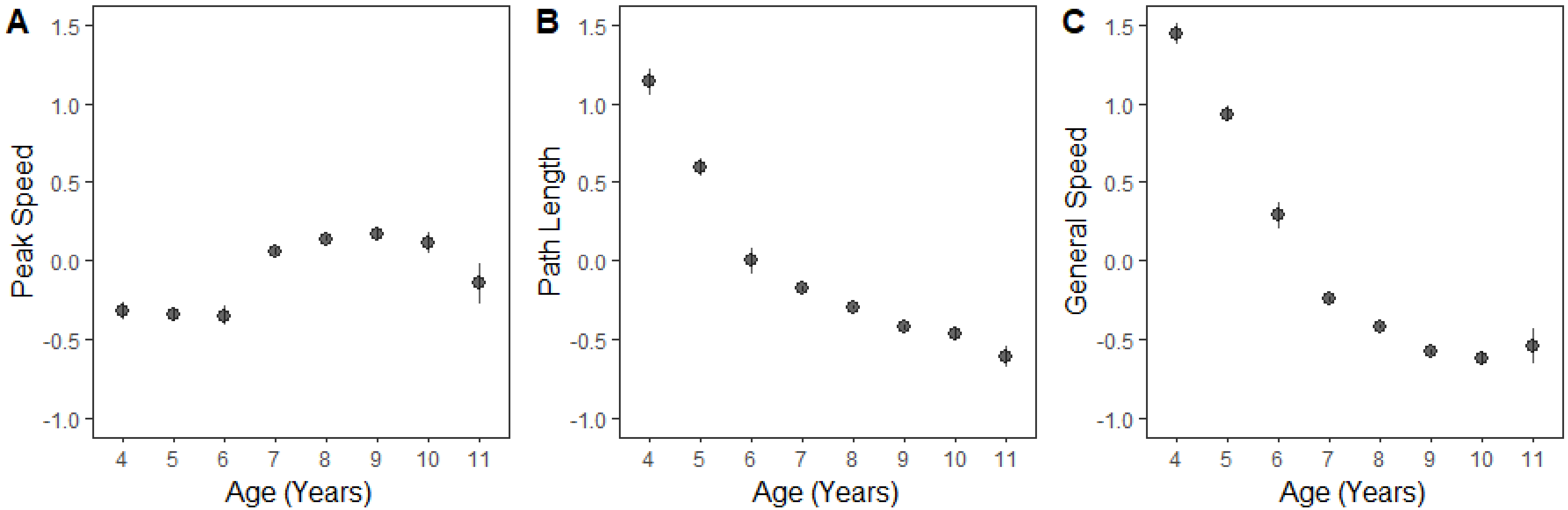
Lower score is indicative of better performance. Error bars represent 95% confidence intervals.

6.2.2.2 Aiming

A significant effect of age was found for all three Aiming components (all $p<.001$). For General Speed and Path Length, improvement with increased age was relatively consistent (see Figure 21). No significant differences were found between nine and ten year olds or ten and eleven year olds for any of the three components (all $p>.05$). As can be seen in Appendix K, the findings for Peak Speed were more inconsistent, with fewer significant differences between age groups. Note that for Peak Speed, a higher score is indicative of increased peak speed and therefore better performance.

Figure 21

Mean performance on each Aiming component by age



Note**: A:** Peak speed; **B:** Path Length; **C:** General Speed.

For Peak Speed, higher score is indicative of better performance. *Error bars represent 95% confidence intervals.*

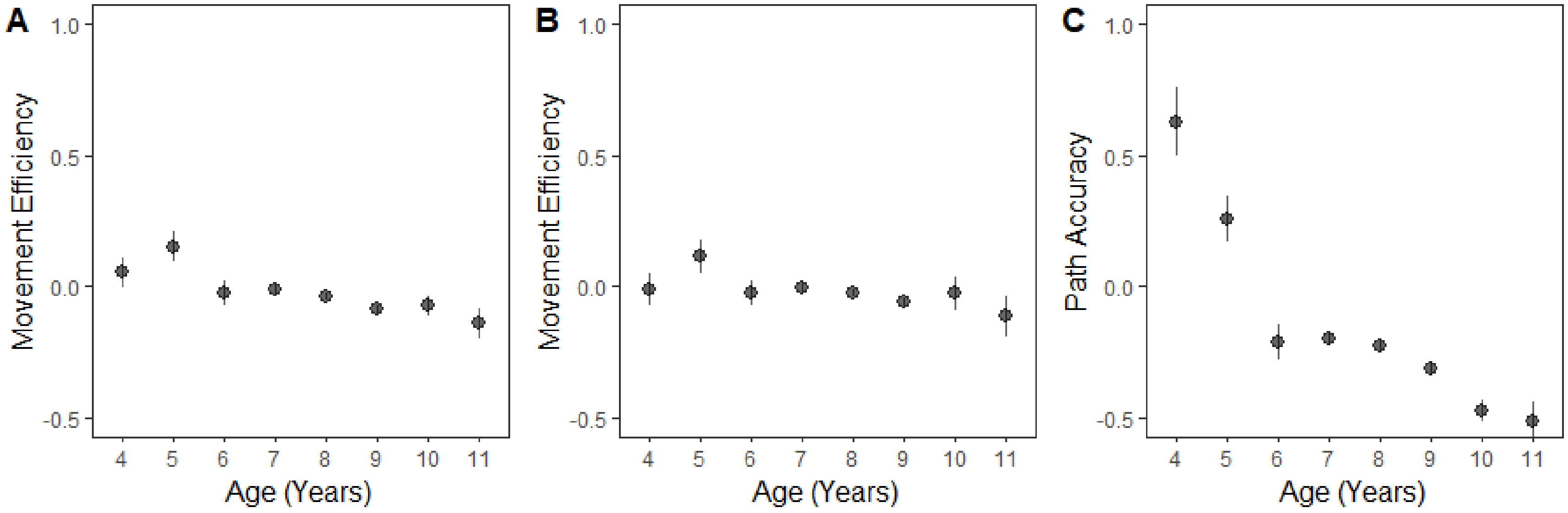
6.2.2.3 Steering

For all three Steering components, a significant effect of age on performance was found at the $p<.001$ level.

Although there was a significant age effect, multiple comparisons revealed inconsistent relationships. For Movement Efficiency A, significant differences were found in the youngest children when compared to their older peers (see Appendix M). Few significant differences were found in children six years and older. For Movement Efficiency B, even fewer significant differences were found across the sample. Significant differences in performance were found only between four and five year olds, five and seven year olds, five and eight year olds, five and nine year olds, five and ten year olds, and seven and nine year olds. In contrast, significant age differences were found more consistently for the Path Accuracy component on the Steering task. Again, most of these differences were found in the youngest children. The developmental trajectories for the Steering task are displayed in Figure 22.

Figure 22

Mean performance on each Steering component by age



Note: ***A:*** *Movement Efficiency Shape A;* ***B:*** *Movement Efficiency Shape B;* ***C:*** *Path Accuracy. Error bars represent 95% confidence intervals.*

6.2.3 Study 1: Discussion

The present findings corroborate previous literature which shows general improvement in sensorimotor control with increasing age (e.g., Alramis et al., 2016; Flatters, Hill, et al., 2014; Kakebeeke et al., 2018).

Whilst the majority of the sensorimotor dimensions showed a clear trend over time, there were some inconsistencies. Both Movement Efficiency A and B within the Steering task showed a more inconsistent improvement. These dimensions both consist of Path Length and Normalised Jerk. Previous research has suggested that with increasing age, children are better able to produce smoother movements which has been explained by maturing corticospinal connections (Armand et al., 1996; Kuhtz-Buschbeck et al., 1998; Müller & Hömberg, 1992; Porter & Lemon, 1993).

Similarly, Path Length relates to the distance travelled during movement, where a smaller distance is indicative of more control (Culmer et al., 2009). Previous research has determined that with increasing age and practice, children show reduced path length during reaching tasks (Konczak & Dichgans, 1997; M.-H. Lee et al., 2017).

However, whilst there was a general trend of improvement with age, performance was much more variable in the present study. This could be explained by the complexity of the task itself, in comparison to the Tracking and Aiming tasks. For example, the Steering task requires children to overtly focus on both temporal and spatial accuracy due to the timing box (see Figure 4). Therefore, instead of following a smooth trajectory through adequate pacing of movement, some children would trace the shape in their own time, then wait for the timing box to "catch up". This approach therefore resulted in many "stop-starts" which would likely increase the normalised jerk score. The variability in performance then, may have occurred due to some children taking this stop-start approach whilst others completing the task as intended, and producing a smoother trajectory, irrespective of their age. These differences in the approach taken may have masked the expected age-related changes.

Peak speed within the Aiming task showed an interesting developmental trend. The large increase in performance between six and seven year olds was particularly stark. Previous research has suggested that children are able to perform motor tasks with increasing speed over the course of childhood due to more efficient activation of the necessary muscles, and selection of the more efficient and quickest corticospinal pathway (Alramis et al., 2016; Hans Forssberg, 1999; Hadders-Algra, 2000; Heinen et al., 1998; Sporns & Edelman, 1993). In addition, Rueckriegel and colleagues also found a dramatic increase in speed of movement between six and eight years, explaining this is due to physiological maturation of the CNS (Rueckriegel et al., 2008). Although there is limited research which investigates peak speed specifically, it is intuitive that a greater peak speed would result in faster movement times. As a result, the present findings may align with previous evidence showing reduced movement times with increasing age (Flatters, Hill, et al., 2014; Smits-Engelsman & Wilson, 2013; P. H. Wilson & Hyde, 2013). This has been previously explained by rapid maturation in the neural networks of the sensorimotor system, providing an reduced time in neural transmission (Durston et al., 2006; P. H. Wilson & Hyde, 2013). The apparent dip in performance at age eleven may be somewhat due to sampling error as compared to the other age groups, fewer children aged eleven were included in the sample. This is evidenced by the much wider confidence intervals compared to other age groups.

As discussed in Section 6.1, the literature often reports a non-monotonic trend in the development of sensorimotor control, in which performance; particularly in Aiming tasks, temporarily drops at around eight years old (Bard et al., 1990; Chicoine et al., 1992; Fayt et al., 1992, 1993; Golenia et al., 2017; Hay, 1979; Pellizzer & Hauert, 1996). This has been explained by the sensorimotor system integrating feedforward and feedback control mechanisms (Desmurget & Grafton, 2000). However, in the present study, no such trend was found, with children's performance improving over time. However, this drop in performance has generally been found in total movement time (which includes acceleration or time to peak speed and deceleration time) or reaction time (Pellizzer & Hauert, 1996). In the present study, however, only time to peak speed was included in the General Speed dimension within the Aiming task, alongside other kinematic variables. Neither deceleration time, nor reaction time was included within any of the sensorimotor dimensions. This difference may explain why the non-monotonic trend was not found in the present study.

6.3 Study 2: Longitudinal analysis of sensorimotor control and the impact of ethnicity

Study 2 used repeated-measures analyses to determine how sensorimotor control changed between two timepoints over the course of early-mid childhood. It also sought to understand how these relationships were influenced by ethnicity.

6.3.1 Study 2: Method

6.3.1.1 Participants

For this study, 1036 children were analysed. These data were obtained from two timepoints (Starting School and Primary School Years sweeps). Demographic information of the sample is detailed in Table 28. As measurements were collected as part of the two data sweeps, ethical approval and informed consent was obtained as part of the Born in Bradford study which is detailed in Chapter 1. At timepoint 1 (T1), all children were tested within the Reception year (age 4-5 years), as part of the Starting School sweep. At timepoint 2 (T2), the data collection process included children aged 7-10 years and spanned over a number of academic years, that were simultaneously participating in the Primary School Years sweep. Due to sample size s, only children within Year 3 (ages 7-8) and Year 4 (ages 8-9) were included in the present analyses. For increased consistency and to account for any further development between Years 3 and 4, participants in these two different year groups were analysed separately. A similar number of children were included within both Year 3 (n = 501) and Year 4 (n = 531).

Table 28

Demographic information for the whole sample and for each Year Group

	Whole Sample	**Year 3 (@ T2)**	**Year 4 (@ T2)**
Mean Age @ T1 (SD)	4 y, 11 mo (4 mo)	4y, 11 mo (4 mo)	5 y, 0 mo (4 mo)
Mean Age @ T2 (SD)	8 y, 6 mo (7 mo)	8 y, 0 mo (4 mo)	9 y, 0 mo (4 mo)
Ethnicity			
White British (%)	286 (27.7)	141 (28.1)	145(27.3)
Pakistani (%)	746 (72.3)	360 (71.9)	386 (72.7)
Handedness			
Left (%)	100 (9.7)	45 (9.0)	55 (10.4)
Right (%)	932 (90.3)	456 (91.0)	476 (89.6)
Sex			
Male (%)	487 (47.2)	228 (45.5)	259 (48.8)
Female (%)	545 (52.8)	273 (54.5)	272 (51.2)
Total	1032	501	531

6.3.1.2 Design

To investigate the age-related effects on sensorimotor control, a longitudinal repeated-measures design was used. All children had measures of sensorimotor control at both T1 (Reception) and T2 (Year 3 *or* Year 4). To investigate the effect of ethnicity in the age-related differences, a mixed design was used.

6.3.1.3 Procedure and materials

Similar to the previously described studies within this thesis, sensorimotor control was measured via CKAT. Ethnicity was again measured via self-report from the mother during the BiB Baseline Questionnaire. For the purpose of the present analyses, weighted means of the factor scores derived in Chapter 3 and Chapter 4 were used. Thus, there was one score for each CKAT task (Tracking, Aiming, Steering). Analyses were not conducted for each of the sensorimotor components within each task (as was the case in Study 1 of this Chapter) as it was not considered practical or possible to draw meaningful conclusions regarding the influence of ethnicity on so many individual aspects of sensorimotor control. Note, also, that for these measures, a lower score is indicative of better performance.

6.3.1.4 Statistical analysis

Linear mixed effects (LME) models were conducted to investigate the development of sensorimotor control between two time points during early and middle childhood. Linear mixed effects modelling is an analytic framework which is particularly useful for studies with repeated measures (Chou et al., 1998; P. J. Curran, 2003). The use of multilevel models accounts for between-subject variability on developmental trajectories via the inclusion of random effects (Quen & Van Den Bergh, 2004). All models used Maximum Likelihood estimations. Time point (T1 or T2) was included as a within-subjects predictor which was nested within participants. The models were built sequentially using a standardised protocol (Field et al., 2012). For Model A, a baseline model was firstly built which included only the outcome (CKAT score) and the intercept. Next, random intercepts were added to allow the outcome to vary at the individual level. Fixed effects were then included in the model (i.e., time point). Lastly, the inclusion of random slopes in the model allowed for the effect of time point to vary by each participant. Random effects were only included in the model if they significantly improved model fit. To understand how the development of sensorimotor control varied by ethnicity in Model B (Research Question 2), an interaction term was then also added to the model (time point x ethnicity). Ethnicity, handedness, sex and SEP were also added as covariates to both model A and B. To assess model fit, each additional step of the model was compared to the preceding step. Goodness-of-fit statistics were inspected to evaluate the increase in explanatory power of the model using AIC and log-likelihood values.

Individual models were built for each CKAT task for both Year 3 and Year 4 pupils separately . This led to six models in total (Tracking: Year 3; Tracking: Year 4; Aiming: Year 3; Aiming: Year 4; Steering: Year 3; and Steering: Year 4. Effect sizes were also calculated to evaluate the effect of time point for White British and Pakistani children, respectively using Pearson's *r*.

6.3.2 Study 2: Results

6.3.2.1 Research Question 1: Impact of timepoint

6.3.2.1.1 Tracking

6.3.2.1.1.1 Year 3

The relationship between timepoint and Tracking performance showed significant variance in intercepts across participants, SD = 0.27 (95% CI: 0.00, 802.95) but the addition of random intercepts alone did not improve model fit, χ^2 (1) = 2.47, *p* = .12. However, the relationship did show significant variance in slopes, SD = 0.29 (95% CI: 5.71, 151174.83), and the addition of both random slopes and intercepts significantly improved model fit compared to the model with random intercepts only, χ^2 (2) = 81.64, p <.001. The slopes and intercepts were not significantly correlated, cor = -.85 (CI: -1.00, 1.00). In the final model, only timepoint, b = -0.22, t(500) = -14.99, p<.001, and ethnicity b = -0.05, t(493) = -2.91, p = .004, were significant fixed effects of Tracking performance (see Table 29). Participants performed significantly better at T2 (M = -0.06, SD = 0.19) compared to T1 (M = 0.16, SD = 0.29) and White British children (M = 0.01, SD = 0.24) performed significantly better than Pakistani children (M = 0.07, SD = 0.28). Neither handedness, SEP, nor sex significantly predicted performance (p>.05).

6.3.2.1.1.2 Year 4

The relationship between timepoint and Tracking performance showed significant variance in intercepts across participants, SD = 0.24 (95% CI: 0.06, 0.91), but again, the inclusion of random intercepts did not significantly improve model fit, χ^2 (1) = 0.00, p = .99. The relationship showed significant variance in the slopes across participants, SD = 0.28 (95% CI: 0.04, 2.08). Adding both random intercepts and random slopes significantly improved model fit compared to the random intercept model, χ^2 (2) = 141.01, p<.001. The slopes and intercepts were not significantly correlated, cor = -.90 (CI: -.99, .98). In the final model, only timepoint (b = -0.22, t(528) = -16.33, p <.001) and SEP Latent Class 5, relative to Class 1 (b = -0.05, t(525) = -2.48, p = .01) significantly predicted Tracking performance (see Table 29). It was found that participants performed significantly better at T2 (M = -0.10, SD = 0.15) compared to T1 (M = 0.12, SD = 0.26) and children from SEP Class 5 (Least Deprived; M = -0.02, SD = 0.27) performed significantly better compared to children in SEP Class 1 (Most Deprived; M = 0.03, SD = 0.25).

Table 29

Regression table showing the effect of timepoint, handedness, and sex on Tracking performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children [continues on next page]

	Year 3					**Year 4**				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model A										
Intercept	0.20	.03	6.11	500	**<.001**	0.12	.02	4.96	528	**<.001**
Handedness: Right	-0.01	.03	-0.23	493	.82	0.01	.02	0.79	528	.43
Sex: Male	0.02	.01	1.26	493	.21	0.01	.01	0.66	528	.51
SEP: Class 2	-0.03	.02	-1.42	493	.16	-0.00	.02	-0.13	525	.90
SEP: Class 3	-0.05	.03	-1.92	493	.06	-0.01	.02	-0.69	525	.49
SEP: Class 4	-0.03	.02	-1.13	493	.26	-0.02	.02	-0.95	525	.34
SEP: Class 5	-0.01	.03	-0.47	493	.64	-0.05	.02	-2.48	525	**.01**
Ethnicity: White British	-0.05	.02	-2.91	493	**.004**	-0.02	.01	-1.44	525	.15
Timepoint:T2	-0.22	.01	-14.99	500	**<.001**	-0.22	.01	-16.33	528	**<.001**

[continued]

Table 29 [continued]

Regression table showing the effect of timepoint, handedness, and sex on Tracking performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children [continues on next page]

	Year 3					Year 4				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model B										
Intercept	0.21	.03	6.29	498	**<.001**	0.13	.03	4.63	526	**<.001**
Handedness: Right	-0.01	.03	-0.23	494	.82	0.01	.02	0.61	526	.54
Sex: Male	0.02	.02	1.26	494	.21	0.03	.01	2.10	526	**.04**
SEP: Class 2	-0.03	.02	-1.42	494	.16	-0.01	.02	-0.73	526	.47
SEP: Class 3	-0.05	.03	-1.92	494	.06	-0.03	.02	-1.12	526	.26
SEP: Class 4	-0.03	.02	-1.13	494	.26	-0.01	.02	-0.29	526	.77
SEP: Class 5	-0.01	.03	-0.47	494	.64	-0.05	.03	-2.04	526	**.04**
Timepoint (T1) x Ethnicity (White British)	-0.09	.03	-2.96	498	**.003**	-0.05	.02	-2.53	526	**.01**
Timepoint (T2) x Ethnicity (White British)	-0.03	.02	-1.76	498	.08	-0.01	.02	-0.55	526	.59

SE = Standard Error. B = Unstandardized coefficient. Df = degrees of freedom

6.3.2.1.2 Aiming

6.3.2.1.2.1 Year 3

The relationship between timepoint and Aiming performance showed significant variance in intercepts across participants, *SD* = 0.82 (95% CI: 0.35, 1.92), χ^2 (1) = 20.87, *p* <.001. In addition, the slopes varied across participants, *SD* = 0.75 (95% CI: 0.10, 5.74), χ^2(2) = 267.45, *p*<.001, and the slopes and intercepts were not significantly correlated, cor = -0.93 (CI: -.99, .99). The final model which included both random intercepts and random slopes found that timepoint, *b* = -1.36, *t*(500) = -35.99, *p*<.001, SEP Latent Class 3 (Employed and no access to money), *b* = -0.12, *t*(493) = -2.06, *p* = .04, and ethnicity, *b*= -0.13, *t*(493) = -3.20, *p* = .002, predicted Aiming performance (see Table 30). Participants performed significantly better at T2 (M = 0.64, SD = 0.41), compared to T1 (M = 2.00, SD = 0.88). In addition, participants in SEP Class 3 (M = 1.21, SD = 0.99) performed significantly better compared to SEP Class 1 (Most deprived; M = 1.43, SD = 1.04) and White British children (M = 1.15, SD = 0.83) performed significantly better than Pakistani children (M = 1.38, SD = 0.83). Handedness nor sex significantly predicted performance (*p*>.05).

6.3.2.1.2.2 Year 4

The relationship between timepoint and Aiming performance showed significant variance in intercepts across participants, SD = 0.72 (95% CI: 0.33, 1.58), χ^2 (1) = 10.58, *p* = .001. In addition, the slopes showed significant variance across participants, SD = 0.68 (95% CI: 0.12, 3.98), χ^2 (2)= 410.89, *p*<.001, and the slopes and intercepts were not significantly correlated, cor = -0.96 (CI: -1.00, .1.00). The final model which included both random intercepts and random slopes found that only timepoint significantly predicted performance, *b* = -1.38, *t*(528) = -42.43, *p* <.001 (see Table 30). Participants performed significantly better at T2 (M = 0.49, SD = 0.30) compared to T1 (M = 1.88, SD = 0.76). Neither handedness, sex, SEP, nor ethnicity significantly predicted performance (*p*>.05).

Table 30

Regression table showing the effect of timepoint, handedness, and sex on Aiming performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children [continues on next page]

	Year 3					Year 4				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model A										
Intercept	2.10	.08	25.73	500	**<.001**	1.88	.06	31.50	528	**<.001**
Handedness: Right	-0.02	.06	-0.30	493	.77	-0.03	.04	-0.76	528	.45
Sex: Male	-0.02	.04	-0.51	493	.61	0.00	.03	0.17	528	.87
SEP: Class 2	-0.04	.05	-0.69	493	.49	0.07	.04	1.93	525	**.05**
SEP: Class 3	-0.13	.06	-2.06	493	**.04**	-0.03	.05	-0.56	525	.57
SEP: Class 4	-0.01	.06	-0.18	493	.85	-0.02	.05	-0.33	525	.74
SEP: Class 5	-0.05	.07	-0.69	493	.49	-0.02	.04	-0.53	525	.59
Ethnicity: White British	-0.13	.04	-3.20	493	**.002**	0.02	.03	0.61	525	.55
Timepoint: T2	-1.36	.04	-35.99	500	**<.001**	-1.38	.03	-42.43	528	**<.001**

[continued]

Table 30 [continued]

Regression table showing the effect of timepoint, handedness, and sex on Aiming performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children

	Year 3					Year 4				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model B										
Intercept	2.16	.08	25.63	498	**<.001**	1.88	.06	30.09	526	**<.001**
Handedness: Right	-0.02	.06	-0.30	494	.77	-0.03	.04	-0.76	526	.45
Sex: Male	-0.02	.04	-0.51	494	.61	0.00	.03	0.17	526	.87
SEP: Class 2	-0.04	.05	-0.69	494	.49	0.07	.04	1.93	526	**.05**
SEP: Class 3	-0.13	.06	-2.05	494	**.04**	-0.03	.05	-0.56	526	.57
SEP: Class 4	-0.01	.06	-0.18	494	.85	-0.02	.05	-0.33	526	.74
SEP: Class 5	-0.05	.07	-0.69	494	.49	-0.02	.04	-0.53	526	.59
Timepoint (T1) x Ethnicity (White British)	-0.35	.09	-4.03	498	**<.001**	0.02	.07	0.14	526	.89
Timepoint (T2) x Ethnicity (White British)	-0.11	.04	-2.66	498	**.008**	0.02	.03	0.62	526	.54

SE = Standard Error. B = Unstandardized coefficient. Df = degrees of freedom

6.3.2.1.3 Steering

6.3.2.1.3.1 Year 3

The relationship between timepoint and Steering performance showed significant variance in intercepts across participants SD = 0.86 (95% CI: 0.69, 1.08) but the addition of random intercepts only did not significantly improve the model fit compared to a model with fixed effects only, χ^2 (1)= 0.09, *p* = .76. Meanwhile, there was significant variance found in slopes across participants, SD = 0.92 (95% CI: 0.63, 1.34), and including both random slopes and intercepts significantly improved fit compared to the random intercept model, χ^2 (2)= 199.14, *p*<.001. The slopes and intercepts were not significantly correlated, cor = .92 (CI: -.99, .99). The final model (including fixed effects, random slopes and random intercepts) showed that timepoint (*b* = -0.31, *t*(500) = -6.78, *p* <.001), sex (*b* = 0.11, *t*(493) = 2.78, *p* = .006), and ethnicity (*b* = -0.13, *t*(493) = -2.87, *p* = .004) significantly predicted performance (see Table 31). Indeed, performance was significantly better at T2 (M = -0.10, SD = 0.48) compared to T1 (M = 0.22, SD = 0.93), females (M = -0.01, SD = 0.67) performed significantly better than males (M = 0.14, SD = 0.85), and White British (M = -0.10, SD = 0.42) performed significantly better than Pakistani children (M = 0.12, SD = 0.85).

6.3.2.1.3.2 Year 4

The relationship between timepoint and Steering performance did not show significant variance in intercepts across participants, nor did the slopes. Therefore, the final model included fixed effects only (see Table 31). Timepoint (b = -0.46, *t*(1053) = -8.58, *p*<.001), ethnicity (*b* = -0.15, *t*(1053) = -2.45, *p* = .01), and SEP Latent Class 5 significantly predicted performance (*b* = -0.20, *t*(1053) =

-2.14, *p* = .03). Again, performance was significantly better at T2 (M = -0.15 , SD = 0.58) compared to T1 (M = 0.31 , SD = 1.10), SEP Latent Class 5 (M = -0.04, SD = 0.68) performed significantly better than SEP Latent Class 1 (M = 0.15 , SD = 1.14), and finally White British children (M = -0.04, SD = 0.58) significantly outperformed Pakistani children (M = 0.12, SD = 1.00).

Table 31

Regression table showing the effect of timepoint, handedness, and sex on Steering performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children [continues on next page]

	Year 3					**Year 4**				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model A										
Intercept	0.10	.09	1.17	500	.24	0.39	.11	3.45	528	**<.001**
Handedness: Right	0.08	.07	1.12	493	.26	-0.00	.09	-0.04	528	.97
Sex: Male	0.11	.04	2.78	493	**.01**	0.10	.05	1.84	528	.07
SEP: Class 2	0.03	.06	0.55	493	.58	-0.04	.08	-0.47	525	.64
SEP: Class 3	0.12	.07	1.86	493	.06	-0.12	.10	-1.25	525	.21
SEP: Class 4	0.01	.06	0.12	493	.90	-0.20	.09	-2.14	525	**.03**
SEP: Class 5	-0.02	.07	-0.25	493	.81	0.10	.05	1.84	525	.07
Ethnicity: White British	-0.13	.04	-2.87	493	**.004**	-0.15	.06	-2.45	525	**.01**
Timepoint: T2	-0.31	.05	-6.78	500	**<.001**	-0.46	.05	-8.58	528	**<.001**

[continued]

Table 31 [continued]

Regression table showing the effect of timepoint, handedness, and sex on Steering performance (Model A), and the interaction between timepoint and ethnicity (Model B) for Year 3 and Year 4 children [continues on next page]

	Year 3					Year 4				
	B	**SE**	***t***	**df**	***p***	**B**	**SE**	***t***	**df**	***p***
Model B										
Intercept	0.17	.09	1.87	498	**.06**	0.41	.11	3.60	526	**<.001**
Handedness: Right	0.08	.07	1.12	494	.26	-0.00	.09	-0.04	526	.96
Sex: Male	0.11	.04	2.78	494	**.01**	0.10	.05	1.84	526	.07
SEP: Class 2	0.03	.06	0.55	494	.58	-0.04	.08	-0.47	526	.64
SEP: Class 3	0.12	.07	1.86	494	.06	-0.12	.10	-1.25	526	.21
SEP: Class 4	0.01	.06	0.12	494	.90	-0.11	.10	-1.12	526	.26
SEP: Class 5	-0.02	.07	-0.25	494	.81	-0.20	.09	-2.14	526	**.03**
Timepoint (T1) x Ethnicity (White British)	-0.36	.09	-3.93	498	**<.001**	-0.23	.09	-2.62	526	**.01**
Timepoint (T2) x Ethnicity (White British)	-0.07	.05	-1.34	498	.18	-0.08	.09	-0.90	526	.37

SE = Standard Error. B = Unstandardized coefficient. Df = degrees of freedom

6.3.2.2 Research Question 2: The impact of ethnicity on change over time

To each of the linear mixed models reported in the preceding section, an interaction term was added (ethnicity x timepoint) to investigate ethnic differences in the trajectory of sensorimotor control. Where significant interactions were found, post-hoc planned contrasts were conducted to identify how ethnic differences differed over time.

6.3.2.2.1 Tracking

6.3.2.2.1.1 Year 3

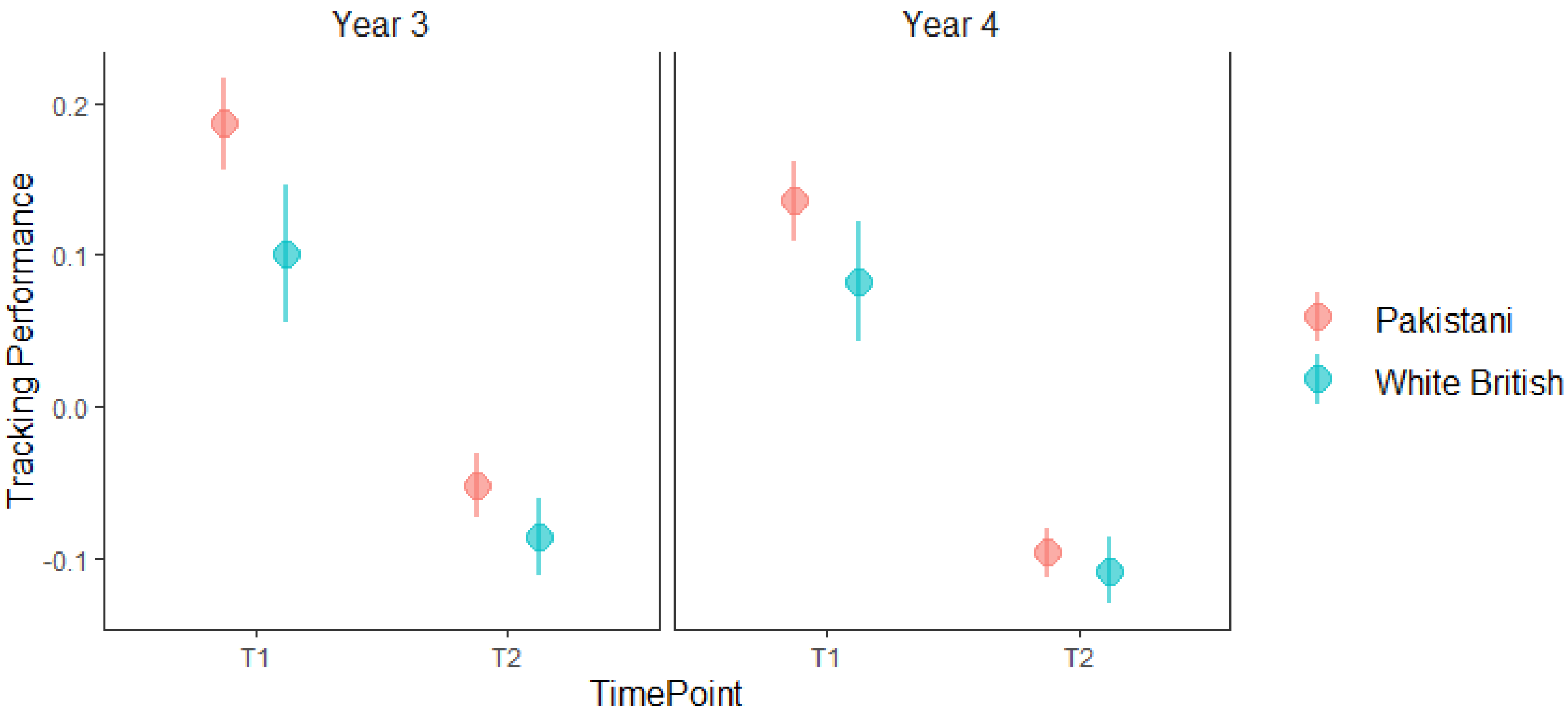
There was a significant interaction between ethnicity and timepoint, $F(2, 498) = 5.43$, $p = .005$, indicating the effect of ethnicity differed between T1 and T2, as presented in Table 29. It was found that at T1, there were significant differences between White British and Pakistani children, $b = -0.09$, $t(498) = -2.96$, $p = .003$, $r = .13$. However, at T2, there were no longer any significant differences found, $b = -0.03$, $t(498) = -1.76$, $p = .08$, $r = .08$. This interaction is illustrated in Figure 23.

6.3.2.2.1.2 Year 4

A significant interaction was found between ethnicity and timepoint, $F(2, 1052) = 3.32$, $p = .04$ (see Table 29). Planned contrasts revealed significant differences in performance between ethnic groups at T1, $b = -0.05$, $t(1052) = -2.53$, $p = .01$, $r = .08$. However at T2, no significant ethnic differences were found, $b = -0.01$, $t(1052) = -0.55$, $p = .59$, $r = .02$. These differences can also be seen in Figure 23.

Figure 23

Tracking performance between Timepoint 1 and Timepoint 2 between ethnic groups, faceted by Year 3 and Year 4 pupils



Note: Children were in either Year 3 or Year 4 at Timepoint 2. At Timepoint 1, ***all*** *children were 4-5 years old. Error bars represent 95% confidence intervals.*

6.3.2.2.2 Aiming

6.3.2.2.2.1 Year 3

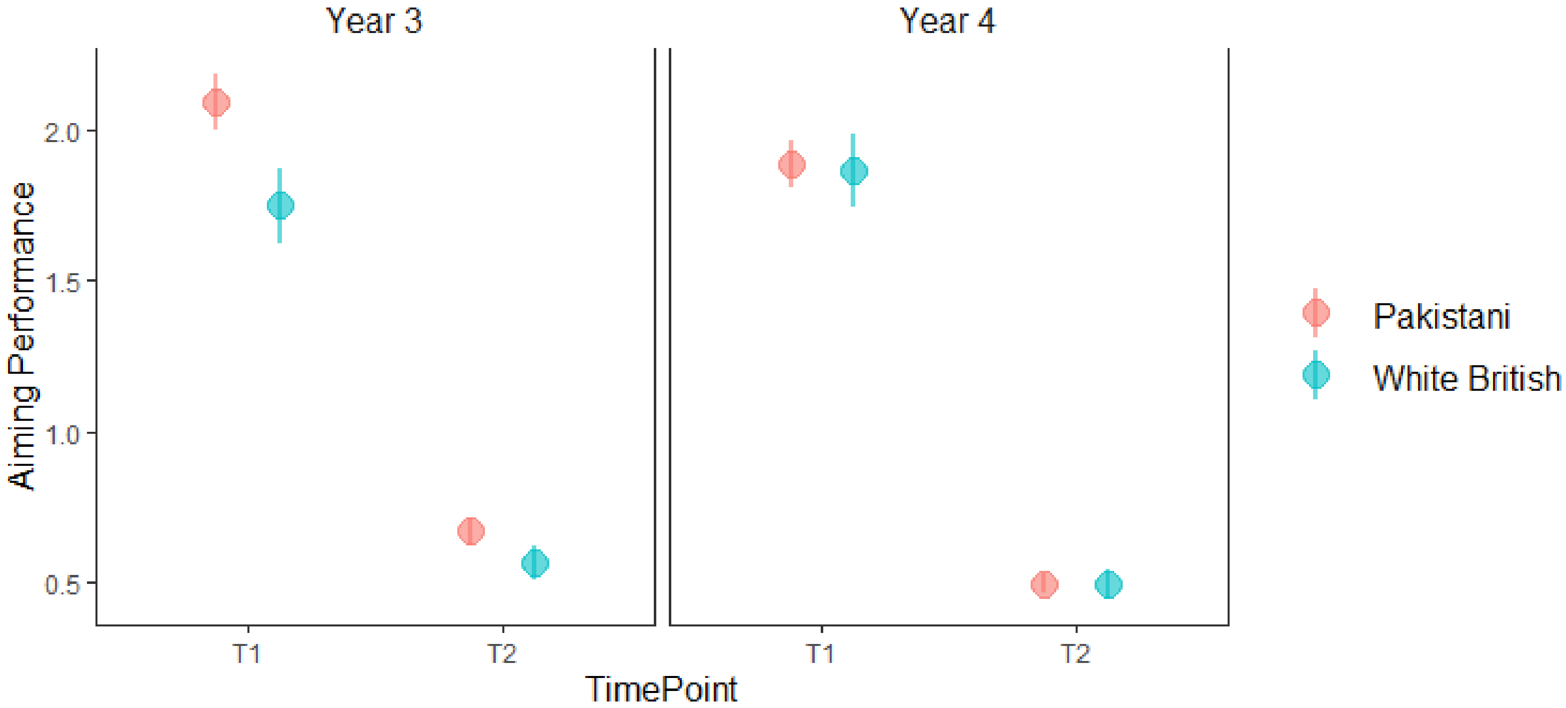
There was a significant interaction between ethnicity and timepoint, $F(2, 498) = 9.20$, $p<.001$ (see Table 30). Planned contrasts revealed that while there were still ethnic differences found at T2 ($b= -0.11$, $t(498) = -2.66$, $p = .01$, $r = .12$), these were substantially reduced compared to the differences found at T1 ($b = -0.35$, $t(498) = -4.03$, $p<.001$, $r = .18$). These differences are illustrated in Figure 24.

6.3.2.2.2.2 Year 4

No significant interaction was found between ethnicity and timepoint, $F(2, 526) = 0.19$, $p = .83$, suggesting that the effect of timepoint was similar for both White British and Pakistani children (see Table 30). Indeed, there were no significant differences across ethnic groups at either T1 ($b = 0.02$, $t(526) = 0.14$, $p = .89$, or at T2 ($b = 0.02$, $t(526) = 0.62$, $p = .54$). This lack of an interaction is illustrated in Figure 24.

Figure 24

Aiming performance between Timepoint 1 and Timepoint 2 between ethnic groups, faceted by Year 3 and Year 4 pupils



Note: Children were in either Year 3 or Year 4 at Timepoint 2. At Timepoint 1, ***all*** *children were 4-5 years old. Error bars represent 95% confidence intervals.*

6.3.2.2.3 Steering

6.3.2.2.3.1 Year 3

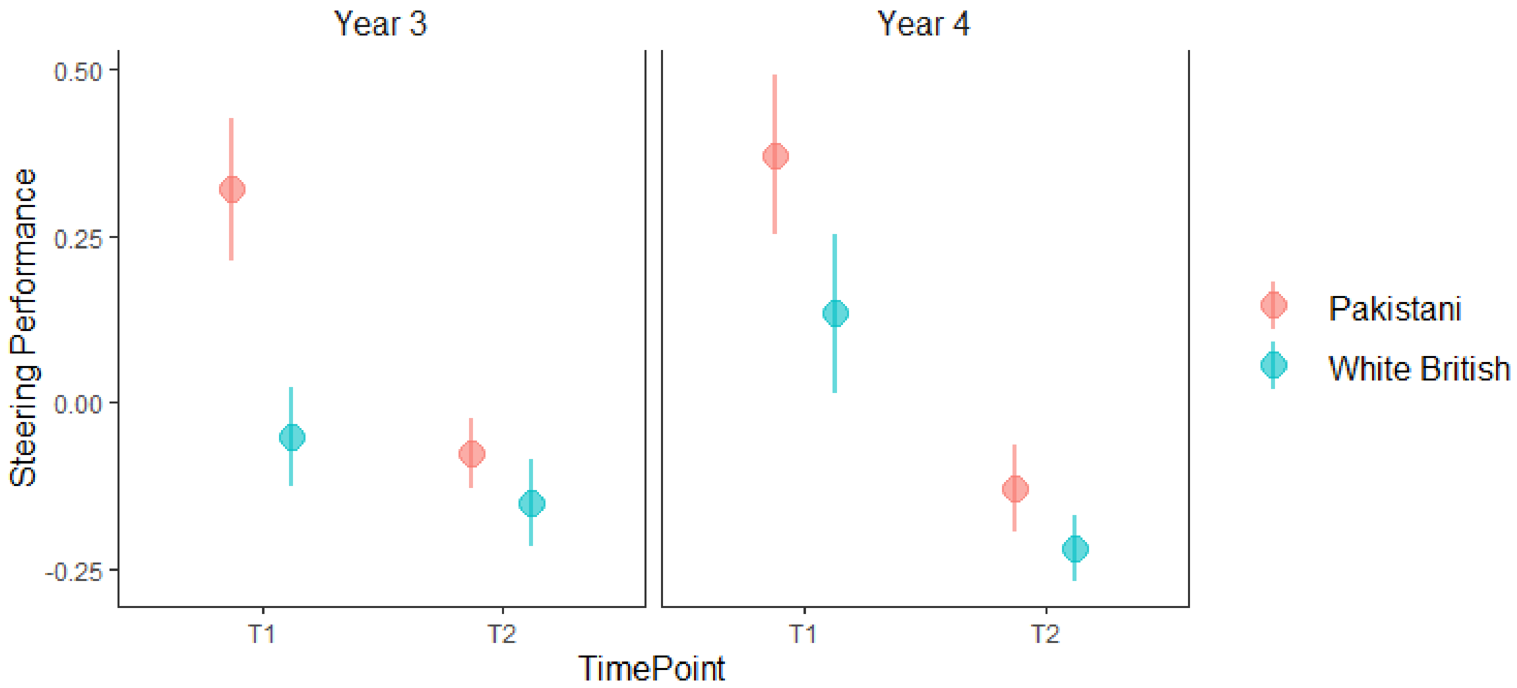
There was a significant interaction between ethnicity and timepoint, $F(2, 498) = 8.37$, $p < .001$ (see Table 31). Indeed, at T1, there was a significant difference across ethnic groups, $b = -0.36$, $t(498) = -3.93$, $p < .001$, $r = .17$, yet this was not significant at T2, $b = -0.07$, $t(498) = -1.34$, $p = .18$, $r = .06$. These differences are illustrated in Figure 25.

6.3.2.2.3.2 Year 4

Lastly, there was a significant interaction between ethnicity and timepoint, $F(2, 1052) = 3.76$, $p = .02$ (see Table 31). Again, ethnic differences were found at T1, $b = -0.23$, $t(1052) = -2.62$, $p = .009$, $r = .04$, but these dissipated at T2, $b = -0.08$, $t(1052) = -0.90$, $p = .37$, $r = .03$. These differences can also be seen in Figure 25.

Figure 25

Steering performance between Timepoint 1 and Timepoint 2 between ethnic groups, faceted by Year 3 and Year 4 pupils



Note: Children were in either Year 3 or Year 4 at Timepoint 2. At Timepoint 1, ***all*** *children were 4-5 years old. Error bars represent 95% confidence intervals.*

6.3.3 Study 2: Discussion

6.3.3.1 The longitudinal impact of sensorimotor control

As expected, significant improvement in CKAT performance was found between T1 and T2. This aligns with previous research that shows an increase in children's fine and sensorimotor skills between early- and mid-childhood, irrespective of the measures used to determine performance (e.g., Alramis et al., 2016; Flatters et al., 2014; Fuelscher et al., 2015; Kakebeeke et al., 2018; Rueckriegel et al., 2008; van Roon et al., 2008; Wilson & Hyde, 2013). These findings also align with the cross-sectional analyses conducted in Study 1 of this chapter. Generally, improvements in children's sensorimotor control are explained by maturation of the CNS, including an increase in white matter volume and decrease in grey matter, and efficiency of neural transmission (Durston et al., 2006; Giedd et al., 1999; Rueckriegel et al., 2008; Sowell et al., 2004; P. H. Wilson & Hyde, 2013).

6.3.3.2 The influence of ethnicity on the longitudinal impact of sensorimotor control

Thus far, there has been no research to the author's knowledge which has investigated how the longitudinal development of sensorimotor control is impacted by ethnicity. Generally, it was found that significant differences between ethnic groups at T1 (4-5 year old children) disappeared by T2 (either 7-8-years-old or 8-9-years-old). The exception to these findings were results concerning the Aiming task. A significant interaction was found between ethnicity and timepoint for the Aiming task for children in Year 3. Post-hoc exploration of this interaction found a significant ethnic difference at both timepoints. The size of the difference however, while still significant, was substantially smaller at T2 compared to T1.

This is illustrated by the smaller beta value in Table 30 and the narrowed difference between points in Figure 24. Contradictorily, for the Year 4 sample, no significant differences between ethnicities were found at either T1 or T2. This was surprising considering all children at T1 were tested during the Reception year of school (aged 4-5 years), regardless of when they were assessed for their T2 performance.

Inconsistencies aside, the general picture that emerges from five out of six of these analyses is that ethnic differences do dissipate over the course of just a few years, and that in some cases, these differences are no longer significant. Thus, these findings are broadly in agreement with previous studies which have found that ethnic differences reduce over time in cognitive and vocabulary tasks (N. R. Smith et al., 2016; Zilanawala et al., 2016) and speak to the diminishing relevance of ethnicity with increasing age in the context of children's sensorimotor development.

There are several potential explanations for these findings. For example, with increasing age, the effect of the home and family environment is likely to have a reduced impact on motor and cognitive development. This has similarly been found in relation to the effect of SEP. Ferreira et al. (2018) found that SEP had a greater impact on younger children's motor skills compared to older children. The authors suggested that the benefit of a positive school environment may come to outweigh the benefit of the home environment as children grow up. This is intuitive, as prior to starting formal education, children spend the majority of their time within the home and are thus more likely to be influenced by whether parents create sufficient opportunities within the home environment to facilitate motor development (L. M. Barnett et al., 2019; Baxter et al., 2016). As the child enters school, they are faced with a plethora of novel opportunities to develop their sensorimotor control and fine motor skills through everyday classroom activities (e.g., drawing, manipulating objects, using scissors) and more formal handwriting instruction (Cameron et al., 2016; Hua et al., 2016). Even in kindergarten, Marr and colleagues report children spend 36-66% of class time engaged in fine motor activities (Marr et al., 2003). As such, children starting school with poorer sensorimotor control are presented with the opportunity to catch up with their more competent peers, and thus, ethnic inequalities would correspondingly begin to narrow over time.

The present findings therefore suggest that with increasing age, there are more influential factors of children's sensorimotor control than ethnicity. Indeed, the ethnic inequalities found at 4-5 years had virtually dissipated by age seven. Also, even though there were ethnic differences found at 4-5 years (as found in Chapter 5), it is important to make note of the size of this effect. The Pearson's *r* statistic for the effect of ethnicity at T1 never exceeded .19, suggesting only a small-medium effect at most (J. Cohen, 1992). However, whilst small in size when interpreted against arbitrary thresholds, it is interesting to compare these effects of ethnicity to the size of the observed age differences. When inspecting absolute scores for each of the tasks, a larger mean difference was found between Pakistani and White British children, compared to mean differences across consecutive age groups (i.e., four and five year olds; seven and eight year olds). This implies that the ethnic differences in sensorimotor control are at least the equivalent of a one year age gap. When compared in this way, these differences are not so trivial. Further research is needed to investigate the impact of these ethnic differences on wider developmental outcomes such as academic achievement.

6.4 General discussion of Study 1 and Study 2

6.4.1 Summary of findings

The aim of the present study was to investigate longitudinal trends in sensorimotor control and how these interacted with ethnicity. Exploratory analyses investigated how each of the sensorimotor dimensions developed over the course of mid-childhood (4-11 years). Data at the first timepoint was collected when children were in the Reception year of primary school (aged 4-5 years), meanwhile at the second timepoint, children were in either Year 3 (aged 7-8 years) or Year 4 (aged 8-9 years).

Regarding age-related differences using cross-sectional analysis of all children, steep improvement in performance was generally found between four and six year old children for all Tracking components except Normalised Jerk. For Normalised Jerk on the Tracking task, performance generally increased over time but the improvement was more linear compared to the other dimensions. Similarly for Aiming, a steep increase in performance between four and six years was found for both Path Length and General Speed. Conversely, for Peak Speed, there was a negligible difference in performance between four and six before a sharp increase at age seven and a possible decline again from age nine to eleven. Of course, caution should be taken when interpreting the findings from the eleven year old children as performance was much more variable due to the lower sample size relative to the other age groups.

Lastly, the Steering task showed less stark improvements in performance compared to the other tasks, particularly Movement Efficiency A and B. These two dimensions also revealed an unexpected sharp decrease in performance at age five. Generally, trends indicated an improvement in performance over time. No significant improvements were found between any consecutive age groups for Movement Efficiency B. However, significant differences *were* found across wider age groups (i.e., five year old children were consistently outperformed by seven, eight, nine, and ten year old children). This indicates that there age-related improvements for this component, just on a smaller scale compared to the other components and sub-tasks.

For the repeated-measures analyses (Study 2), significant improvement was found between the first and second timepoint for all three tasks, irrespective of whether T2 testing was conducted in Year 3 or Year 4. This was as expected. In addition, a significant interaction between ethnicity and timepoint was found for the Tracking and Steering tasks in both the Year 3 and Year 4 samples. A significant interaction was found for the Aiming task for the Year 3 sample, with the effect of ethnicity reducing at T2 compared to T1. However, a significant effect of ethnicity on performance was found at both timepoints. No significant interaction was found for the Aiming tasks in the Year 4 sample. Indeed, there were no significant ethnic differences found at either T1 or T2.

Altogether, these findings suggest that children in the Pakistani sample initially show slightly poorer sensorimotor control but then catch up over time. This aligns with recent evidence which suggests that children with early “moderate coordination difficulties” that do not reach a clinical level (as determined by the MABC-2), catch up with their typically-developing, average performing peers over time, without the need for intervention (McQuillan et al., 2021). However, the impact of these early differences on other aspects of health and development remains unclear.

6.4.2 Strengths and limitations

While the study is one of the first to study the longitudinal effects of sensorimotor control, its ability to infer the shape of developmental trajectories over the period investigated (4-11 years) was limited by the inclusion of only two timepoints. More informative and detailed patterns of the development of sensorimotor control over the course of childhood would be possible with additional intervening timepoints. With more data points, more detailed growth curve analyses would be possible, to follow the development of the same children's sensorimotor control over time. Only two timepoints were included due to the longitudinal data here being collected within large data sweeps situated within the larger Born in Bradford cohort study. It is important to also note the difference between the two data sweeps in terms of the age ranges tested too. For example, at T1, all children were 4-5 years, yet at T2, children were tested within the age ranges of 7-11 years. As such, the sample was split by year group at T2 into Year 3 and Year 4. This was to differentiate between participants in the cohort who were, on average, either followed up four or five years after their first CKAT assessment (i.e., in Year 3 or Year 4, respectively).

In addition, while fewer timepoints were available, using data from BiB did provide the opportunity to access a much larger sample from a bi-ethnic population. The sparseness of the timepoints for the repeated-measures analysis in Study 2 was also remedied somewhat by the inclusion of the cross-sectional analysis in Study

1 where a more general overview of the trajectory of various aspects of sensorimotor control was possible.

6.4.3 Implications and future research

The present findings give greater insight into the extent to which ethnicity influences sensorimotor development over the course of childhood, and how those from ethnic minority groups show signs of “catching up” to their White British peers. However, it is currently unclear as to *why* these ethnic differences in sensorimotor control initially arise or why they diminish over time. Further research should seek to address this, perhaps to see if several explanations for reduced ethnic differences over time in previous research looking at academic achievement, can also be applied to explaining these similar patterns of attenuation in the effects of ethnicity on sensorimotor development.

For example, Wilson et al. (2006) propose that children from ethnic minority groups may not have English as their first language which may present as a challenge initially as they navigate the classroom environment. However, as their language skills develop, these children are better able to engage with learning. However, unlike academic achievement and educational outcomes, it is unlikely that language will have as large an impact on sensorimotor control compared to other domains, such as academic achievement. Thus, there are likely additional mechanisms underpinning these findings.

Wilson et al. (2006) also suggest that the ethnic composition of the school environment could influence the impact of ethnicity on educational outcomes. This corroborates previous literature which suggests that a high ethnic density may serve as a protective mechanism for the adverse effects of belonging to an ethnic “minority” group (Bécares et al., 2009, 2018; Das-Munshi et al., 2010; K.

E. Pickett et al., 2009; K. E. Pickett & Wilkinson, 2008). However, within Bradford classrooms, the high proportion of South Asian and Pakistani children is much larger than the UK average, particularly inner city Bradford. Thus, future research could investigate the effect of ethnic density serving as a protective factor for sensorimotor control by comparing ethnic differences in schools with varying proportions of ethnic “minority” children.

Additionally, the present study highlights significant, albeit small, ethnic differences in sensorimotor control at age 4-5 years. This research could be extended to include mediation analyses to determine the extent to which ethnic differences in sensorimotor control impact academic achievement at both 4-5 years (e.g., EYSP scores) and in later childhood (e.g., SATs scores) or mental health using the Strengths and Difficulties Questionnaire (R. Goodman, 1997). Both of these outcome measures are currently available within the Born in Bradford dataset. Such research has been conducted within a US-based cohort study: the Early Childhood Longitudinal Study (ECLS-K; Luo et al., 2007). The authors found that fine motor skill significantly mediated the relationship between ethnicity (East Asian American versus European American) and mathematics achievement. It would be interesting to explore if similar results were replicated when comparing White British and Pakistani children within a UK-based cohort.

6.4.4 Conclusion

In conclusion, the present study found that most aspects of sensorimotor control improve with increasing age across the primary school years, with the greatest improvements found between four and six years. Additionally, repeated-measures analyses show that children on an individual level do show significant improvement over time. Lastly, the current chapter suggests that any early ethnic differences in sensorimotor control are not enduring and tend to dissipate before the end of primary school. This is promising, as it implies that Pakistani children do not remain at a disadvantage throughout the course of childhood, with regard to sensorimotor control. Therefore, it may be a better use of resources to prioritise progress in domains other than sensorimotor control, where children do not naturally catch up over time. It also suggests that there may be more influential factors contributing to children's sensorimotor control than ethnicity alone. Currently, the effect of these early differences in sensorimotor control on other aspects of health is not known. Future research would benefit from understanding how these early ethnic differences affect other aspects of development and how other modifiable sociodemographic factors impact sensorimotor control.

Chapter 7 General Discussion

Sensorimotor control provides the ability to interact with the environment by converting sensory information into a goal-directed action (Edwards et al., 2019; Franklin & Wolpert, 2011; Tresilian, 2012). As discussed at length in Chapter 1, it underpins the ability to seamlessly execute movements for activities of daily living, partake in physical activity, and produce legible handwriting (Cools et al., 2011; Kilbreath & Heard, 2005; Lubans et al., 2010; Ng & Button, 2018; Rosenblum et al., 2010; Shire et al., 2016; Smits-Engelsman et al., 2001; Snapp-Childs, Casserly, et al., 2013).

This, of course, can be impacted by various sociodemographic factors. For example, previous research has found a link between SEP and motor skills (Adkins et al., 2017; Comuk-Balci et al., 2016; Mcphillips & Jordan-Black, 2007; Morley et al., 2015). Similarly, some research has also found ethnic inequalities in motor skills (Adeyemi-Walker et al., 2018; Eyre et al., 2018; Mayson et al., 2007). There is, however, a complex interaction between these variables on children's motor control which may affect the conclusions drawn (Bécares et al., 2012; Cheng et al., 2015; Nazroo, 1998, 2003; Uphoff et al., 2015). Thus, it is essential that these factors are not investigated as independent silos. After reviewing the literature, there was scant research found which focused on how these two sociodemographic factors interactively impact children's sensorimotor control. In addition, it was evident that studies exploring social determinants of health, including motor skills, do not always use the most optimal or appropriate methodology. Furthermore, these relationships have not been studied in large-scale studies across the primary school years.

As a result, this thesis sought to refine and apply existing methods to understand social determinants of sensorimotor control (ethnicity and SEP) both longitudinally and cross-sectionally and explore how these factors interact. To do so, a more inclusive, ethnic-specific measure of SEP was reproduced using latent class analysis to provide a more holistic proxy measure compared to individual conventional indicators. Dimension reduction techniques (Principal Component Analysis and Confirmatory Factor Analysis) were also used in tandem to determine the most appropriate way to quantify sensorimotor performance of an existing kinematic tool (CKAT). Analyses were conducted on a sample taken from a large, longitudinal cohort of bi-ethnic children. This sample had greater proportions of individuals from Pakistani and disadvantaged backgrounds than the UK average (City of Bradford Metropolitan District Council, 2020b; Raynor et al., 2008; Valentine, 2005; John Wright et al., 2013), providing a unique dataset to explore the effect of these social determinants on children's sensorimotor control. Specifically, the studies contained within this thesis aimed to determine: (i) the extent to which ethnicity impacts school-starters' sensorimotor control and whether this relationship weakened after controlling for SEP, (ii) how SEP impacts sensorimotor control, (iii) how the method of quantifying these measures impacts the relationships, and (iv) the longitudinal development of sensorimotor control over the primary school years. This is the first research of its kind to assess the demographic predictors of sensorimotor control within this sample and the first to investigate these data longitudinally. A summary of the key findings for each study will be reiterated before discussing the implications of the research contained within this thesis, methodological limitations and directions for future research.

7.1 Summary of the experimental findings

7.1.1 Chapter 2

Chapter 2 aimed to replicate the work of Fairley et al. (2014) to produce an ethnic-specific latent measure of socioeconomic position to use in split-group analyses to determine the extent to which SEP predicts children's sensorimotor control (Chapter 5). Replication of the derivation of these measures was necessary as these are not available within the Born in Bradford Data Dictionary. Nineteen independent indicators of socioeconomic circumstances were included in the models such as maternal education, spending priorities, and subjective poverty. As expected, the results mirrored those of Fairley et al. (2014), finding that for both Pakistani and White British samples, four latent classes best fit the data. There were, however, some differences in the circumstances that made up each of these classes, suggesting that an ethnic-specific SEP may be more appropriate to account for these differences when investigating within-group differences. Importantly, these ethnic-specific SEP classes are not appropriate for use when determining differences between ethnic groups.

7.1.2 Chapters 3 & 4

Chapters 3 and 4 aimed to reduce the number of dimensions of sensorimotor control produced by the Clinical-Kinematic Assessment Tool using Principal Components Analysis and Confirmatory Factor Analysis, respectively. While kinematic assessment tools offer a more precise and objective alternative to subjective observational assessments, there are tens of potential kinematic variables to consider when quantifying performance. This can lead to cherry-picking or selecting inappropriate and/or redundant kinematic metrics (Murphy & Aguinis, 2019). Instead, exploratory and confirmatory dimension reduction techniques such as PCA and CFA provide the opportunity to strike an appropriate balance between explaining the largest amount of systematic variance and making theoretically justifiable decisions. It was predicted that the dimensionality of CKAT output data could be reduced to a smaller number of meaningful sensorimotor components.

Within each task, a mean score of all conditions was created before entering these median values into three individual PCA models: 48 items for Tracking, 24 for Aiming, and eight for Steering. The appropriate number of components were selected using eigenvalues, cumulative variance, and scree plots. In cases where the number of appropriate components to extract was not clear, CFA was conducted on both potential models. Following the PCA, the models were refined using CFA to ensure they fit a novel, unseen dataset. This allowed the author to use existing theoretical frameworks to adjust the models and rectify any anomalies that the PCA included. Following up the PCA with CFA using a novel sample demonstrated that the models were valid across multiple samples. Thus, there is evidence to suggest that the proposed models are both mathematically and theoretically sound.

Together, these two chapters found that Tracking, Aiming, and Steering would be quantified most optimally using eight, three, and three sensorimotor components, respectively. Previous literature using CKAT often takes a one-metric-per-task approach to quantifying performance (e.g., Flatters et al., 2014; Hill et al., 2021), however by including a larger range of kinematic metrics, there are arguably more aspects of children’s sensorimotor control considered as more systematic variance is explained. As demonstrated in Chapters 5 and 6, these scores can be used as independent component scores (e.g., Study 1 of Chapter 6), used to create a weighted mean task score (e.g., Study 2 of Chapter 6) or produce an Overall Score across all three tasks (e.g., Chapter 5). These various forms of the sensorimotor factor scores highlight the flexibility available dependent on specific research questions at hand.

7.1.3 Chapter 5

Chapter 5 was a two-part study which sought to understand how ethnicity and socioeconomic status individually and collectively impacted sensorimotor control in 4-5-year-old children. These analyses were conducted using both the "conventional" measures of SES (maternal education, receipt of means-tested benefits and IMD) and CKAT (one metric per task: RMSE, Path Length Time and pPA) and the "revised" methods, latent SEP and CKAT factor scores, respectively. Study 1, using the conventional methods, illustrated that ethnicity significantly predicted Overall CKAT score, even after controlling for all three measures of SES. In addition, the findings indicated that only maternal education and IMD were significant predictors of performance but not receipt of means-tested benefits. This corroborates previous literature which suggests the proxy measure of SES used can impact the relationships found (Cools et al., 2011). In addition, there was no significant moderation found between ethnicity, SES and Overall CKAT Score, regardless of which SES proxy measure was used. This suggests that the impact of SES on Overall CKAT is similar, regardless of one's ethnic group.

Study 2 found similar results. Ethnicity was still a significant predictor when controlling for cohort-wide latent SEP, with White British children significantly outperforming their Pakistani peers. Additionally, there was a significant effect of SEP, with children from the two least deprived groups performing significantly better than the most deprived group. The impact of using the ethnic-specific latent measure of SEP was tested by conducting a split-group analysis of the effect of SEP on CKAT performance. For Pakistani children, there was a significant difference between the most and least deprived groups when using the ethnic-specific SEP, however no differences were found when using the cohort-wide measure. For White British children, differences in children's performance were found across socioeconomic groups, regardless of which measure was used.

Whilst these studies do suggest that ethnicity is a significant predictor of sensorimotor control, putting these differences into context is important. For example, adding ethnicity to the model explained little additional unique variance, questioning the extent to which it would impact children's abilities in applied settings. This highlights that other social determinants may play a much larger role in influencing children's sensorimotor control.

7.1.4 Chapter 6

Chapter 6, the final experimental chapter, aimed to understand the longitudinal development of sensorimotor control over the course of childhood and how this is impacted by ethnicity. To do so, several analyses were conducted. Firstly, cross-sectional, exploratory analyses aimed to study the general developmental trajectory of sensorimotor control over the course of the primary school years. This was performed on every component (derived in Chapter 3 and Chapter 4) for all three tasks, individually and allowed the exploration of how the different mechanisms underpinning sensorimotor control develop over time. Additionally, repeated-measures analyses were conducted to understand how children's sensorimotor control improved across two timepoints during primary school (4-5 years and 7-8 or 8-9 years) and how this differed across ethnic groups.

As expected, the cross-sectional analyses revealed a general increase in performance across all components, indicated by reduced error scores. Greater developmental gains were found for many sensorimotor components between four and six years of age with a slower rate of improvement at around nine years, supporting previous literature (e.g., Gaul & Issartel, 2016; Wilson & Hyde, 2013). Some components such as Movement Efficiency within the Steering task, however, did show less consistent age-related improvements. As discussed in Chapter 6 though, this could be, in part, due to the complexity and difficulty of the Steering task compared to Tracking and Aiming. Aligning with predictions, the repeated-measures analyses indicated significant improvement between the two timepoints (Reception versus Year 3 or Year 4).

When incorporating ethnicity, a significant interaction was found between ethnicity and timepoint. Post-hoc analyses found that differences at the first timepoint diminished by the second, indicating that the effect of ethnicity on sensorimotor control reduces with increasing age. This was the case across all tasks. This study extends the work of Chapter 5 which found significant ethnic differences in Overall performance of sensorimotor control. This implies that with increasing age, ethnic inequalities reduce, supporting previous literature (Sammons, 1995; X. Zhang et al., 2020; Zilanawala et al., 2016).

Together, these findings indicate that similar age-related trajectories are found across all tasks and components, so it is appropriate to combine these into overall scores for some analyses to increase interpretability of more general relationships (i.e., Chapter 5). However, when the aim is to understand the specific mechanisms of sensorimotor control in more detail, it is viable to use the individual components. These findings support the work of Chapters 3 and 4 by demonstrating the flexibility of quantifying sensorimotor control using factor scores. This is the first instance of using the longitudinal sensorimotor data within the Born in Bradford cohort to understand the development of children's sensorimotor control.

7.2 Implications

Collectively, the studies contained within this thesis have several implications for research, policy and practice. These include highlighting the importance of empirically driven selection of measurement variables, the need to reduce ethnic inequalities in children's sensorimotor control, and need for further investigation of the wider and long-term impact of these differences.

Firstly, one of the key findings of this work was evidence to support the importance of empirically driven selection of measurement variables. It was evident that using measures of SEP and sensorimotor control which are empirically determined and capture a larger proportion of systematic variance were better able to detect subtle differences in relationships between sociodemographic factors and sensorimotor performance. Similar conclusions may be found in future research using other sociodemographic factors such as biological sex (Bolger et al., 2018; Flatters, Hill, et al., 2014; Morley et al., 2015). For example, previous research investigating sex-related differences in sensorimotor control using CKAT did not identify statistically significant differences on the Tracking task when measured using RMSE (Flatters, Hill, et al., 2014). In addition, the authors concluded that the sex differences that were found were minimal and unlikely to have lasting impact. However, measuring CKAT with the scoring method derived within this thesis may have detected larger, more meaningful differences between the two groups when incorporating wider aspects of sensorimotor control and thus highlighting a need for targeted intervention. This is supported by the present research which found sex significantly predicted performance across tasks. In addition, it is possible to understand the specific aspects where these differences lie when using more specific scoring. Previous research has broken down movements into individual sensorimotor components, finding sex differences across the different aspects of movement. For example, females have shown reduced spatial accuracy in goal-directed movements compared to males and increased movement times, yet no significant sex differences were found for temporal accuracy or “decision time” (Casamento-Moran et al., 2017; Lynn & Ja-Song, 1992). Indeed, after finding that accurate online corrections were made quicker by female participants than males, Hansen and Elliott (2009) concluded that males were more likely to “sacrifice the accuracy of completion of the task for the speed of completion” (p.28). Such detailed analysis of these individual aspects of movement would not be possible when using a “one-metric per task” approach to measuring sensorimotor performance. Similar individual differences may also be masked across various sociodemographic groups such as various ages, ethnicities, SEP-classes etc. Thus, this research provides evidence to support the use of such empirically driven variables within future analyses. Relatedly, as these newly derived scores of sensorimotor control were developed using data from the Born in Bradford cohort, these measures are available for use by other researchers within BiB, avoiding arbitrary cherry-picking of kinematic variables and encouraging the use of more detailed and inclusive sensorimotor data.

Another implication of the work contained within this thesis is the opportunity of using the large dataset of sensorimotor performance to generate age-appropriate norms for determining benchmark performance to compare individuals against. Within paediatric health and medicine, age-appropriate norms are frequently used to assess children's current level of development (Kelle, 2010). While even "normal" development is not homogenous across all children and there are individual differences in terms of individual trajectories, age-appropriate norms are useful for giving parents realistic expectations of their children (Boatella-Costa et al., 2007; Kelle, 2010; Y. Noble & Boyd, 2012). Age-related norms are available for a range of movement assessments, including the MABC-2 (Henderson et al., 2007), TGMD-2 (Ulrich, 2000), and BOT-2 (Bruininks & Bruininks, 2005) and are useful for highlighting children who are not performing as expected for their age.

Such age-appropriate norms are not currently available for CKAT and although not originally intended as a diagnostic tool, it could be used as a pre-screening assessment for all children as they enter formal education. With the increased risk of a plethora of adversities due to impeded motor skills as discussed in Chapter 1, such as poor academic achievement (Cameron et al., 2016; Giles et al., 2018), mental health difficulties (L. J. B. Hill et al., 2016; Mancini et al., 2018), and reduced levels of physical activity (L. M. Barnett et al., 2011; Temple et al., 2019), identifying children at risk is pivotal. Through early identification of these children, these related adversities may be diminished or avoided through targeted sensorimotor intervention. In addition, although motor skills vary along a spectrum of abilities, difficulties at a clinical level are not infrequent. Recent research suggests that 12-17.4% of 4-6-year-old children are at risk of DCD, equating to at least one child per average classroom (Amador-Ruiz et al., 2018; De Milander et al., 2016b, 2016a). Children not performing as expected for their age would be identified as those who may benefit from additional support in the classroom. In extreme cases, poor performance for age on CKAT could be used as an incentive for referral to a physiotherapist or occupational therapist for additional diagnostic screening for movement disorders such as DCD. Further detail regarding targeted intervention for those at risk is described later in this section.

Normative data have also been previously used to assess the appropriateness of various assessment tools of motor control within other populations (Chow et al., 2001; Hirata et al., 2018; Mayson et al., 2007; Tripathi et al., 2008). As the present research highlights, ethnic differences are apparent, particularly in early childhood, meaning normative data requires adjustment of these differences, accordingly. This supports previous research which has found similar adjustments of age-related norms are necessary when using the MABC-2 across different populations such as Japanese (Hirata et al., 2018), Thai (Jaikaew & Satiansukpong, 2019) and Dutch (Fleurkens-Peeters et al., 2018) samples. Thus, it may be appropriate to generate CKAT norms which are specific to ethnicity.

Lastly, if age-appropriate norms are extended to include typically-developing adult populations too, CKAT could be used to gauge recovery or progress in groups undergoing rehabilitation or treatment for movement disorders such as stroke or cerebral palsy (Fitoussi et al., 2011; Koesler et al., 2009; Nowak, 2008; Rudisch et al., 2016; Wu et al., 2007). Previous research has already used an early version of CKAT to research intracranial aneurysm treatment following stroke (Raw et al., 2017). However, using the current scoring would increase the level of detail obtained. The advantage of using CKAT in such scenarios is that it is easily transportable, making at-home assessments viable, minimising the inconvenience placed on the patient to attend primary healthcare settings.

In addition to highlighting the importance of accurate, empirically determined measurement of sensorimotor control, the current thesis does also demonstrate a similar advantage of such techniques with regard to socioeconomic position. It was evident that using a comprehensive, latent measure of SEP which better reflects the multifaceted construct was better able to detect differences in sensorimotor control compared to a single measure. As previously discussed, SEP encompasses a range of attributes including individual's social status, prestige, wealth and access to resources, both objectively and subjectively (Braveman et al., 2001; Fairley et al., 2014; Galobardes et al., 2006; Howe et al., 2012; Krieger et al., 1997; Nazroo, 1998). These findings provide additional support to the evidence base of the importance of using measurement tools which reflect these many aspects. This has important implications for future research as it advocates the use of composite and multifaceted measures when designing future studies. Using a measure which takes into account multiple aspects of socioeconomic circumstances and also weights these aspects appropriately avoids inconsistencies in the conclusions drawn as a result of the proxy measure of SEP used. Such discrepancies have been found in previous research investigating the relationships between SEP and motor skills when using different individual predictors of SEP (e.g., Cools et al., 2011; Lejarraga et al., 2002) which can lead to conflicting evidence.

Using a comprehensive SEP variable also avoids biases which can arise as a result of individual differences. These biases may be more prevalent in particular populations such as when using education as the indicator but the individual in question has qualifications obtained outside of the UK or taken a vocational, rather than conventionally "academic" route (Braveman et al., 2005; Sherar et al., 2016). Thus, future research should aim to collect data concerning a range of predictors of SEP to gauge individuals' circumstances most accurately, particularly if interested in its relationship with children's sensorimotor control, or development more generally.

Additionally, there was a distinct benefit of using measures of SEP which were specific to the ethnic group in question. For example, in Pakistani individuals, greater socioeconomic differences were captured when using the ethnic-specific measure. This highlights that similar measures should be incorporated when investigating socioeconomic effects on various outcomes within different ethnic-populations and that a "one size fits all" approach cannot be taken with regard to SEP (Braveman et al., 2005). This is supported by previous research which suggests that measures of SEP may not be equivalent across different ethnicities and there may be differences in circumstances, despite some conventional predictors of SEP being identical (Kelaher et al., 2009; Shavers, 2007). Future studies aiming to look at SEP across diverse populations should acknowledge these differences and consider a specific SEP measure. However, as previously noted, these measures are not appropriate when comparing health, performance or development *between* different ethnic groups (Fairley et al., 2014).

In addition to providing evidence to inform practice on the measurement of variables within sociodemographic and/or sensorimotor control research, the present thesis also provides insights into ethnic differences of sensorimotor control within early childhood. It was found that Pakistani children may be at an increased disadvantage in terms of their sensorimotor control during the first year of formal education. However, it is promising that these ethnic differences were found to dissipate over time. As discussed in Chapter 6, there are several possibilities as to what is driving this reduction in ethnic differences. One possible explanation is that children spend a large proportion of time in the classroom environment compared to the home once they reach school age, providing a plethora of opportunities to refine and develop their sensorimotor control and fine motor skills through everyday classroom activities such as handwriting and other fine motor tasks (Caçola, 2014; Cameron et al., 2016; Hua et al., 2016; Marr et al., 2003). Additionally, the school environment in UK state schools is relatively homogenous, regardless of ethnicity with all children receiving relatively equal access to opportunities, provisions, and stimulation, putting children on an even playing field. On the contrary, the home may vary more widely from child to child and across ethnic groups. Thus, with increased access to these resources at school, children of Pakistani ethnicity have the opportunity to catch up to their White British peers. While previous research has suggested that up to two-thirds of the progress made by ethnic minority children in terms of academic performance is a result of increased language competence (Dustmann et al., 2010). However, this is unlikely to be the case for sensorimotor control, therefore further research is needed to understand the mechanisms underpinning this progress in Pakistani children.

Although these children do catch up over time, it does highlight the importance of early intervention and provision of education for stimulating sensorimotor skills during the early years, particularly in ethnic minority groups. This is especially important as it is not currently clear whether this initial ethnic disparity causes lasting impact on other aspects of development. One approach could be to improve parents' education and empower them to provide their child with an enriching and stimulating home environment. Such approaches have been successfully implemented to improve children's language skills, specifically those from ethnic minority backgrounds. Mendez et al. (2010) found that parents receiving the intervention increased the frequency of reading to their child, improved the home learning environment, encouraged positive parent-child interactions with educational activities and improved parent-teacher relationships. At the end of the intervention, it was found that children in the intervention group had superior receptive vocabulary compared to controls. Thus, the present research may serve as an incentive that similar preventative initiatives may be appropriate for ensuring children enter school with a competent level of sensorimotor control.

In addition to improving parental education and providing preventative strategies, sensorimotor control has been significantly improved following various child-focused programmes during early childhood. For example, Bingham and Snapp-Childs (2019) found that age differences in performance on a kinematic task at pre-test were eliminated at post-test following a specific sensorimotor intervention. Furthermore, classroom interventions have also suggested potential for improving children's sensorimotor and fine motor skills. Helping Handwriting Shine (Shire, Atkinson, et al., 2020) is an initiative that has been successfully implemented during the first year of school which involves sensorimotor activities and handwriting skills. Interventions such as these may be useful to help children who may be initially struggling to "catch up" to their peers and reduce any early ethnic differences found.

7.3 Limitations

The present research is of course, not without limitations and the work contained within this thesis was conducted within the remits of a three-year doctoral degree. Firstly, although the statistical analysis used to derive the revised measures of SEP and sensorimotor control (PCA, LCA, CFA) are more empirically driven than selecting variables based upon theoretical assumptions only, there is some subjectivity involved. For example, other researchers may have interpretated findings slightly differently and thus, the components or variables derived may vary somewhat. Therefore, the relationships in which these are used may have subtle differences. Whilst a possibility, using an empirically driven method is still superior.

Although not investigated in the current thesis, there is a potential limitation regarding how ethnicity was measured. For example, the data used was derived from the Baseline Questionnaire of the Born in Bradford study. Ethnicity was a self-reported measure based on the Census and was used to group individuals into White British, Pakistani and “Other”. However, as Ford and Harawa (2010) highlight, ethnicity is a subjective and complex construct and thus while reducing it to only three groups makes analyses and interpretation easier, it does not allow for nuances. In addition, ethnicity is a sensitive and personal construct and so by using only three ethnic groups, it could be interpreted as non-inclusive for individuals who identify as multi-racial or multi-ethnic. Similarly, Bradford is a unique city, with a high ethnic density (John Wright et al., 2013). Thus, it is not clear how well these findings would translate to other ethnic groups or between White British and Pakistani samples across the UK. For example, areas with high ethnic densities have been previously found to act as a buffer effect for the inequalities often faced by ethnic minority groups (Bécares et al., 2009; Karlsen et al., 2002; K. E. Pickett & Wilkinson, 2008; Uphoff et al., 2016). With Bradford schools comprising a large proportion of Pakistani children, particularly within the inner city, this “buffer” effect as a result of ethnic density could explain why these children were found to “catch up” in mid-childhood (Valentine, 2005; John Wright et al., 2013). However, despite the potential lack of generalisability, the findings *can* be used to inform practice, policy and further research which is tailored for Bradford specifically.

The generalisability of the sample used within the present thesis may be considered a potential limitation, since all participants resided in the city of Bradford, UK. However, Bradford may be an appropriate microcosm for other large UK cities where there is a high ethnic density of “minority” groups. As the 2011 Census demonstrates, the proportion of Asian or Asian British individuals surpasses that within Bradford in several districts within England including Leicester, several boroughs within London, and Blackburn[4] (Office for National Statistics, 2012). Therefore, similar findings would be predicted in such districts where there is a large ethnic minority population. Further research should be conducted, however to determine the appropriateness of such generalisations. In the event that such generalisations are not appropriate, the present research reveals the complex relationship between ethnicity and children’s sensorimotor control, specific to Bradford pupils where targeted policy can be implemented, accordingly.

[4] Note that “Asian or Asian British” includes individuals identifying as Indian, Pakistani, Bangladeshi, Chinese or any other Asian background

Lastly, the present research builds on the current literature by using repeated measures to understand the longitudinal relationships of sensorimotor control. Repeated measures provide the opportunity to account for individual differences (Imlach Gunasekara et al., 2014). However, the present research does only include two timepoints, limiting the extent to which current findings may extend across the course of childhood. As Born in Bradford is very much still an active cohort study with data collection ongoing, this may be a line for future research as more data become available.

7.4 Future Directions

Whilst the present research does reveal some novel findings, there are several potential avenues that should be investigated to further disentangle the complexities between socioeconomic position, ethnicity and children's sensorimotor control.

Whilst the current research suggests that ethnic differences in sensorimotor control diminish over the course of childhood, further research should aim to investigate the extent to which these early differences have on other aspects of development. As discussed in Chapter 1, the ability to execute sensory-guided movements accurately is associated with a wide range of developmental outcomes such as academic achievement, physical activity, and mental health (Cairney et al., 2010; Cameron et al., 2016; Crane et al., 2017; Giles et al., 2018; Harrowell et al., 2018; L. J. B. Hill et al., 2016; Hudson et al., 2020). Thus, it would be of interest to understand whether these early ethnic differences in sensorimotor control have a longer term, wider impact on such developmental outcomes.

In a similar vein, as the significant differences between White British and Pakistani children diminishes with increasing age and such a small amount of unique variance is explained when this *is* significant, what are the other potential determiners of children's sensorimotor control? Possibilities could include the amount of formal handwriting practice performed within the classroom per week or use of video games or other digital technology. For example, previous research has found a positive association between videogaming and fine motor skills in trainee laparoscopic surgeons (e.g., Rosser et al., 2007). In addition, there is evidence suggesting the need for competent manual dexterity to interact efficiently with touch screen devices with positive associations found between the use of early touch-screen devices and acquisition of fine motor milestones (Bedford et al., 2016).

Lastly, to address the limitations around the generalisability of the current research outside of Bradford, future directions should include conducting similar research in other populations. Although the socioeconomic data contained within the current thesis is very rich, there are other cohort studies around the UK which collect similarly detailed demographic information. For example, ALSPAC is a large cohort study which includes participants from Bristol and surrounding areas in North Somerset (Golding et al., 2001). With a smaller proportion of South Asian individuals and a smaller ethnic density, it would be interesting to understand whether similar ethnic patterns arise within this population.

7.5 Concluding remarks

To conclude, the research contained within this thesis aimed to understand the sociodemographic predictors of sensorimotor control and its development over the primary school years. Findings suggest that there are ethnic differences in school-starters, but these differences diminish by age 7 onwards and other factors are likely to have a greater impact. It was also revealed that one’s SEP can influence sensorimotor control, supporting previous research. However, the extent to which SEP plays a role does depend upon the way it is measured and whether ethnicity is accounted for. Furthermore, a key takeaway from the research is the importance of careful consideration of the variables used to measure and conceptualise important constructs within developmental research using children from bi-ethnic, deprived backgrounds and how these can impact the conclusions drawn.

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Appendix A

Quality control of the sensorimotor data from the Primary School Years data sweep

Under the supervision of their primary supervisor and lead of the Born in Bradford data management team, the author was responsible for reviewing the sensorimotor data from the Primary School Years sweep for quality control purposes. These data are used in analyses in Chapter 5 and Chapter 6. Cases were omitted from further analyses primarily for one or more of the following reasons: incompleteness; duplication or issues occurring during testing which were recorded in an accompanying field note.

Firstly, incompleteness occurred when a participant had missing data for one or more trials in a given task. This generally occurred due to technical faults such as software crashes. Importantly, to conserve as much data as possible, the data were reviewed on a task by task basis: incomplete Tracking task but complete Aiming and Steering tasks meant omission of the Tracking trials only, rather than the entire case. Thus, sample sizes varied across the three tasks.

Secondly, duplicated data arose when the participant identifying information (e.g., Child ID) was identical across one or more sessions. In some cases, this was legitimate (e.g., when a participant began a testing session but this had to be completed in a second session due to logistical or technical issues). For these instances, an accompanying field note was recorded explaining the circumstances and sessions were combined. Where both the participant information and kinematic recordings were identical across multiple sessions, one session was retained and the other(s) omitted. However, if, due to human error, the participant information was recorded incorrectly, resulting in two cases with the same Child IDs but different kinematic data, both sessions were omitted from analyses.

Lastly, at the end of each session, the experimenter was provided the option to record anything of note that should be considered when analysing the data as a field note. The field notes were each inspected by the author and primary supervisor and reviewed on a case by case basis for exclusion. Examples of cases warranting exclusion: technical issues (e.g., software crashes), non-compliant participants (e.g. not following task instructions) or participants raising the stylus from the tablet on multiple occasions (therefore limiting the accuracy of the kinematic data obtained).

Data were reviewed on a task by task basis, and thus sample sizes varied for Tracking, Aiming, and Steering. For example, if issues arose for the Tracking task but complete data were provided for the Aiming and Steering tasks, only data for the Tracking task would be omitted rather than the entire case to limit data loss.

Appendix B

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Slow + With Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.41***	.03	-0.50	-0.33
	6	-1.21***	.05	-1.35	-1.07
	7	-1.19***	.02	-1.26	-1.13
	8	-1.24***	.02	-1.31	-1.18
	9	-1.35***	.02	-1.41	-1.28
	10	-1.43***	.04	-1.54	-1.33
	11	-1.52***	.09	-1.78	-1.27
5	6	-0.80***	.05	-0.94	-0.65
	7	-0.78***	.02	-0.84	-0.72
	8	-0.83***	.02	-0.89	-0.77
	9	-0.93***	.02	-1.00	-0.86
	10	-1.02***	.04	-1.12	-0.91
	11	-1.11***	.09	-1.36	-0.86

[continued]

Appendix B [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Slow + With Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.02	.05	-0.12	0.15
	8	-0.03	.05	-0.16	0.10
	9	-0.13*	.05	-0.27	0.00
	10	-0.22***	.05	-0.38	-0.07
	11	-0.31*	.10	-0.59	-0.03
7	8	-0.05**	.01	-0.09	-0.01
	9	-0.15***	.02	-0.20	-0.11
	10	-0.24***	.03	-0.33	-0.15
	11	-0.33**	.09	-0.58	-0.08
8	9	-0.10***	.01	-0.15	-0.06
	10	-0.19***	.03	-0.28	-0.10
	11	-0.18**	.09	-0.53	-0.03
9	10	-0.09	.03	-0.18	0.01
	11	-0.18	.09	-0.43	0.07
10	11	-0.09	.09	-0.36	0.17

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix C

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Slow + No Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.37***	.03	-0.46	-0.28
	6	-0.94***	.05	-1.10	-0.78
	7	-0.97***	.03	-1.04	-0.89
	8	-1.02***	.02	-1.10	-0.95
	9	-1.11***	.03	-1.19	-1.03
	10	-1.13***	.04	-1.25	-1.02
	11	-1.21***	.10	-1.50	-0.93
5	6	-0.57***	.05	-0.72	-0.41
	7	-0.59***	.02	-0.66	-0.53
	8	-0.65***	.02	-0.72	-0.58
	9	-0.74***	.02	-0.81	-0.67
	10	-0.76***	.04	-0.88	-0.65
	11	-0.84***	.10	-1.12	-0.56

[continued]

Appendix C [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Slow + No Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.03	.05	-0.18	0.12
	8	-0.08	.05	-0.23	0.06
	9	-0.17**	.05	-0.32	-0.02
	10	-0.19*	.06	-0.37	-0.02
	11	-0.27	.11	-0.58	0.04
7	8	-0.06**	.01	-0.10	-0.02
	9	-0.14***	.02	-0.19	-0.10
	10	-0.17***	.03	-0.27	-0.06
	11	-0.25	.09	-0.52	0.03
8	9	-0.09***	.02	-0.14	-0.04
	10	-0.11*	.03	-0.21	-0.01
	11	-0.19	.09	-0.47	0.09
9	10	-0.02	.04	-0.13	0.08
	11	-0.10	.09	-0.38	0.18
10	11	-0.08	.10	-0.37	0.21

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix D

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Medium + No Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.44***	.03	-0.53	-0.35
	6	-0.96***	.05	-1.12	-0.80
	7	-1.08***	.03	-1.15	-1.00
	8	-1.16***	.02	-1.23	-1.09
	9	-1.29***	.03	-1.36	-1.21
	10	-1.36***	.04	-1.48	-1.25
	11	-1.36***	.10	-1.65	-1.08
5	6	-0.53***	.05	-0.68	-0.37
	7	-0.64***	.02	-0.71	-0.57
	8	-0.72***	.02	-0.79	-0.66
	9	-0.85***	.02	-0.92	-0.78
	10	-0.93***	.04	-1.04	-0.81
	11	-0.93***	.10	-1.21	-0.64

[continued]

Appendix D [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Medium + No Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.11	.05	-0.26	0.03
	8	-0.20**	.05	-0.35	-0.05
	9	-0.32***	.05	-0.47	-0.17
	10	-0.40***	.06	-0.58	-0.23
	11	-0.40**	.11	-0.72	-0.09
7	8	-0.08***	.01	-0.12	-0.04
	9	-0.21***	.02	-0.26	-0.16
	10	-0.29***	.04	-0.39	-0.18
	11	-0.29*	.10	-0.57	-0.01
8	9	-0.13***	.02	-0.17	-0.08
	10	-0.21***	.03	-0.31	-0.10
	11	-0.21	.10	-0.48	0.07
9	10	-0.08	.04	-0.18	0.03
	11	-0.08	.10	-0.36	0.20
10	11	0.00	.10	-0.29	0.30

* *p*≤.05; ** *p*≤.01; *** *p*≤.001

Appendix E

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Medium + With Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.41***	.03	-0.51	-0.35
	6	-1.26***	.05	-1.41	-1.12
	7	-1.24***	.02	-1.31	-1.17
	8	-1.32***	.02	-1.38	-1.25
	9	-1.43***	.02	-1.50	-1.36
	10	-1.54***	.04	-1.65	-1.43
	11	-1.63***	.09	-1.89	-1.37
5	6	-0.83***	.05	-0.97	-0.69
	7	-0.81***	.02	-0.87	-0.75
	8	-0.89***	.02	-0.95	-0.83
	9	-1.00***	.02	-1.07	-0.94
	10	-1.11***	.04	-1.21	-1.00
	11	-1.20***	.09	-1.46	-0.94

[continued]

Appendix E [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Medium + With Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.02	.05	-0.11	0.16
	8	-0.06	.05	-0.19	0.08
	9	-0.17***	.05	-0.31	-0.04
	10	-0.27***	.05	-0.43	-0.12
	11	-0.37**	.10	-0.65	-0.08
7	8	-0.08***	.01	-0.11	-0.04
	9	-0.19***	.02	-0.24	-0.15
	10	-0.30***	.03	-0.39	-0.20
	11	-0.39***	.09	-0.64	-0.14
8	9	-0.12***	.01	-0.16	-0.07
	10	-0.22***	.03	-0.31	-0.13
	11	-0.31**	.09	-0.56	-0.06
9	10	-0.10*	.03	-0.20	-0.01
	11	-0.20	.09	-0.45	0.06
10	11	-0.09	.09	-0.36	0.17

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix F

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Fast + With Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.36***	.03	-0.45	-0.27
	6	-1.03***	.05	-1.18	-0.87
	7	-1.20***	.03	-1.27	-1.13
	8	-1.32***	.02	-1.39	-1.25
	9	-1.46***	.03	-1.54	-1.39
	10	-1.61***	.04	-1.73	-1.49
	11	-1.68***	.10	-1.96	-1.39
5	6	-0.67***	.05	-0.82	-0.51
	7	-0.84***	.02	-0.96	-0.77
	8	-0.96***	.02	-1.03	-0.89
	9	-1.10***	.02	-1.18	-1.03
	10	-1.25***	.04	-1.37	-1.14
	11	-1.32***	.10	-1.60	-1.03

[continued]

Appendix F [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Fast + With Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.17**	.05	-0.32	-0.03
	8	-0.29***	.05	-0.44	-0.15
	9	-0.44***	.05	-0.59	-0.29
	10	-0.59***	.06	-0.76	-0.41
	11	-0.65***	.11	-0.96	-0.34
7	8	-0.12***	.01	-0.16	-0.08
	9	-0.26***	.02	-0.31	-0.21
	10	-0.47***	.03	-0.51	-0.31
	11	-0.48***	.09	-0.75	-0.20
8	9	-0.14***	.02	-0.19	-0.10
	10	-0.29***	.03	-0.39	-0.19
	11	-0.36**	.09	-0.63	-0.08
9	10	-0.15***	.04	-0.25	-0.04
	11	-0.21	.09	-0.49	0.06
10	11	-0.06	.10	-0.36	0.23

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix G

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Fast + No Guide) [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.44***	.03	-0.54	-0.35
	6	-0.93***	.06	-1.10	-0.77
	7	-1.13***	.03	-1.21	-1.06
	8	-1.22***	.03	-1.30	-1.15
	9	-1.36***	.03	-1.44	-1.28
	10	-1.45***	.10	-1.57	-1.33
	11	-1.45***	.04	-1.75	-1.16
5	6	-0.49***	.06	-0.66	-0.33
	7	-0.69***	.02	-0.76	-0.62
	8	-0.78***	.02	-0.85	-0.71
	9	-0.91***	.03	-0.99	-0.84
	10	-1.01***	.04	-1.13	-0.89
	11	-1.01***	.10	-1.30	-0.72

[continued]

Appendix G [continued]

Table of multiple comparisons for age-related differences within Tracking: Dynamic Accuracy (Fast + No Guide)

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.20**	.05	-0.35	-0.05
	8	-0.29***	.05	-0.44	-0.14
	9	-0.42***	.05	-0.58	-0.27
	10	-0.52***	.06	-0.70	-0.34
	11	-0.52***	.11	-0.84	-0.20
7	8	-0.09***	.01	-0.13	-0.05
	9	-0.22***	.02	-0.27	-0.17
	10	-0.32***	.10	-0.42	-0.21
	11	-0.32*	.10	-0.61	-0.03
8	9	-0.13***	.02	-0.18	-0.08
	10	-0.23***	.04	-0.33	-0.12
	11	-0.23	.10	-0.52	0.06
9	10	-0.10	.04	-0.20	0.01
	11	-0.10	.10	-0.39	0.19
10	11	-0.00	.10	-0.31	0.30

* $p \le .05$; ** $p \le .01$; *** $p \le .001$

Appendix H

Table of multiple comparisons for age-related differences within Tracking: Normalised Jerk [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.21***	.03	-0.31	-0.11
	6	-0.59***	.06	-0.76	-0.42
	7	-0.42***	.03	-0.50	-0.35
	8	-0.48***	.03	-0.55	-0.40
	9	-0.64***	.04	-0.73	-0.56
	10	-0.62***	.04	-0.75	-0.50
	11	-0.80***	.10	-1.10	-0.50
5	6	-0.38***	.06	-0.55	-0.21
	7	-0.21***	.02	-0.29	-0.14
	8	-0.27***	.02	-0.34	-0.19
	9	-0.43***	.03	-0.51	-0.35
	10	-0.41***	.04	-0.54	-0.29
	11	-0.59***	.10	-0.89	-0.29

[continued]

Appendix H [continued]

Table of multiple comparisons for age-related differences within Tracking: Normalised Jerk

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.17*	.05	0.01	0.32
	8	0.11	.05	-0.04	0.27
	9	-0.05	.05	-0.21	0.11
	10	-0.03	.06	-0.22	0.15
	11	-0.21	.11	-0.54	0.12
7	8	-0.05**	.01	-0.10	-0.01
	9	-0.22***	.02	-0.27	-0.17
	10	-0.20***	.04	-0.31	-0.09
	11	-0.37**	.10	-0.67	-0.08
8	9	-0.17***	.02	-0.22	-0.12
	10	-0.15**	.04	-0.26	-0.04
	11	-0.32*	.10	-0.62	-0.02
9	10	0.02	.04	-0.09	0.13
	11	-0.16	.10	-0.45	0.14
10	11	-0.17	.11	-0.49	0.14

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix I

Table of multiple comparisons for age-related differences within Tracking: Path Length [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.25***	.03	-0.32	-0.17
	6	-0.70***	.05	-0.84	-0.56
	7	-0.73***	.02	-0.79	-0.67
	8	-0.84***	.02	-0.90	-0.78
	9	-0.99***	.02	-1.06	-0.93
	10	-1.02***	.03	-1.12	-0.92
	11	-1.13***	.08	-1.37	-0.89
5	6	-0.45***	.05	-0.59	-0.32
	7	-0.48***	.02	-0.54	-0.42
	8	-0.59***	.02	-0.65	-0.54
	9	-0.75***	.02	-0.81	-0.68
	10	-0.78***	.03	-0.87	-0.68
	11	-0.88***	.08	-1.12	-0.64

[continued]

Appendix I [continues]

Table of multiple comparisons for age-related differences within Tracking: Path Length

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.03	.04	-0.16	0.10
	8	-0.14*	.04	-0.26	-0.01
	9	-0.29***	.04	-0.42	-0.17
	10	-0.32***	.05	-0.47	-0.18
	11	-0.43***	.09	-0.69	-0.16
7	8	-0.11***	.01	-0.14	-0.08
	9	-0.26***	.01	-0.31	-0.22
	10	-0.29***	.03	-0.38	-0.21
	11	-0.40***	.08	-0.63	-0.16
8	9	-0.15***	.01	-0.19	-0.11
	10	-0.18***	.03	-0.27	-0.10
	11	-0.29**	.08	-0.52	-0.05
9	10	-0.03	.03	-0.12	0.06
	11	-0.14	.08	-0.37	0.10
10	11	-0.11	.08	-0.35	0.14

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix J

Table of multiple comparisons for age-related differences within Aiming: General Speed [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.51***	.03	-0.59	-0.43
	6	-1.16***	.05	-1.29	-1.02
	7	-1.69***	.02	-1.75	-1.63
	8	-1.87***	.02	-1.93	-1.81
	9	-2.03***	.02	-2.09	-1.97
	10	-2.07***	.03	-2.17	-1.97
	11	-1.99***	.08	-2.23	-1.75
5	6	-0.64***	.05	-0.78	-0.51
	7	-1.18***	.02	-1.23	-1.12
	8	-1.36***	.02	-1.42	-1.30
	9	-1.52***	.02	-1.58	-1.54
	10	-1.56***	.03	-1.66	-1.46
	11	-1.48***	.08	-1.72	-1.24

[continued]

Appendix J [continued]

Table of multiple comparisons for age-related differences within Aiming: General Speed [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.53***	.04	-0.66	-0.41
	8	-0.72***	.04	-0.84	-0.59
	9	-0.87***	.04	-1.00	-0.75
	10	-0.91***	.05	-1.06	-0.77
	11	-0.83***	.09	-1.10	-0.57
7	8	-0.18***	.01	-0.22	-0.15
	9	-0.34***	.01	-0.38	-0.30
	10	-0.38***	.03	-0.47	-0.29
	11	-0.30**	.08	-0.54	-0.07
8	9	-0.16***	.01	-0.20	-0.12
	10	-0.20***	.03	-0.28	-0.11
	11	-0.12	.08	-0.35	0.11
9	10	-0.04	.03	-0.13	0.05
	11	0.04	.08	-0.20	0.27
10	11	.08	.08	-0.17	0.33

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix K

Table of multiple comparisons for age-related differences within Aiming: Peak Speed [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.02	.03	-0.12	0.07
	6	-0.03	.06	-0.20	0.14
	7	0.38***	.03	0.31	0.46
	8	0.46***	.03	0.39	0.54
	9	0.49***	.03	0.41	0.58
	10	0.44***	.04	0.31	0.57
	11	0.18	.10	-0.13	0.48
5	6	-0.01	.06	-0.17	0.16
	7	0.41***	.02	0.33	0.48
	8	0.49***	.02	0.42	0.56
	9	0.52***	.03	0.44	0.59
	10	0.46***	.04	0.34	0.59
	11	0.20	.10	-0.10	0.50

[continued]

Appendix K [continued]

Table of multiple comparisons for age-related differences within Aiming: Peak Speed

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.41***	.05	0.26	0.57
	8	0.49***	.05	0.34	0.65
	9	0.52***	.05	0.36	0.68
	10	0.47***	.06	0.29	0.66
	11	0.21	.11	-0.12	0.54
7	8	0.08***	.01	0.04	0.12
	9	0.11***	.02	0.06	0.16
	10	0.06	.04	-0.05	0.17
	11	-0.21	.10	-0.50	0.09
8	9	0.03	.02	-0.02	0.08
	10	-0.02	.04	-0.13	0.09
	11	-0.29	.10	-0.58	0.01
9	10	-0.05	.04	-0.16	0.06
	11	-0.32*	.10	-0.61	-0.02
10	11	-0.26	.11	-0.58	0.05

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix L

Table of multiple comparisons for age-related differences within Aiming: Path Length [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.55***	.03	-0.63	-0.46
	6	-1.14***	.05	-1.29	-0.99
	7	-1.32***	.02	-1.39	-1.25
	8	-1.44***	.02	-1.51	-1.37
	9	-1.57***	.02	-1.64	-1.49
	10	-1.61***	.04	-1.72	-1.50
	11	-1.76***	.09		
5	6	-0.59***	.05	-0.74	-0.45
	7	-0.77***	.02	-0.83	-0.71
	8	-0.89***	.02	-0.95	-0.83
	9	-1.02***	.02	-1.08	-0.95
	10	-1.06***	.04	-1.17	-0.95
	11	-1.21***	.09	-1.47	-0.94

[continued]

Appendix L [continued]

Table of multiple comparisons for age-related differences within Aiming: Path Length

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	-0.18**	.05	-0.32	-0.04
	8	-0.30***	.05	-0.43	-0.16
	9	-0.42***	.05	-0.56	-0.28
	10	-0.47***	.06	-0.63	-0.31
	11	-0.61***	.10	-0.91	-0.32
7	8	-0.12***	.01	-0.16	-0.08
	9	-0.25***	.02	-0.29	-0.20
	10	-0.29***	.03	-0.39	-0.20
	11	-0.44***	.09	-0.70	-0.18
8	9	-0.13***	.02	-0.17	-0.08
	10	-0.32***	.09	-0.27	-0.08
	11	-0.32**	.09	-0.58	-0.06
9	10	-0.05	.03	-0.15	0.05
	11	-0.19	.09	-0.45	0.07
10	11	-0.14	.09	-0.42	0.13

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix M

Table of multiple comparisons for age-related differences within Steering: Movement Efficiency B [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	0.12**	.03	0.03	0.21
	6	-0.02	.05	-0.17	0.14
	7	0.01	.02	-0.06	0.08
	8	-0.01	.02	-0.08	0.06
	9	-0.05	.03	-0.13	0.03
	10	-0.02	.04	-0.13	0.10
	11	-0.10	.10	-0.38	0.18
5	6	-0.14	.05	-0.30	0.02
	7	-0.12***	.02	-0.18	-0.05
	8	-0.14***	.02	-0.20	-0.07
	9	-0.17***	.02	-0.25	-0.10
	10	-0.14**	.04	-0.26	-0.03
	11	-0.23	.10	-0.51	0.05

[continued]

Appendix M [continued]

Table of multiple comparisons for age-related differences within Steering: Movement Efficiency B

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.02	.05	-0.12	0.17
	8	0.00	.05	-0.14	0.15
	9	-0.03	.05	-0.18	0.11
	10	-0.00	.06	-0.17	0.17
	11	-0.09	.11	-0.40	0.22
7	8	-0.02	.01	-0.06	0.02
	9	-0.06*	.02	-0.11	-0.01
	10	-0.02	.03	-0.13	0.08
	11	-0.11	.09	-0.39	0.17
8	9	-0.04	.02	-0.08	0.01
	10	-0.00	.03	-0.11	0.10
	11	-0.09	.09	-0.37	0.19
9	10	0.03	.04	-0.07	0.14
	11	-0.05	.09	-0.33	0.22
10	11	-0.09	.10	-0.38	0.20

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix N

Table of multiple comparisons for age-related differences within Steering: Movement Efficiency A [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	0.10*	.03	0.01	0.18
	6	-0.08	.05	-0.23	0.07
	7	-0.07*	.02	-0.14	0.00
	8	-0.09	.02	-0.16	-0.03
	9	-0.14***	.02	-0.21	-0.07
	10	-0.13*	.04	-0.24	-0.02
	11	-0.20	.09	-0.46	0.07
5	6	-0.18***	.05	-0.32	-0.03
	7	-0.17***	.02	-0.23	-0.10
	8	-0.19***	.02	-0.25	-0.13
	9	-0.24***	.02	-0.31	-0.17
	10	-0.23***	.04	-0.33	-0.12
	11	-0.29*	.09	-0.56	-0.03

[continued]

Appendix N [continued]

Table of multiple comparisons for age-related differences within Steering: Movement Efficiency A [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.01	.05	-0.13	0.15
	8	-0.01	.05	-0.15	0.13
	9	-0.06	.05	-0.20	0.08
	10	-0.05	.06	-0.21	0.12
	11	-0.12	.10	-0.41	0.18
7	8	-0.02	.01	-0.06	0.01
	9	-0.07***	.02	-0.12	-0.03
	10	-0.06	.03	-0.16	0.04
	11	-0.13	.09	-0.39	0.13
8	9	-0.05*	.02	-0.09	-0.00
	10	-0.04	.03	-0.13	0.06
	11	-0.10	.03	-0.36	0.16
9	10	0.01	.03	-0.09	0.11
	11	-0.05	.09	-0.32	0.21
10	11	-0.07	.09	-0.34	0.21

* $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Appendix O

Table of multiple comparisons for age-related differences within Steering: Path Accuracy [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
4	5	-0.37***	.04	-0.50	-0.24
	6	-0.84***	.08	-1.07	-0.61
	7	-0.83***	.04	-0.94	-0.72
	8	-0.86***	.04	-0.96	-0.75
	9	-0.94***	.04	-1.05	-0.83
	10	-1.10***	.06	-1.27	-0.93
	11	-1.15***	.14	-1.56	-0.74
5	6	-0.47***	.08	-0.69	-0.24
	7	-0.46***	.03	-0.56	-0.36
	8	-0.49***	.03	-0.58	-0.39
	9	-0.57***	.04	-0.67	-0.46
	10	-0.73***	.06	-0.90	-0.56
	11	-0.77***	.14	-1.18	-0.37

[continued]

Appendix O [continued]

Table of multiple comparisons for age-related differences within Steering: Path Accuracy [continues on next page]

Age Group (I)	Age Group (J)	Mean Difference (J – I)	Std. Error	Lower Bound	Upper Bound
6	7	0.01	.08	-0.21	0.22
	8	-0.02	.07	-0.23	0.19
	9	-0.10	.07	-0.32	0.11
	10	-0.26*	.09	-0.52	-0.01
	11	-0.31	.15	-0.76	0.14
7	8	-0.03	.02	-0.09	0.03
	9	-0.11***	.02	-0.18	-0.04
	10	-0.27***	.05	-0.42	-0.12
	11	-0.32	.14	-0.72	0.09
8	9	-0.08	.02	-0.15	-0.02
	10	-0.25***	.05	-0.39	-0.10
	11	-0.28	.14	-0.69	0.11
9	10	-0.16*	.05	-0.31	-0.01
	11	-0.20	.14	-0.61	0.20
10	11	-0.04	.14	-0.47	0.38

* $p\leq.05$; ** $p\leq.01$; *** $p\leq.001$