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METHOD ARTICLE

Key kinematic measures of sensorimotor control identified via data reduction techniques in a population study (Born in Bradford)

[version 1; peer review: 2 approved with reservations]

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Abstract

Background

Sensorimotor processes underpin skilled human behaviour and can thus act as an important marker of neurological status. Kinematic assessments offer objective measures of sensorimotor control but can generate countless output variables. This study sought to guide future analyses of such data by determining the key variables that capture children's sensorimotor control on a standardised assessment battery deployed in cohort studies.

Methods

The Born in Bradford (BiB) longitudinal cohort study has collected sensorimotor data from 22,266 children aged 4–11 years via a computerised kinematic assessment battery ("CKAT"). CKAT measures three sensorimotor processing tasks (Tracking, Aiming, Steering). The BiB CKAT data were analysed using a "train then test" approach with two independent samples. Independent models were constructed for Tracking, Aiming, and Steering. The data were analysed using Principal Components Analysis followed by Confirmatory Factor Analysis.

Results

The kinematic data could be reduced to 4-7 principal components per

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task (decreased from >600 individual data points). These components reflect a wide range of core sensorimotor competencies including measures of both spatial and temporal accuracy. Further analyses using the derived variables showed these components capture the age-related differences reported in the literature (via a range of measures selected previously in a necessarily arbitrary way by study authors).

Conclusions

We identified the key variables of interest within the rich kinematic measures generated by a standardised tool for assessing sensorimotor control processes (CKAT). This work can guide future use of such data by providing a principled framework for the selection of the appropriate variables for analysis (where otherwise high levels of redundancy cause researchers to make arbitrary decisions). These methods could and should be applied in any form of kinematic assessment.

Plain Language Summary

Human movement guided by sensory input (e.g., vision) plays a key role in physical, mental, and educational development. These movements can be measured to see how body position changes over time (an approach known as “kinematic analysis”). Kinematic analysis can be used to assess a child’s movement skills and provides a “gold standard” measurement approach. These assessments provide a lot of information but the researcher then needs to decide which measures to analyse (decisions often made on intuition). We addressed this issue by analysing the “Clinical-Kinematic Assessment Tool” (CKAT) used in the Born in Bradford (BiB) study involving 22,266 children aged 4–11 years. We used powerful statistical techniques to determine which measures should be selected from the greater than 600 measures available per child. We showed there are between four and seven measures for each CKAT task that researchers need to analyse when studying the development of a child’s movement skills. These measures provide a complete description of the child’s movement without requiring additional and uninformative analyses. We show that our measures describe the improved skill levels shown by children as they grow up. This work will help researchers be efficient and make effective use of valuable information that can help us understand child development. Our work focussed on CKAT measures within BiB but we argue that this approach should be used with all assessments of human movement.

Keywords

sensorimotor, longitudinal cohort, kinematics, data reduction, principal components analysis, confirmatory factor analysis

This article is included in the Born in Bradford gateway.

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Introduction

Sensorimotor control enables voluntary, goal-directed movements in response to sensory information (Ingram & Wolpert, 2011; Tresilian, 2012; Wolpert *et al.*, 1998). The measurement of sensorimotor control development is important because poor-for-age skills have far-reaching implications, including difficulties relating to: socio-emotional wellbeing (Hill *et al.*, 2016); cognitive functioning (Klupp *et al.*, 2021); and academic achievement (Cameron *et al.*, 2016; Giles *et al.*, 2018; Grissmer *et al.*, 2010; Harrowell *et al.*, 2017).

Unfortunately, good quality, valid, reliable, and objective measures of children's sensorimotor status are relatively rare in large longitudinal birth cohort studies. Most large birth cohorts only collect parental reports comprising: (i) judgements of whether their child can perform certain motor skills by a specific age (i.e., "motor milestones"); (ii) estimated ages at which they recall their child achieving such milestones. Examples of this approach include the UK's Millennium Cohort Study (Johnson *et al.*, 2015); the Danish National Birth Cohort (Hestbæk *et al.*, 2023); the Norwegian Mother, Father and Child Cohort (Øksendal *et al.*, 2022); the Copenhagen Perinatal Cohort (Flensborg-Madsen *et al.*, 2019).

Some cohort studies (e.g., the Avon Longitudinal Study of Parents and Children (Lingam *et al.*, 2009); the Early Childhood Longitudinal Study-Birth cohort (Lee *et al.*, 2017)), have introduced more rigor by designing their own in-person, observational assessment methods. These tools are typically "short form" versions of more comprehensive one-to-one clinical assessments used in the diagnosis of movement disorders (Blank *et al.*, 2019). For example, the ALSPAC Coordination Test (Taylor *et al.*, 2018) is a truncated version of the Movement Assessment Battery for Children 2 (Henderson *et al.*, 2007). However, the time- and resource-intensive nature of such methods often means they are only practical to deliver at one timepoint (e.g., in ALSPAC approximately 7,000 participants were assessed once, at seven years of age, as part of a voluntary visit to a larger assessment clinic). Furthermore, this method of assessment relies heavily on the competence of the assessors, who require extensive training but remain susceptible to making inaccurate or biased interpretations (Hróbjartsson *et al.*, 2013; Smits-Engelsman *et al.*, 2008).

In light of these challenges, the BiB longitudinal birth cohort study (Wright *et al.*, 2013) selected a portable computerised assessment method to measure sensorimotor control. CKAT (Culmer *et al.*, 2009; Flatters *et al.*, 2014a; Mon-Williams *et al.*, 2007) assesses performance on sensorimotor tasks that capture three different categories of visuomotor transformation. The three tasks require participants to use a handheld stylus to interact with visual stimuli presented on a touchscreen tablet computer. The assessment was conducted with circa 3,000 participants between the ages of 4– 5 years (Shire *et al.*, 2020) and a further 9,500 were tested between 7–10 years of age (Hill *et al.*, 2022), many for a second time. In 2024, a third round of data collection started to capture performance through adolescence.

CKAT produces high-fidelity, end-point kinematic data for each participant on each task. These data describe the properties of movement in terms of the endpoint spatiotemporal characteristics - including velocity and acceleration (Cunningham *et al.*, 2019; Hall, 2018; Mon-Williams *et al.*, 2007; Singer *et al.*, 2016). In other words, kinematic recordings measure *how* a movement is performed (Eddy *et al.*, 2020; Logan *et al.*, 2018; True *et al.*, 2017). Consequently, kinematic measures can reveal subtle differences in aspects of children's sensorimotor control that are important in explaining population variation. For example, kinematic analyses can be used to identify specific impairments in the sensorimotor functioning of children with various neurodevelopmental disorders, including: DCD (Hyde & Wilson, 2011; Miller *et al.*, 2019); 22q11.2 deletion syndrome (Cunningham *et al.*, 2019); ADHD (Laniel *et al.*, 2020), and autism (Miller *et al.*, 2019). Such differences are much less likely to be detected using more traditional, observational methodologies (Hulteen *et al.*, 2020; Ramos *et al.*, 1997).

Unfortunately, the complexity of the data output from kinematic assessments (e.g., CKAT) means that decisions need to be made about which variables should be used in analyses given that analysis of an output containing hundreds of individual data points per participant is not always feasible (Wood *et al.*, 2018). Principal Components Analysis (PCA) is a data reduction technique that can be used to determine which metrics explain the largest amount of variance of an attribute or variable within a large dataset (Jolliffe, 2002; Ringnér, 2008). A relevant example of its successful application comes from research that has used this technique to reduce the complexity of the data collected by a kinematic assessment tool used to measure upper-limb functioning in stroke survivors (Wood *et al.*, 2018). Wood and colleagues (2018) found that up to 20 kinematic variables could be reduced to just three to five independent components.

PCA identifies the most parsimonious model for summarising a dataset. However, subsequent Confirmatory Factor Analysis (CFA) is recommended to maximise confidence in the wider application of PCA informed statistical models. CFA is a hypothesis-driven approach that can be used to assess model fit following PCA (Brown, 2015; Jackson *et al.*, 2009; Matsunaga, 2010). CFA can drive model re-specification (such as the omission of "poorly behaved indicators" (Brown, 2006, p. 106)) and identify the most appropriate model from potential options. Thus, the most mathematically *and* theoretically plausible solution is retained through verifying replicable patterns across more than one sample (Bandalos, 1996; Maccallum *et al.*, 1999).

The aim of the present study was to use exploratory data reduction and confirmatory techniques to identify a stable set of kinematic components that are valid descriptors of children's sensorimotor control as measured using the CKAT battery within the BiB cohort. We further aimed to check that the derived kinematic components showed the well documented changes in sensorimotor control with age (Flatters *et al.*, 2014a).

Methods

Ethical approval

Ethical approval for the re-analysis of these data was granted by University of Leeds ethics committee (reference: PSC-826). Ethical approvals for the Starting School data collection were obtained from ethics committees at the University of Leeds (reference: 13-0220) and the University of York (reference:12/26). Ethical approval for data linkage within the BiB cohort was obtained from the Bradford Leeds Research Ethics Committee (reference: 07/H1302/112). Ethical approval for the data collection for the Primary School Years sweep was obtained from the NHS Health Research Authority's Yorkshire and the Humber - Bradford Leeds Research Ethics Committee (reference: 16/YH/0062) on the 24th March 2016. All data were obtained via data requests from BiB's Executive Committee.

Design

A "train then test" approach was used to first derive and validate models that could then be used to obtain a novel set of kinematic metrics. This method required compiling two samples of CKAT data. The first of the two datasets was used as a "training" sample to develop the models, via PCA. The second dataset was then used to "validate" these models within a larger, novel sample of children participating in the BiB longitudinal birth cohort (Wright *et al.*, 2013), via CFA. Following this validation, it was possible to use these models to derive a reduced subset of kinematic variables for each BiB participant from their CKAT data. These variables were then analysed as outcomes in a series of between-subject analyses that explored the relationship between these novel measures of sensorimotor control and age at the time of assessment.

Participants

The Training dataset was collated from five previously published studies and PhD dissertations associated with BiB. All these projects involved the use of CKAT in school-based research conducted between 2012 and 2014 (Flatters *et al.*, 2014a; Hill *et al.*, 2016; Sheridan, 2015; Shire, 2016). It included 1740 participants from eight primary schools within West Yorkshire, UK, with an age range of 4-12 years (M = 7 years, 10 months, SD = 2 years, 0 months). Missing data were excluded on a task-by-task basis if more than one data point on any metric was missing. Thus, the sample size for each CKAT sub-task varied: Tracking (n = 1730), Aiming (n = 1323), and Steering (n = 1727).

The validation data were collated from two datasets within the BiB longitudinal birth cohort study (Wright *et al.*, 2013): Starting School (Shire *et al.*, 2020) and Primary School Years (Bird *et al.*, 2019; Hill *et al.*, 2022). Data collection for the Starting School sub-cohort was conducted over the course of two academic years (2012–2014) and included 3,444 children aged 4–5 years from 77 Bradford schools. The Primary School Years sweep consisted of 17,774 children aged 7–11 years old with data collection running between 2016 and 2019 across 86 Bradford schools. Participant data were again excluded on a task-by-task basis and thus the sample sizes for each CKAT sub-task varied: Tracking (n = 22,239); Aiming (n = 20,030); Steering (n = 22,266).

Although data in each of these datasets were independent and collected at different time-points, the demographics of each sample were similar (see Table 1)

Materials & procedure

Sensorimotor data were collected using CKAT. CKAT is a tablet-based kinematic device which measures sensorimotor behaviours via unimanual interactions with a hand-held manipulandum (Culmer *et al.*, 2009). It comprises three sub-tasks: Tracking; Aiming; and Steering, each containing several conditions (see Figure 1). A more in-depth explanation of the CKAT battery (including the software architecture)

Table 1. Demographic information for the Training and Validation samples.

	Training Sample	Validation Sample
n	1740	22406
Gender (%)		
Males	862 (49.5%)	9042 (40.3%)
Females	878 (50.5%)	9397 (41.9%)
Not Specified	0	3967 (17.7%)*
Mean Age [Range]	7 yrs, 10 m [4 yrs, 0 m-12 yrs, 2 m]	7 yrs, 10 m [4 yrs, 0 m-11yrs, 9m]
Handedness (%)		
Left	199 (11.4%)	2218 (9.9%)
Right	1535 (88.2%)	20143 (89.9%)
Not Specified	6 (0.3%)	45 (0.2%)

* Note: A large proportion of unspecified gender for this sample was due to these data being unavailable for children who were included within the Starting School data sweep but who were not part of the original BiB birth cohort

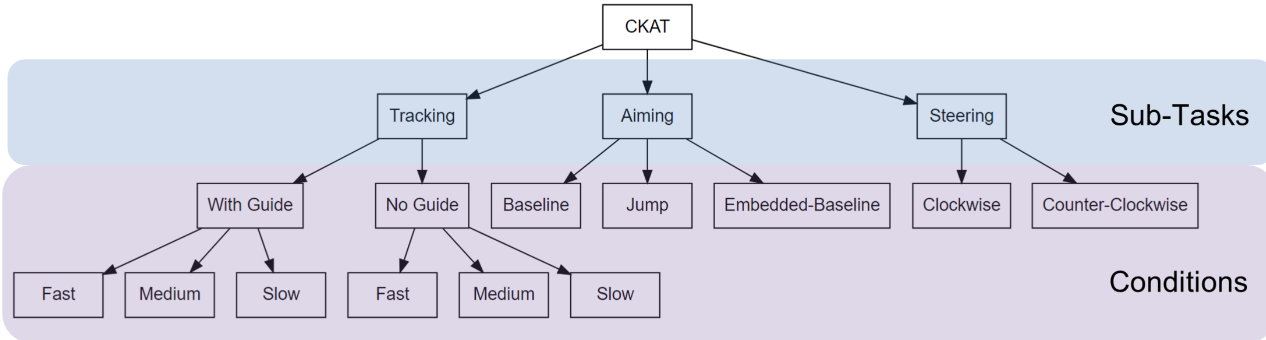

Figure 1. Flow diagram of the conditions included within each task of the CKAT battery.

is published elsewhere (Culmer *et al.*, 2009; Flatters *et al.*, 2014a), as are detailed descriptions of its deployment as part of data collection sweeps carried out in the BiB cohort when children were aged 4–5 years (Shire *et al.*, 2020) and 7–9 years (Hill *et al.*, 2022).

Tracking

The Tracking sub-task requires participants to use the stylus to track a moving target around the screen in a series of sinusoidal waves. It consists of two conditions related to the presence or absence of a visual guide that indicates the target trajectory (see Figure 2). The "No Guide" condition is completed first, with three revolutions completed at each of three variable speeds: slow, medium, and fast (nine trials in total). The same procedure is then repeated for the "With Guide" condition but this time with the assistance of a spatial guide.

For each of the six conditions, there are six sensorimotor metrics automatically produced as part of the output from the Tracking task (Path Length, X Gain, Y Gain, Mean Root Mean Squared Error, Standard Deviation of the Root Mean Squared Error, and Path Accuracy) which are described in Table 2. Prior use of CKAT in published peer-reviewed research has typically only used the mean Root Mean Squared Error (RMSE) to reflect performance on this task (Flatters *et al.*, 2014a; Flatters *et al.*, 2014b; Hill *et al.*, 2016; Raw *et al.*, 2012). Thus, it is evident a large amount of information is recorded but not currently used within analyses.

Aiming

Aiming requires participants to make a series of 75 aiming movements towards individually presented targets in a pseudo-randomised order as quickly and accurately as possible (see Figure 3). Upon arrival at each target, it disappears and is instantaneously presented in a new target location. The Aiming task comprises three target presentations which were included as independent conditions within the present analyses: Baseline, Jump, and Embedded-Baseline. The target locations are fixed during Baseline and Embedded-Baseline trials. During the Jump condition, however, the target location changes to the next in sequence as the participant reaches within 40mm of it. This measure of online corrective movement is commonly used throughout the literature and often referred to as the "step-perturbation paradigm" (Hyde & Wilson, 2011; Mackrous & Proteau, 2016; Plumb *et al.*, 2008). Table 2 displays shows the seven metrics (Path Length, Peak Speed, Time to Peak Speed, Deceleration Time, Reaction Time, Movement Time, and Path Length Time) that are automatically outputted for the Aiming task. Previously, performance has been gauged using only the Path Length Time (Flatters *et al.*, 2014a; Shire *et al.*, 2016).

Steering

The final task, Steering (previously referred to as "Tracing"; see (Flatters *et al.*, 2014a) requires participants to accurately trace an abstract path (5mm wide) from one side of the screen to the other (see Figure 4). During this task, participants are also required to keep within a box which moves along the path to constrain movement speed (total time: 35 seconds). There are two conditions: Left to Right (L-R) and Right to Left (R-L) which are identical in shape but are mirrored vertically (see Figure 4). One trial per condition was analysed.

Fewer metrics are recorded for the Steering task: three metrics (Path Length, Path Accuracy, and Path Length Time) across the two conditions (see Table 2). Historically, studies of CKAT have computed a spatiotemporal measure termed "Penalised Path Accuracy" using Path Length Time and Path Accuracy. However, there are still aspects of performance which are not captured and, historically, analyses have not previously accounted for potential differences between the two paths.

Analysis

Data analysis was conducted in a two-stage process for each CKAT task. Firstly, PCA was conducted on the Training data to construct independent models for each of the tasks to differentiate between the distinct components underpinning performance on each. Next, CFA was conducted on the

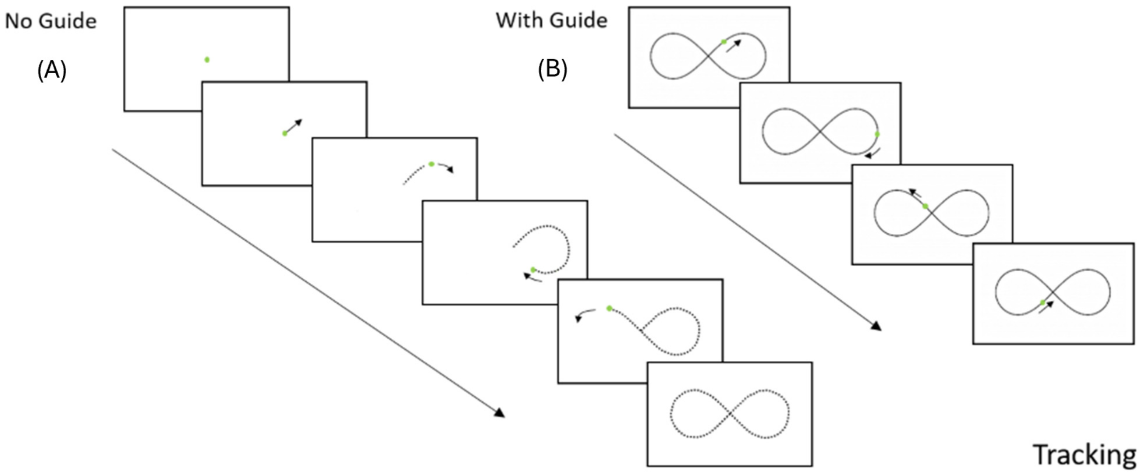

Figure 2. Schematic of Tracking Sub-task. A) No Guide condition **B**) With Guide condition.

Table 2. Description of each metric automatically calculated by the Clinical-Kinematic Assessment Tool.

	Metric	Unit of measurement	Description
All Sub-Tasks	Path Length	mm	Distance travelled from start to end of movement
Task-Specific			
Aiming Only	Peak Speed	mm/s	Fastest speed reached within the movement (mm/s)
	Time to Peak Speed	Seconds	Time taken to reach peak speed (secs)
	Deceleration Time	Seconds	Amount of time from peak speed to end of movement (secs)
	Reaction Time	Seconds	Time between presentation of the stimulus & reaching a threshold of specified speed*
	Movement Time	Seconds	Time taken between movement first exceeding the velocity threshold then falling back below*
Tracking Only	X Gain	*NA*	The degree to which the movement corresponds to the target sine wave on X axis by evaluating the normalised amplitude around the target frequency
	Y Gain	*NA*	The degree to which the movement corresponds to the target sine wave on Y axis by evaluating the normalised amplitude around the target frequency
	Mean RMSE	*NA*	The mean error related to both speed & spatial accuracy averaged across time points
	Standard Deviation of RMSE	*NA*	The SD of the RMSE measurements referred to in the previous row (i.e., amount of variability in tracking errors)
Tracking & Steering	Path Accuracy	*NA*	Measure of spatial errors against a reference trajectory
Aiming & Steering	Path Length Time	Seconds	Time taken to create path length

goodness-of-fit indices and corresponding thresholds: SRMR (<.08); RMSEA (<.08) and CFI (>.90). Hypothesis-driven amendments were made to increase the interpretability by making alterations which principally sought to reduce theoretical inconsistencies in the relationships between the observed variables and the latent variables (e.g., omitting items

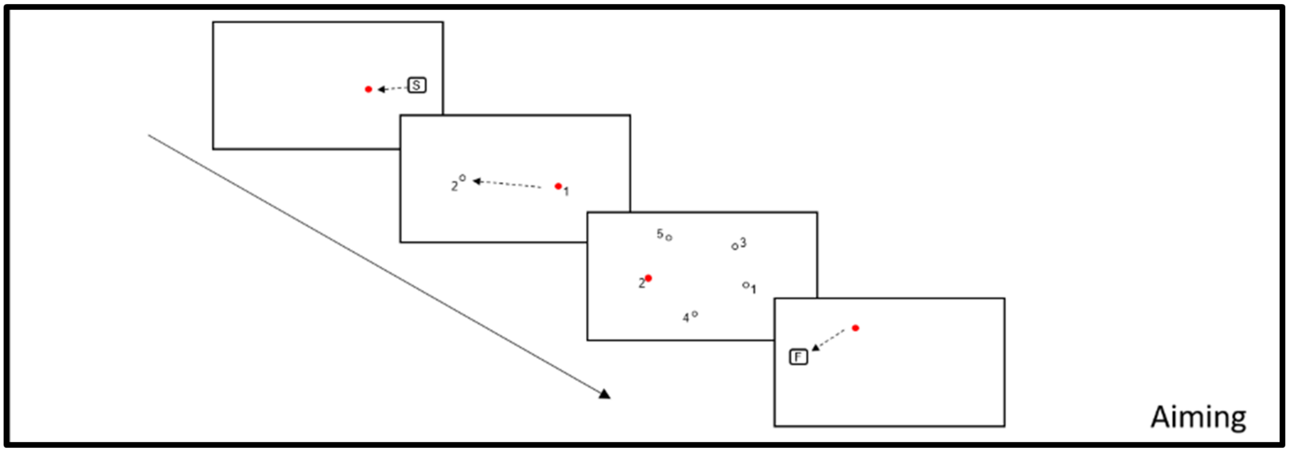

Figure 3. Schematic of Aiming Sub-task.

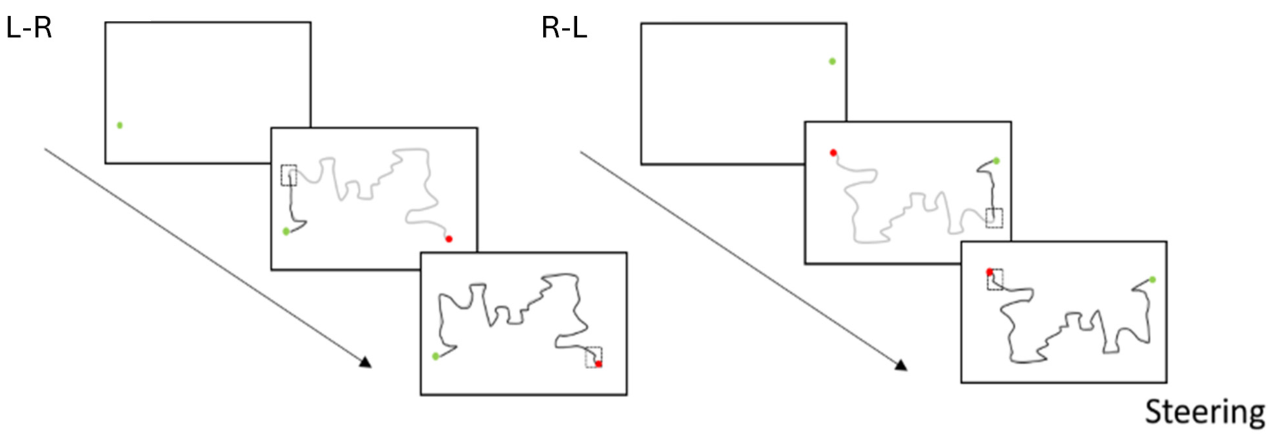

Figure 4. Schematic of Steering Sub-task.

Validation data to determine whether the models proposed by the PCA could be applied to a novel dataset. CFA also guided any necessary re-specification of the models. 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 selection of the most suitable model from several plausible options suggested by the PCA.

Principal Components Analysis (PCA)

Prior to analysis, a mean value for each metric within each task was calculated for each observation to minimise random trial-to-trial variability. Data were scaled and standardised. PCA was conducted in R (R Core Team, 2020) using the *psych* package (Revelle, 2019). When selecting the number of components to retain, Kaiser's criterion suggests eigenvalues >1 are acceptable (Kaiser, 1974). However, it is recommended that these values are not inspected in isolation to avoid misinterpretation of the structure of the data. We therefore also considered scree plots and cumulative variance (Cattell, 1966; Jolliffe, 2002; Zwick & Velicer, 1986). Multiple potential models were interpreted further where the most appropriate number of components to retain was not obvious. Rotations were used to improve interpretability by making loading patterns more distinct (Finch *et al.*, 2017; Kellow, 2006; Yaremko *et al.*, 1986). For models that were sufficiently correlated, oblique rotations (*Oblimin*) were applied (Tabachnick & Fidell, 2019). Items with component loadings ≥.50 were deemed to contribute a substantial amount of variance and were retained in interpretations (Comrey & Lee, 1992).

Confirmatory Factor Analysis (CFA)

Data preparation (averaging across trials, scaling, and standardising) was identical to the PCA to ensure uniformity. CFA was conducted using the *lavaan* package (Version 0.6.5; (Rosseel, 2012) for R (Version 4.0.0; R Core Team, 2020). Models were estimated using the Maximum Likelihood (ML) method and model fit was guided by the following which did not logically relate to other highly loaded items within that component). Lastly, Modification Indices (MI) were examined in parallel to Estimated Parameter Change (EPC) to identify metrics with high shared covariance (Brown, 2015; Jöreskog, 1993; Kaplan, 1990). Additional paths were included in models to correlate error terms with a high MI value if sound theoretical justification could be provided. BIC values were inspected to assess and compare models following re-specification.

Use case: Exploring age-related differences in sensorimotor control within the BiB cohort

Following the PCA and CFAs, additional analyses were conducted as a "use case" to sense-check the derived variables. Scores for BiB participants on validated dimensions were derived from their raw kinematic data via CKAT. Scores on each of these dimensions were then combined using weighted means within sub-tasks to increase interpretability. This produced three independent scores for Tracking, Aiming, and Steering which comprised appropriately weighted contributions of the most important dimensions of sensorimotor control. Higher scores indicated increased performance. These independent scores were then treated as outcome variables in a trio of between-subject ANOVA analyses that explored the effect of age in years (at time of CKAT testing) on each of these sub-task-specific measures of manual sensorimotor control. Where significant, subsequent post-hoc analyses were conducted using multiple comparisons with Tukey corrections.

Results

Tracking

PCA. The Kaiser-Meyer-Olkin (KMO) test verified the sampling adequacy (KMO = .93) and the correlation between items was found to be sufficient (χ^2 (630) = 72012.9, $p < .001$). Analyses indicated seven components were required to fit the data, explaining 79% of the total variance.

Six components were reflective of the six specific conditions within this task (Table 3), with the same four metrics loading consistently on each: X Gain, Y Gain, Mean RMSE and SD of RMSE (with the exception of the Medium + With Guide condition, where Mean RMSE was approaching the threshold at 0.49). The final component reflected performance on the Path Length metric specifically across five of the six conditions. The exception was path length for the Fast + With Guide condition which instead clustered with the other metrics in the Fast + With Guide condition (Mean RMSE, SD of RMSE, X Gain, Y Gain).

One metric, Path Accuracy, was inconsistent and only reached the threshold in the amount of variance explained in three of the six condition-specific components. This suggested that further exploration of Path Accuracy through CFA was needed to determine whether the metric systematically contributes to explaining unique variance or if it should be omitted.

CFA. An iterative process of re-specification indicated that several items should be omitted from the model when applied to the validation dataset. This included the omission of the Mean RMSE values, as it was redundant to include both the mean and SD of the RMSE value. In addition, the Mean RMSE did not consistently meet the threshold across all condition-specific components and fit statistics improved substantially when it was omitted from the model.

Fast + No Guide: Path Length was deemed anomalous by loading but inspection of the MI determined it was necessary to allow this cross-loading. It was also evident that the inclusion of the Path Length metric was also necessary in the fastest speed conditions. This could be due to increased task difficulty resulting in poorer performance and thus requiring more information. Following these modifications, goodness-of-fit indices demonstrated that this was the most appropriate latent model to describe performance on the Tracking task from a theoretical, mathematical, and practical perspective, χ^2(276, N = 22139) = 52498.84, p <.001, CFI = .89, SRMR = .08, RMSEA = .10, although the threshold for CFI was not quite reached. Thus, model was interpreted as comprising six condition-specific "Dynamic Accuracy" components, plus one component representing (see Figure 5).

Aiming

PCA. The sampling adequacy was met (KMO = .81). All KMO values for individual items were >.67, and items were significantly correlated (χ^2 (270) = 67578.46, $p < .001$). Analyses indicated a three-component solution was most appropriate (explaining 83% variance).

The three components were interpreted as representing General Speed; Movement Efficiency; and Peak Speed. For example, one component comprised metrics related to speed of response and the temporal aspects of movement; metrics primarily relating to Path Length and other aspects of spatial abilities loaded onto a second component. The final component almost exclusively contained metrics capturing Peak Speed (see Table 4).

CFA. The potential redundancy of some items was considered to make the model meaningful and interpretable. The Embedded-Baseline condition was omitted from the model as these trials were identical to the Baseline condition and simply used as a "filler" to insert between Jump trials; arguably explaining no additional systematic variation in sensorimotor control. In addition, Movement Time was also omitted as it was deemed redundant and did not load consistently on any of the PCA components.

Following inspection of the MI, the model was developed to allow correlated error terms between Baseline Reaction Time and Baseline Time to Peak Speed (MI = 26170.74, EPC = .44), plus Jump Path Length Time and Jump Time to Peak Speed (MI = 12167.06, EPC = .69). Thus, the final proposed CFA model approached good model fit and was intuitive with the same metrics generally clustering together (χ^2 (30, N = 20035) = 15673.54, $p < .001$, CFI = .91, SRMR = .05, RMSEA = .16). Unlike the Tracking task, the metrics clustered

Table 3. Component loadings on a seven-component model for the Tracking Sub-task following oblique rotation (N = 1730).

Item	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Slow + No Guide: Path Length	.09	.05	.04	**.61**	.00	.15	.18
Slow + No Guide: Path Accuracy	.15	-.03	**.55**	.12	.04	.25	.12
Slow + No Guide: X Gain	.03	-.03	**-.90**	.13	-.07	.10	.07
Slow + No Guide: Y Gain	-.09	.08	**-.90**	.08	.01	.00	.02
Slow + No Guide: RMSE	.08	.12	**.75**	-.03	.15	.05	.01
Slow + No Guide: SD	.03	.05	**.89**	.11	.01	-.02	-.01
Medium + No Guide: Path Length	.08	.11	-.02	**.74**	-.14	.20	-.06
Medium + No Guide: Path Accuracy	.09	.00	.13	.19	.34	.37	.15
Medium + No Guide: X Gain	.11	.00	-.10	.13	**-.83**	.09	-.13
Medium + No Guide: Y Gain	.02	.11	-.12	.03	**-.80**	-.08	-.05
Medium + No Guide: RMSE	.03	.19	.14	.04	**.63**	.13	.10
Medium + No Guide: SD	.01	.11	.07	.25	**.75**	.07	.04
Fast + No Guide: Path Length	.08	-.07	-.07	**.65**	.04	.02	**-.55**
Fast + No Guide: Path Accuracy	.07	.06	.09	.16	-.05	.40	.46
Fast + No Guide: X Gain	-.06	-.17	-.01	.22	-.14	-.01	**-.71**
Fast + No Guide: Y Gain	-.17	.02	.03	.02	-.15	-.01	**-.77**
Fast + No Guide: RMSE	.12	.27	.08	.01	.14	.10	**.53**
Fast + No Guide: SD	.13	.13	.02	.16	.12	-.05	**.67**
Slow + With Guide: Path Length	.47	.05	.01	**.54**	.00	-.05	.06
Slow + With Guide: Path Accuracy	.11	-.04	.19	.31	-.04	.50	.16
Slow + With Guide: X Gain	**-.85**	.01	-.09	-.02	.05	-.08	-.07
Slow + With Guide: Y Gain	**-.92**	.03	-.05	.03	.07	.00	-.05
Slow + With Guide: RMSE	**.85**	.06	.10	-.04	.02	.02	.05
Slow + With Guide: SD	**.88**	.04	.05	.11	.02	-.03	.02
Medium + With Guide: Path Length	.08	-.04	-.10	**.72**	.25	-.07	-.05
Medium + With Guide: Path Accuracy	-.01	-.03	.16	.27	.04	**.66**	.17
Medium + With Guide: X Gain	-.30	-.14	.00	.12	-.16	**-.62**	.04
Medium + With Guide: Y Gain	-.32	-.11	.02	.09	-.18	**-.59**	.06
Medium + With Guide: RMSE	.31	.27	-.07	-.26	.25	.49	-.07
Medium + With Guide: SD	.31	.19	-.09	-.12	.25	**.54**	-.08
Fast + With Guide: Path Length	.16	**-.78**	-.07	.35	.15	-.04	-.02
Fast + With Guide: Path Accuracy	-.13	.15	.20	.36	-.07	**.54**	.21
Fast + With Guide: X Gain	-.06	**-.81**	-.05	-.06	.03	-.10	-.08
Fast + With Guide: Y Gain	-.01	**-.75**	-.03	-.11	.00	-.14	-.07
Fast + With Guide: RMSE	.05	**.86**	.04	.01	.06	-.04	.05
Fast + With Guide: SD	.08	**.89**	.00	.14	.10	-.12	.00
Eigenvalues	5.02	4.63	4.24	3.27	3.61	4.06	3.44
% Total Variance	14%	13%	12%	9%	10%	11%	10%

Note: Component loadings over .50 appear in bold and red typeface. RMSE = Root Mean Squared Error; SD = Standard Deviation. PC = Principal Component.

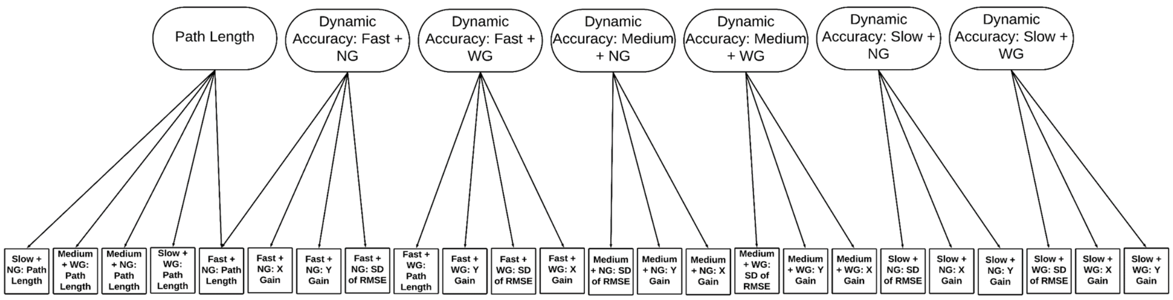

Figure 5. Path diagram of the final model for the Tracking Sub-task. *Note*: NG = No Guide; WG = With Guide; RMSE = Root Mean Squared Error; SD = Standard Deviation.

without distinction across the conditions. Figure 6 shows the path diagram of the Aiming task.

Steering

PCA. The KMO test was relatively low, KMO = .47. Correlations between items were deemed sufficient according to Bartlett's test of sphericity, χ^2 (15) = 2293.9, p < .001. It was evident that a three-component (Model A) or four-component (Model B) model were most appropriate, contributing 77% and 87% of the total variance, respectively. Once more, an oblique rotation was applied to improve interpretability. There was one instance of cross-loading (Path Length Time B) onto Components 1 and 3 (Table 5). It was hypothesised that this item might require omission when applying the model to the validation data. In contrast, the four-component model suggested no cross-loading items but did suggest some inconsistencies as to which metrics clustered together (see Table 5).

CFA. Some model re-specification was conducted to improve model fit and reduce inconsistencies across both potential models. The Path Length Time metric was omitted across both models as these metrics explained the smallest amount of unique variance and showed evidence of cross-loading (Model A) for both the Left-to-Right and Right-to-Left paths. This was supported by no component consisting solely of items related to Path Length Time. In addition, the Steering task was somewhat temporally constrained with the inclusion of the timed box (see Methods for further detail) and thus, it appeared that it might be less useful to include this temporal metric. The four-component model was most intuitive when this metric was omitted with each of the four remaining metrics loading onto independent components.

No further modifications were deemed necessary. The final model contained four components, interpreted as L-R Path Accuracy, R-L Path Accuracy, L-R Path Length, and R-L Path Length (Figure 7).

Use case

Analysis of age-related differences for each of the three sub-tasks was conducted using between-subject ANOVAs. It was evident that there were some outliers present in the data that should be omitted from further analysis following checking of the data distribution. This was done using the interquartile range (i.e., omitting values 1.5 times lower than the first quartile or 1.5 times above the third quartile). In doing so, 1448 cases (7.2%) were removed from the Tracking sample, 1182 for Aiming (6.8%), and 1371 for Steering (6.9%).

For Tracking (Figure 8), there was a significant effect of age on performance (F(7, 18575) = 849.1, p<.001, η^2 = 0.24). Post-hoc multiple comparisons found five year olds significantly outperformed four year olds (Mean Diff. [95% CI] = 0.16 [0.13, 0.20], p<.001), six year olds significantly outperformed five year olds (Mean Diff. [95% CI] = 0.39 [0.35, 0.44], p<.001), eight year olds significantly outperformed seven year olds (Mean Diff. [95% CI] =0.05, [0.04, 0.06]), nine year olds significantly outperformed eight year olds (Mean Diff. [95% CI] =0.09, [0.07, 0.10], p<.001), and ten year olds significantly outperformed nine year olds (Mean Diff. [95% CI] = 0.08, [0.06, 0.11], p<.001). No significant differences were found between six- and seven-year-olds, nor ten- and eleven-year-olds (p>.05).

For Aiming (Figure 9), there was a significant effect of age on performance (F(7, 16069) = 1068, p<.001, η^2 = 0.32). Post-hoc multiple comparisons found that five year olds significantly outperformed four year olds (Mean Diff. [95% CI] = 0.11, [0.07, 0.15], p<.001), six year olds significantly outperformed five year olds (Mean Diff. [95% CI] = 0.25 [0.20, 0.30], p<.001), seven year olds significantly outperformed six year olds (Mean Diff. [95% CI] = 0.31, [0.27, 0.36], p<.001), eight year olds significantly outperformed seven year olds (Mean Diff. [95% CI] = 0.13 , [0.12, 0.14], p<.001), and nine year olds significantly outperformed eight year olds (Mean Diff. [95% CI] = 0.11 [0.10, 0.13] p<.001). No significant differences were found between nine- and ten-year-olds, nor ten- and eleven-year-olds (both p>.05).

For Steering (Figure 10), a significant effect of age was found on performance (F(7, 18533) = 393.3, p<.001, η^2 = 0.13). Post-hoc multiple comparisons found that five year olds significantly outperformed four year olds (Mean Diff. [95%

Table 4. Component loadings on a four-component model (Model A) and three-component model (Model B) for the Aiming Sub-task following oblique rotation (N = 1323).

Item	PC1	PC2	PC3
Embedded RT	**1.03**	-.12	.09
Jump RT	**1.02**	-.18	.08
Baseline RT	**1.02**	-.11	.04
Baseline TPS	**.93**	.02	-.03
Embedded TPS	**.89**	.11	.06
Baseline PLT	**.79**	.21	-.14
Jump PLT	**.76**	.29	-.07
Jump TPS	**.71**	.11	0.12
Embedded PLT	**.68**	.38	-.07
Jump MT	**.66**	.39	-.09
Baseline MT	**.51**	.45	-.25
Jump DT	.36	.37	.06
Embedded PL	-.08	**.94**	.23
Jump PL	.00	**.87**	.23
Embedded DT	.07	**.83**	-.23
Embedded MT	.25	**.75**	-.16
Baseline PL	.25	**.65**	.24
Baseline DT	.37	**.51**	-.29
Embedded PS	-.03	.09	**.92**
Baseline PS	.05	-.05	**.87**
Jump PS	.09	.15	**.88**
Eigenvalues	9.07	5.45	2.87
% of Total Variance	43%	26%	14%

Note: Component loadings over .50 appear in bold and red typeface. RT = Reaction Time, TPS = Time to Peak Speed, PLT = Path Length Time, MT = Movement Time, DT = Deceleration Time, PL = Path Length, PS = Peak Speed, PC = Principal Component.

CI] = 0.04 [0.02, 0.05], p<.001), six year olds significantly outperformed five year olds (Mean Diff. [95% CI] = 0.16 [0.14, 0.19], p<.001), eight year olds significantly outperformed seven year olds (Mean Diff. [95% CI] = 0.02 [0.01, 0.03], p<.001) nine year olds significantly outperformed eight year olds (Mean Diff. [95% CI] = 0.04 [0.03, 0.05], p<.001) ten year olds significantly outperformed nine year olds (Mean Diff. [95% CI] = 0.06 [0.04, 0.07], p<.001) and ten year olds significantly outperformed eleven year olds (Mean Diff. [95% CI] = 0.09 [0.04, 0.13], p=.005). No significant differences were found between six- and seven-year-olds (p>.05).

Discussion

We used data reduction and confirmatory techniques to identify the core kinematic components that captured individual differences in three sensorimotor processing tasks. Our findings showed that sensorimotor control could be quantified via seven dimensions within a Tracking task, three dimensions for Aiming, and four for Steering. Quantifying performance in this way provided an appropriate balance between theoretical and practical considerations. The factor structures had an acceptable model fit when validated against a large, novel dataset. Thus, we can place confidence in the ability of such model structures to account for performance on these sensorimotor tasks.

The reduction of data to a single measure has previously occurred in both kinematic (e.g., Hill *et al.*, 2016) and traditional assessments of sensorimotor ability (e.g., Henderson *et al.*, 2007). However, our findings show that information is lost when research condenses motor control to a single "overall" measure (French *et al.*, 2018). The use of the variables identified in this study better captures the multi-faceted nature of sensorimotor control. For example, path length was better described as an independent component in the Tracking task (see Figure 5) but performance in Aiming was more appropriately quantified by a variable which considered performance across several related metrics of sensorimotor control.

This study has identified additional metrics that have not been routinely analysed in previous studies (cf., Flatters *et al.*, 2014a; Flatters *et al.*, 2014b; Hill *et al.*, 2016; Raw *et al.*, 2012). For example, Tracking, Aiming, and Steering performance on the CKAT battery is most often quantified by Root Mean Squared Error, Path Length Time, and Penalised Path Accuracy, respectively. However, we found that Path Length explains 9% of total variance in the Tracking task but has not been previously analysed. Likewise, Peak Speed independently accounted for 14% of the total variance in aiming but has not appeared in earlier analyses.

The findings also suggest where analyses are less useful. Step-perturbation tasks are common in the motor control literature (Heath *et al.*, 1998; Pélisson *et al.*, 1986; Plumb *et al.*, 2008; Wilmut *et al.*, 2006) and included in the CKAT battery. It is commonly accepted that the execution of such movements taps into online control mechanisms which are not captured by "Baseline" trials (Culmer *et al.*, 2009; Latash, 2012; Plumb *et al.*, 2008). However, the present analyses did not find differentiation between jump and baseline trials suggesting that these conditions may not shed light on different sensorimotor processes as is often assumed.

A major strength of the current study is the large sample sizes used to train and validate these models. It is vital to conduct exploratory and confirmatory analyses on independent samples to prevent overfitting (Fokkema & Greiff, 2017). However, the validation sample did not contain any six-year-old children. This is due to the nature of the cohort, which tested children at school entry (aged 4–5 years) and then once again in English school years 3-6 (7–10 years). However, six-year-olds were included within the original PCA samples

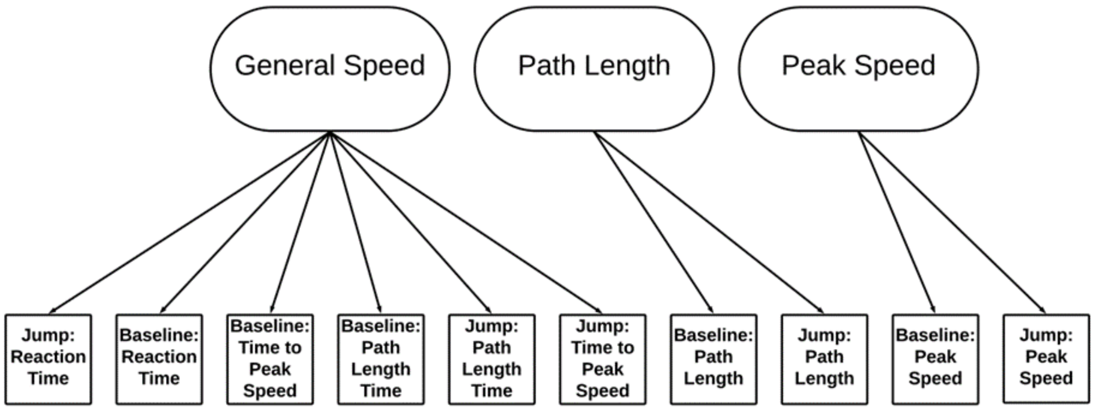

Figure 6. Path diagram of the final model for the Aiming Sub-task.

Table 5. Component loadings on a three-component model (Model A) and four-component model (Model B) for the Steering Sub-task following oblique rotation (N = 1727).

	Model A			Model B			
Item (Condition)	**PC1**	**PC2**	**PC3**	**PC1**	**PC2**	**PC3**	**PC4**
Path Length (L-R)	.29	**.86**	.04	**.89**	.05	.01	.23
Path Length (R-L)	.10	-.01	**.95**	-.02	.05	**.97**	-.01
Path Length Time (L-R)	-.36	**.79**	-.03	**.74**	-.07	-.02	-.44
Path Length Time (R-L)	**-.62**	.09	**.56**	.12	**-.73**	.46	-.02
Path Accuracy (L-R)	**.79**	-.08	.06	.05	.03	-.02	**.94**
Path Accuracy (R-L)	**.84**	.12	.12	.08	**.88**	.25	.06
Eigenvalues	1.93	1.40	1.26	1.38	1.39	1.22	1.21
% of Total Variance	32%	23%	21%	23%	23%	20%	20%

Note: Component loadings over .50 appear in bold & red typeface. L-R = Left-to-Right; R-L = Right-to-Left.

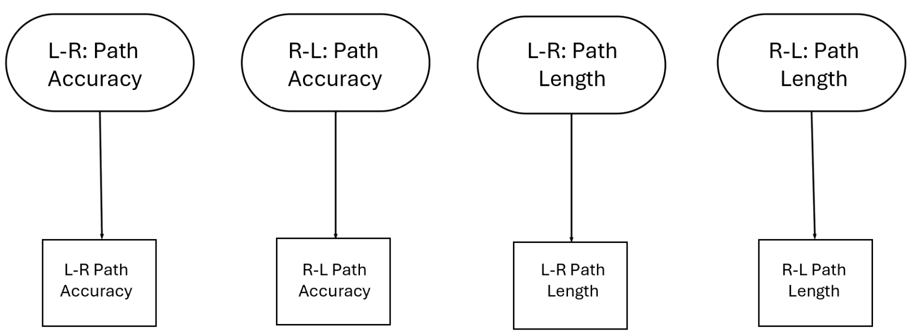

Figure 7. Path diagram of the final model for the Steering Sub-task. *Note*: L-R = Left-to-Right, R-L = Right-to-Left.

in which the original models were built and so performance from this population is still represented. In addition, the final models do reflect some additional ad hoc refinement (e.g., allowing the error to co-vary across items or truncating the battery by omitting conditions). However, all modifications made were driven by existing theory to prevent the risk of a Type 1 error as recommended by Schreiber *et al.* (2006).

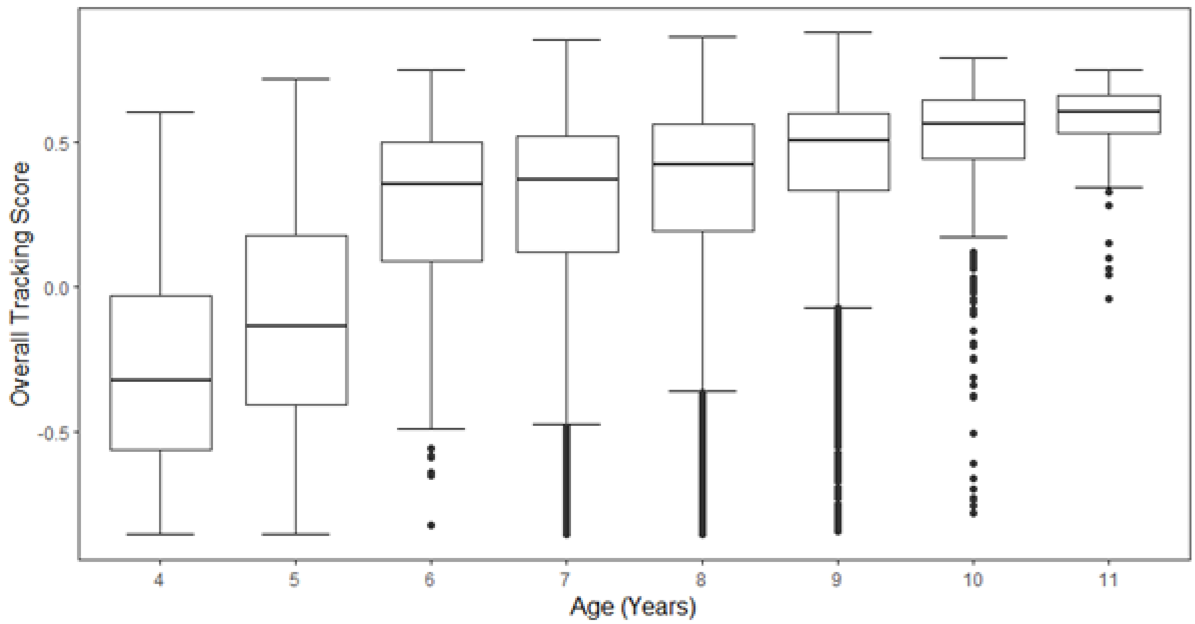

Figure 8. **Age distribution of performance on the Tracking subtask.**

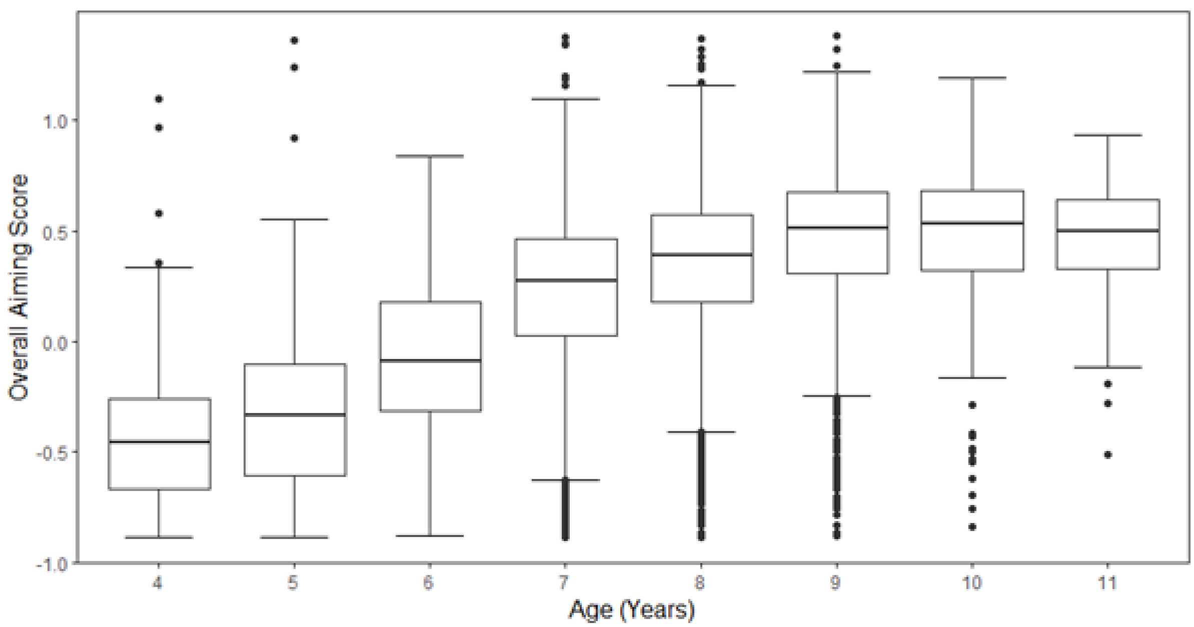

Figure 9. **Age distribution of performance on the Aiming subtask.**

Conclusions

The collection of kinematic data at scale is increasingly feasible (Brookes *et al.*, 2020; Schwarz *et al.*, 2019). However, investigation into the most theoretically and empirically justifiable analyses is required to fully leverage the value of these new technologies (An & Chao, 1984). Thus, the methods described in this manuscript could and should be applied in any form of kinematic assessment (for examples of tablet-based tools that use kinematic outputs see (Accardo *et al.*, 2013; Lee *et al.*, 2014; Matic & Gomez-Marin, 2019; Vianello *et al.*, 2017). These methods will then unleash the power of kinematic analysis in a wide range of settings including intervention efficacy review; investigation of developmental trajectories in healthy and clinical populations; and

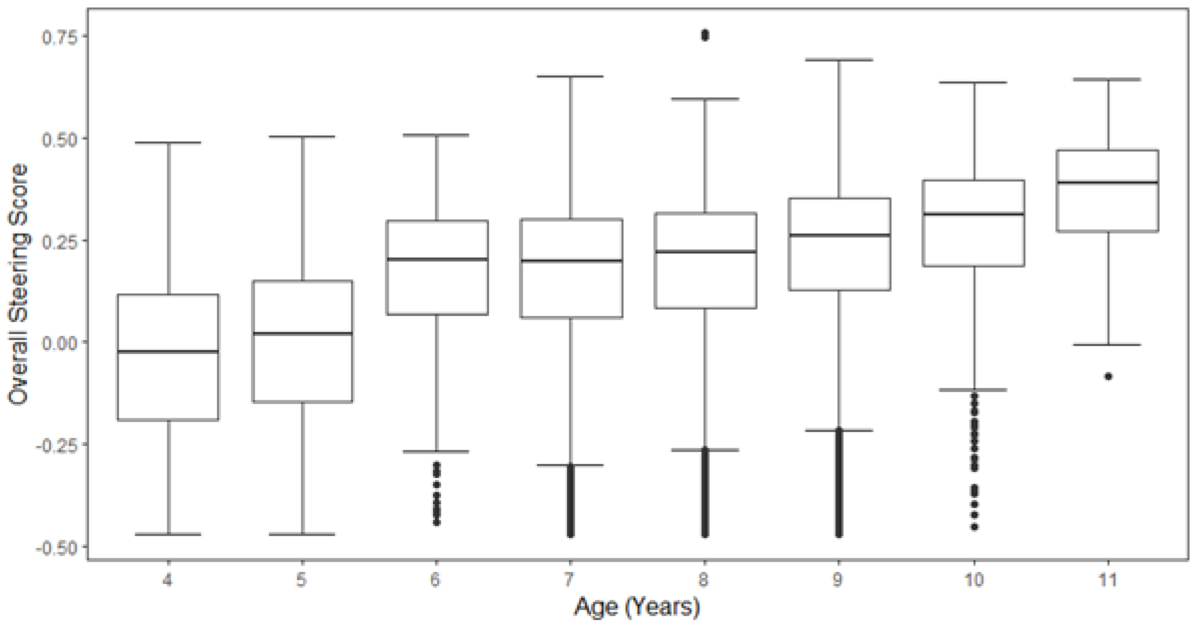

Figure 10. Age distribution of performance on the Steering subtask.

deeper exploration of the theoretical mechanisms of sensorimotor control. The present study has identified key variables for analysis in the large cohort studies (such as BiB) that use CKAT. Our hope is that this framework can now guide researchers in the selection of appropriate metrics to use when exploring sensorimotor control and its relationship with multiple life outcomes in rich datasets such as BiB.

Ethics and consent

Ethical approval for the re-analysis of these data was granted by University of Leeds ethics committee (reference: PSC-826). Ethical approvals for the Starting School data collection were obtained from ethics committees at the University of Leeds (reference: 13-0220) and the University of York (reference:12/26). Ethical approval for data linkage within the BiB cohort was obtained from the Bradford Leeds Research Ethics Committee (reference: 07/H1302/112). Ethical approval for the data collection for the Primary School Years sweep was obtained from the NHS Health Research Authority's Yorkshire and the Humber - Bradford Leeds Research Ethics Committee (reference: 16/YH/0062) on the 24th March 2016. All data were obtained via data requests from BiB's Executive Committee.

Data availability

Underlying data

Scientists are encouraged to make use of the BiB data, which are available through a system of managed open access.

Before you contact BiB, please make sure you have read our Guidance for Collaborators. Our BiB executive review proposals monthly and we will endeavour to respond to your request as soon as possible. You can find out about all the different datasets which are available here. If you are unsure if we have the data that you need, please contact a member of the BiB team (borninbradford@bthft.nhs.uk).

Once you have formulated your request please complete the 'Expression of Interest' form available here and email the BiB research team (borninbradford@bthft.nhs.uk).

If your request is approved, we will ask you to sign a data sharing contract and a data sharing agreement; if your request involves biological samples, we will ask you to complete a material transfer agreement.

Extended data

Open Science Framework: Markdown report containing explanation of how to derive the sensorimotor variables from the raw CKAT output. https://doi.org/10.17605/OSF.IO/TSVX6.

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Reviewer Report 12 November 2024

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The authors aim to determine key variables that capture sensorimotor control among children at different ages (and presumably motor development). This was specifically done in a large study sample of more than 22000 healthy children (the Born in Bradford (BiB) cohort). The authors used data reduction (principal component analysis) and confirmatory factor analyses in their design, which is a considerable strength given the large sample size of both the training and validation samples. The analysis was based on three tablet-based tasks – Tracking, aiming and steering – from which kinematic data were extracted. Notably, kinematics in this context refers to performance-based variables and not biomechanical variables such as joint angles, angular velocities etc.).
Although a well-designed study, several issues need to be addressed:

1. While an adequately performed methods paper, I find myself questioning its applicability to other populations. The purpose seems to show the feasibility of these methods on large cohorts, that also contain such kinematic data. This is not that common for patient populations, it would seem. What is the applicability of this study then for smaller cohorts? Alternatively, with such robust methods, I would expect some discussion on the actual results regarding typically developing children. Yet this is absence.
2. The constant use of the term “sensorimotor control” as the construct of evaluation is misplaced in my view. The term refers to complex integrated processes (both internal and external) of obtaining, processing and translating of sensory information into complex motor actions. I hardly think that three specific and relatively similar upper limb tasks (the steering in particular seems to share quite a lot with the tracking task), and the inclusion of functional summary outcome measures can provide sufficient information to quantify such a complex term. For example, a statement in the second paragraph of the discussion refers to the "multi-faceted nature of sensorimotor control" and explains how it was captured in the current study in a rather unconvincing way. The authors provide an example of two specific variables but it is unclear how these selected variables support their argument. Throughout the paper, the authors also use wording like “sensorimotor data”, sensorimotor behaviour”, “sensorimotor metrics” and “manual sensorimotor control”, which are often a bit of empty terms in the context of their mentioning. Moreover, prominent features of

movement control (e.g., smoothness, muscle synergies, inter-joint variability) are not considered in this an analysis, despite reflecting various features of "sensorimotor control". The authors can perhaps change this to ‘sensorimotor function’ but should also modify and tone-down the generalisability of their findings and put them in a more appropriate context. Moreover, statements such as “the power of kinematic analysis” should also be toned down, given the wider context of the term “kinematic analysis”. Other possible types of analyses often delve into the inspection of movement patterns by inspecting multi-joint coordination patterns. As such, they are clearly distinct from functional outcome inspections or the use of more general kinematic measures such as movement time, path length time and path accuracy.

3. On a related topic, the authors seem to generalise their findings to the general population and neglect to touch upon the issue of motor development, which is likely the main contributor to the observed differences and consequently to the variables that contribute the most to the variability. They should perhaps try to discuss the inherent age/developmental differences in sensorimotor integration, as this is most likely the source of the observed age effects. In fact, reading through the discussion and conclusion, I forgot for a moment that the cohort was comprised of pre-pubertal children, as the implications seem to refer to the “healthy and clinical populations” (i.e., all ages). Sentences such as: “…suggesting that these conditions may not shed light on different sensorimotor processes as is often assumed” miss the context of it being tested on still-developing children. There seems to be something missing here and there are various potential discussion points that should be explored. Yet, the discussion seems a bit superficial in most places, with several “we found this, others found that” statements with little elaboration as to what the findings actually means. I encourage the authors to develop their arguments more.
   Granted, this is a method paper and the purpose is to demonstrate the method’s feasibility on large samples. Still, why were these particular dimensions / variables the relevant ones? What do they signify? Given my first argument on the applicability to smaller (and heterogeneic) samples, the authors should consider at least discussing their results in the context of their significance to 'sensorimotor control'.
   As a reader, I would be interested in some assumptions of causation and suggested explanations to the findings, rather than just “Path length explains 9% of the total variance in the Tracking task”. Especially if people are to apply the findings to other populations. I do not see any reason why path length would be more or less relevant than path length time. Without any hypothesis, this seems like fishing given based only on a probable selection from a large number of variables without any motivation or explanation of what they might signify.
4. Some details of the methods are missing or unclear. Specifically, the PCA details. The authors mention that Kaiser’s criterion was considered when determining the numbers of components to retain (which is the standard). Yet, the authors “considered” scree plots and cumulative variance. Which one was it? Was the elbow criterion of the scree plot considered the one used? Then, the Kaiser’s criterion should generally be redundant. What was the criterion for the cumulative variance? Certainly not too high since this would also include eigen values < 1. The authors then state that that they selected the most appropriate number of components. Considering the different criteria, what was considered appropriate?
5. Regarding the age comparisons, have the authors considered the influence of sex? The participants’ sex should potentially be included as factor/covariate in the statistical models. It might influence to some degree given possible sex differences in motor development.

Specific issues:

1. Please change “gender” to “sex”, as is more appropriate in such studies.
2. Note an incomplete sentence – the last sentence of the “Tracking” section of the results seems to be cut and with some grammatical issues: “Thus, model was interpreted as comprising six condition-specific “Dynamic Accuracy” components, plus one component representing (see Figure 5).”
3. In the second paragraph of the discussion, the word “occurred” should be changed to ‘utilised’ / ‘used’ or similar.

Is the rationale for developing the new method (or application) clearly explained?
Partly

Is the description of the method technically sound?
Yes

Are sufficient details provided to allow replication of the method development and its use by others?
Partly

If any results are presented, are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions about the method and its performance adequately supported by the findings presented in the article?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Motor control and brain function in the context of sport injuries.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Reviewer Report 15 October 2024

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The paper by Wood and colleagues reports on the unique Born in Bradford (BIB) study of over 22 thousand children aged 4-11. A battery of tests involving three main tasks (Tracking, Aiming, and Steering) was applied followed by the principal component analysis (PCA) with factor extraction. The three tasks required participants to use a handheld stylus to interact with visual stimuli presented on a touchscreen tablet computer. The kinematic data measured at the level of the implement were reduced to 4-7 PCs per task. The authors conclude that analysis at the level of a few kinematic characteristics can be used to track the progression of sensorimotor development. They also discuss possible applications of the method to analysis of sensorimotor control in children with atypical development.

The study seems to be well designed (see below) and the dataset is unique. A strong feature of the design is that the researchers used a training set to develop their models and the second dataset to validate the models. The biggest problem with this “Methods” paper is in the presentation of the experimental procedures, some of the steps in the analysis, and statistical methods, which is too brief and incomplete to allow other researchers to use this method for studies of typical and atypical motor development.

For studies of children, the appearance of targets and their specific features, including sizes and colors, may be very important. These details are not presented. The description of the Tracking task includes: to track a moving target around the screen in a series of sinusoidal waves. This description is too general. What were the frequencies and amplitudes of the waves? What were the specific features of the “box” mentioned in the description of the Steering task?

The principal component analysis (PCA) is described too briefly. This analysis involves factorization of correlation or covariation matrices computed across pairs of variables within a large set. It is not clear what data were used to assemble the matrices, how the values were computed, and whether correlation or covariation matrices were used. Some of the expressions are too general to allow reproduction in future studies. In particular, what are “sufficiently correlated models”? The text describes software packages and specific names of the software tools without explaining what these tools do and what the limitations of their application are.

Further description of the data handling and statistical tools is also too scanty. How was “sense-check” performed? What are “validated dimensions”? What are “appropriately weighted contributions”? It is not clear how the “independent scores” were computed. Were the data checked for normality and sphericity before ANOVA? Were corrections of degrees-of-freedom applied? What were the factors and levels in the ANOVA? Was this a single-factor ANOVA with Age as the factor? If so, what were the age bins used as levels? The reader has to guess answers to all these questions, which are frequently not obvious.

The design of the study involved testing a large group of children multiple times at different ages and measuring a set of outcome variables expressed in different units. In general, this design requires repeated-measures MANOVA. However, ANOVA was used, and repeated measures are not mentioned. This has to be justified. The large number of subjects is a very important feature of the study. Recommending the method for studies of persons with atypical development when the number of subjects is commonly on the order of 10-20 and outcome variables are compared across groups requires more detailed analysis of statistics.

The main goal of the study is presented as to capture children’s sensorimotor control. For example, the following statement is quoted from the Abstract: “The aim of the present study was to use exploratory data reduction and confirmatory techniques to identify a stable set of kinematic components that are valid descriptors of children’s sensorimotor control.“ The methods, however, capture features of behavior of a hand-held implement, which are equally affected by neural control factors, body biomechanics, reflex feedback loops, and external forces (gravity and friction). It needs to be proven that the identified variables of interest indeed reflect sensorimotor control processes (which is not a well-defined construct to start with). It seems more prudent to describe the study as one addressing issues of sensorimotor behavior. It is also recommended to emphasize in the title and Abstract that the kinematic analysis used only the data of the implement, because most studies at the level of kinematics involve variables related to anatomical elements of the body such as joints and segments.

A couple of minor comments related to Results. What does it mean that a solution is “most appropriate”? PCs are usually numbered in the order of descending values for the variance accounted for (VAF). In Table 2, the PCs are ordered differently. Are these PCs or factors?

Is the rationale for developing the new method (or application) clearly explained?
Yes

Is the description of the method technically sound?
Partly

Are sufficient details provided to allow replication of the method development and its use by others?
No

If any results are presented, are all the source data underlying the results available to ensure full reproducibility?
Partly

Are the conclusions about the method and its performance adequately supported by the findings presented in the article?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: neural control of movement

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.