Quantifying the weights of sensory influences on postural control across development

MARK A. SCHMUCKLER[1]

[1] University of Toronto Scarborough, ON, Canada

Correspondence to: Mark A. Schmuckler
Department of Psychology, University of Toronto Scarborough, 1265 Military Trail, Scarborough, ON, M1C 1A4
email: mark.schmuckler@utoronto.ca
https://doi.org/10.20338/bjmb.v18i1.430

HIGHLIGHTS

- Postural control across development is well described by a multicomponential approach
- Multisensory weights change with age; proprioception is the most critical by 5-7 yrs
- Increasing body size is related to better stability initially and flipping by 5-7-yrs
- Posture is best predicted using the degree of stability of different sensory sources

ABBREVIATIONS

LFC Light fingertip contact

PUBLICATION DATA

Received 29 05 2024
Accepted 04 10 2024
Published 31 10 2024

ABSTRACT

BACKGROUND: This study examined the weighting of multisensory and anthropometric factors in driving children’s and adult’s postural control.
METHOD: A data set was created by aggregating individual participants’ postural stability measures from four target studies, employing participants ranging in age from 3 to 11 years, along with young adults. Using a meta-regression approach, this aggregate data set was then predicted from dummy codings of the including visual, haptic, and proprioceptive sensory inputs manipulated in these studies, as well as the anthropometric factor of participant height. Two forms of coding regimens were examined – one capturing simple presence versus absence of sensory sources, and one quantifying the degree of stability provided by sensory sources.
RESULTS: The results of this study revealed that proprioceptive input had the strongest impact on stability, followed by roughly equivalent visual and haptic inputs, and finally anthropometric factors. Developmentally, this pattern of findings was stable by 5- to 7-years of age. Although both coding schemes predicted posture, the degree of stability coding scheme provided consistently superior predictions.
INTERPRETATION: These findings are discussed with respect to a multicomponential approach to postural control, a framework that emphasizes the importance of multiple component factors in characterizing complex behavior.

KEYWORDS: Postural control | Multisensory influences | Anthropometric factors | Multicomponential approach to posture | Meta-regression

INTRODUCTION

The last four to five decades have witnessed the critical importance played by multisensory information in postural control, including visual influences[1,2], haptic influences[3], and even auditory influences[4].

With respect to visual information, one exemplar of the role of this input involves the classic Romberg effect[5], a neurological test comparing balance during static stance with and without vision (eyes open versus closed). Typically, participants display increased instability with their eyes closed, relative to open, an effect that has been observed across development[6]. Additional evidence for the role of vision has been provided in the “moving room” paradigm[1]. In this paradigm, movement of the walls of a room produces compensatory postural sway in participants across development[1,7,8,9,10,11].

Evidence for haptic influences on posture is similarly robust[3,6]. For instance, Jeka and Lackner[3] showed that when adults lightly touch a support surface (light fingertip contact, or LFC) they exhibit increased stability, relative to not touching a surface. Developmentally, this effect has been observed across multiple ages[6,12,13]. Finally, just as with vision, if the support surface oscillates, observers similarly produce compensatory sway[14].

Balance is also influenced by proprioceptive input. Classic work on proprioception has examined the impact on posture of standing surface perturbations[15], surface orientation/tilt[16], and surface rigidity[15]. Although less common, stance width can also be considered as proprioceptive input, and has also been found to influence balance in both children and adults[12,13]. Together, all of these findings support a theoretical framework emphasizing the importance of multisensory factors on balance across the life span.

Although powerful, one question yet unanswered by this framework involves the role of factors other than multisensory components in constraining balance. For instance, researchers have highlighted the importance of anthropometric body size, with balance negatively correlated with body mass[17,18]. Other work has demonstrated that height is related to postural control[9,12,13].

Another component implicated as important for posture involves athletic ability. Work in this vein has examined whether posture is differentially influenced by the “level” of sports ability”[19], whether different sports produce variation in postural control[19,20], and the developmental relation between sports and balance[20]. For instance, Bhati et al.[20] found that increased participation in sports requiring dynamic postural changes (e.g., dance, martial arts) were correlated with increased postural stability in unsteady stances. These findings led these authors to suggest a “multicomponential” approach, more akin to dynamic systems theory[21,22], in which body-size factors and sports participation co-exist as critical influences along with multisensory components.

Another limitation with the multisensory approach involves a concrete specification of the impact of the varying multisensory influences. Research investigating multisensory factors typically refers to the weighting or reweighting of sensory components[23]. Unfortunately, sensory weighting in these contexts is at best a relative concept, one without an exact specification of the sensory weights.

Additionally, there is a question as to how the weighting of sensory factors might change across development. Although multiple researchers have suggested that children do not exhibit adultlike balance until mid-childhood or later[24,25], explications of such differences have been primarily descriptive. One possibility is that differences in balance control could arise from varying reliance on different sensory inputs across development. Thus, any quantification of sensory weights would profit from tracking how sensory weights change across developmental time.

The goal of this study is to further explicate a multicomponential framework to postural development. As described earlier, this approach highlights the role of multiple component processes (multisensory, anthropometric, experiential, and so on) in driving motor skill acquisition. Key to this approach is the quantification of the developmental trajectory of such components, along with their relative weights, in producing motor behavior. Accordingly, this study focuses on these critical aspects.

To quantify these weights, this study uses the technique of “meta-regression”[26]. Often used in conjunction with meta-analysis, meta-regression uses regression analyses to compare findings across different studies, and allows for the assessment of co-variate effects on dependent responses. According to Baker et al.[26], “meta-regression explores whether a linear association exists between variables and a comparative treatment effect, along with the direction of that association. Meta-regression is a more sophisticated method than subgroup analysis for exploring heterogeneity and has the potential advantage of efficiently allowing the evaluation of one or more covariables simultaneously” (p. 1427).

In this study, meta-regression is used to directly estimate the impact of multisensory and anthropometric factors. Theoretically, these factors are assumed to be centrally important influences on balance control, as indicated by the frequency with which they are manipulated in the literature. Practically, these factors were chosen because of the availability of a robust data set, aggregated across a small number of comparable experiments. The power of this analysis arises through employing individual participant data, as opposed to averaged data across multiple studies (as in meta-analysis). Interestingly, in meta-regression, the use of individual participant data can be preferable to averaged data, particularly when exploring participant-level factors[26].

THE DATA SETS

This analysis employed data from four recently published experiments investigating the impact of a range of sensory inputs on postural control. Table 1 lists the experiments included, and delineates the participants, multisensory inputs examined, and experimental manipulations investigated in these studies.

All of these studies manipulated visual information, with three studies comparing the presence versus absence of visual input[6,12,13], whereas the fourth study[11] provided oscillatory visual input via a moving room. Three of these studies[6,12,13] also manipulated haptic information. These manipulations included the presence of LFC with a stable support surface, LFC with an unstable support surface, haptic input produced via holding a small object, and the absence of haptic input altogether. Additionally, two of these studies[12,13] manipulated proprioceptive input via modifications of stance width.

Finally, three of these studies studies[6,11,12] tested developmental differences, employing participants between 3 and 11 years, along with young adults (university students). Accordingly, it was possible to create five age groups from this data: 3- to 5-year olds, 5- to 7-year olds, 7- to 9-year olds, 9- to 11-year olds, and (young) adults.

CODING OF SENSORY FACTORS

Assessing the weighting of components factors was accomplished by creating an aggregate data set across the experiments, in which a single dependent measure was analyzed with respect to dummy codings of sensory inputs, along with anthropometric participant measures. For this analysis, mean velocity was employed as the critical dependent variable. This measure was used in all of these experiments, and is among the most informative sway parameters[27].

Table 1. Information regarding the four data sets employed in this analysis.

Experiment	Sensory Manipulations Visual	 Haptic	 Proprioceptive
Schmuckler (2017) • Age Groups: ○ 3- to 5-Year-Olds ○ Young Adults	0.2 Hz Flow 0.4 Hz Flow Multifrequency Flow No Visual Flow	No Haptic Input (No Touch)	Shoulder Width (SW)
Schmuckler & Tang (2019) • Age Groups: ○ 3- to 5-Year-Olds ○ 7- to 9-Year-Olds ○ Young Adults	Visual Input (Light) No Visual Input (Dark)	Haptic Input (Stable Touch) Haptic Input (Unstable Touch) Haptic Input (Object Touch) No Haptic Input (No Touch)	Shoulder Width (SW)
Cheung & Schmuckler (2021) • Age Groups: ○ 3- to 6-Year-Olds ○ 6- to 11-Year-Olds	Visual Input (Light) No Visual Input (Dark)	Haptic Input (Stable Touch) Haptic Input (Unstable Touch) No Haptic Input (No Touch)	Shoulder Width (SW) Chaplin (CH) Feet Together (FT) Tandem (TD)
Cheung & Schmuckler (2024) • Age Groups: ○ Young Adults	Visual Input (Light) No Visual Input (Dark)	Haptic Input (Stable Touch) Haptic Input (Unstable Touch) No Haptic Input (No Touch)	Shoulder Width (SW) Chaplin (CH) Feet Together (FT) Tandem (TD)

Essential to this analysis is ensuring that the coding of sensory factors captures critical differences between multisensory conditions. One straightforward coding scheme involves indicating presence versus absence of a sensory factor, applying a numeric code if the input is present, and a different code if the input is absent. Table 2 presents examples of this type of code. In this table, a given input received a code of "2" when present, and a code of "1" when absent. Thus, in Schmuckler[11], because the primary manipulation involved varying frequencies of visual flow (0.2 Hz, 0.6 Hz, unpredictable) along with no visual flow, when flow was present the code was "2" (present), and when absent it was "1". Because this study did not provide external haptic input, this information would be considered absent, receiving a code of "1". Finally, because participants adopted a simple shoulder width stance, proprioceptive input would be considered present[a], and coded as "2". In comparison, Cheung and Schmuckler[12,13], manipulated visual, haptic, and proprioceptive inputs. Thus, conditions in which these sensory inputs were present (eyes open, LFC with stable/unstable supports, shoulder width stance) would be coded as "2" (present), and conditions in which they were absent (eyes closed, no LFC, all remaining stance widths) would be coded as "1" (absent).

Although workable, this coding regimen is limited in that it ignores the fact that these experimental variations produced differentiated degrees of sensory input. Thus, a more nuanced approach could indicate the degree to which the sensory input contributes to postural stability. Table 3 presents this coding. Now, the visual flow manipulations of Schmuckler[11] are coded with respect to their relative contributions to stability, with the no movement coded as "3" (high stability), the two oscillatory conditions coded as "2" (moderate stability), and the unpredictable flow condition coded as "1" (low stability); haptic and proprioceptive would now be coded as "1" (low – no LFC) and "3" (high – shoulder width stance), respectively. For Cheung and Schmuckler[12,13], codes of "3" would occur for the highly stable conditions (eyes open, LFC with a stable support, shoulder width stance), "2" for moderate stability (LFC with an unstable support, Chaplin and feet together stances), and "1" for low stability conditions (eyes closed, no LFC, tandem stance).

[a] In this case, the distinction between present and absent is modified somewhat. Because it is difficult to have a condition in which there is, literally, no proprioceptive information from one's feet, it is better to think of this code as "maximally present", relative to other proprioceptive conditions.

Table 2. Coding of sensory inputs, presence versus absence

Sensory Information			Sensory Input Code (1 = Absent, 2 = Present)		
Schmuckler (2017)					
Visual	Haptic	Proprioceptive	Visual	Haptic	Proprioceptive
0.2 Hz	No Touch	Shoulder Width	2	1	2
0.6 Hz	No Touch	Shoulder Width	2	1	2
Multifrequency	No Touch	Shoulder Width	2	1	2
No Movement	No Touch	Shoulder Width	1	1	2
Schmuckler & Tang (2019)					
Light	Stable Touch	Shoulder Width	2	1	2
Dark	Stable Touch	Shoulder Width	1	1	2
Light	Unstable Touch	Shoulder Width	2	2	2
Dark	Unstable Touch	Shoulder Width	1	2	2
Light	Object Touch	Shoulder Width	2	2	2
Dark	Object Touch	Shoulder Width	1	2	2
Light	No Touch	Shoulder Width	2	2	2
Dark	No Touch	Shoulder Width	1	2	2
Cheung & Schmuckler (2021, 2024)					
Light	Stable Touch	Shoulder Width	2	1	2
Dark	Stable Touch	Shoulder Width	1	1	2
Light	Stable Touch	Chaplin	2	1	1
Dark	Stable Touch	Chaplin	1	1	1
Light	Stable Touch	Feet Together	2	1	1
Dark	Stable Touch	Feet Together	1	1	1
Light	Stable Touch	Tandem	2	1	1
Dark	Stable Touch	Tandem	1	1	1
Light	Unstable Touch	Shoulder Width	2	2	2
Dark	Unstable Touch	Shoulder Width	1	2	2
Light	Unstable Touch	Chaplin	2	2	1
Dark	Unstable Touch	Chaplin	1	2	1
Light	Unstable Touch	Feet Together	2	2	1
Dark	Unstable Touch	Feet Together	1	2	1
Light	Unstable Touch	Tandem	2	2	1
Dark	Unstable Touch	Tandem	1	2	1
Light	No Touch	Shoulder Width	2	2	2
Dark	No Touch	Shoulder Width	1	2	2
Light	No Touch	Chaplin	2	2	1
Dark	No Touch	Chaplin	1	2	1
Light	No Touch	Feet Together	2	2	1
Dark	No Touch	Feet Together	1	2	1
Light	No Touch	Tandem	2	2	1
Dark	No Touch	Tandem	1	2	1

One advantage to these coding systems is that they are suitable for characterizing a wide range of influences on balance. Coding presence versus absence of some form of information is clearly possible, regardless of whether this factor is motoric, sensory, cognitive, or social; accordingly, this scheme has wide cross-domain applicability. As for the degree of stability regimen, this framework also could be expanded to encompass the relative amount of information availability, irrespective of the specific domain in question. Thus, if one were exploring cognitive influences, such as in a dual-task context, one could consider the degree of difficulty of processing required for a task, and code this input accordingly. As such, this approach towards quantifying components has considerable flexibility.

Table 3. Coding of Sensory Inputs – Degree of Stability

Sensory Information			Sensory Input Code (1 = Low, 2 = Medium, 3 = High)		
Schmuckler (2017)					
Visual	Haptic	Proprioceptive	Visual	Haptic	Proprioceptive
0.2 Hz	No Touch	Shoulder Width	2	1	3
0.6 Hz	No Touch	Shoulder Width	2	1	3
Multifrequency	No Touch	Shoulder Width	1	1	3
No Movement	No Touch	Shoulder Width	3	1	3
Schmuckler & Tang (2019)					
Light	Stable Touch	Shoulder Width	3	3	3
Dark	Stable Touch	Shoulder Width	1	3	3
Light	Unstable Touch	Shoulder Width	3	2	3
Dark	Unstable Touch	Shoulder Width	1	3	3
Light	Object Touch	Shoulder Width	3	2	3
Dark	Object Touch	Shoulder Width	1	2	3
Light	No Touch	Shoulder Width	3	1	3
Dark	No Touch	Shoulder Width	1	1	3
Cheung & Schmuckler (2021, 2024)					
Light	Stable Touch	Shoulder Width	3	3	3
Dark	Stable Touch	Shoulder Width	1	3	3
Light	Stable Touch	Chaplin	3	3	2
Dark	Stable Touch	Chaplin	1	3	2
Light	Stable Touch	Feet Together	3	3	2
Dark	Stable Touch	Feet Together	1	3	2
Light	Stable Touch	Tandem	3	3	1
Dark	Stable Touch	Tandem	1	3	1
Light	Unstable Touch	Shoulder Width	3	2	3
Dark	Unstable Touch	Shoulder Width	1	2	3
Light	Unstable Touch	Chaplin	3	2	2
Dark	Unstable Touch	Chaplin	1	2	2
Light	Unstable Touch	Feet Together	3	2	2
Dark	Unstable Touch	Feet Together	1	2	2
Light	Unstable Touch	Tandem	3	2	1
Dark	Unstable Touch	Tandem	1	2	1
Light	No Touch	Shoulder Width	3	1	3
Dark	No Touch	Shoulder Width	1	1	3
Light	No Touch	Chaplin	3	1	2
Dark	No Touch	Chaplin	1	1	2
Light	No Touch	Feet Together	3	1	2
Dark	No Touch	Feet Together	1	1	2
Light	No Touch	Tandem	3	1	1
Dark	No Touch	Tandem	1	1	1

RESULTS AND DISCUSSION

The data set for this analysis was created by aggregating across all conditions for all participants in the four target studies. In all there were 208 participants in this study, categorized into separate age groups of 3- to 5-years (N = 52), 5- to 7-years (N = 33), 7- to 9-years (N = 34), 9- to 11-years (N = 19), and adults (N = 70). Demographic and anthropometric information for these samples appears in Table 4.

Table 4. Averaged Anthropometric Measures for the Age Groups

	3- to 5-years	5- to 7-years	7- to 9-years	9- to 11-years	Adults
Age (yrs)	4.01	5.93	7.89	9.74	20.32
Height (cm)	101.72	114.76	125.37	138.23	168.77
Leg Length (cm)	46.78	53.64	61.94	69.29	82.76
Weight (kg)	16.17	21.43	25.45	32.94	63.72
Shoulders (cm)	49.90	60.28	44.91	66.83	48.26
Waist (cm)	86.60	105.63	83.42	114.39	78.55
Ponderal Index	15.37	14.29	12.88	12.33	13.21
Shoulder/Waist	0.57	0.58	0.55	0.60	0.62

As a preliminary step, the sensory and anthropometric factors were intercorrelated to assess their respective collinearity; Tables 5 and 6 display these correlations. Unsurprisingly, there were no significant correlations across the sensory codes (Table 5), with strong correlations between the two coding regimens within each sensory input[b]. Correlations for anthropometric variables (Table 6), both aggregated across all participants, and within individual age groups, reveals that, for the aggregated data, there were (again unsurprising) strong correlations between body size variables (height, leg length, weight) and body dimension variables (shoulder width, waist width, Ponderal Index, and shoulder/waist ratio). More surprisingly, body size and body dimension were also correlated, a finding at odds with previous developmental work[12], but not with adult findings[13]. One explanation is that these correlations were driven by overall anthropometric increases across the wide age range of the data set. Supporting this idea, within the individual age groups body size variables were generally unrelated to body dimension factors (excepting the 3- to 5-year-olds and adults).

Table 5. Intercorrelations Between the Sensory Codes

	Visual DS	Haptic P/A	Haptic DS	Proprioceptive P/A	Proprioceptive DS
Visual P/A	.899****	-.144	-.135	.125	.113
Visual DS		.000	.000	.000	.000
Haptic P/A			.937****	.000	.000
Haptic DS				-.135	-.123
Proprioceptive P/A					.906****

P/A: Present / Absent Coding; DS: Degree of Stability Coding
**** $p < .001$

The principal analysis for this investigation involved using multiple regression to predict postural stability from the two multisensory input codes and the anthropometric factors[c]. For the anthropometric factor, participants' heights were employed. Although body weight is more common when examining anthropometric influences on posture, such work typically focuses on obesity and balance[29]. Given that no measure of obesity was gather in these studies, and that height and weight were strongly related, height seem the more optimal variable in this case.

[b] Schmuckler[11] contained four conditions, Schmuckler and Tang[6] contained eight conditions, and Cheung & Schmuckler[12,13] contained 16 conditions; accordingly, there were 28 unique sensory code combinations across these studies. Thus, the sensory code intercorrelations were calculated based on these 28 unique combinations. Additionally, because Cheung and Schmuckler[12,13] employed both stable and unstable LFC conditions, intercorrelations could be calculated employing high stability (stable touch) or medium stability (unstable touch) quantifications. In fact, there is little difference in intercorrelations as a function of high versus medium stability coding. Accordingly, for simplicity, Table 5 shows the correlations employing the stable touch codes for the degree of stability measures.
[c] The application of multiple regression for these analyses could produce a variety of concerns, including issues regarding the non-independence of sets of dependent variables arising from including values across all conditions for each participant in each study, or that what might be considered ordinal (or at best interval) data are being employed in parametric procedures. With regards to the first issue, although the non-independence of data is simply a fact in this analysis, the principal issue regarding independence typically centers on the independent variables. In contrast, for dependent variables, the primary issue is generally whether these values are representative of the population involved. Based on these criteria, the issue of non-independence simply does not seem a serious concern for this analysis. With respect to the second issue, although it is axiomatically assumed that ordinal data should not be analyzed with parametric procedures, the years have actually witnessed a lively debate regarding this issue. Concerns regarding the use of such procedures have been allayed by noting that applying different scoring systems seldom produce critical differences in interpretations of results, and that one can look at the assignment of integers to ordinal data simply as monotonic transformations, analogous to procedures such as log or square root transformations (see Mangalindan et al[28] footnote 2, for a general discussion of this issue).

Table 6. Intercorrelations Between Anthropometric Measures

	Height	Leg Length	Weight	Shoulders	Waist	Ponderal	SW Ratio
All Participants							
Age	.928***	.810***	.901***	-.111	-.181*	-.246****	.191*
Height		.917****	.933****	-.022	-.077	-.373****	.182*
Leg Length			.852****	-.008	-.046	-.366****	.147
Weight				-.063	-.110	-.060	.137
Shoulders					.858***	-.116	.318****
Waist						-.087	-.179*
Ponderal							-.132
3- to 5-Year-Olds							
Age	.649****	.207	.444***	.242	.249	-.472***	.032
Height		.446***	.810**	.415*	.430*	-.594****	.121
Leg Length			.404**	.403*	.382*	-.218	.275
Weight				.425*	.452*	-.032	.072
Shoulders					.938****	-.190	.458*
Waist						-.187	.140
Ponderal							-.114
5- to 7-Year-Olds							
Age	.627****	.559****	.364*	.074	.029	-.422***	.108
Height		.861****	.709****	.091	.183	-.616****	-.131
Leg Length			.519****	-.049	-.001	-.667****	-.053
Weight				-.120	-.025	.089	-.196
Shoulders					.858****	-.243	.298
Waist						-.259	-.225
Ponderal							-.042
7- to 9-Year-Olds							
Age	.570***	.618****	.280	-.059	.034	-.387*	-.128
Height		.855****	.722****	.157	.185	-.323	.007
Leg Length			.611****	.135	.080	-.293	.084
Weight				.082	.057	.411*	.101
Shoulders					.794****	-.095	.420*
Waist						-.158	-.155
Ponderal							.106
9- to 11-Year-Olds							
Age	.581***	.565***	.381	.068	.380	-.087	-.468*
Height		.809****	.820****	.218	.340	.152	-.157
Leg Length			.658****	.138	.325	.099	-.300
Weight				.047	.107	.685****	-.078
Shoulders					.815**	-.199	.342
Waist						-.225	-.257
Ponderal							.022
Adults							
Age	.118	-.151	.110	-.377***	-.266*	.067	-.079
Height		.642****	.606****	.474****	.393***	-.180	.012
Leg Length			.463****	.382***	.499****	-.030	-.162
Weight				.597****	.815****	.665****	-.399***
Shoulders					.643****	.317*	.211
Waist						.664****	-.598****
Ponderal							-.512****

* p < .05; ** p < .01; *** p < .005; **** p < .001

Figure 1 presents the results of the predictive models, displaying the multiple Rs, and graphing the standardized beta coefficients for the sensory codes for both coding schemes, along with participants’ height. These analyses were conducted separately for the individual age groups, as well aggregating across age. Most fundamentally, the multisensory inputs and anthropometric factors successfully predicted postural sway in the aggregate, and within the individual age groups. Of course, this result is expected given that these factors produced significant effects in their original publications. More interestingly, the predictive power of these factors increased across age, producing increasing multiple Rs across age groups. Counter-intuitively, although previous work highlights 5- to 7-years as a transition period in the adoption of adultlike posture, based on these patterns there is no qualitatively discernible distinction in predicting postural stability beginning at this age range. Rather, developmental change in stability follows a more linear, quantitative path.

Also notable are the findings with respect to the two sensory coding systems. Cutting across these two systems is the fact that both successfully modelled postural sway, producing the same pattern of fits and relative weights for the various factors. Distinguishing these coding schemes, there clearly was advantageous explanatory power for the more nuanced degrees of stability coding system, relative to the presence versus absence coding system. To this author’s knowledge, this is one of the first attempts to quantitatively assess the degree to which a given sensory input provides differentiated input for postural maintenance. As such, the evidence for objectively quantifying the degree of postural stability offered by a given sensory input, and the subsequent impact on balance predicted by this quantification is an important contribution. One consequence of this result is the implication for greater precision in describing postural control experiments, including the exact nature of the sensory input, how such information contributes to stability, and so on. As an example, Cheung and Schmuckler’s[12,13] proprioceptive manipulations varied the area of participants’ base of support along fore-aft and mediolateral dimensions. Such variation is quantifiable, and produces different predictions of body sway in fore-aft and mediolateral body axes. Thus, attending to multisensory input on these levels provides a nuanced characterization of balance control.

Most centrally, this work successfully quantified the weighting of sensory components and anthropometric factors for balance across age. Interestingly, of the sensory inputs, proprioceptive information emerged as the most heavily weighted factor impacting balance. Furthermore, this predominance of proprioception became stable by 5- to 7-years, the age range at which multiple researchers have indicated the adoption of adult-like postural control by children. In contrast, visual and haptic inputs were of lesser, and relatively equivalent import, with a slightly greater weight for vision. This pattern also stabilizes at 5- to 7-years, further highlighting this age as a transition point in postural development.

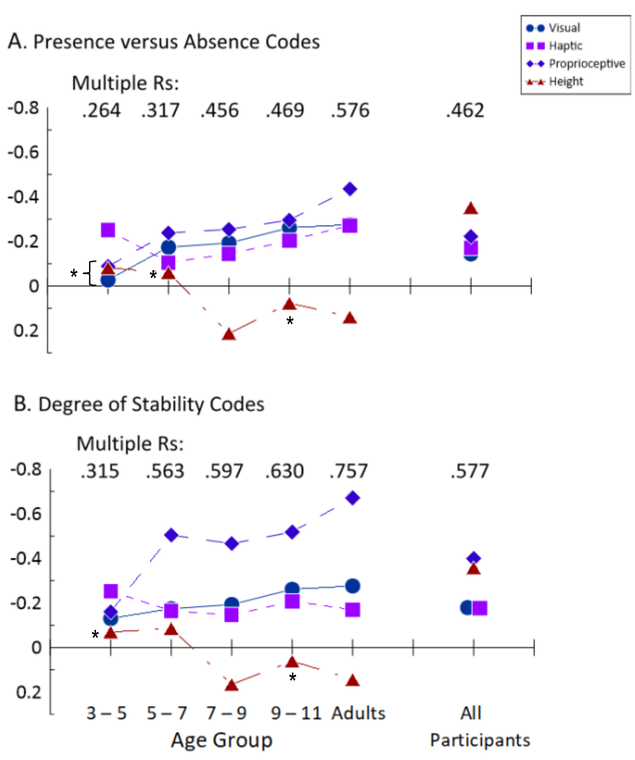

Figure 1. Multiple Rs and beta weights for visual, haptic, proprioceptive, and height factors, for the presence versus absence sensory code (A), and the degree of stability sensory code (B). Non-significant correlations/beta weights are indicated with an “*”.

This quantification of sensory inputs across developmental time is, undoubtably, one of the central findings of this work, and in fact formed the raison d’etre for this study. And the fact that proprioceptive input, operationalized as varying stance widths, was the most consistently influential factor on balance raises a multitude of questions. For instance, given this result, it clearly becomes of interest to further expand the type of proprioceptive manipulations within a multisensory context[30]. By far, the most common proprioceptive manipulation involves vibration of the Achilles tendon[30], although support surface rigidity[31], wedge standing[32], ankle dorsi and plantar flexion[33] manipulations have also been used. Unfortunately developmental using such methods is reasonable scarce (but see [34]). Accordingly, employing a wider range of proprioceptive manipulations, and tracking the developmental relations between such variation and other sensory manipulations would be extremely informative.

Another question involves why, among these multisensory components, participants become increasing reliant on proprioceptive input? One characteristic distinguishing proprioception is that it is body-centered, and thus generally consistent across environments (leaving aside ground surface variations). Given its inherent body-centered nature, it is thus unsurprising that the weighting of proprioceptive input is the most delineated. Because major shifts in body size have long since ended by young adulthood, one might anticipate seeing a principal emphasis on a body-centric factor by this age.

In terms of participant height, with respect to the individual age groups, (relatively) early in life (3- to 5-years and 5- to 7-years), height and balance were positively associated. However, this relation reversed once participants achieved adult-like balance, with increasing height related to decreased postural stability. In explaining this pattern, Cheung and Schmuckler[12,13] argued that, early in life, this positive relation reflected the role of height as a proxy for increasing motor maturity, including both physical and experiential components. As children age and gain better control of their bodies, with this maturity roughly indexed by height, balance control improves. Once children achieve a stable level of motor skill, the relation between height and balance inverts, with taller participants less stable than shorter participants. Although counter-intuitive, this result is predictable based on inverted pendulum models of balance[35].

Also notable is that height generally had a weaker impact than the sensory factors. Upon reflection, this relation is understandable. Body size changes slowly across the lifespan (excepting growth spurts), and hence provides opportunities for adaptation to their relative impacts. In contrast, sensory input changes continually depending on environmental conditions, even potentially on a moment by moment basis. Accordingly, it makes sense for the postural system to downweight anthropometric factors.

Expanding beyond the context of multisensory and anthropometric factors, the current findings align with the “multicomponential” view of balance control described earlier. As suggested, this multicomponential view is conceptually related to systems approaches[21,22] in which complex behaviors are the emergent property of a set of component systems changing over development. Such approaches have provided compelling explanatory frameworks for motor behavior[36], cognitive skills[37], and social abilities[38], among others

Of course, this framework raises the question of what other factors may play a role in postural control. One possibility involves social and/or interpersonal influences. Previous research has demonstrated that interpersonal factors can drive coordinated postural movements between actors[39,40]. For example, working with elderly adults, Johanssen et al.[39] found that interpersonal light touch reduced postural sway, with a modestly significant 0 phase lag correlation in sway. Such findings highlight the compellingness of interpersonal interaction as an arena for additional research.

Despite the positive contributions of this work, some limitations to this approach should be acknowledged. One issue is that, regardless of the previously discussed advantages of using individual participant data, these findings were nevertheless derived from only a small set of studies. Along with statistical issues (see note c), it would be simply reassuring to see these results expanded by including additional experimental contexts. Similarly, given the goal of charting the changing influences on balance of a swath of component processes, the age group categorizations employed (2 year groupings) seems a bit gross for a fine-grained developmental analysis. And finally, although remarkably flexible, the dummy coding approach might be considered too reductionistic, potentially losing critical information regarding the components investigated. In response to these issues, the first two concerns are addressed relatively straightforwardly by the inclusion of additional data across multiple experiments, environments, and components. As for the concern about reductionism, the ultimate efficacy of any framework is adjudged by its ability to adequately characterize the empirical findings at hand. In this case, future work will either support the power of this approach, or call its fundamental tenets into question.

In conclusion, this study provides a compelling proof of the power of approaches such as meta-regression to explore complex domains of motor functioning. This work has provided quantifiable insight into the relative impacts of multisensory and anthropometric factors, and how such influences vary across developmental time. These results have implications for processes such as sensory reweighting across developmental time, and potentially in real time experimental contexts. And finally, this analysis has important theoretical implications, highlighting the need for an expansion of multisensory frameworks to more global multicomponential characterizations. Future work can only add to the power of this approach, providing additional experimental manipulations, resulting in more refined and delineated developmental models of balance.

REFERENCES

1. Lee DN, Aronson E. Visual proprioceptive control of standing in human infants. *Percept Psychophys.* 1974;15:529-532. doi: 10.3758/BF03199297.
2. Rougier P. The influence of having the eyelids open or closed on undisturbed postural control. *Neurosci Res.* 2003;47:73-83. doi: 10.1016/s0168-0102(03)00187-1.
3. Jeka JJ, Lackner JR. Fingertip contact influences human postural control. *Exp Brain Res.* 1994;100:495-502. doi: 10.1007/bf02738408.
4. Ross JM, Balasubramaniam R. Auditory white noise reduces postural fluctuations even in the absense of vision. *Exp Brain Res.* 2015;233:2357-2363. doi: 10.1007/s00221-015-4304-y.
5. Njiokiktjien CJ, Van Parys JaP. Romberg's sign expressed in a quotient. II. Pathology. *Agressologie.* 1976;17,D:19-24.
6. Schmuckler MA, Tang A. Multisensory factors in postural control: Varieties of visual and haptic effects. *Gait & Posture.* 2019;71:87-91. doi: 10.1016/j.gaitpost.2019.04.018.
7. Stoffregen TA, Schmuckler MA, Gibson EJ. Use of central and peripheral optical flow in stance and locomotion in young walkers. *Perception.* 1987;16:113-119. doi: 10.1068/p160113.
8. Schmuckler MA, Gibson EJ. The effect of imposed optical flow on guided locomotion in young walkers. *Brit J of Devel Psychol.* 1989;7:193-206. doi: 10.1111/j.2044-835X.1989.tb00800.x.
9. Schmuckler MA. Children's postural sway in response to low and high frequency information for oscillation. *J Exp Psychol Hum Percept Perform.* 1997;23:528-545. doi: 10.1037/0096-1523.23.2.528.
10. Stoffregen TA. Flow structure versus retinal location in the optical control of stance. *J Exp Psychol Hum Percept Perform.* 1985;11:554-565. doi: 10.1037/0096-1523.11.5.554.
11. Schmuckler MA. Postural response to predictable and non-predictable visual flow in children and adults *J Exp Child Psychol.* 2017;163:32-52. doi: 10.1016/j.jecp.2017.06.005.
12. Cheung TCK, Schmuckler MA. Multisensory and biomechanical influences on postural control in children. *J Exp Child Psychol.* 2024;238:105796. doi: 10.1016/j.jecp.2023.105796.
13. Cheung TCK, Schmuckler MA. Multisensory postural control in adults: Variation in visual, proprioceptive, and somatosensory inputs. *Hum Move Sci.* 2021;79:102845. doi: 10.1016/j.humov.2021.102845.
14. Barela JA, Jeka JJ, Clark JE. Postural control in children. Coupling to dynamic somatosensory information. *Exp Brain Res.* 2003;150:434-442. doi: 10.1007/s00221-003-1441-5.
15. Creath R, Kiemel T, Horak FB, Peterka RJ, Jeka JJ. A unified view of quiet and perturbed stance: Simultaneous co-existing excitable modes. *Neurosci Lett.* 2005;377:75-80. doi: 10.1016/j.neulet.2004.11.071.
16. Assländer L, Peterka RJ. Sensory reweighting dynamics following removal and addition of visual and proprioceptive cues. *J Neurophysiol.* 2016;116:272-285. doi: 10.1152/jn.01145.2015.
17. Mcgraw B, Mcclenaghan BA, Williams HG, Dickerson J, Ward DS. Gait and postural stability in obese and non obese prepubertal boys. *Arch Phys Med Rehabil.* 2000;81:484-489. doi: 10.1053/mr.2000.3782.
18. Hue O, Simoneau M, Marcotte J, Berrigan F, Doré J, Marceau P, et al. Body weight is a strong predictor of postural stability. *Gait & Posture.* 2007;26:32-38. doi: 10.1016/j.gaitpost.2006.07.005.
19. Zemková E. Sport-specific balance. *Sports Med.* 2014;44:579-590. doi: 10.1007/s40279-013-0130-1.
20. Bhati P, Cheung TCK, Sithamparanathan G, Schmuckler MA. Striking a balance in sports: The interrelation between children's sports experience, body size, and posture. *AIMS Neuroscience.* 2022;9:288-302. doi: 10.3934/Neuroscience.2022016.
21. Perone S, Simmering VR. Applications of dynamic systems theory to cognition and development: New Frontiers. *Adv Child Dev Behav.* 2017;52:43-80. doi: 10.1016/bs.acdb.2016.10.002.
22. Thelen E, Smith LB. Dynamic systems theory. In: Lerner RM, Damon W (eds). *Handbook of child psychology: Theoretical models of human development*. New York: John Wiley & Sons; 2006:pp.258-312.
23. Polastri PF, Barela JA, Kiemel T, Jeka JJ. Dynamics of inter-modality re-weighting during human postural control. *Exp Brain Res.* 2012:99-108. doi: 10.1007/s00221-012-3244-z.
24. Riach CL, Hayes KC. Maturation of postural sway in young children. *Dev Med Child Neurol.* 1987;29:650-658. doi: 10.1111/j.1469-8749.1987.tb08507.x.
25. Shumway-Cooke A, Woollacott MJ. The growth of postural stability: Postural control from a developmental perspective. *J Motor Beh.* 1985;17:131-147. doi: 10.1080/00222895.1985.10735341.
26. Baker WL, White CM, C. CJ, Kluger J, Coleman CI. Understanding heterogeneity in meta-analysis: The role of meta-regression. *The International Journal of Clinical Practice.* 2009;63:1426-1434. doi: 10.1111/j.1742-1241.2009.02168.x.
27. Raymakers JA, Samson MM, Verhaar HJJ. The assessment of body sway and the choice of the stability parameter(s). *Gait & Posture.* 2005;21:48-58.
28. Mangalindan DMJ, Schmuckler MA, Li S-A. The impact of object carriage on independent locomotion. *Inf Beh and Dev.* 2014;37:76-85. doi: 10.1016/j.infbeh.2013.12.008.

29. Meng H, Gorniak SL. Effects of adiposity on postural control and cognition in older adults. *Gait & Posture.* 2020;82:147-152. doi: 10.1016/j.gaitpost.2020.09.004.
30. Goodman R, Tremblay L. Using proprioception to control ongoing actions: Dominance of vision or altered proprioceptive weighing? *Exp Brain Res.* 2018;236:1897-1910. doi: 10.1007/s00221-018-5258-7.
31. Schut IM, Engelhart D, Pasma JH, Aarts RGKM, Schouten AC. Compliant support surfaces affect sensory reweighting during balance control. *Gait & Posture.* 2017;53:241-247. doi: 10.1016/j.gaitpost.2017.02.004.
32. Ganesan M, Lee Y-J, Aruin AS. The effect of lateral or medial wedges on control of postural sway in standing. *Gait & Posture.* 2014;39:899-903. doi: 10.1016/j.gaitpost.2013.11.019.
33. Song Q, Zhang X, Mao M, Sun W, Zhang C, Chen Y, et al. Relationship of proprioception, cutaneous sensitivity, and muscle strength with the balance control among older adults. *Journal of Sport and Health Science.* 2021;10:585-593. doi: 10.1016/j.jshs.2021.07.005.
34. Mckay SM, Wu J, Angulo-Barroso RM. Effect of Achilles tendon vibration on posture in children. *Gait & Posture.* 2014;40:32-37. doi: 10.1016/j.gaitpost.2014.02.002.
35. Winter DA. *Biomechanics and motor control of human movement (4th Edition)*. 4th Edition ed. Hoboken, NJ: John Wiley; 2009.
36. Spencer JP, Vereijken B, Diedrich FJ, Thelen E. Posture and the emergence of manual skill. *Devel Sci.* 2000;3. doi: 10.1111/1467-7687.00115.
37. Clearfield MW, Dineva E, Smith LB, Diedrich FJ, Thelen E. Cue salience and infant perseverative reaching: Tests of the dynamic field theory. *Devel Sci.* 2009;12:26-40.
38. Fogel A. Dynamic systems research on interindividual communication: The transformation of meaning making. *Journal of Developmental Processes.* 2006;1:7-30.
39. Johanssen L, Guzman-Garcia A, Wing AM. Interpersonal light touch assists balance in the elderly. *J Motor Beh.* 2009;41:397-399.
40. Johanssen L, Wing AM, Hatzitaki V. Contrasting effects of finger and shoulder interpersonal light touch on standing balance. *J Neurophysiol.* 2011;107:215-225. doi: 10.1152/jn.00149.2011.

Citation: Schmuckler MA. (2024). Quantifying the weights of sensory influences on postural control across development. *Brazilian Journal of Motor Behavior*, 18(1):e430.

Funding: The research discussed in this manuscript, as well as the manuscript preparation, was funded by NSERC Discovery Grant awarded to M. A. Schmuckler.
Competing interests: The authors have declared that no competing interests exist.
DOI: https://doi.org/10.20338/bjmb.v18i1.430