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Large reaching datasets quantify the impact of age, sex/gender, and experience on motor control

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As we age, our movements become slower and less precise—but the extent of this decline remains unclear. To address this, we harmonized data from 2390 participants across four published studies using a standard center-out reaching task. We found that older age was associated with a steady decline in reaction time (–1.3 ms/year), movement time (–4.3 ms/year), and movement precision (–0.04°/year). Although the rate of decline did not differ by sex/gender, females consistently reacted more slowly (–6.4 ms), moved more slowly (–44.6 ms), and exhibited greater precision (+ 0.6°) across the adult lifespan. Using the dataset that included experiential measures, we found that sex/gender differences were markedly reduced once factors, such as video game use, daily computer usage, and daily sleep, were taken into account, whereas age remained a consistent predictor of motor decline. Together, these findings provide a large-scale examination of age, sex/gender, and experiential effects on motor control, offering a normative benchmark to inform future clinical interventions aimed at preserving motor function across the lifespan.

As we get older, our movements become slower and less precise[1–9]. But exactly how much remains unclear for several reasons. First, many studies on age-related slowing rely on simple reaction time tasks, typically measured by the speed of button presses[2,5–7,10–12]. Given that these tasks place minimal demands on precision and often conflate distinct components of motor control (e.g., reaction time and movement time), they offer only a narrow view into the impact of aging on motor performance.

Second, many studies of age-related slowing rely on complex psychophysical tasks that impose substantial cognitive demands on participants. For instance, older adults often move more slowly and less precisely when continuously tracking a moving target[4,13–16]. However, these tasks tap into more than just motor control—they may require sustained attention, working memory, and the ability to predict the target's motion[17–21]. This makes it unclear whether the age-related deficits arise from challenges in deciding where to move, or from executing the movement itself[22–25].

Third, studies using simple center-out reaching tasks—a standard method for quantifying motor control—often lack the statistical power to detect an age-related effect. Typically, these studies are conducted in person with highly precise motion-sensing equipment but include fewer than 100 participants (10 individuals/decade); most studies divide people into arbitrary "young" and "old" categories[26–29], often with fewer than 20 participants per group, ignoring how age may impact motor performance across the continuous lifespan.

Compounding this issue, most studies have overlooked the contributions of sex/gender and experience on motor performance. Evidence for sex/gender differences is controversial: some studies report faster and more precise movements in men compared to women[1,6,11,30], whereas other studies find the opposite pattern[4,10,31,32]. Moreover, experiential factors—such as video game experience, sleep, handedness, input device (mouse vs. trackpad), computer use, and visual acuity—have not been systematically examined. Neglecting these factors is problematic not only because they may shape the neural and behavioral foundations of motor control[11,30,31,33], but also because they may mediate or even mask observed effects of age and sex/gender[34,35].

To fill this gap, we re-analyzed data from 2390 participants across four published studies using a standard center-out reaching task—yielding a large dataset of its kind. Leveraging Bayesian multilevel modeling, we quantified the effects of aging (as a continuous variable) and sex/gender on reaction time, movement time, and movement precision. Additionally, in the one dataset that included experiential factors ($n = 1228$), we examined whether variables, such as video game experience, sleep, handedness, input device (mouse vs. trackpad), computer use, and visual acuity, also influenced

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Table 1 | Summary of the four datasets included in our reanalysis

Feature/study	1. Coderre et al.[36]	2. Tsay et al.[37]	3. Ruitenberg[32] et al.	4. Shafto et al.[38]
N	632	1228	212	318
Age	43.3 [19.8, 80]	29.6 [18, 74]	38.7 [20, 65.7]	54.4 [22, 84.1]
Sex/gender (F:M)	355:277	622:606	108:104	160:158
Location	Canada	USA	The Netherlands	UK
Apparatus	Robotic manipulandum	Trackpad/mouse	Dual-axis joystick	Stylus
Number of targets	4 or 8	1	8	4
Average trials	45	20	8	24
Target distance (cm)	5	6	5	5
Reaction time (ms)	316.4 [229.8, 492.6]	270.1 [128.8, 470.5]	516.4 [346, 726.8]	312.6 [258.9, 405.4]
Movement time (ms)	1063.3 [764.6, 1480.2]	233 [46.7, 932.4]	190.9 [67.6, 574.4]	414.9 [305.7, 560.2]
Movement angle SD (°)	6.5 [1.1, 25.8]	4.3 [1.3, 9.6]	4.2 [2.1, 8.2]	11.1 [4.3, 33]

Each dataset varied in sample size (*N*), participant demographics (age, sex/gender), geographic location of data collection, experimental apparatus, and task parameters. Apparatus ranged from robotic manipulanda to consumer input devices (e.g., mouse, joystick, and stylus). Key task features—including number of targets, target distance, average number of trials per participant, and average performance metrics (reaction time, movement time, and movement precision measured as the standard deviation of movement angle)—are listed for each study. Values are reported as means [95% range of the sample]. Note that Coderre et al.[36] was part of a larger dataset from the LIMB lab, led by Stephen Scott, and obtained via personal communication. The data were collected using a combination of Kinarm exoskeleton and endpoint robots. Distributions of age, sex/gender, reaction time, movement time, and movement angle SD are plotted in the Supplementary Material (A) in Fig. S1A, B.

motor control. We hypothesized that aging would be associated with slower and less precise movements, while remaining agnostic about the influence of sex/gender and experiential variables. Together, these findings offer a large-scale characterization of motor control across age and sex/gender, establishing a normative benchmark to guide future clinical interventions aimed at preserving motor function across the adult lifespan.

Methods

Study identification

To examine the impact of aging and sex/gender on motor control, we identified published datasets that met five strict inclusion criteria: (1) the study used an upper-extremity center-out reaching task, a canonical paradigm in motor control research. (2) The study treated age as a continuous variable to capture gradual changes over the lifespan. (3) The study compared performance across sex/gender. (4) The study included all three key performance measures of motor control—reaction time, movement time, and movement precision (standard deviation of movement angle). These measures did not need to be explicitly reported in the original manuscript but had to be available in the raw data. (5) The study had a sample size of at least 100 participants, ensuring at least 10 individuals per decade for the analysis of age effects. Our search identified four datasets (Table 1[32,36–38]).

Ethical consideration

The four studies included were conducted under corresponding institutional ethics approval: (1) Queen's University, Providence Care, and the University of Calgary (study 1); (2) UC Berkeley Committee for Protection of Human Subjects, 2016-02-8439 (study 2); (3) Psychology Research Ethics Committee, Leiden University with consent obtained from participants or parents/guardians for minors (study 3); and (4) the local ethics committee, Cambridgeshire 2 Research Ethics Committee (reference10:/H0308/50), in accordance with the Declaration of Helsinki (study 4). Written informed consent was obtained from all participants in each of the four original studies, as approved by the respective institutional ethics committees.

Our reanalysis was not preregistered and relied exclusively on anonymized data obtained through public repositories or data-sharing agreements; no new data were collected. Ethical approval for reanalysis and public dissemination of all code and datasets was granted by Carnegie Mellon University. Sex/gender was self-reported in the original studies, which did not differentiate between sex and gender identity; accordingly, we use the combined term "sex/gender" throughout. Data on race or ethnicity were not collected in any of the four datasets.

General procedure

Each study followed a similar center-out reaching protocol (Fig. 1A, B). An example protocol is provided below from[37]: all participants used their own laptop or desktop computer to access the webpage that hosted the experiment (see a demo of the task at https://multiclamp-c2.web.app/). The participants made reaching movements by moving the computer cursor with their mouse or trackpad (Fig. 1A, B). The size and position of stimuli were scaled based on each participant's screen size. For ease of exposition, the stimulus parameters reported below are for a typical monitor size of 13 inches (1366 × 768 pixels), and the procedure reported below is for the one-target version of the task.

On each trial, participants executed a planar movement from the center of the workspace to a peripheral target. The start position was marked by a white annulus (0.5 cm diameter), and the target was indicated by a blue circle of the same size, positioned 6 cm away. Each participant was assigned a single target location, randomly selected from eight possible positions (cardinal: 0°, 90°, 180°, and 270°; diagonal: 45°, 135°, 225°, and 315°) and remained consistent throughout the experiment.

To initiate each trial, the participant moved the cursor, represented by a white dot on their screen, into the start location. Once the participant maintained the cursor in the start position for 500 ms, the target appeared. The participant was instructed to reach to the target using the cursor. If the movement was not completed within 500 ms, the message "too slow" was displayed in red 20-point Times New Roman font at the center of the screen for 750 ms. The visual cursor was always provided as feedback throughout the entire movement. While all four studies employed a similar center-out reaching procedure, they differed in sample size, apparatus, demographics, and geographical location, as summarized in Table 1.

Data pre-processing

We applied the following exclusion criteria: (1) excluded samples with missing demographic information; (2) restricted the sample to individuals aged 18 and older to isolate aging effects and minimize developmental influences; and (3) excluded individuals with a history of neurological or psychiatric disorders. No participants were excluded based on vision status, as all were able to see the visual stimuli required to complete the reaching task. After preprocessing, we retained 632 of 638 samples from Coderre et al.[36] (part of a larger dataset from the LIMB lab led by Stephen Scott acquired via personal communication), 1228 of 2282 from Tsay et al.[37] 212 of 385 from Ruitenberg et al.[32], and 318 of 318 from Shafto et al.[38] (also published in a subsequent study from the Cam-CAN center[39]), yielding a final sample of 2390 unique participants.

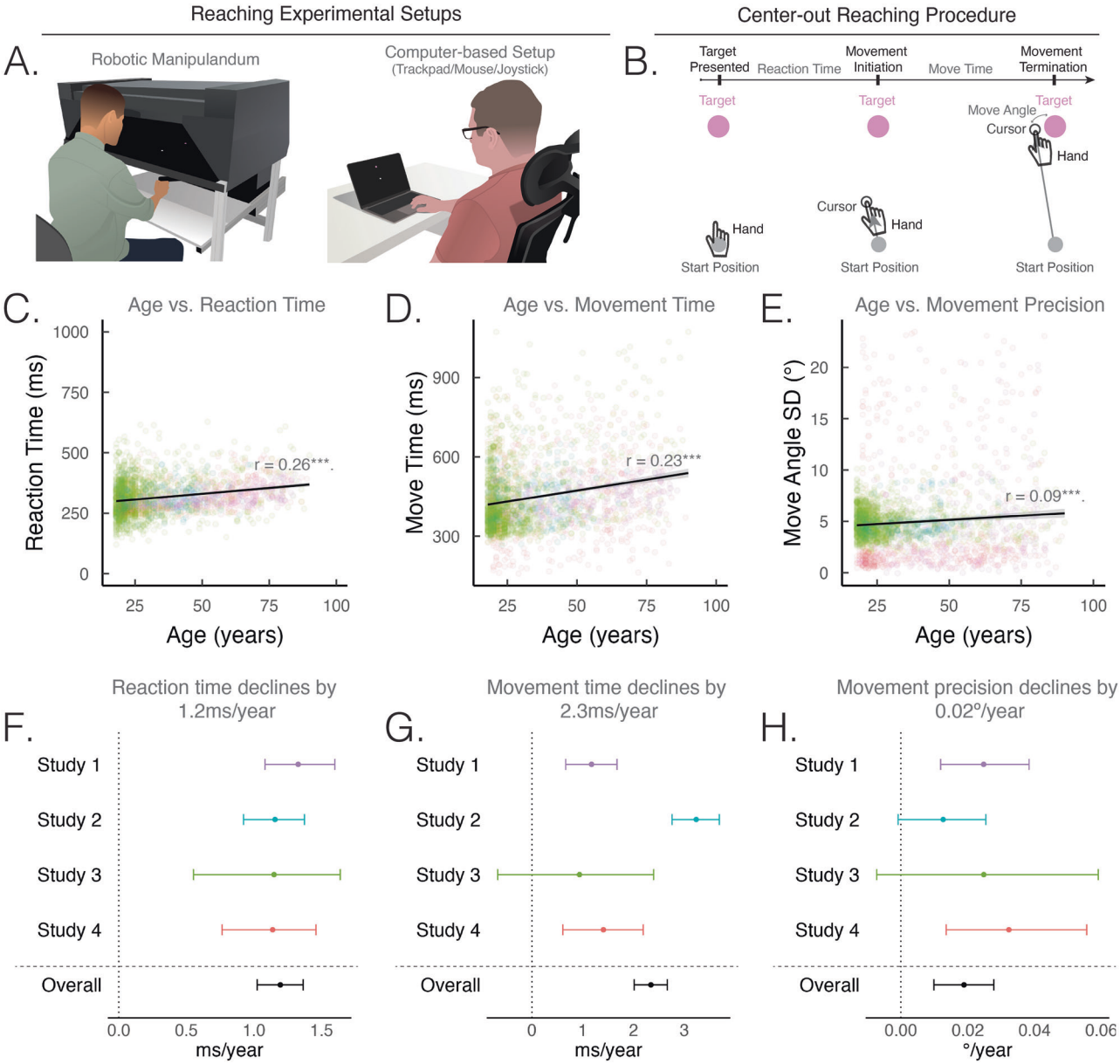

Fig. 1 | Motor control declines gradually with age. A Experimental setup from four large-scale reaching datasets. **B** In a standard center-out reaching task, a visual target appears (pink circle), prompting participants to initiate a movement. The trial terminates when the visual cursor (black circle) crosses the target distance. Reaction time is defined as the delay from target onset to movement initiation; movement time as the time from movement onset to target crossing; movement angle as the angle of the hand at target crossing; and movement precision as the standard deviation of movement angle across trials. Reaction time (**C**), movement time (**D**), and movement precision (**E**) all exhibit a gradual decline with age. To enhance cross-study comparability and visualization, we normalized each dependent variable by subtracting its study-specific mean and adding the grand mean across all datasets. This approach aligns the scales while preserving meaningful between-group differences. **F**–**H** Bayesian estimates of the effect of aging on motor control. Dot denotes the mean posterior estimate; error bars denote the 95% credible interval of the posterior distribution. Positive values reflect increases in reaction time, movement time, and movement precision, after accounting for study-level differences. Statistics are based on $n = 2390$ participants across four datasets (study 1 = 632, study 2 = 1228, study 3 = 212, and study 4 = 318).

Dependent variables

To examine how aging affects motor control, we analyzed three key variables: reaction time, movement time, and movement precision (quantified as the standard deviation of hand angle across trials). Reaction time was defined as the interval from target appearance to movement initiation. Movement time spanned from movement initiation to termination. Movement angle was measured as the cursor's angular deviation from the target at the moment it crossed the target radius. Only baseline trials (prior to any adaptation) were analyzed to assess pure motor control.

Study characteristics—such as movement distance and number of targets—can influence overall performance: longer distances typically increase movement times, and more targets can slow reaction times. Variations in movement onset definitions and apparatus further contribute to differences in absolute performance levels across studies. However, our primary interest lies not in these raw values—the study-specific intercepts—but in how performance changes with age, reflected in the slope of these relationships. Since methodological differences are unlikely to systematically vary with age, they should not bias age-related trends. Additionally, our hierarchical Bayesian approach explicitly models study-level variability,

allowing us to harmonize data across studies and enhance the robustness and generalizability of our conclusions.

Bayesian multilevel modeling

We used a hierarchical Bayesian statistical model to harmonize our four datasets. Our model includes the following parameters:

Overall (population-level) intercept: $\alpha \sim \mathrm{N}(500, 500)$.
Overall age effect: $\beta_{\mathrm{Age}} \sim \mathrm{N}(0, 20)$.
Overall sex/gender effect: $\beta_{\mathrm{Sex/Gender}} \sim \mathrm{N}(0, 100)$.
Residual overall error (σ): $\sigma \sim \mathrm{Ca}(0, 100)$.
Study-specific intercepts: $u_{\alpha,\mathrm{j}} \sim \mathrm{N}(0, \sigma_{\alpha}^2)$.
Study-specific age effects: $u_{\beta_{\mathrm{Age}},\mathrm{j}} \sim N(0, \sigma_{\beta_{\mathrm{Age}}}^2)$.
Study-specific sex/gender effects: $u_{\beta_{\mathrm{Sex/Gender}},\mathrm{j}} \sim N(0, \sigma_{\beta_{\mathrm{Sex}}}^2)$.
Residual error of study-specific intercepts: $\sigma_{\alpha,\mathrm{j}} \sim \mathrm{Ca}(0, 500)$.
Residual error of study-specific age effects: $\sigma_{\beta_{\mathrm{Age}},\mathrm{j}} \sim \mathrm{Ca}(0, 2.5)$.
Residual error of study-specific sex/gender effects: $\sigma_{\beta_{\mathrm{Sex}},\mathrm{j}} \sim \mathrm{Ca}(0, 20)$.

These priors are chosen to be weakly informative so that the data drive the inference with reasonable constraints[40–42]. Data distribution was assumed to be normal, but this was not formally tested. We tested alternative priors, and the pattern of results remained consistent. j here denotes the index of the study each observation is associated with, where n is the index of the individual observation. N denotes a normal distribution, and Ca denotes a half Cauchy distribution. With the parameters, our multilevel Bayesian model is defined as follows:

$$\widehat{Response}_n = \alpha + u_{\alpha}, j + \left(\beta_{\mathrm{Age}} + u_{\beta_{\mathrm{Age}},j}\right) \cdot \mathrm{Age}_n + \left(\beta_{\mathrm{Sex/Gender}} + u_{\beta_{\mathrm{Sex/Gender}},j}\right) \cdot \mathrm{Sex/Gender}_n + \epsilon_n,$$

where $\epsilon_{\mathrm{n}} \sim \mathrm{N}(0, \frac{\sigma^2}{\sqrt{NTrials_n}})$ represents the residual error. Here, $N\mathrm{Trials}_{\mathrm{n}}$ denotes the number of trials for each participant. We include this term to account for potential effects of differing trial counts across the four experiments (notably, our conclusions do not qualitatively change if this term is removed).

Exploratory analysis of study 2[37]

We conducted a linear Bayesian regression (nonhierarchical) to reanalyze data from study 2[37], incorporating both demographic and experiential variables. In addition to age and sex, the model included: input device (mouse/trackpad: 536/692), handedness (left/right: 108/1120), video game frequency (self-reported Likert scale from −2 to 2, where −2 = strongly disagree and 2 = strongly agree with "I play a lot of video games"; mean [95% sample range]: −0.4 [−2, 2]), daily computer usage (6.8 h [1, 12]), daily sleep (7.1 h [5, 10]), and self-reported vision status (correctable/uncorrectable: 1137/91). These variables were selected since (1) they represent experiential or behavioral factors rather than fixed demographic characteristics, allowing us to examine modifiable influences on motor control, and (2) they were available with sufficient completeness in the dataset. Weakly informative priors were specified as follows:

Intercept: $\alpha \sim \mathrm{N}(0, 100)$.
Age effect: $\beta_{\mathrm{Age}} \sim \mathrm{N}(0, 20)$.
Sex/gender effect: $\beta_{\mathrm{Sex}} \sim \mathrm{N}(0, 50)$.
Handedness effect: $\beta_{\mathrm{Hand}} \sim \mathrm{N}(0, 50)$.
Device effect: $\beta_{\mathrm{Device}} \sim \mathrm{N}(0, 50)$.
Vision effect: $\beta_{\mathrm{Vision}} \sim N(0, 50)$.
Video games frequency effect: $\beta_{\mathrm{Game}} \sim N(0, 50)$.
Sleep effect: $\beta_{\mathrm{Sleep}} \sim N(0, 50)$.
Computer usage effect: $\beta_{\mathrm{Comp}} \sim N(0, 50)$.
Residual error: $\sigma \sim \mathrm{Ca}(0, 25)$.

The prior distributions were chosen to be narrower—though still weakly informative—than those used for models across studies. With these parameters, our Bayesian model is defined as follows:

$$\widehat{Response}_{\mathrm{n}} = \alpha + \beta_{\mathrm{Age}}\mathrm{Age}_{\mathrm{n}} + \beta_{\mathrm{Sex}}\mathrm{Sex}_{\mathrm{n}} + \beta_{\mathrm{Hand}}\mathrm{Hand}_{\mathrm{n}} + \beta_{\mathrm{Device}}\mathrm{Device}_{\mathrm{n}} + \beta_{\mathrm{Vision}}\mathrm{Vision}_{\mathrm{n}} + \beta_{\mathrm{Game}}\mathrm{Game}_{\mathrm{n}} + \beta_{\mathrm{Sleep}}\mathrm{Sleep}_{\mathrm{n}} + \beta_{\mathrm{Comp}}\mathrm{Comp}_{\mathrm{n}} + \epsilon_{\mathrm{n}},$$

Bayesian probability comparison

To assess whether experiential factors mediated the effects of age or sex/gender on motor control, we compared posterior estimates from models with and without experiential covariates. For each posterior draw, we computed the difference in parameter estimates between the two models, yielding a posterior distribution of differences. We then calculated the posterior probability that this difference was greater than zero, expressed as P_{diff}. Values near 0.5 indicate little evidence for a systematic difference between models, whereas values approaching 0 or 1 (equivalently, very high or low $P_{\mathrm{diff}} < 0.05$ or >0.95) indicate stronger evidence that including experiential factors altered the effect.

General model fitting procedure

We implemented our models in Rstan[43]. Stan uses the No-U-turn sampler, an adaptive variant of Hamiltonian Monte Carlo that efficiently explores high-dimensional parameter spaces while avoiding the random walk behavior of traditional MCMC methods[44]. For Bayesian inference, we ran 8000 iterations for each of the four independent chains, discarding the first 4000 iterations per chain as warm-up to ensure convergence, and ensured that all $\hat{R}$ values were close to 1, indicating good model convergence. The large number of iterations ensure that, though we used weakly informative priors, the estimates could still converge to stable posterior distributions. In practice, with such number of iterations, the estimates converge to similar range and effect sizes despite differences in prior distributions. Posterior distributions are presented in Supplementary Material (B) in Figs. S2–4 and Table S2.

Sensitivity analysis

To evaluate whether our dataset was sensitive enough to detect the smallest effects of theoretical interest (SESOI) for age-related changes in motor control, we conducted a one-sided sensitivity analysis[45]. Although no established thresholds define meaningful motor decline with age, we reasoned that everyday performance would be detectably impacted by a slowing greater than 1 ms/year in reaction time (≈50 ms over 50 years), 1 ms/year in movement time, or a 0.005°/year reduction in movement precision. These values defined our SESOI. Based on this criterion, the minimum detectable slopes at 95% power were 0.34 ms/year for reaction time, 1.34 ms/year for movement time, and 0.033°/year for precision—values several times smaller than our SESOI thresholds. Thus, the sensitivity analysis confirms that our dataset was sufficiently powered to detect effects exceeding the SESOI.

Results

We asked a simple but foundational question: how rapidly does motor control decline with age? To answer this, we conducted a re-analysis of four large-scale studies that met several strict inclusion criteria (see "Methods"). These studies yielded a dataset of 2390 participants spanning a wide age range (see Fig. S1; 18–90 years old) and a balanced sex/gender distribution (F/M: 0.52/0.48)—making it one of the richest collections of reaching data to date (Table 1).

We focused on three core indicators of motor control. Reaction time—the delay between target onset and movement initiation-reflects sensorimotor readiness. Movement time—the duration of the movement—indexes the efficiency of motor execution. Movement precision, captured by the standard deviation of movement angle, reflects the consistency/noise of motor output. These measures are captured by center-out reaching tasks, as simple button presses place minimal demands on sensorimotor precision, whereas complex motor tasks often introduce cognitive confounds such as attention, working memory, and decision-making.

As shown in Table 1, reaction time, movement time, and movement precision vary across studies, likely reflecting differences in equipment (Fig. 1A), task protocols (Fig. 1B), and participant sampling. Rather than treat this heterogeneity as unexplainable noise, we leveraged it using Bayesian multilevel regression[46,47], which allowed us to harmonize data across diverse experimental contexts, enabling us to examine the effects of age and sex/gender while properly accounting for study-specific variability. As a result, it yields more precise and generalizable inferences than any single study could provide.

Aging degrades motor control

It is well-known that motor control tends to slow with age—but our dataset quantifies this association with high precision. As shown in Fig. 1C–H, each increase in age was associated with approximately 1.3 ms slower reaction time ([1.1, 1.5], $r = 0.25$ [0.21, 0.28], 4.3 ms longer movement time ([3.5, 5.1]; $r = 0.18$ [0.15, 0.22), and 0.04° reduced movement precision ([0.02, 0.06]; $r = 0.10$ [0.06, 0.14]). Values reflect posterior means and 95% percentile-based credible intervals from our Bayesian multi-level model.

Despite differences in apparatus, settings, and populations (Table 1), the results were remarkably consistent. All four studies showed the same pattern: reaction and movement times increased with age, while precision declined. Notably, this aging pattern persisted even when the largest dataset (study 2) was excluded: older age was associated with increases in reaction time by about 1.6 ([1.3, 1.9]), movement time by 1.7 ms ([1.2, 2.3]), and reductions in precision by 0.05° per year ([0.02, 0.08]), underscoring the robustness of these findings.

Males prioritized speed, whereas females favored precision

As noted in the Introduction, the impact of sex/gender on motor control remains controversial. Leveraging our large, well-powered dataset, we examined these differences with high precision. There were credible sex/gender differences in motor performance: females were associated with 6.4 ms [0.0, 12.8] slower reaction time and 44.6 ms [22.8, 65.5] slower movement time—but were 0.6° [0.01, 1.2] more precise than males (Fig. 2D–F). This pattern hints at a speed-accuracy trade-off: males prioritized speed at the expense of precision, while females favored precision over speed.

Additionally, the impact of aging on motor control did not significantly differ by sex/gender. Specifically, in a model with the interaction term, the credible interval for the interaction crossed zero (0.13 [−0.2, 0.5] for reaction time; −0.15 [−1.35, 1.10] for movement time; −0.03 [−0.1, 0.004] for movement precision). Moreover, adding the interaction term did not significantly alter the main effects of age and sex (see "Methods"; Bayesian probability comparison of posterior distributions denoted as $P_{diff} > 0.05$ and <0.95 for all comparisons). For age, P_{diff} values were 0.64 for reaction time, 0.41 for movement time, and 0.29 for movement precision; for sex/gender, P_{diff} values were 0.59 for reaction time, 0.42 for movement time, and 0.22 for movement precision. These results reinforced that the steady age-related decline in motor control was comparable across sexes/genders. Thus, we used the more parsimonious model, without the interaction term, for reporting and in the following models.

Whereas age effects persisted beyond experience, sex/gender effects were weak and largely experience-driven

Here, we asked how the association between age and sex/gender on motor control is mediated by experience. For instance, older adults may favor different input devices (e.g., mouse vs. trackpad), and males and females often differ in video game exposure[48,49]—both of which can influence motor performance.

To test this, we conducted a follow-up analysis of study 2, the only dataset among the four that included detailed self-reported experiential measures (sleep, computer usage, vision, video game experience, mouse type, and handedness). We evaluated how the posterior probabilities of age and sex/gender effects differed between two models: one including experiential factors and one without[50–52]. We considered experience an important mediator if the posterior estimates for age or sex/gender showed little overlap ($P_{diff} < 0.05$ or >0.95; see "Methods").

Age remained a robust predictor across all motor control variables, even after accounting for experiential factors in our mediation analysis (Fig. 2G–I). Across all three variables, experiential factors exerted no credible influence on age, with substantial overlap in the posterior estimates of the main effects (Table 2). In both models, age continued to predict significant slowing. Taken together, these findings indicate that age exerts a strong influence on motor control, likely reflecting biological changes (e.g., loss of muscle mass, reduced visual acuity) rather than differences in experience.

Sex/gender effects were more mixed (Fig. 2G–I and Table 2). For reaction time, the effect of sex/gender diminished once experiential factors were included, with posterior estimates showing reduced overlap between the two models ($P_{diff} = 0.02$; with experience: 2.1 ms [–6.1, 10.6]; without experience: 18.9 ms [9.5, 28.3]). In contrast, movement time and movement precision were not credibly influenced by experiential factors (movement time: $P_{diff} = 0.24$; with experience: 7.8 ms [–31.9, 47.8]; without experience: 27.5 ms [–9.0, 64.8]; movement precision: $P_{diff} = 0.5$; with experience: –0.1° [–0.8, 0.6]; without experience: –0.09° [–0.7, 0.6]). Indeed, in the Tsay et al.[37] dataset, sex/gender had little impact on motor control, with effects emerging only when all four datasets were aggregated. Taken together, these results suggest that sex/gender differences in motor control are partly attributable to experiential factors, but the effects are weak to begin with.

We uncovered several previously underappreciated experiential influences on motor control (Fig. 2G–I and Table 2). Mouse users responded markedly faster than trackpad users (−43.5 ms [−52.9, −34.1]) while showing comparable movement time (23.0 ms [−16.5, 63.1]) and precision (0.1° [−0.7, 0.8]). Sleep exerted a surprising cost, with each additional hour associated with slower reaction times (3.4 ms/h [0.0, 7.2]). In contrast, heavier computer use was linked to faster movement (−9.1 ms/h [−16.0, −2.3]) but no changes in reaction or precision. Greater video game exposure predicted both faster reactions (−4.4 ms per rating unit [−8.1, −0.8]) and faster movements (−22.4 ms [−38.7, −6.2]) without compromising precision (0.02° [−0.2, 0.3]). Vision also mattered: correctable vision supported superior movement precision (−1.4° [−2.6, −0.1]) with no effect on reaction (2.2 ms [−14.2, 18.9]) or movement speed (2.3 ms [−55.4, 59.7]). Together, these results demonstrate that everyday experiences—from device use to sleep, gaming, and vision—leave a measurable imprint on motor performance, revealing sources of variability often overlooked in studies of motor control.

Discussion

Our findings precisely quantify how motor control changes across the adult lifespan—and how those changes differ by sex/gender and experiential factors. By combining diverse datasets with Bayesian multi-level modeling, we provide a robust and generalizable portrait of motor aging.

How do our estimates compare with smaller-*N* studies not included in our analysis?

To contextualize our findings, we extracted age-related changes in reaction and movement times from published reaching and aiming studies meeting two criteria: (1) the task involved discrete reaching movements, and (2) age was reported either categorically (young vs. older adults) or continuously. Across these studies, reaction time slowed by 0.7–2.5 ms/year and movement time by 3–5 ms/year (Table 3). Our estimates—1.3 ms/year for reaction time and 4.3 ms/year for movement time—fall squarely within these ranges. While this comparison is descriptive and not intended to support formal inference, the convergence across studies strengthens confidence in the robustness, validity, and generalizability of our findings across diverse tasks, settings, and populations.

What drives age-related motor decline?

Each additional year of age was associated with a 1.3 ms slower reaction time, a 4.3 ms slower movement time, and a 0.04° reduction in movement

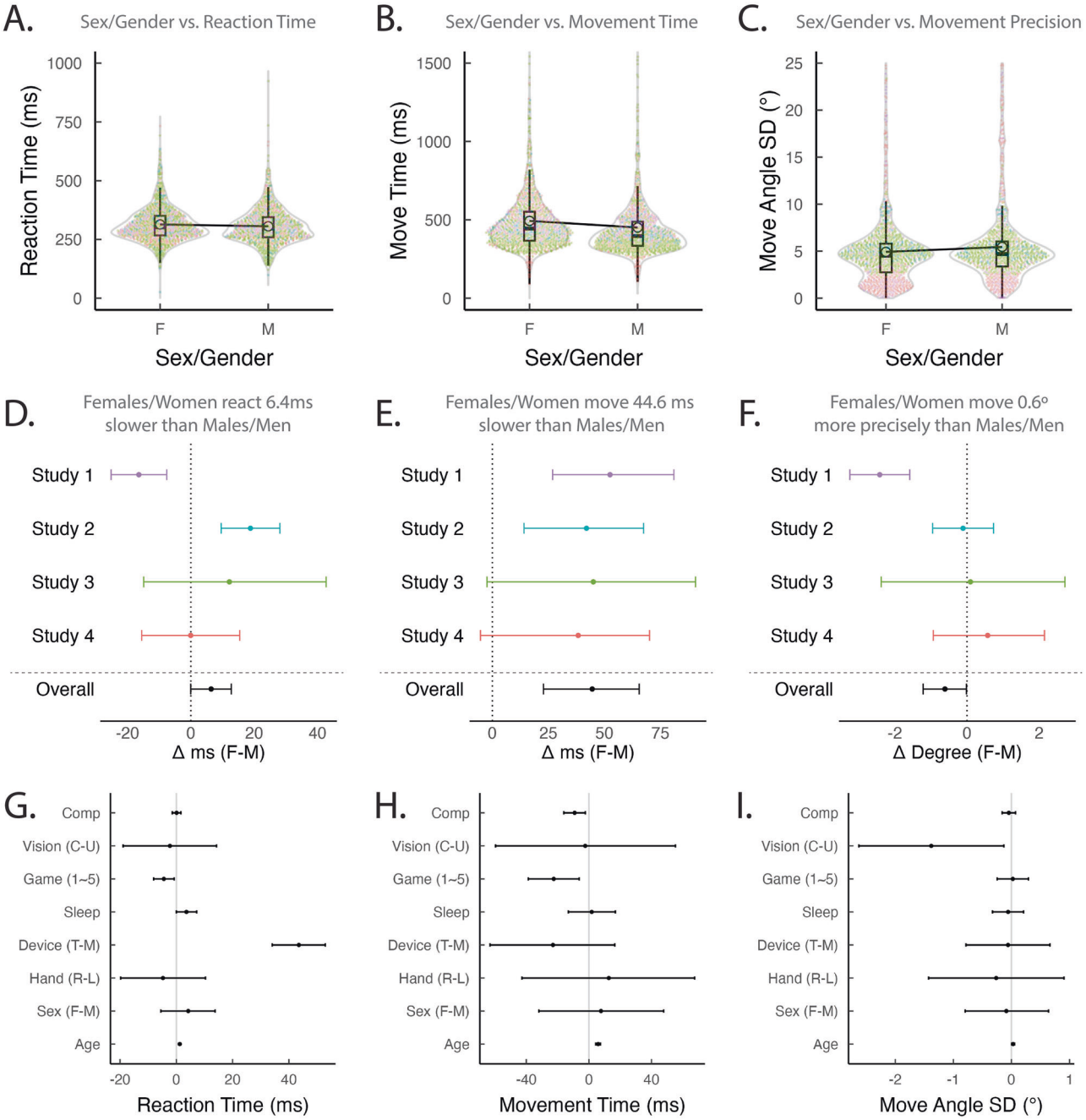

Fig. 2 | The impact of sex/gender and experiential factors on motor control. Reaction time (**A**), movement time (**B**), and movement precision (**C**) differs across sex/genders. To improve comparability across studies, we normalized each measure by subtracting its study-specific mean and adding the grand mean across all datasets. **D**–**F** Bayesian estimates of sex/gender effects on motor control. Dots indicate posterior means; error bars show 95% credible intervals. Positive values reflect increases in reaction time, movement time, or movement precision, after adjusting for study-level differences. **G**–**I** Exploratory analysis from Tsay et al.[37] assessing how biological and experiential factors shape motor control. Age effects remained robust across all variables, consistent with a biological basis for motor decline. In contrast, sex/gender effects largely disappeared after accounting for experiential variables, such as handedness (right-handed vs. left-handed), input device (trackpad vs. mouse), video game experience (rating of frequency from 1 to 5), vision quality (correctable vs. uncorrectable), sleep, and computer usage. See "Methods" for full variable definitions and modeling details. Analyses include $n = 2390$ participants across all four datasets (study 1 = 632, study 2 = 1228, study 3 = 212, and study 4 = 318); **G**–**I** use only the Tsay et al.[37] dataset ($n = 1228$).

precision. Though modest annually, these effects accumulate: between ages 18 and 90, reaction time slows by ~85 ms, movement time by ~170 ms, and precision declines by ~1.4°. Such differences can distinguish a smooth reach for a cup from knocking it over—or the ability to respond safely when driving.

Motor skills may decline with age for many reasons—and these explanations are not mutually exclusive. One possibility is experiential: In cross-sectional studies like ours, older adults may be less familiar with modern technology, potentially affecting performance. However, even after controlling for experiential factors, such as device type, sleep, vision, video game experience, and computer usage, age remained a strong and consistent predictor of slower and less precise movement. This pattern held across datasets and experimental setups, pointing to more fundamental biological drivers of motor decline.

Several biological mechanisms could underlie this decline. On the sensory side, aging may degrade visual acuity and proprioception, making it

Table 2 | Summaries of effect sizes for follow-up analysis

		Reaction time	Movement time	Movement precision
Age	With	1.2 ms/year [0.9, 1.5]	5.9 ms [4.4, 7.4]	0.03 ms [0.0, 0.05]
	Without	1.0 ms/year [0.7, 1.3]	6.9 ms/year [5.5, 8.3]	0.03°/year [0.01, 0.05]
	P_{diff}	0.82	0.83	0.54
Sex (F-M)	With	4.2 ms [−5.5, 13.7]	7.8 ms [−31.9, 47.8]	−0.1° [−0.8, 0.6]
	Without	18.9 ms [9.5, 28.3]	27.5 ms [−9.0, 64.8]	−0.09° [−0.7, 0.6]
	P_{diff}	0.02	0.24	0.5
Handedness (R-L)		−4.8 ms [−19/8, 10.3]	12.7 ms [−42.7, 67.6]	−0.3 ms [−1.4, 0.9]
Device (T-M)		43.5 ms [34.1, 52.9]	−23.0 ms [−63.2, 16.5]	−0.1 ms [−0.8, 0.7]
Videogame		−4.4 ms [−8.1, 0.8]	−22.4 ms [−38.7, −6.2]	0.02 ms [−0.2, 0.3]
Sleep		3.6 ms/h [0.0, 7.2]	1.8 ms [−13.1, 16.9]	−0.06 ms [−0.3, 0.2]
Computer usage		0.1 ms/h [−1.4, 1.6]	−9.1 ms [−16.0, −2.3]	−0.05 ms [−0.2, −0.1]
Vision (C-U)		−2.3 ms [−18.9, 14.3]	−2.3 [−59.7, 55.4]	−1.4 ms [−2.6, −0.1]

Posterior mean estimates and 95% credible intervals (in brackets) are reported for the effects of age, handedness (right–left), sex (female–male), device (trackpad–mouse), video game experience, sleep, computer usage, and vision (corrected–uncorrected) on reaction time, movement time, and movement precision.

harder to locate targets or sense limb position. On the neural level, age is associated with reduced white matter integrity[53], disrupted interhemispheric inhibition[54], altered functional connectivity[55], dedifferentiation of neural representations[56], and broader structural and chemical changes in the brain[3]. At the periphery, muscle atrophy[57] may impair precision. Even metabolism may play a role: moving quickly becomes more energetically costly with age, making slower movements a rational, energy-conserving strategy[29]. Future research could tease apart these influences to pinpoint how much of age-related motor decline reflects experience, how much reflects biology—and why.

What drives sex/gender differences in motor control?

We found that females tend to react and move more slowly but with greater precision, whereas males react and move more quickly but less precisely. Although the effects on reaction and movement time were consistent across studies, the precision effect was less reliable, highlighting the need for future research to confirm this pattern.

Why might this speed-accuracy trade-off arise? One possibility is that it reflects sex/gender differences in feedback vs feedforward motor control strategies: females may rely more on cautious, online feedback control, while males favor faster, ballistic feedforward control[11]. Alternatively, it may reflect a difference in optimal vs robust motor control strategies, with females favoring optimal control (prioritizing accuracy) and males favoring robust control (prioritizing speed). Future work is needed to disentangle these alternatives[58].

Crucially, our results suggest these sex/gender differences may not be rooted in biology but mediated by experience. Sex/gender was correlated with experiential variables—such as gaming experience[48,59,60] and device type[61]—and once these were accounted for, the sex/gender effects on reaction time sharply attenuated. This serves as a caution: apparent sex/gender dimorphisms may in fact reflect experiential ones[62–64]. Rather than asking whether males and females differ, we should ask why—and look more closely at the roles of experience and context in shaping motor performance.

What is the impact of experience on motor control?

We found that several experiential factors—such as device type, video game experience, computer usage, and vision—significantly influenced motor performance. These results align with prior work showing that frequent computer users and video gamers tend to react and move faster[49,65–70], likely reflecting enhanced visuomotor coordination from repeated practice.

Our findings also converge with reports of slower reaction times in trackpad compared to mouse users, potentially reflecting hardware differences in motion detection[61,71] or the greater planning demands of finger movements relative to wrist movements[72]. Similarly, it is unsurprising that poorer vision leads to less precise and accurate performance[73,74]; however, our study quantifies this effect, providing a benchmark for comparing individuals with and without visual deficits.

In contrast to the variables above, handedness and the amount of sleep prior to the task had no appreciable effect on motor control, consistent with many prior studies[75–77]. Future work could test whether sleep influences more complex motor behaviors—particularly those requiring greater cognitive and executive control—beyond the center-out reaching task examined here. With a more comprehensive dataset, it would also be possible to assess how motor control differs between the dominant and nondominant hand[4,78–80] This is especially relevant for rehabilitation, since in conditions such as stroke, the affected hand is not always the dominant one.

These findings suggest that individual differences in experience are not just unexplainable noise—they shape sensorimotor behavior in meaningful ways. They should be considered when establishing normative benchmarks for human performance and may serve as a starting point for probing how real-world experiences drive plasticity in sensorimotor systems—and how such changes manifest in the brain. These findings also point to the need for future research to investigate why and how these experiential factors influence motor performance.

Limitations

We chose the center-out reaching task as a representative measure of motor control because it strikes a balance between simplicity and precision. Unlike complex tasks like trajectory tracking, it minimizes cognitive demands; unlike gross motor tasks, such as sit-to-stand and keypress tasks, it enables a fine-grained dissection of distinct phases of motor control. By quantifying how age, sex/gender, and experience influence sensorimotor control, this approach provides a foundation for future studies to revisit more complex tasks and disentangle effects driven by core motor control changes from those reflecting cognitive or other processes.

Although our studies used different input devices—leading to expected differences in mean motor performance (see Table 1)—the effects of aging were strikingly consistent across datasets. To rigorously account for both study-specific and general effects, we applied a Bayesian multilevel modeling[51,81,82] approach to harmonize the data—a method increasingly recognized as best practice in large-scale behavioral research. While input device introduces some variability, the consistent pattern of results across studies underscores the robustness of these effects, suggesting they reflect differences in motor control rather than artifacts of hardware differences.

Despite its size, our dataset does not fully represent the general population. Left-handers are underrepresented, we lack data on non-

Table 3 | Summary of age-related changes in performance metrics across published studies and the current dataset

Study	*N* (younger/ older)	Age range (years)	Reported effect	Converted effect (per year)
Goggin & Meeuwsen[28]	12/12	23 vs. 73	MT: 418 ms (young) vs 676 ms (old)	5.2 ms/year
Darbutas et al.[27]	20/20	21 vs. 63	RT: 260 ms (young) vs 290 ms (old)	0.76 ms/year
Hardwick et al.[96]	Continuous $N = 54$	21–80	$r = 0.30$ (age vs RT)	0.48 ms/year
Summerside et al.[29]	20/20	26 vs. 72	RT: 292 ms (young) vs. 401 ms (old)	2.5 ms/year
Krüger et al.[26]	18/18	24 vs. 67	RT: 335 ms (young) vs. 420 ms (old)	2.0 ms/year
Summary of previous studies	18/18	24 vs. 69	MT: 418 ms (young) vs. 676 ms (old) RT: 295.6 ms (young) vs. 370 ms (old)	**RT: 1.4 ms/year** **MT: 5.2 ms/year**
Our study	Continuous $N = 2390$	18–90		**RT: 1.3 ms/year [1.1, 1.5]** **MT: 4.3 ms/year [3.5, 5.1]**

Results are converted, where possible, into annualized effects (ms/year) to enable direct comparison across studies with differing designs (categorical vs. continuous age).
Bold text highlights the close correspondence between prior findings on age-related kinematics and the results of the present study.

dominant hand performance, and although socioeconomic status was not measured, our sample likely skews wealthy. Indeed, our evaluation of experiential factors was limited to the single dataset that collected such measures. Future studies should incorporate additional experiential variables—such as physical activity, occupation, and musical training—that may also shape motor control across the lifespan.

One may ask why we use the term sex/gender rather than sex or gender alone. We streamlined our use of sex/gender because the original studies from which we obtained data did not distinguish between the two. We confirmed with the authors of all four datasets that sex and gender were not differentiated in their demographic surveys. Specifically, in studies 2, 3, and 4, the variable was self-reported as sex; in study 1, it was labeled sex/gender without further specification. Following the recommendations from[83], we use the term sex/gender as the most encompassing, inclusive, and accurate terminology, given that the original datasets did not distinguish between the two. We recognize that a true normative dataset would distinguish between sex and gender, and we urge future studies to do so, given evidence that these constructs are distinct and can differentially modulate brain activity[84].

We acknowledge that our analyses tested only a linear effect of age and thus cannot exclude the possibility that other trajectories may better capture age-related decline in motor control. Broader sampling across the lifespan—including developmental stages—would allow future work to systematically test alternative trajectories and more precisely characterize how motor control evolves with age. We intentionally excluded children here to avoid conflating developmental changes with aging effects. Nonetheless, expanding this "living" dataset to include children and other underrepresented groups will be essential for building a comprehensive normative benchmark of sensorimotor control across ages, sexes/genders, geographies, and experience levels.

Toward a normative benchmark for sensorimotor health

We outline complementary strategies to establish a comprehensive benchmark for sensorimotor control. First, expand the dataset through coordinated data-sharing initiatives. To this end, we have established OpenMotor, a repository where researchers can deposit motor datasets to accelerate progress in the field (see OSF page: https://osf.io/aknqj/). Second, integrate precision tools—such as the Kinarm robot—into routine clinical assessments, akin to standard measures like blood pressure[36,85–88]. Third, incorporate scalable online motor assessments to enable cost-effective monitoring of sensorimotor health at the population level[89–93]. Together, these efforts can establish a robust normative benchmark for aging, supporting early detection of age-related motor decline and improving diagnosis of movement and cognitive impairments in older adults[94,95].

Data availability

All data are openly available on the Open Science Framework (OSF) via the OpenMotor repository (https://osf.io/aknqj/), which hosts the complete dataset analyzed in this study. Following the included publication[36], Stephen Scott's group continued collecting behavioral data using the same protocol and generously shared these additional unpublished data upon request; these have also been deposited in the OpenMotor database.

Code availability

All analysis scripts and figure-generation code are openly available in the OpenMotor repository on the Open Science Framework (OSF; https://osf.io/aknqj/).

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Author contributions

Aoran Zhang implemented the analyses and drafted and revised the manuscript. Jonathan S. Tsay conceived and supervised the project, contributed key datasets, and co-wrote and revised the manuscript. Matthew Warburton contributed to the code and manuscript revisions. Marit F.L. Ruitenberg and Stephen Scott contributed original datasets and provided conceptual and methodological input during manuscript preparation and revision.

Competing interests

The authors declare no competing interests.

Additional information

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