Supplementary Information
Tapping force variability influences temporal precision in paced finger tapping

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All data and code to reproduce our results and figures are available in the following OSF project https://doi.org/10.17605/osf.io/8VMQJ and GitHub repository https://github.com/SMDynamicsLab/Force2026. Data preprocessing: `VersaciLaje2026_1_preprocess_data.m`. Script to reproduce Figures 2, 4, 5, 6, S1, S2: `VersaciLaje2026_2_figures.m`. Effect sizes calculation: `VersaciLaje2026_3_effect_size.Rmd`.

Variable conversion for sample size justification

The relationship between intertap interval ITI_n and asynchrony e_n is (Chen et al., 1997):

$$ITI_n = ISI + e_{n+1} - e_n$$

where ISI is the (constant) interstimulus interval. Thus the relationship between their variances is:

$$\mathrm{Var}(ITI) = \mathrm{Var}(e_{n+1}) + \mathrm{Var}(e_n) - 2\mathrm{Cov}(e_{n+1}; e_n)$$

By using $\mathrm{Cov}(A; B) = \sigma_A \sigma_B \,\mathrm{Corr}(A; B)$ and $\mathrm{Var}(e_{n+1}) = \mathrm{Var}(e_n) \equiv \mathrm{Var}(e)$ we can write:

$$\begin{aligned}
\mathrm{Var}(ITI) &= 2\mathrm{Var}(e) - 2\mathrm{Var}(e)\,\mathrm{Corr}(e_{n+1}; e_n) \\
\mathrm{Var}(ITI) &= 2(1 - \mathrm{Autocorr}(e; lag = 1))\,\mathrm{Var}(e) \\
SD_A &= SD_{ITI} / \sqrt{1 - \mathrm{Autocorr}(e; lag = 1)}
\end{aligned}$$

where $SD_A^2 = \mathrm{Var}(e)$ and $SD_{ITI}^2 = \mathrm{Var}(ITI)$. We now use the experimental result that $\mathrm{Autocorr}(e; lag = 1) = 0.4$ (Repp, 2011, figure 8; Semjen et al., 2000, figure 4G) and get the desired relationship:

$$SD_A = SD_{ITI} / \sqrt{1.2}$$

Maximum Likelihood Estimation

Assuming two main sensory feedback modalities from the tap (auditory and tactile), according to the maximum likelihood estimation (MLE) the integrated perceived occurrence time of the tap t_{tap} is the weighted average of the perceptions from individual modalities t_{aud} and t_{tact}:

$$t_{\mathrm{tap}} = \omega_{\mathrm{aud}}\, t_{\mathrm{aud}} + \omega_{\mathrm{tact}}\, t_{\mathrm{tact}}$$

where ω_{aud} and ω_{tact} are the weights of each sensory modality that can be expressed in terms of the corresponding variances:

$$\omega_{\mathrm{aud}} = \frac{\sigma^2_{\mathrm{tact}}}{\sigma^2_{\mathrm{tact}} + \sigma^2_{\mathrm{aud}}} \quad , \quad \omega_{\mathrm{tact}} = \frac{\sigma^2_{\mathrm{aud}}}{\sigma^2_{\mathrm{tact}} + \sigma^2_{\mathrm{aud}}}$$

where σ^2_{tact} and σ^2_{aud} are the variances in the auditory and tactile perception of the occurrence time of the tap, respectively, and $\omega_{\mathrm{aud}} + \omega_{\mathrm{tact}} = 1$ (Ernst & Banks, 2002). We don't consider visual feedback because the line of sight was blocked during the experiment, and similarly we don't consider either direct auditory feedback because participants were isolated from ambient sound by headphones (approximately 30 dB attenuation; Franken et al., 2019) and proprioceptive feedback because in this experimental paradigm it is likely less important than tactile (Aschersleben et al., 2004).

Correspondingly, the variability σ_{tap} of the integrated percept is defined as (Ernst, 2006):

$$\sigma^2_{\mathrm{tap}} = \frac{\sigma^2_{\mathrm{tact}}\,\sigma^2_{\mathrm{aud}}}{\sigma^2_{\mathrm{tact}} + \sigma^2_{\mathrm{aud}}}$$

This relationship is valid for all feedback conditions by setting the sigmas accordingly. It can be rewritten as

$$\sigma^2_{\mathrm{tap}} = \alpha\, \sigma^2_{\mathrm{tact}} \qquad \text{(S1)}$$

with

$$q = \frac{\sigma^2_{\mathrm{aud}}}{\sigma^2_{\mathrm{tact}} + \sigma^2_{\mathrm{aud}}} \leq 1$$

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Source	Measure	Figure	Condition	Comments
Inuit et al., 2002	Intertap interval *CV* of intertap interval	2B 5B	Adult, taps 1–3 Adult, taps 1–3	Estimated $SD_{ITI} = CV_{ITI} \times ITI$, then estimated SD_A as shown in the text.
	CV of force	5A	Adult, tap 1–3	-
Sasaki et al., 2011	*SD* of intertap interval	3C,D	All ages, both ISIs, both conditions	Estimated SD_A as shown in the text.
	Mean force *SD* of force	5A,B 5E,F	All ages, both ISIs, both conditions	Estimated CV_F by *SD*/mean ratio.

Table S1

Literature sources for sample size justification by power analysis.

Note that Eq. S1 is an increasing function of σ^2_{tact}, thus there is a direct relationship between σ^2_{tap} and σ^2_{tact} in any condition.

In our work, the NoFBK condition can be represented by $\sigma^2_{\text{aud}} \to \infty$ leading to $q = 1$, whereas in the WithFBK condition σ^2_{aud} has a finite value leading to $q < 1$:

$$\sigma^2_{\text{tap}} = q\,\sigma^2_{\text{tact}} \qquad \begin{cases} q = 1 & \text{(NoFBK)} \\ q < 1 & \text{(WithFBK)} \end{cases}$$

This tells us that the ratio between σ^2_{tap} and σ^2_{tact} is smaller in the WithFBK condition than in the NoFBK condition.

Linear regression

All models were implemented in Matlab with functions `fitlme` and `anova` (see code file `VersaciLaje2024_2_figures.m` in the GitHub repository). Effect sizes η^2_p and η^2_G (Lakens, 2013; Bakeman, 2005; Olejnik & Algina, 2003) were computed from the sums of squares using functions `afex::aov_4` and `effectsize::eta_squared` in R (see code file `VersaciLaje2024_3_effect_size.Rmd` in the GitHub repository).

Force conversion

Supplementary Figure S3 shows the electrical wiring of the force sensor and Arduino. The FSR is a variable resistance (R_{FSR}) whose value decreases as force is acted on it (at constant contact area). When the load on the sensor is zero its resistance is very large and the voltage at node P is close to zero. When the sensor is pressed its resistance decreases and the voltage at P increases towards 5 V. The relationship between recorded voltage at P and acting force can be expressed as follows. The current i through R_{FSR} is $i = V0/(R_{\text{FSR}} - R)$ and voltage at P is $V_P = iR$. Solving for the sensor resistance we first get: $R_{\text{FSR}} = R(V_0/V_P - 1)$. According to the technical specifications (https://www.sparkfun.com/datasheets/Sensors/Pressure/fsrguide.pdf), the approximate relationship between acting force and sensor resistance for any contact area is $F \sim 1/R_{\text{FSR}}$. We can thus use $F = k/R_{\text{FSR}}$ for all participants (assuming similar contact areas between participants) and express acting force in arbitrary units. By substituting R_{FSR} we get the relationship between recorded voltage and acting force: $F = k\,V_P/(R(V_0 - V_P))$. The resulting force values were multiplied by 10^4 to obtain values in the range 0 – 5 (arbitrary units).

Factor	**Estimate**	**98.75% CI**	**F df**	**F value**	p	η_p^2	η_G^2
Intercept	12.29	$[8.53; 16.06]$	$F(1,81)$	69.57	1.6×10^{-12}	-	-
Feedback	3.07	$[-1.00; 7.15]$	$F(1,81)$	3.71	0.057	0.05	0.03
Attention	0.58	$[-4.37; 5.53]$	$F(1,81)$	0.09	0.76	0.07	0.05
CVF	42.20	$[22.13; 62.27]$	$F(1,81)$	28.86	7.3×10^{-7}	0.21	0.2
Feedback:Attention	0.11	$[-2.32; 2.54]$	$F(1,81)$	0.013	0.9	6.6×10^{-5}	4.9×10^{-5}
Feedback:CVF	-24.75	$[-44.61; -4.89]$	$F(1,81)$	10.13	0.002	0.08	0.06
Attention:CVF	-12.70	$[-38.98; 13.57]$	$F(1,81)$	1.52	0.22	3.7×10^{-3}	2.7×10^{-3}

Table S2

ANOVA results on the coefficients of a linear mixed model for SD_A vs CV_F in Figure 2:
`SDA ~ 1 + Feedback + Attention + CVF + Feedback:Attention + Feedback:CVF + Attention:CVF + (1|Subject)`. *All p-values are to be compared to the Bonferroni-corrected level $\alpha = 0.0125$ (four comparisons).*

Factor	**Estimate**	**98.75% CI**	**F df**	**F value**	p	η_p^2	η_G^2
Intercept	0.07	$[0.022; 0.119]$	$F(1,81)$	13.83	0.0003	-	-
Feedback	0.009	$[-0.026; 0.045]$	$F(1,81)$	0.49	0.48	0.03	7.5×10^{-3}
Attention	0.013	$[-0.054; 0.081]$	$F(1,81)$	0.27	0.6	0.4	0.01
F	0.096	$[0.073; 0.119]$	$F(1,81)$	114.28	3.9×10^{-17}	0.76	0.75
Feedback:Attention	-0.016	$[-0.052; 0.019]$	$F(1,81)$	1.44	0.23	3.7×10^{-3}	8.7×10^{-4}
Feedback:F	0.011	$[-0.005; 0.029]$	$F(1,81)$	3.09	0.08	0.03	7.7×10^{-3}
Attention:F	-0.021	$[-0.055; 0.013]$	$F(1,81)$	2.55	0.11	0.02	5.5×10^{-3}

Table S3

ANOVA results on the coefficients of a linear mixed model for SD_F vs F in Figure 4:
`SDF ~ 1 + Feedback + Attention + F + Feedback:Attention + Feedback:F + Attention:F + (1|Subject)`. *All p-values are to be compared to the Bonferroni-corrected level $\alpha = 0.0125$ (four comparisons).*

Factor	**Estimate**	**98.75% CI**	**F df**	**F value**	p	η_p^2	η_G^2
Intercept	0.11	$[0.081; 0.15]$	$F(1,81)$	71.33	9.9×10^{-13}	-	-
Feedback	0.035	$[-0.0007; 0.071]$	$F(1,81)$	6.27	0.014	0.02	0.01
Attention	-0.014	$[-0.060; 0.032]$	$F(1,81)$	0.61	0.43	0.01	6.8×10^{-3}
1/F	0.055	$[0.029; 0.081]$	$F(1,81)$	29.42	5.9×10^{-7}	0.47	0.46
Feedback:Attention	0.0023	$[-0.038; 0.042]$	$F(1,81)$	0.022	0.88	4×10^{-3}	2×10^{-4}
Feedback:(1/F)	-0.019	$[-0.041; 0.0033]$	$F(1,81)$	4.74	0.032	0.03	0.02
Attention:(1/F)	0.0019	$[-0.027; 0.031]$	$F(1,81)$	0.029	0.86	0.001	5.5×10^{-4}

Table S4

ANOVA results on the coefficients of a linear mixed model for CV_F vs $1/F$ in Figure 5:
`CVF ~ 1 + Feedback + Attention + (1/F) + Feedback:Attention + Feedback:(1/F) + Attention:(1/F) + (1|Subject)`. *All p-values are to be compared to the Bonferroni-corrected level $\alpha = 0.0125$ (four comparisons).*

Factor	**Estimate**	**98.75% CI**	**F df**	**F value**	p	η_p^2	η_G^2
Intercept	-1.65	$[-2.38; -0.92]$	$F(1,81)$	33.52	1.3×10^{-7}	-	-
Feedback	0.21	$[-0.27; 0.70]$	$F(1,81)$	1.26	0.26	0.04	7×10^{-3}
Attention	1.47	$[0.49; 2.45]$	$F(1,81)$	14.83	2.3×10^{-4}	1.3×10^{-4}	2.2×10^{-5}
log(normF)	2.16	$[1.74; 2.59]$	$F(1,81)$	166.79	2.3×10^{-21}	0.82	0.82
Feedback:Attention	-0.84	$[-1.27; -0.45]$	$F(1,81)$	30.5	3.9×10^{-7}	2.6×10^{-3}	4.5×10^{-4}
Feedback:log(normF)	-0.1	$[-0.39; 0.18]$	$F(1,81)$	0.9	0.34	2.4×10^{-3}	4.2×10^{-4}
Attention:log(normF)	-0.28	$[-0.86; 0.28]$	$F(1,81)$	1.66	0.2	0.03	5.1×10^{-3}

Table S5

ANOVA results on the coefficients of a linear mixed model for log(normMSJ) vs log(normF) in Figure 6: `log(normMSJ) ~ 1 + Feedback+Attention + log(normF) + Feedback:Attention + Feedback:log(normF) + Attention:log(normF) + (1|Subject)`. *All p-values are to be compared to the Bonferroni-corrected level $\alpha = 0.0125$ (four comparisons).*

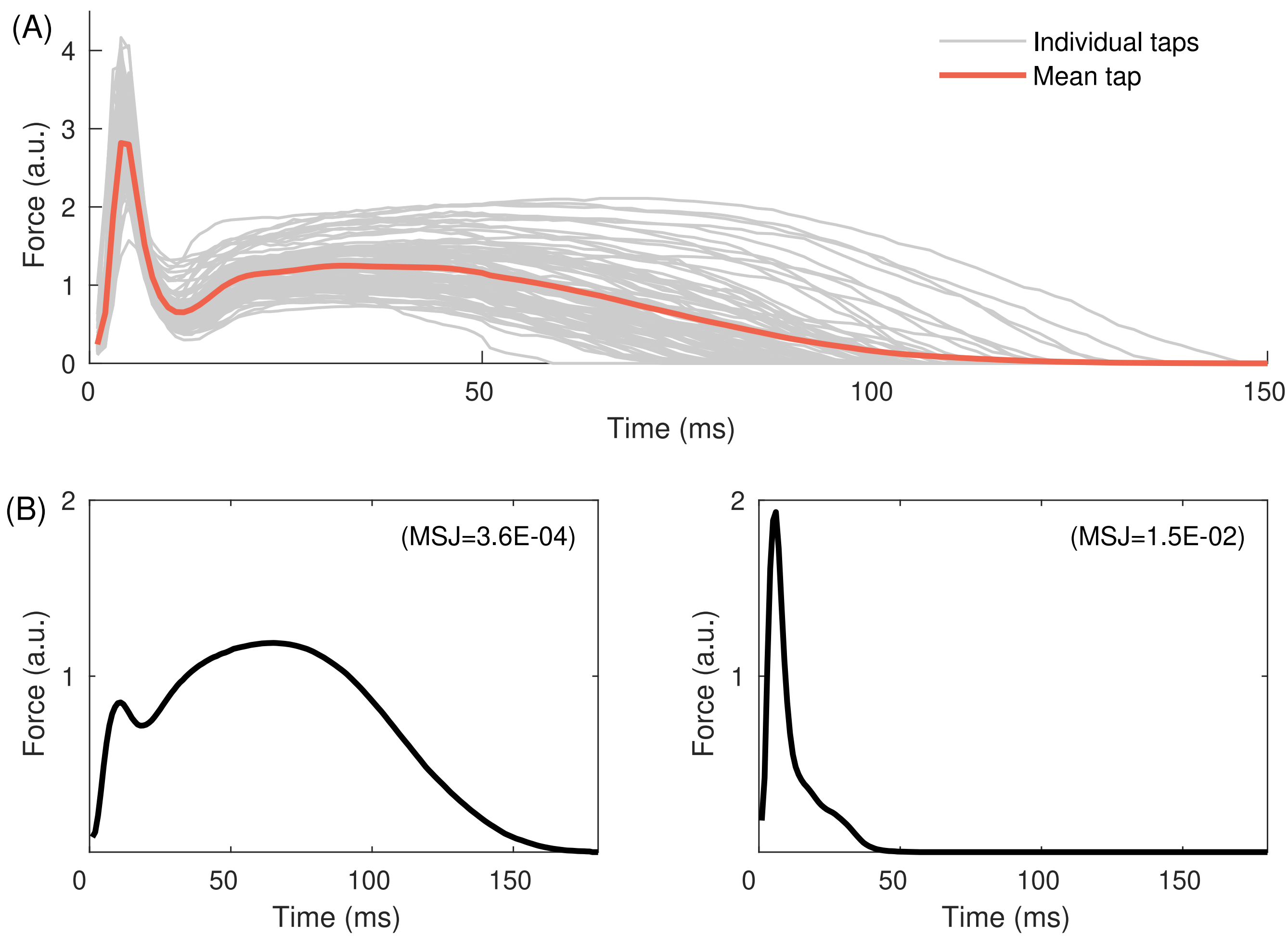

Figure S1

(A) Force profiles from a single participant in a single condition (HIGH NoFBK). (B) Examples of two mean force profiles with very different MSJ values (low and high sharpness, respectively; ratio high/low around 40) from two different participants in the same condition.

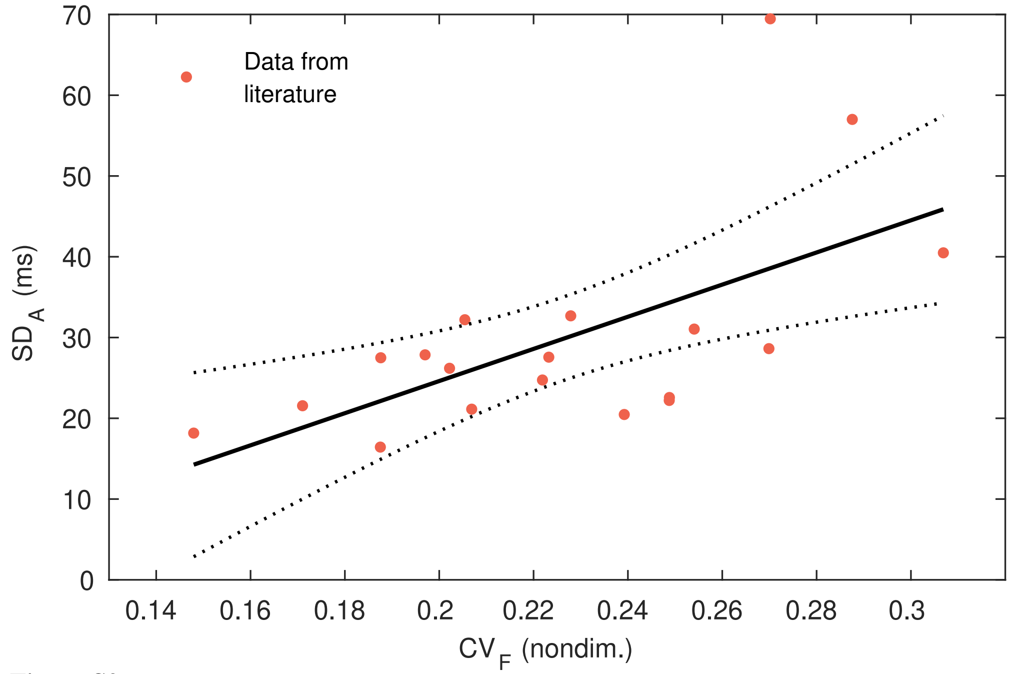

Figure S2

Data gathered from the literature for sample size estimation based on power analysis (Supplementary Table S1). Pearson correlation coefficient is $r = 0.619$. Solid line is linear regression; dashed lines represent the 95% confidence interval of the regression.

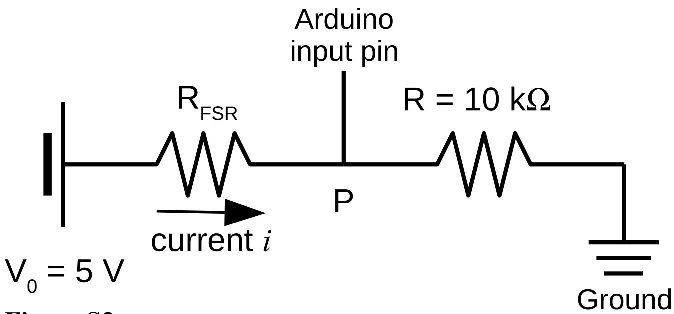

Figure S3

Electrical wiring between the force sensor and the Arduino for the force recording. R: fixed-value resistance; R_{FSR}: FSR sensor variable resistance; the recorded voltage in point P is V_P.

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