

Supplementary information

Table S1 | Hierarchical model comparison for acceleration differences ($M(\Delta a)$) on tango expertise and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1054.450	-1042.245	530.225	–	–	–	–
Model 1: Random Intercept	4	-1184.261	-1167.988	596.131	1 vs 2	131.811	< .001	–
Model 2: + Expertise	5	-1187.746	-1167.403	598.873	2 vs 3	5.484	.019	.097
Model 3: + Condition	8	-1308.275	-1275.727	662.137	3 vs 4	126.529	< .001	.029
Model 4: + Interaction	11	-1302.879	-1258.126	662.440	4 vs 5	0.604	.895	> .000

Note. df = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, p = p -value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model. Allowing, in a first step in model 1, interindividual differences in the participant (varying intercepts) significantly improved the model fit compared to the grand-mean baseline model ($\chi^2 = 131.81$, $p < .001$, $\Delta AIC = -129.81$, $\Delta BIC = -125.74$). This demonstrated substantial and significant variance between pairs, yielding an ICC of .89 (see Supplementary Table S13). Building upon and adding the main effect of tango expertise significantly improved the model ($\chi^2 = 5.48$, $p = .019$, $\Delta AIC = -3.49$, $\Delta BIC = 0.59$), indicating a significant main effect, as shown in Figure 3. The subsequent inclusion of condition resulted in a further significant improvement in the model fit ($\chi^2 = 126.53$, $p < .001$, $\Delta AIC = -120.53$, $\Delta BIC = -108.32$), demonstrating a strong main effect. Finally, adding the interaction term between tango expertise and condition did not significantly improve the model fit ($\chi^2 = 0.60$, $p = .895$, $\Delta AIC = 5.40$, $\Delta BIC = 17.61$). As the interaction term did not significantly improve model fit, the additive model including both main effects was retained as the most parsimonious model (see Supplementary Table S13, left; for completeness, the full model including the interaction is also reported in Supplementary Table S13, right).

Table S2 | Hierarchical model comparison for dispersion of acceleration differences ($SD(\Delta a)$) on tango expertise and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	<i>p</i>	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1803.970	-1791.764	904.985	–	–	–	–
Model 1: Random Intercept	4	-1841.362	-1825.088	924.681	1 vs 2	39.392	< .001	–
Model 2: + Expertise	5	-1839.452	-1819.110	924.726	2 vs 3	0.090	.764	.001
Model 3: + Condition	8	-2014.077	-1981.529	1015.038	3 vs 4	180.624	< .001	.245
Model 4: + Interaction	11	-2008.666	-1963.913	1015.333	4 vs 5	0.589	.899	.001

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model. Allowing interindividual differences in participants (varying intercepts) in model 1 significantly improved the model fit compared to the grand mean baseline model ($\chi^2 = 39.39$, $p < .001$, Δ AIC = -37.39, Δ BIC = -33.32). This demonstrated substantial and significant variance between pairs, yielding an ICC of 0.38 (see Supplementary Table S14). Including the main effect of tango expertise did not further improve the model ($\chi^2 = 0.09$, $p = .764$, Δ AIC = 1.91, Δ BIC = 5.98), indicating that there was no significant expertise-related effect. However, adding condition to the model significantly improved the fit ($\chi^2 = 180.62$, $p < .001$, Δ AIC = -174.63, Δ BIC = -162.42), showing a strong main effect. Finally, adding the interaction between tango expertise and condition did not significantly improve the model fit ($\chi^2 = 0.59$, $p = .899$, Δ AIC = 5.41, Δ BIC = 17.616), indicating that the two variables do not interact. As the interaction term did not significantly improve model fit, the additive model including both main effects was retained as the most parsimonious model (see Supplementary Table S14, left; for completeness, the full model including the interaction is also reported in Supplementary Table S14, right).

Table S3 | Hierarchical model comparison for temporal differences ($M(\Delta t)$) on tango expertise and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1784.024	-1771.819	895.012	–	–	–	–
Model 1: Random Intercept	4	-1906.250	-1889.977	957.125	1 vs 2	124.226	< .001	–
Model 2: + Expertise	5	-1904.418	-1884.076	957.209	2 vs 3	0.168	.682	.002
Model 3: + Condition	8	-2127.040	-2094.493	1071.520	3 vs 4	228.622	< .001	.213
Model 4: + Interaction	11	-2130.159	-2085.407	1076.080	4 vs 5	9.119	.028	.007

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model. Allowing interindividual differences in the participants (varying intercepts) in model 1 significantly improved the model fit compared to the grand mean baseline model ($\chi^2 = 124.23$, $p < .001$, Δ AIC = -122.23, Δ BIC = -118.16), showing a substantial variance between pairs with an ICC of 0.65 (see Supplementary Table S15). Further considering tango expertise did not significantly improve the model fit ($\chi^2 = 0.17$, $p = .682$, Δ AIC = 1.83, Δ BIC = 5.90), indicating no respective main effect. However, the subsequent addition of condition resulted in a significant improvement ($\chi^2 = 228.62$, $p < .001$, Δ AIC = -222.62, Δ BIC = -210.42), demonstrating a strong main effect of condition. Finally, including the interaction term between tango expertise and condition improved the model fit in terms of significance ($\chi^2 = 9.12$, $p = .028$, Δ AIC = -3.12, Δ BIC=9.09); at the same time, however, the conservative Δ BIC=9.09 penalizes model complexity and indicates that the simpler model without an interaction is of higher value. Consequently, we decided to disregard the interaction effect (see Supplementary Table S15, left; for completeness, the full model including the interaction is also reported in Supplementary Table S15, right).

Table S4 | Hierarchical model comparison for dispersion of temporal differences ($SD(\Delta t)$) on tango expertise and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-2564.611	-2552.406	1285.306	–	–	–	–
Model 1: Random Intercept	4	-2618.486	-2602.212	1313.243	1 vs 2	55.874	< .001	–
Model 2: + Expertise	5	-2619.564	-2599.222	1314.782	2 vs 3	3.079	.079	.023
Model 3: + Condition	8	-2817.923	-2785.376	1416.962	3 vs 4	204.359	< .001	.262
Model 4: + Interaction	11	-2821.512	-2776.759	1421.756	4 vs 5	9.588	.022	.009

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model. When interindividual differences of the participant were allowed in a first step in model 1 (varying intercepts), the model fit, compared to the grand mean baseline model, was significantly improved ($\chi^2 = 55.87$, $p < .001$, $\Delta AIC = -53.88$, $\Delta BIC = -49.81$), the significant variance between pairs yielding an ICC of 0.43 (see Supplementary Table S16). Further inclusion of the main effect of tango expertise did not significantly improve the model ($\chi^2 = 3.08$, $p = .079$, $\Delta AIC = -1.08$, $\Delta BIC = 2.99$), indicating no significant main effect. In contrast, adding condition resulted in a further significant improvement in the model fit ($\chi^2 = 204.36$, $p < .001$, $\Delta AIC = -198.36$, $\Delta BIC = -186.15$), demonstrating a strong main effect. Finally, including the interaction term between tango expertise and condition did also improve the model fit in terms of significance ($\chi^2 = 9.59$, $p = .022$, $\Delta AIC = -3.59$, $\Delta BIC = 8.62$), while the conservative $\Delta BIC=8.62$ penalizes model complexity and therefore indicates that the simpler model without an interaction is of higher value (see Supplementary Table S16, left; for completeness, the full model including the interaction is also reported in Supplementary Table S16, right).

Table S5 | Hierarchical model comparison for acceleration differences ($M(\Delta a)$) on tango experience (years) and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1054.450	-1042.245	530.225	–	–	–	–
Model 1: Random Intercept	4	-1184.261	-1167.988	596.131	1 vs 2	131.811	< .001	–
Model 2: + Experience	5	-1190.402	-1170.060	600.201	2 vs 3	8.141	.004	.140
Model 3: + Condition	8	-1310.913	-1278.366	663.457	3 vs 4	126.511	< .001	.028
Model 4: + Interaction	11	-1316.344	-1271.591	669.172	4 vs 5	11.431	.010	.002

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model.

Table S6 | Multilevel regression of acceleration differences ($M(\Delta a)$) on tango experience (years) and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>
Intercept	0.104	–	0.034	[0.038, 0.170]	3.064 (381)	.002	0.107	–	0.034	[0.040, 0.174]	3.124 (378)	.002
Tango experience (years)	0.009	0.373	0.003	[0.003, 0.015]	2.960 (46)	.005	0.009	0.359	0.003	[0.003, 0.015]	2.804 (46)	.007
No-audition	-0.032	–	0.005	[-0.042, -0.021]	-5.979 (381)	< .001	-0.023	–	0.010	[-0.042, -0.003]	-2.262 (378)	.024
No-haptics	-0.047	–	0.005	[-0.057, -0.037]	-8.843 (381)	< .001	-0.068	–	0.010	[-0.087, -0.048]	-6.795 (378)	< .001
No-vision	0.014	–	0.005	[0.004, 0.025]	2.681 (381)	.008	0.011	–	0.010	[-0.008, 0.031]	1.123 (378)	.262
Tango experience (years) × No-audition	–	–	–	–	–	–	-0.001	–	0.001	[-0.003, 0.001]	-1.057 (378)	.291
Tango experience (years) × No-haptics	–	–	–	–	–	–	0.002	–	0.001	[0.001, 0.004]	2.498 (378)	.013
Tango experience (years) × No-vision	–	–	–	–	–	–	0.000	–	0.001	[-0.001, 0.002]	0.354 (378)	.723
<i>Random effects</i>												
Intercept variance (τ_{00})	0.014	–	–	–	–	–	0.014	–	–	–	–	–
Residual variance (σ^2)	0.002	–	–	–	–	–	0.002	–	–	–	–	–
ICC	.893	–	–	–	–	–	.895	–	–	–	–	–
Marginal R^2	.168	–	–	–	–	–	.170	–	–	–	–	–
Conditional R^2	.911	–	–	–	–	–	.913	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.002	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, *CI* = Confidence interval, *t*(df) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; Pinheiro & Bates, 2000), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 5.

Table S7 | Hierarchical model comparison for dispersion of temporal differences ($SD(\Delta a)$) on tango experience (years) and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1803.970	-1791.764	904.985	–	–	–	–
Model 1: Random Intercept	4	-1841.362	-1825.088	924.681	1 vs 2	39.392	< .001	–
Model 2: + Experience	5	-1841.240	-1820.898	925.620	2 vs 3	1.878	.171	.013
Model 3: + Condition	8	-2015.853	-1983.306	1015.927	3 vs 4	180.613	< .001	.245
Model 4: + Interaction	11	-2010.659	-1965.907	1016.330	4 vs 5	0.806	.848	.001

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model.

Table S8 | Multilevel regression of dispersion of acceleration differences ($SD(\Delta a)$) on tango experience (years) and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>
Intercept	0.133	–	0.005	[0.123, 0.143]	25.994 (381)	< .001	0.131	–	0.006	[0.120, 0.142]	23.321 (378)	< .001
Tango experience (years)	-0.001	-0.115	0.000	[-0.002, 0.000]	-1.372 (46)	.177	-0.000	-0.080	0.001	[-0.001, 0.001]	-0.835 (46)	.408
No-audition	0.006	–	0.003	[0.000, 0.011]	2.045 (381)	.042	0.007	–	0.005	[-0.003, 0.017]	1.361 (378)	.174
No-haptics	0.040	–	0.003	[0.035, 0.045]	14.596 (381)	< .001	0.044	–	0.005	[0.033, 0.054]	8.324 (378)	< .001
No-vision	0.012	–	0.003	[0.007, 0.017]	4.338 (381)	< .001	0.014	–	0.005	[0.004, 0.025]	2.743 (378)	.006
Tango experience (years) × No-audition	–	–	–	–	–	–	-0.000	–	0.000	[-0.001, 0.001]	-0.346 (378)	.729
Tango experience (years) × No-haptics	–	–	–	–	–	–	-0.000	–	0.000	[-0.001, 0.001]	-0.854 (378)	.393
Tango experience (years) × No-vision	–	–	–	–	–	–	-0.000	–	0.000	[-0.001, 0.001]	-0.573 (378)	.567
<i>Random effects</i>												
Intercept variance (τ_{00})	0.000	–	–	–	–	–	0.000	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.374	–	–	–	–	–	.375	–	–	–	–	–
Marginal R^2	.258	–	–	–	–	–	.259	–	–	–	–	–
Conditional R^2	.535	–	–	–	–	–	.537	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.001	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(*df*) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 7.

Table S9 | Hierarchical model comparison for temporal differences ($M(\Delta t)$) on tango experience (years) and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	<i>p</i>	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-1784.024	-1771.819	895.012	–	–	–	–
Model 1: Random Intercept	4	-1906.250	-1889.977	957.125	1 vs 2	124.226	< .001	–
Model 2: + Experience	5	-1906.131	-1885.789	958.066	2 vs 3	1.881	.170	.021
Model 3: + Condition	8	-2128.722	-2096.175	1072.361	3 vs 4	228.591	< .001	.212
Model 4: + Interaction	11	-2134.578	-2089.825	1078.289	4 vs 5	11.855	.008	.008

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model.

Table S10 | Multilevel regression of temporal differences ($M(\Delta t)$) on tango experience (years) and condition

Predictor	Model 3: + Condition						Model 4: + Interaction					
	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>
Intercept	-0.040	–	0.007	[-0.053, -0.027]	-6.027 (381)	< .001	-0.036	–	0.007	[-0.050, -0.023]	-5.224 (378)	< .001
Tango experience (years)	0.001	0.143	0.001	[-0.000, 0.002]	1.369 (46)	.178	0.000	0.072	0.001	[-0.001, 0.002]	0.650 (46)	.519
No-audition	0.030	–	0.002	[0.025, 0.034]	12.727 (381)	< .001	0.017	–	0.004	[0.009, 0.026]	3.941 (378)	< .001
No-haptics	-0.014	–	0.002	[-0.019, -0.009]	-6.042 (381)	< .001	-0.017	–	0.004	[-0.026, -0.009]	-3.969 (378)	< .001
No-vision	-0.001	–	0.002	[-0.006, 0.003]	-0.601 (381)	.548	-0.003	–	0.004	[-0.011, 0.006]	-0.586 (378)	.558
Tango experience (years) × No-audition	–	–	–	–	–	–	0.001	–	0.000	[0.001, 0.002]	3.280 (378)	.001
Tango experience (years) × No-haptics	–	–	–	–	–	–	0.000	–	0.000	[-0.000, 0.001]	0.901 (378)	.368
Tango experience (years) × No-vision	–	–	–	–	–	–	0.000	–	0.000	[-0.001, 0.001]	0.300 (378)	.764
<i>Random effects</i>												
Intercept variance (τ_{00})	0.001	–	–	–	–	–	0.001	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.642	–	–	–	–	–	.649	–	–	–	–	–
Marginal R^2	.233	–	–	–	–	–	.241	–	–	–	–	–
Conditional R^2	.725	–	–	–	–	–	.733	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.008	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(*df*) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 9.

Table S11 | Hierarchical model comparison for dispersion of temporal differences ($SD(\Delta t)$) on tango experience (years) and condition

Model	df	AIC	BIC	logLik	Test	L.Ratio	p	Δ Marginal R^2
Model 0: GLS (No Random Effects)	3	-2564.611	-2552.406	1285.306	–	–	–	–
Model 1: Random Intercept	4	-2618.486	-2602.212	1313.243	1 vs 2	55.874	< .001	–
Model 2: + Experience	5	-2619.640	-2599.298	1314.820	2 vs 3	3.154	.076	.024
Model 3: + Condition	8	-2817.994	-2785.446	1416.997	3 vs 4	204.354	< .001	.262
Model 4: + Interaction	11	-2817.980	-2773.228	1419.990	4 vs 5	5.987	.112	.006

Note. *df* = Degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = Log-likelihood, L.Ratio = Log-likelihood ratio test against the previous model, *p* = *p*-value, Δ Marginal R^2 = Change in marginal R^2 (variance explained by fixed effects) compared to the previous model.

Table S12 | Multilevel regression of dispersion of temporal differences ($SD(\Delta t)$) on tango experience (years) and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>
Intercept	0.041	–	0.002	[0.037, 0.045]	18.927 (381)	< .001	0.040	–	0.002	[0.035, 0.044]	16.954 (378)	< .001
Tango experience (years)	-0.000	-0.154	0.000	[-0.001, 0.000]	-1.792 (46)	.080	-0.000	-0.105	0.000	[-0.001, 0.000]	-1.090 (46)	.281
No-audition	0.006	–	0.001	[0.004, 0.008]	5.633 (381)	< .001	0.008	–	0.002	[0.004, 0.012]	3.794 (378)	< .001
No-haptics	0.018	–	0.001	[0.015, 0.020]	16.221 (381)	< .001	0.017	–	0.002	[0.013, 0.021]	8.149 (378)	< .001
No-vision	0.005	–	0.001	[0.003, 0.007]	4.355 (381)	< .001	0.008	–	0.002	[0.004, 0.012]	3.966 (378)	< .001
Tango experience (years) × No-audition	–	–	–	–	–	–	-0.000	–	0.000	[-0.001, 0.000]	-0.983 (378)	.326
Tango experience (years) × No-haptics	–	–	–	–	–	–	0.000	–	0.000	[-0.000, 0.000]	0.416 (378)	.678
Tango experience (years) × No-vision	–	–	–	–	–	–	-0.000	–	0.000	[-0.001, -0.000]	-1.961 (378)	.051
<i>Random effects</i>												
Intercept variance (τ_{00})	0.000	–	–	–	–	–	0.000	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.428	–	–	–	–	–	.432	–	–	–	–	–
Marginal R^2	.286	–	–	–	–	–	.292	–	–	–	–	–
Conditional R^2	.592	–	–	–	–	–	.598	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.006	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(*df*) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 11.

Table S13 | Multilevel regression of acceleration differences ($M(\Delta a)$) on tango expertise and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (<i>df</i>)	<i>p</i>
Intercept	0.189	–	0.018	[0.153, 0.225]	10.327 (381)	< .001	0.189	–	0.018	[0.153, 0.225]	10.292 (378)	< .001
Tango expertise	0.056	0.311	0.023	[0.009, 0.102]	2.399 (46)	.021	0.056	0.311	0.023	[0.009, 0.102]	2.369 (46)	.022
No-audition	-0.032	–	0.005	[-0.042, -0.021]	-5.979 (381)	< .001	-0.032	–	0.005	[-0.042, -0.021]	-5.973 (378)	< .001
No-haptics	-0.047	–	0.005	[-0.057, -0.037]	-8.843 (381)	< .001	-0.047	–	0.005	[-0.057, -0.037]	-8.819 (378)	< .001
No-vision	0.014	–	0.005	[0.004, 0.025]	2.682 (381)	.008	0.014	–	0.005	[0.004, 0.025]	2.672 (378)	.008
Tango expertise × No-audition	–	–	–	–	–	–	-0.003	–	0.007	[-0.016, 0.010]	-0.466 (378)	.642
Tango expertise × No-haptics	–	–	–	–	–	–	0.002	–	0.007	[-0.011, 0.016]	0.360 (378)	.719
Tango expertise × No-vision	–	–	–	–	–	–	0.000	–	0.007	[-0.013, 0.014]	0.055 (378)	.956
<i>Random effects</i>												
Intercept variance (τ_{00})	0.015	–	–	–	–	–	0.015	–	–	–	–	–
Residual variance (σ^2)	0.002	–	–	–	–	–	0.002	–	–	–	–	–
ICC	.898	–	–	–	–	–	.898	–	–	–	–	–
Marginal R^2	.125	–	–	–	–	–	.125	–	–	–	–	–
Conditional R^2	.911	–	–	–	–	–	.911	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.000	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(*df*) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 1.

Table S14 | Multilevel regression of dispersion of acceleration differences ($SD(\Delta a)$) on tango expertise and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>
Intercept	0.127	–	0.003	[0.121, 0.133]	42.884 (381)	< .001	0.127	–	0.003	[0.121, 0.133]	42.737 (378)	< .001
Tango expertise	-0.001	-0.026	0.003	[-0.008, 0.006]	-0.300 (46)	.765	-0.001	-0.022	0.004	[-0.008, 0.007]	-0.229 (46)	.820
No-audition	0.006	–	0.003	[0.000, 0.011]	2.044 (381)	.042	0.006	–	0.003	[0.000, 0.011]	2.039 (378)	.042
No-haptics	0.040	–	0.003	[0.035, 0.045]	14.596 (381)	< .001	0.040	–	0.003	[0.035, 0.045]	14.557 (378)	< .001
No-vision	0.012	–	0.003	[0.007, 0.017]	4.338 (381)	< .001	0.012	–	0.003	[0.007, 0.017]	4.325 (378)	< .001
Tango expertise × No-audition	–	–	–	–	–	–	0.000	–	0.004	[-0.007, 0.007]	0.051 (378)	.960
Tango expertise × No-haptics	–	–	–	–	–	–	0.001	–	0.004	[-0.006, 0.008]	0.292 (378)	.770
Tango expertise × No-vision	–	–	–	–	–	–	-0.002	–	0.003	[-0.009, 0.005]	-0.515 (378)	.607
<i>Random effects</i>												
Intercept variance (τ_{00})	0.000	–	–	–	–	–	0.000	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.384	–	–	–	–	–	.385	–	–	–	–	–
Marginal R^2	.246	–	–	–	–	–	.246	–	–	–	–	–
Conditional R^2	.535	–	–	–	–	–	.536	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.001	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(df) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 2.

Table S15 | Multilevel regression of temporal differences ($M(\Delta t)$) on tango expertise and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>
Intercept	-0.033	–	0.004	[-0.040, -0.025]	-8.823 (381)	< .001	-0.033	–	0.004	[-0.040, -0.025]	-8.800 (378)	< .001
Tango expertise	-0.002	-0.045	0.004	[-0.011, 0.007]	-0.418 (46)	.678	-0.004	-0.090	0.005	[-0.013, 0.006]	-0.799 (46)	.428
No-audition	0.030	–	0.002	[0.025, 0.034]	12.727 (381)	< .001	0.030	–	0.002	[0.025, 0.034]	12.847 (378)	< .001
No-haptics	-0.014	–	0.002	[-0.019, -0.009]	-6.043 (381)	< .001	-0.014	–	0.002	[-0.019, -0.010]	-6.140 (378)	< .001
No-vision	-0.001	–	0.002	[-0.006, 0.003]	-0.602 (381)	.548	-0.001	–	0.002	[-0.006, 0.003]	-0.647 (378)	.518
Tango expertise × No-audition	–	–	–	–	–	–	0.008	–	0.003	[0.002, 0.014]	2.658 (378)	.008
Tango expertise × No-haptics	–	–	–	–	–	–	0.001	–	0.003	[-0.004, 0.007]	0.463 (378)	.644
Tango expertise × No-vision	–	–	–	–	–	–	-0.001	–	0.003	[-0.006, 0.005]	-0.247 (378)	.805
<i>Random effects</i>												
Intercept variance (τ_{00})	0.001	–	–	–	–	–	0.001	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.650	–	–	–	–	–	.655	–	–	–	–	–
Marginal R^2	.215	–	–	–	–	–	.221	–	–	–	–	–
Conditional R^2	.725	–	–	–	–	–	.731	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.007	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(df) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 3.

Table S16 | Multilevel regression of dispersion of temporal differences ($SD(\Delta t)$) on tango expertise and condition

Model 3: + Condition							Model 4: + Interaction					
Predictor	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>	<i>B</i>	β	<i>SE</i>	95% CI	<i>t</i> (df)	<i>p</i>
Intercept	0.038	–	0.001	[0.035, 0.040]	30.740 (381)	< .001	0.038	–	0.001	[0.035, 0.040]	30.731 (378)	< .001
Tango expertise	-0.002	-0.152	0.001	[-0.005, 0.000]	-1.771 (46)	.083	-0.002	-0.145	0.002	[-0.005, 0.001]	-1.501 (46)	.140
No-audition	0.006	–	0.001	[0.004, 0.008]	5.633 (381)	< .001	0.006	–	0.001	[0.004, 0.008]	5.692 (378)	< .001
No-haptics	0.018	–	0.001	[0.015, 0.020]	16.221 (381)	< .001	0.018	–	0.001	[0.015, 0.020]	16.383 (378)	< .001
No-vision	0.005	–	0.001	[0.003, 0.007]	4.355 (381)	< .001	0.005	–	0.001	[0.003, 0.007]	4.429 (378)	< .001
Tango expertise × No-audition	–	–	–	–	–	–	0.000	–	0.001	[-0.003, 0.003]	0.035 (378)	.972
Tango expertise × No-haptics	–	–	–	–	–	–	0.002	–	0.001	[-0.001, 0.005]	1.492 (378)	.136
Tango expertise × No-vision	–	–	–	–	–	–	-0.003	–	0.001	[-0.005, 0.000]	-1.883 (378)	.060
<i>Random effects</i>												
Intercept variance (τ_{00})	0.000	–	–	–	–	–	0.000	–	–	–	–	–
Residual variance (σ^2)	0.000	–	–	–	–	–	0.000	–	–	–	–	–
ICC	.429	–	–	–	–	–	.435	–	–	–	–	–
Marginal R^2	.285	–	–	–	–	–	.294	–	–	–	–	–
Conditional R^2	.592	–	–	–	–	–	.601	–	–	–	–	–
Δ Marginal R^2	–	–	–	–	–	–	.009	–	–	–	–	–

Note. *B* = Unstandardized regression coefficient, β = Standardized regression coefficient, *SE* = Standard error, CI = Confidence interval, *t*(df) = *t*-statistic with degrees of freedom (within-group containment method as implemented in nlme::lme; ⁴⁵), *p* = *p*-value, Tango expertise (z-transformed ratings), τ_{00} = Random intercept variance (between-subject variance), σ^2 = Residual variance (within-subject variance), ICC = Intraclass correlation coefficient (adjusted, calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$), Marginal R^2 = Variance explained by fixed effects, Conditional R^2 = Variance explained by fixed and random effects, Δ Marginal R^2 = Change in marginal R^2 from Model 3 to Model 4. The categorical predictor 'Condition' was dummy-coded with the 'Unrestricted' condition as a reference category (coded 0). The three sensory restriction conditions ('No-audition', 'No-haptics', and 'No-vision') were each coded 1 for the corresponding restriction. Model statistics: *N*participants = 48, *N*observations = 432. Multilevel model comparison in Table 4.

Supplementary information: Mathematical derivation of the predicted values

To predict the theoretical parameters of the unrestricted condition (*all*), our mathematical derivation fundamentally relies on the theoretical parameters of the three restricted conditions: no-audition (*noa*), no-haptics (*noh*), and no-vision (*nov*). We employ a Bayesian maximum likelihood estimation approach. The sensory modalities integrated in this task are auditory (*a*), haptics (*h*), and visual (*v*).

Following the established principles of Bayesian cue combination [11], this mathematical derivation relies on the following core assumptions:

1. All sensory cues originate from the same underlying physical event.
2. The sensory measurements are conditionally independent given the underlying event, meaning that the noise in one modality provides no information about the noise in another.
3. The internal sensory representations are Gaussian-distributed.
4. The prior expectation distribution is assumed to be flat, meaning the integrated estimate relies entirely on the combined likelihood of the sensory inputs.

Under these assumptions, optimal multisensory integration combines the individual sensory inputs by weighting them according to their respective reliabilities. The reliability of each sensory cue is mathematically expressed as its precision (J), which is defined as the inverse of its variance ($J = \frac{1}{\sigma^2}$).

The following equations demonstrate how the theoretical standard deviation (σ_{all}) and mean (μ_{all}) for the integration of all three modalities can be algebraically derived entirely from the parameters of the bimodal restricted conditions (where one modality is respectively excluded: *noa*, *noh*, *nov*). This substitution method elegantly bypasses the need to computationally isolate the parameters of the single sensory components.

Finally, it is important to note that while actual behavioral performance inevitably includes late motor noise (added after sensory integration), we utilized the empirically observed values for *noa*, *noh*, and *nov* as the direct inputs for these restricted parameters in order to calculate the theoretically optimal unrestricted prediction (*all*). Consequently, the resulting mathematical prediction represents a purely perceptual integration process that deliberately neglects late motor noise. The consequences of neglecting this motor noise are discussed in the main manuscript.

1. Derivation of the predicted standard deviation (σ_{all}):

$$\Rightarrow J_a = \frac{1}{\sigma_a^2} \quad ; \quad J_h = \frac{1}{\sigma_h^2} \quad ; \quad J_v = \frac{1}{\sigma_v^2}$$

$$J_{all} = J_a + J_h + J_v$$

$$J_{noa} = J_h + J_v \quad ; \quad J_{noh} = J_a + J_v \quad ; \quad J_{nov} = J_a + J_h$$

$$\Rightarrow 2J_{all} = J_{noa} + J_{noh} + J_{nov}$$

$$\Rightarrow J_{all} = \frac{J_{noa} + J_{noh} + J_{nov}}{2}$$

$$\Rightarrow \frac{1}{\sigma_{all}^2} = \frac{\frac{1}{\sigma_{noa}^2} + \frac{1}{\sigma_{noh}^2} + \frac{1}{\sigma_{nov}^2}}{2}$$

$$\Rightarrow \underline{\underline{\sigma_{all}}} = \sqrt{\frac{2}{\frac{1}{\sigma_{noa}^2} + \frac{1}{\sigma_{noh}^2} + \frac{1}{\sigma_{nov}^2}}}$$

2. Derivation of the predicted mean (μ_{all}):

First, we define the precision-weighted mean for the unrestricted condition and isolate the terms for the single modalities from the bimodal restricted conditions:

$$\mu_{all} = \frac{J_a \cdot \mu_a + J_h \cdot \mu_h + J_v \cdot \mu_v}{J_a + J_h + J_v}$$

$$\mu_{noh} = \frac{J_a \cdot \mu_a + J_v \cdot \mu_v}{\underbrace{J_a + J_v}_{J_{noh}}} \Rightarrow J_a \cdot \mu_a = \mu_{noh} \cdot J_{noh} - J_v \cdot \mu_v$$

$$J_h \cdot \mu_h = \mu_{nov} \cdot J_{nov} - J_a \cdot \mu_a$$

$$J_v \cdot \mu_v = \mu_{noa} \cdot J_{noa} - J_h \cdot \mu_h$$

3. Substitution and final resolution for the overall mean:

By substituting the isolated terms into the initial equation for μ_{all} , the mean of the unrestricted condition can be resolved entirely through the restricted conditions:

$$\begin{aligned}
 \mu_{all} &= \frac{\mu_{noh} \cdot J_{noh} - J_v \cdot \mu_v + \mu_{nov} \cdot J_{nov} - J_a \cdot \mu_a + \mu_{noa} \cdot J_{noa} - J_h \cdot \mu_h}{J_a + J_h + J_v} \\
 \mu_{all} &= \frac{\mu_{noh} \cdot J_{noh} + \mu_{nov} \cdot J_{nov} + \mu_{noa} \cdot J_{noa} - (J_v \cdot \mu_v + J_a \cdot \mu_a + J_h \cdot \mu_h)}{J_a + J_h + J_v} \\
 \Rightarrow \mu_{all} + \underbrace{\frac{J_v \cdot \mu_v + J_a \cdot \mu_a + J_h \cdot \mu_h}{J_a + J_h + J_v}}_{\mu_{all}} &= \frac{\mu_{noh} \cdot J_{noh} + \mu_{nov} \cdot J_{nov} + \mu_{noa} \cdot J_{noa}}{J_a + J_h + J_v} \\
 \Rightarrow \underline{\underline{\mu_{all}}} &= \frac{\mu_{noh} \cdot J_{noh} + \mu_{nov} \cdot J_{nov} + \mu_{noa} \cdot J_{noa}}{\underbrace{2(J_a + J_h + J_v)}_{J_{noa} + J_{noh} + J_{nov}}} = \frac{\mu_{noh} \cdot J_{noh} + \mu_{nov} \cdot J_{nov} + \mu_{noa} \cdot J_{noa}}{\underline{\underline{J_{noa} + J_{noh} + J_{nov}}}}
 \end{aligned}$$

The posterior mean estimate is identical to μ_{all} .