Modeling Touch Input for Users with Motor Impairments: Empirical Insights into Training Size Requirements

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Abstract

We present empirical insights into modeling touch input performance, in terms of time and offset to targets, using Gaussian models and a cross-validation framework based on prediction coverage and bias of z-scores with log-likelihood analysis. Our results, from data collected from seven participants with upper-body motor impairments, indicate an optimum window of 8 to 24 touch observations before models plateau in performance. We interpret our findings through the lens of ability-based design, and propose a four-step procedure—observe, model, revise, and share—for implementing touch targets adaptive to users' motor abilities. The procedure is lightweight, requiring only basic numerical computations of touch time and offset measurements available on all platforms, making it readily deployable across a variety of touchscreen devices.

CCS Concepts

• **Human-centered computing** → **Gestural input**; **Accessibility technologies**; **Empirical studies in accessibility**.

Keywords

Touch input, motor impairments, touch gestures, touch time, offset, Gaussian models, touch targets

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1 Introduction

Touch is a fundamental input modality for modern devices, yet it assumes specific motor abilities and dexterity in the fingers, wrists, and arms, not always feasible. For people with upper-body motor impairments, touch input performance varies according to their specific abilities [6], the interaction session [17], and the characteristics of touch targets [10]. Consequently, researchers have proposed dedicated techniques to improve touch input accuracy [18] and to make interfaces adaptable to users' specific abilities [8]. Despite extensive modeling of touch input for the general population [1,2,12] including the use of deep learning approaches [4,15], few results exist for users with motor impairments, even for basic touch input models. Fundamental questions, such as how many touch observations are required to reliably build Gaussian models [1,17], remain largely unaddressed for users with motor impairments.

In this context, we contribute empirical results evaluating Gaussian models of touch time and offset from the target center using a cross-validation framework of prediction coverage and bias of z-scores with log-likelihood analysis. Specifically, we ask *how many user-specific data points are required for robust touch input modeling?,* and report findings from seven participants with various upper-body motor abilities. We position our contribution within the ability-based design paradigm [23], which emphasizes interface adaptations by modeling user abilities [19].

2 Related Work

A large body of research exists on touch input modeling for the general user population. For example, Henze et al. [11] reported, from a large dataset of 100+ million touches, a systematic skew in touch input and proposed a compensation function to correct it. Holz and Baudisch [12] revealed systematic errors in capacitive touchscreen input caused by an incomplete understanding of how users acquire targets; by using visual features at the top of the fingers, they reduced error offsets from 4.0 mm to 1.6 mm. Computational models have also been developed. For example, Vatavu et al. [21] derived Gaussian models of touch duration and offset to discriminate between children's and adults' touches; Bi and Zhai [2] applied the Dual Gaussian Distribution Model and the Bayesian Touch Criterion [1] to predict touch success rates; and, more recently, Chu et al. [4] developed TouchType-GAN, a deep learning architecture that generates realistic touch typing from text input.

By contrast, modeling touch input for users with motor impairments has received less attention. Examples include Guerreiro et

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Id	Condition	WHODAS†	Time (ms)			Offset (mm)		
			mean	95% CI	SD	mean	95% CI	SD
P_1	Spinal cord injury C4-C5	52.1	58.0	[49.7−66.4]	29.3	3.4	[2.9−3.9]	1.7
P_2	Spinal cord injury T7	41.7	97.0	[84.2−109.8]	44.9	3.2	[2.8−3.5]	1.3
P_3	Traumatic brain injury	45.8	247.7	[197.6−297.8]	176.3	10.5	[6.0−15.0]	16.0
P_4	Spinal cord injury T3-T4	23.0	93.2	[86.1−100.4]	25.1	3.0	[2.6−3.5]	1.6
P_5	Spina bifida	39.6	51.5	[43.0−59.9]	29.7	2.8	[2.3−3.3]	1.7
P_6	Spinal cord injury C4-C5	68.7	1563.3	[1328.0−1798.7]	828.2	8.8	[4.0−13.6]	16.9
P_7	Multiple sclerosis	39.6	92.2	[83.4−100.9]	30.7	2.5	[2.1−2.9]	1.4

†Calculated by administering the 12-item version of WHODAS 2.0 [25], an instrument developed by the World Health Organization that produces standardized disability profiles with scores between 0 and 100 (larger values indicate more advanced disability). According to normative data reports [1], individuals scoring between 20 and 100 at the WHODAS 2.0 questionnaire are in the top 10% of the population distribution likely to have clinically significant disabilities.

Figure 1: User-specific results of touch input performance (means, 95% CIs, and standard deviations). *Note:* Cell background gradients correspond to the magnitude of mean touch time and offset values to visually highlight inter-participant variability.

al. [10], who recommended a 12 mm diameter for circular targets, later extended to 18 mm in Findlater et al. [6] to reduce error rates to 7%; Montague et al. [17] derived Gaussian models for touch features (location, duration, movement, and offset), achieving 95.1% accuracy in session-specific recognizers; and Mott and Wobbrock's [18] Cluster Touch technique collects touch examples from individual users to apply corrective offsets to their touch points, with 15% increase in accuracy. While these studies have improved touch input accessibility, they do not explore user-specific modeling in depth, a critical aspect for understanding individual performance; in fact, Findlater et al. [7], in their analysis of a large dataset of mouse and touchscreen interactions from 700+ participants, cautioned against making assumptions about individuals' input performance based on age or self-reported motor impairments alone.

3 Experiment

To support our modeling evaluations of touch input for users with motor impairments, we conducted a data collection experiment.

3.1 Participants

We recruited seven participants with motor impairments (five male and two female), aged 45 to 64 years (M=52.4, SD=7.2) using convenience sampling. Participants' WHODAS 2.0 scores[1] ranged from 23.0 to 68.7 (M=44.4, SD=13.9); see Figure 1 for demographics and a summary of their touch input performance in terms of time and offset measures. All participants were regular smartphone users.

3.2 Apparatus

We developed a custom Android mobile application integrating gamification elements, as in prior work [11,17,24], to support participant engagement. The task required touching a target displayed at random locations on the screen. The target size was fixed at 15 mm, based on recommendations from [6,10]. The application was installed on each participant's smartphone, which had comparable screen resolutions (1080×2220 to 1080×2400) and dpi (393 to 425). For each participant, we collected touch points in N=50 trials after a familiarization stage that involved playing the game with five practice trials. We computed Time, in milliseconds, as the interval between the first finger-down and last finger-up events, and Offset, in millimeters according to each smartphone's dpi, as the Euclidean distance between the touch point at finger lift-off and the target center. These measures were selected for their simplicity and ease of collection across all platforms.

3.3 Modeling and Statistical Analysis

By following prior work [1,17,21] that implemented various Gaussian model parametrizations of touch input, we adopted a simple statistical formalism to model users based on their actual touch input performance $\left\{(x_{i,j}) \mid i{=}1\ldots M, j{=}1\ldots N\right\}$, where $x_{i,j}$ denotes the j-th observation of the i-th measure, assuming a Gaussian generative model parameterized by a sample mean m_i and standard deviation s_i computed from N observations. While this assumption may not perfectly capture all aspects of user touch input behavior, it represents a pragmatic starting point for our scope. User-specific models are built by randomly sampling N observations from each user's data and estimating $m_i{=}(1/N)\sum_{j=1}^{N} x_{i,j}$ and $s_i{=}\left((1/N-1)\sum_{j=1}^{N}(x_{i,j}-m_i)^2\right)^{1/2}$, where $N{-}1$ implements Bessel's correction for an unbiased estimator of the population variance [22]. To evaluate predictive performance, we draw an additional held-out observation x^* from the same user and assess its consistency with the model. Because the model parameters are estimated from finite data, the predictive distribution of x^* is given by $x^* \sim \mathcal{N}\left(m_i, s_i^2\,(1+1/N)\right)$, where the factor $1{+}1/N$ accounts for uncertainty in the estimated mean [9]. This procedure is repeated R=1000 times using independent random resampling,[2] resulting in

[1]World Health Organization Disability Assessment Schedule, version 2.0 [25].

[2]For notational simplicity, we write m_i and s_i instead of $m_i^{(r)}$ and $s_i^{(r)}$, noting that a new model is computed at each repetition $r{=}1\ldots R$.

a distribution of predictive statistics, which enables us to evaluate model efficacy using three orthogonal statistical checks:

(1) ***Predictive coverage*** evaluates whether the predictive variance is correctly calibrated with respect to the model's nominal 95% coverage. For each repetition x^*, we compute a predictive z-score as $z = \frac{x^*-m_i}{s_i(1+1/N)^{1/2}}$. Under the model assumptions, z follows a Student t distribution with $N-1$ degrees of freedom, which converges to a Gaussian distribution $\mathcal{N}(m_i, s_i^2)$ for large N. Coverage is computed as the proportion of repetitions satisfying $|z| \leq t_{0.975,N-1}$, where we use the 97.5th percentile of the t distribution (1.96 for the Gaussian distribution for large N). To assess whether the observed coverage differs from the nominal 95%, we perform a binomial test with success probability 0.95, and report the corresponding 95% confidence interval and p-value.
(2) ***Predictive bias*** evaluates whether the model's predictions are correctly centered. For each measure, we compute the mean predictive z-score, $\bar{z}=(1/R)\sum_{r=1}^{R} z_r$, and test the null hypothesis H_0: $E[z]=0$ using one-sample t-tests.
(3) ***Predictive log-likelihood*** evaluates predictive accuracy. For each held-out observation x^*, we compute its log-probability under the corresponding predictive distribution and summarize model performance using the average predictive log-likelihood $\bar{\ell}=(1/R)\sum_{r=1}^{R}\log\mathcal{N}\big(x^* \mid m_i, s_i^2\,(1+1/N)\big)$. Across different conditions for N (see next), we analyze how $\bar{\ell}$ improves as the number of observations increases.

These predictive checks assess complementary aspects of model generalization to unseen observations represented by user touch input characteristics. To compare model performance under different training conditions, we vary the number of observations in a geometric progression (powers of two) with additional intermediate values, $N \in \{2, 4, 8, 16, 24, 32, 48\}$, resulting in seven distinct experimental conditions for the model's training set size.

4 Results

We first provide an overview of participants' touch input performance, highlighting inter-participant differences (Figure 1), and continue with model evaluations. Lastly, we distill these findings into design implications for adaptive touch targets.

4.1 Inter-Participant Differences in Touch Input Performance

Our results revealed substantial inter-participant differences in both Time and Offset. Some participants were fast (e.g., a mean touch time of 58.0 ms for P_1), whereas others required more time (e.g., 247.7 ms for P_3, a 4× increase relative to P_1) or considerably more time (1563.3 ms for P_6, representing a 6.3× increase relative to P_3 and 27× relative to P_1); see Figure 1. Similarly, some participants were highly accurate (e.g., mean offset of 2.5 mm for P_7), whereas others exhibited larger offsets (10.5 mm and 8.8 mm for P_3 and P_6, respectively, corresponding to 4× and 3.5× lower accuracy). These results motivate user-specific modeling in line with ability-based design [23] and, consequently, we present results individually for each participant (Figures 2 to 4) in the next subsections.

4.2 Performance of Time and Offset Models

Figure 2 shows the predictive z-score coverage for the Time and Offset models relative to the expected 95% coverage of a Gaussian distribution. The minimal training condition (N=2) clearly stands out as underperforming for the Time models with coverage ranging from 68.0% (P_4) to 86.4% (P_3), and an increasing trend in performance can be observed for most participants as N increases for both Time and Offset. However, signs of overtraining are also visible, particularly for Time, where coverage decreases for P_1 and P_2 (88.5% and 87.9% at N=48) and approaches 100% for P_5 and P_6.

Figure 3 shows predictive z-score bias relative to the null reference $E[z]$=0. Excepting the low-data conditions (N=2 and N=4), generally exhibiting positive skew and wider confidence intervals (e.g., $\bar{z}$=1.8 for Time and $\bar{z}$=2.1 for Offset in P_3), a stabilizing trend toward the expected zero can be observed across all participants.

Lastly, Figure 4 shows the log-likelihood values of the models. We deliberately omitted visual representation of N=2 and N=4 as they extended well beyond the range of the other conditions and represented the poorest model performance, ranging from −2045.7 to −35.4 for N=2 and from −62.5 to −4.8 for N=4 for Time with a similar pattern observed for Offset. However, model performance improves substantially from N=8: with the exception of P_3 and P_6, which exhibited the highest variance (Figure 1), most participants' models reach a plateau beginning at N=8.

5 Design Implications

Our results indicate that effective user-specific modeling is feasible with just few observations, a simple statistical formalism, and touch measures easily acquirable on all platforms. Our key finding is the balanced amount of training data required for feasible modeling: very limited data ($N \leq 4$) lead to poor coverage and biased predictions, whereas increasing the amount of data improves model performance only up to a point, after which it plateaus. Due to inter-individual differences in touch input, no single threshold may be optimal for N; however, training data sizes between N=8 and N=24 provided the best overall performance in our study in terms of both coverage (Figure 2) and bias (Figure 3), with N=8 also marking the onset of the log-likelihood plateau (Figure 4). Following ability-based design [23], we propose a four-step procedure for integrating these findings into adaptive touch targets:

❶ ***Observe.*** Start with touch target size recommendations, e.g., 7–10 mm[3,4] up to 12–18 mm [6,10] and delay adaptive adjustments until a minimal number of user-specific observations are collected. At least $N \geq 8$ data points are required, although the exact threshold depends on model validation results (see next steps). Whether to perform an initial calibration or adapt on the fly is left to the designer's consideration. In either case, the designer adopts an *accountability* stance [23], changing the interface rather than expecting users to change.

❷ ***Model.*** Construct lightweight, user-specific models of touch duration and offset using a statistical approach that allows rapid validation of z-scores prediction coverage and bias. This follows the *ability* principle [23], placing the focus on

[3] https://m2.material.io/design/usability/accessibility.html#layout-and-typography
[4] https://learn.microsoft.com/en-us/windows/apps/develop/input/guidelines-for-targeting

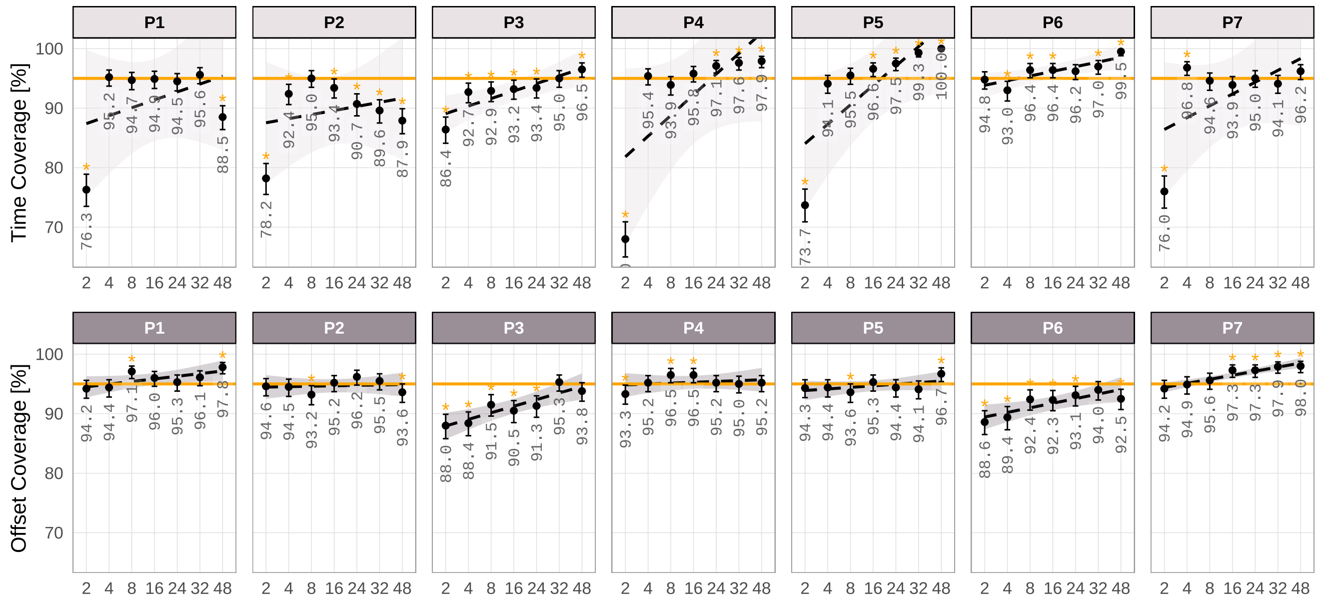

Figure 2: Predictive coverage for Time (top) and Offset (bottom) models (values closer to 95% indicate better performance). Note how performance (coverage) generally increases for most participants as the number of data points grows from 2 to 48. *Notes:* asterisks show statistical significance (p<.05) for deviating from the expected 95% coverage (orange line); error bars show 95% CIs, the dashed line shows the linear regression fit, and the shaded area represents the 95% CI around the fit.

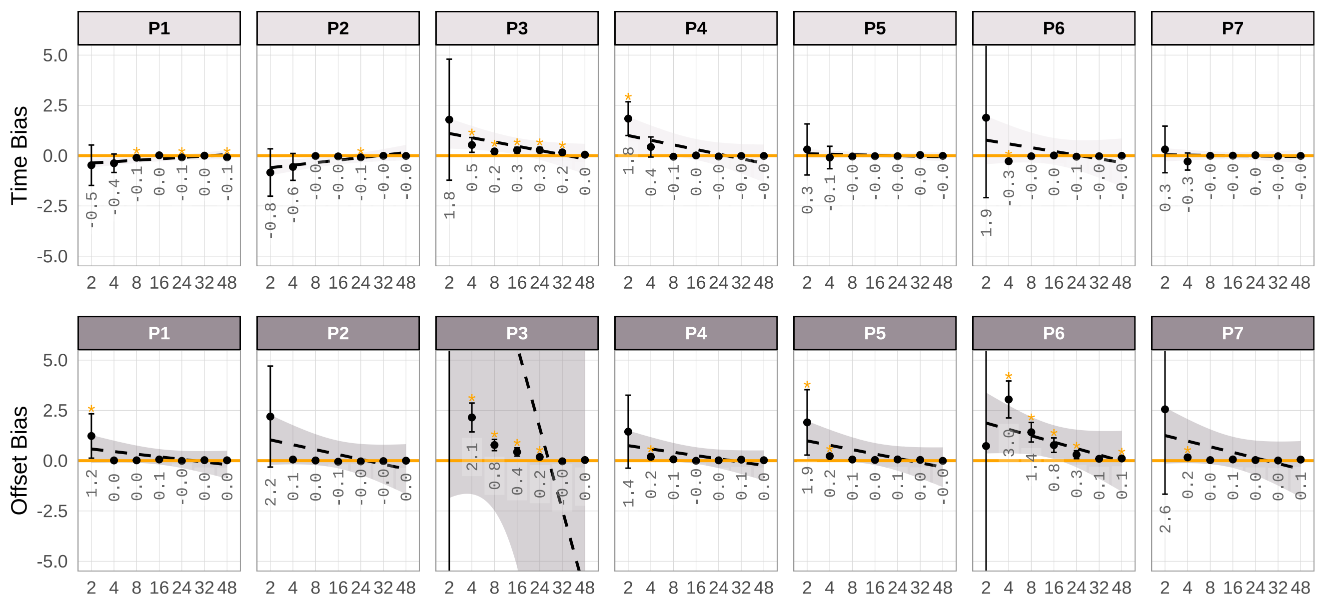

Figure 3: Predictive bias for Time (top) and Offset (bottom) models (values closer to zero indicate better performance). Note how bias generally decreases for most participants as the number of data points grows from 2 to 48. *Notes:* asterisks show statistical significance (p<.05) for deviating from zero (orange line); error bars show 95% CIs (a few, for N=2, too wide to fit properly within the plots); the dashed line shows the linear regression fit, and the shaded area the 95% CI around the fit.

users' actual touch performance in terms of Time and Offset measurements. For example, menu options can be resized based on an Offset model, while thresholds for short and long touches can be personalized based on a Time model.

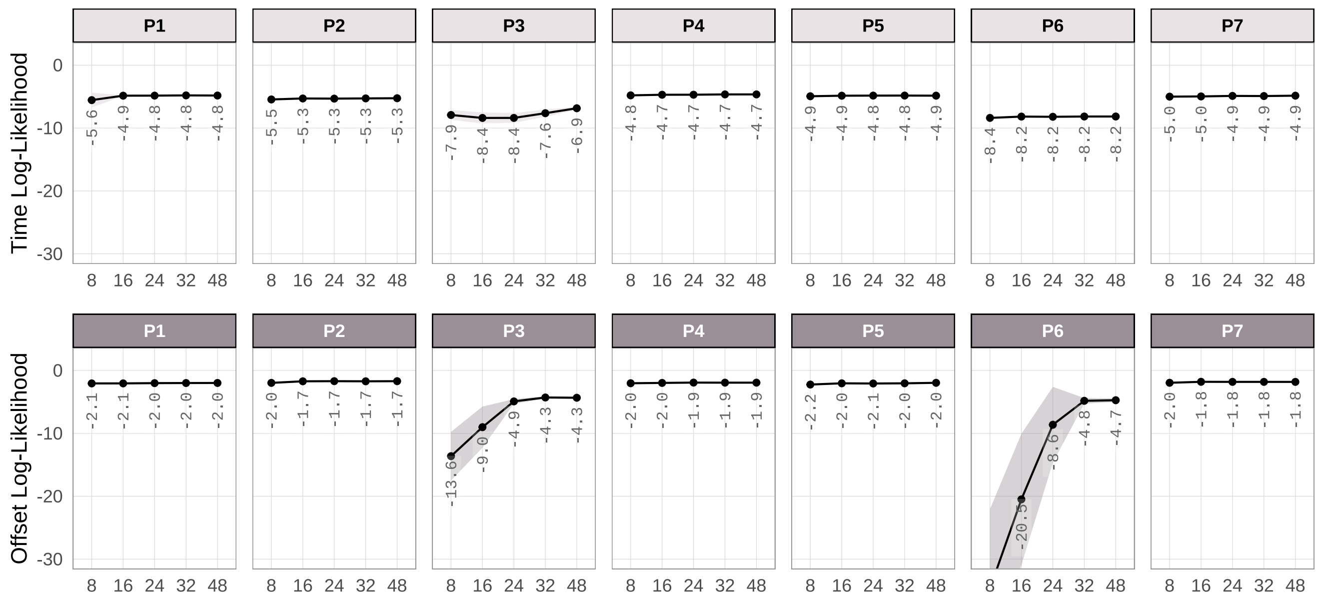

Figure 4: Predictive log-likelihood for Time (top) and Offset (bottom) models (higher values indicate better performance). Note how models performance for most participants typically plateau from N=8 data points onward. *Notes:* values for N=2 and N=4 were omitted due to extremely low log-likelihoods (very poor models), which did not fit within the plots; the shaded regions indicate 95% CIs around the mean log-likelihoods (in most cases, too small to be visually noticeable).

Our formalism (Subsection 3.3) uses default touch measures, requires few training compared to ML/DL models [3,4], does not rely on external libraries, and can be readily implemented on any platform, including custom prototypes with minimal software support—aligning with the *availability* principle [23], which encourages the use of affordable and widely available software and hardware resources.

❸ ***Revise.*** Update models using sliding windows of recent observations and monitor model performance for possible plateaus or degradation. This follows the *performance* principle [23], where the system monitors user performance to provide the best possible match with their abilities. Per our findings, windows of N=8 to N=24 touch observations ensure good accuracy and avoid overfitting. For example, menu button sizes can be adjusted gradually: early in use, only subtle adjustments are applied, with larger changes once prediction confidence stabilizes over continuous interaction. In line with in-the-wild observations [17], revising accommodates those situations where an individual's touch input abilities are significantly different between sessions.

❹ ***Share.*** Enable cross-application sharing of learned touch models on the user's device to reduce redundant data collection and modeling. This approach further emphasizes the *ability* and *availability* principles [23], enabling knowledge about a user's touch input behavior to be reused across applications for efficient, consistent personalization.

6 Conclusion, Limitations, and Future Work

We reported empirical results on the training size requirements for building user-specific models of touch input in individuals with motor impairments. Our findings pointed to a window of 8 to 24 observations as generally sufficient when using a straightforward statistical formalism of Gaussian modeling involving touch duration and offset measures, which is easy to implement across platforms. However, caution is warranted regarding the generalizability of these results because of the small sample size and the assumption of normal distribution, which may not fully capture the variability in touch input performance for all users with motor impairments.

To address these limitations and consolidate our findings, future work should investigate a larger sample, alternative distributional models, and examine more measures, such as touch variability and drift [13], which capture touch dynamics rather than its endpoint. Also, we focused on touch input only, but future evaluations could also address other modalities, such as stroke gestures [16] or eye gaze and eyelid-assisted input for mobile devices [5]. More complex modeling with multivariate Gaussian distributions [20] will account for how the different touch input measures co-vary. Also, insights into how practitioners integrate the four-step procedure into their interfaces or with existing toolkits [14] will be particularly useful. Advancing these directions will consolidate touch input modeling for users with motor impairments toward a richer understanding of ability-aware adaptive interfaces for mobile devices.

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References

[1] Xiaojun Bi and Shumin Zhai. 2013. Bayesian Touch: A Statistical Criterion of Target Selection with Finger Touch. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology (UIST '13)*. ACM, New York, NY, USA, 51–60. doi:10.1145/2501988.2502058

[2] Xiaojun Bi and Shumin Zhai. 2016. Predicting Finger-Touch Accuracy Based on the Dual Gaussian Distribution Model. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 313–319. doi:10.1145/2984511.2984546

[3] Daniel Buschek and Florian Alt. 2015. TouchML: A Machine Learning Toolkit for Modelling Spatial Touch Targeting Behaviour. In *Proceedings of the 20th International Conference on Intelligent User Interfaces (IUI '15)*. ACM, New York, NY, USA, 110–114. doi:10.1145/2678025.2701381

[4] Jeremy Chu, Yan Ma, Shumin Zhai, Xianfeng David Gu, and Xiaojun Bi. 2023. TouchType-GAN: Modeling Touch Typing with Generative Adversarial Network. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. ACM, New York, NY, USA, Article 29, 13 pages. doi:10.1145/3586183.3606760

[5] Mingming Fan, Zhen Li, and Franklin Mingzhe Li. 2021. Eyelid Gestures for People with Motor Impairments. *Commun. ACM* 65, 1 (Dec. 2021), 108–115. doi:10.1145/3498367

[6] Leah Findlater, Karyn Moffatt, Jon E. Froehlich, Meethu Malu, and Joan Zhang. 2017. Comparing Touchscreen and Mouse Input Performance by People With and Without Upper Body Motor Impairments. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 6056–6061. doi:10.1145/3025453.3025603

[7] Leah Findlater and Lotus Zhang. 2020. Input Accessibility: A Large Dataset and Summary Analysis of Age, Motor Ability and Input Performance. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '20)*. ACM, NY, USA, Article 17, 6 pages. doi:10.1145/3373625.3417031

[8] Krzysztof Z. Gajos, Jacob O. Wobbrock, and Daniel S. Weld. 2008. Improving the Performance of Motor-Impaired Users with Automatically-Generated, Ability-based Interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, New York, NY, USA, 1257–1266. doi:10.1145/1357054.1357250

[9] Seymour Geisser. 1993. *Predictive Inference* (1st ed.). Chapman and Hall/CRC, New York, NY, USA. doi:10.1201/9780203742310

[10] Tiago Guerreiro, Hugo Nicolau, Joaquim Jorge, and Daniel Gonçalves. 2010. Towards Accessible Touch Interfaces. In *Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '10)*. ACM, New York, NY, USA, 19–26. doi:10.1145/1878803.1878809

[11] Niels Henze, Enrico Rukzio, and Susanne Boll. 2011. 100,000,000 Taps: Analysis and Improvement of Touch Performance in the Large. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. ACM, New York, NY, USA, 133–142. doi:10.1145/2037373.2037395

[12] Christian Holz and Patrick Baudisch. 2011. Understanding Touch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 2501–2510. doi:10.1145/1978942.1979308

[13] Junhan Kong, Mingyuan Zhong, James Fogarty, and Jacob O. Wobbrock. 2022. Quantifying Touch: New Metrics for Characterizing What Happens During a Touch. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '22)*. ACM, New York, NY, USA, Article 33, 13 pages. doi:10.1145/3517428.3544804

[14] Junhan Kong, Mingyuan Zhong, James Fogarty, and Jacob O. Wobbrock. 2024. The Ability-Based Design Mobile Toolkit (ABD-MT): Developer Support for Runtime Interface Adaptation Based on Users' Abilities. *Proc. ACM Hum.-Comput. Interact.* 8, MHCI, Article 277 (Sept. 2024), 26 pages. doi:10.1145/3676524

[15] Abinaya Kumar, Aishwarya Radjesh, Sven Mayer, and Huy Viet Le. 2019. Improving the Input Accuracy of Touchscreens using Deep Learning. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (CHI EA '19)*. ACM, New York, NY, USA, 6 pages. doi:10.1145/3290607.3312928

[16] Nathan Magrofuoco, Arthur Sluÿters, Paolo Roselli, and Jean Vanderdonckt. 2025. Comparative Testing of 2D Stroke Gesture Recognizers in Multiple Contexts. *Proc. ACM Hum.-Comput. Interact.* 9, 4, Article EICS005 (June 2025), 36 pages. doi:10.1145/3733051

[17] Kyle Montague, Hugo Nicolau, and Vicki L. Hanson. 2014. Motor-Impaired Touchscreen Interactions in the Wild. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. ACM, New York, NY, USA, 123–130. doi:10.1145/2661334.2661362

[18] Martez E. Mott and Jacob O. Wobbrock. 2019. Cluster Touch: Improving Touch Accuracy on Smartphones for People with Motor and Situational Impairments. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, 1–14. doi:10.1145/3290605.3300257

[19] Amelie Nolte, Jacob Wobbrock, Torben Volkmann, and Nicole Jochems. 2022. Implementing Ability-Based Design: A Systematic Approach to Conceptual User Modeling. *ACM Trans. Access. Comput.* 15, 4, Article 34 (Oct. 2022), 26 pages. doi:10.1145/3551646

[20] Yung L. Tong. 1990. *The Multivariate Normal Distribution*. Springer, New York, NY, USA. doi:10.1007/978-1-4613-9655-0

[21] Radu-Daniel Vatavu, Lisa Anthony, and Quincy Brown. 2015. Child or Adult? Inferring Smartphone Users' Age Group from Touch Measurements Alone. In *Proceedings of the 15th IFIP TC.13 Int. Conference on Human-Computer Interaction (INTERACT '15)*. Springer, Cham, 1–9. doi:10.1007/978-3-319-22723-8_1

[22] Eric W. Weisstein. 2025. Bessel's Correction. From MathWorld–A Wolfram Resource. https://mathworld.wolfram.com/BesselsCorrection.html Accessed: December 2025.

[23] Jacob O. Wobbrock, Krzysztof Z. Gajos, Shaun K. Kane, and Gregg C. Vanderheiden. 2018. Ability-based Design. *Commun. ACM* 61, 6 (May 2018), 62–71. doi:10.1145/3148051

[24] Julia Woodward, Alex Shaw, Annie Luc, Brittany Craig, Juthika Das, Jr. Hall, Phillip, Akshay Holla, Germaine Irwin, Danielle Sikich, Quincy Brown, and Lisa Anthony. 2016. Characterizing How Interface Complexity Affects Children's Touchscreen Interactions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1921–1933. doi:10.1145/2858036.2858200

[25] Tevfik Bedirhan Üstün, Nenad Kostanjsek, S. Chatterji, and J. Rehm. 2010. *Measuring Health and Disability Manual for WHO Disability Assessment Schedule WHODAS 2.0.* World Health Organization, Geneva, Switzerland. https://www.who.int/standards/classifications/international-classification-of-functioning-disability-and-health/who-disability-assessment-schedule