A Nonlinear Model for Mouse Pointing Task Movement Time Analysis Based on Both System and Human Effects

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***Abstract*—This paper provides a detailed model for analyzing movement time performance during rapid goal-directed point-and-click motions with a computer mouse. Twelve typically developed individuals and eleven youths with cerebral palsy conducted point and click computer tasks from which the model was developed. The proposed model is nonlinear and based on both system (target width and movement amplitude) and human effects (erroneous clicks, number of submovements, number of slip-offs, curvature index, and average speed). To ensure successful targeting by youths with cerebral palsy, the index of difficulty was limited to a range of 1.58 – 3.0 bits. For consistency, the same range was used with both groups. The most significant contributing human effect to movement time was found to be the curvature index for both typically developed individuals and individuals with cerebral palsy. This model will assist in algorithm development to improve cursor speed and accuracy for youths with cerebral palsy.**

***Index Terms*—Fitts's law, human performance modeling, movement time, point-and-click, speed-accuracy trade-off.**

I. Introduction

THE ABILITY to manipulate a computer cursor is important for many applications such as word processing, game playing, and Web browsing. Point-and-click interfaces are generally developed with the aim of making applications practical and user-friendly; generally evaluated by Fitts's law. Fitts's law has served as one of the most successful models of human-computer interactions. It has been used as a theoretical framework for computer input device evaluation [1], [2] and as a tool for developing and improving interfaces as well as the logical basis for modeling. Conversely, Fitts's law does not fully describe human performance (e.g., errors introduced into the model by human behavior). The central focus of Fitts's pointing paradigm is based on the motor control part of pointing, where users perform rapid goal-directed movements. Fitts's law models are often developed in a controlled environment where the user knows the exact position of the target. Furthermore, it was originally conceived before the existence of the computer mouse, so the task was inherently different. However, in real world human computer interactions, a mouse is generally used and the environment is not controlled; an individual could be dealing with factors such as multiple possible targets or environmental interference such as taking a phone call [3]. The idea of modeling both the system and human effects for point-and-click tasks has been researched previously [1]. For example, Hwang *et al.* [4] made use of human effects to better understand computer–human interaction for youths with motion impairment to provide full computer access.

Our research contributes to the literature on human computer interaction by developing a theoretical model based on both system and human effects to describe the performance (movement time) of point-and-click tasks. Model validation is undertaken by comparing the proposed model against previous models using the Akaike information criterion (AIC) and the coefficient of determination, R^2, statistical measures. This paper initially presents a literature review of movement time models for rapid movement tasks. It then develops a model, for typically developed individuals and individuals with cerebral palsy, which incorporates the human effect with the system effect. The system effect is defined in this paper as the target width and amplitude (distance between centers of two targets). The human effect parameters are defined as variables that are caused by human behavior, such as erroneous clicks or slip-offs.

II. Literature Review

Rapid goal-directed movements are categorized by two models: the iterative correction model, which is the basis of Fitts's law [5], and the impulse variability model (for ballistic movement) [6]. The iterative correction model is based on spatially constrained movements where participants are required to reach the target with width, W, placed at distance, A, as fast as possible. The measured movement time is used as a reflection of task performance; it is a time minimization task [7]. The impulse variability model is based on a form of temporally constrained movement; participants are required to reach towards the target for a specified movement time, creating a time-matching movement task [6], [7]. The goal of this task is to get as close as possible to the target within the time constraints. However, these two models cannot be independently applied to all pointing movements. They have been integrated into the optimized initial model [8] which is a hybrid of the two models. The optimized initial model describes the movement by two phases of submovements (rapid primary and slow secondary). Firstly, a rapid primary movement is conducted toward the target. If the movement attains the target, then the task is completed. On the other hand, if the movement lands outside the target, a slower corrective movement is required. This process carries on until

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the target is attained. The primary goal of the task is to reach the target as fast as possible; thus, in an ideal scenario, the subject should perform a single high-velocity movement toward the target. In reality, the ideal scenario seldom occurs as the initial movement undershoots or overshoots the target in most cases.

On the other hand, Soukoreff and Mackenzie [2] argued that Fitts's law is applied to movements where pauses midtrial do not exist (pauses violate the requirement that movements be rapid). Another impracticality is that the movement time data have to be normally distributed (by removing distance or time outliers beyond three standard deviations from the average of movement distance or time) [2]. Motion-impaired users experience instability of movement; therefore, the existence of a pause component is expected. In addition, Fitts's law takes into account only certain system effects (target width and movement amplitude) while neglecting the effects of human behavior [1]. Behavior significantly influences movement characteristics of motion-impaired users [4], [9].

For rapid goal-directed (aimed) movements, Fitts's law (1954) [5] expresses the relationship between three parameters: movement time (dependent variable); movement amplitude (independent variable, A); and target size (independent variable, W) [(1)]. The Fitts's law model originated from direct pointing, where the hand taps physical objects. Fitts's law is used to predict the movement time to reach the target. The prediction formula is a linear function of the index of difficulty. Fitts's law does not form a full picture of point-and-click computer tasks as it does not take into account sources of error particular to using a mouse [10].

The most common representation of Fitts's law is the Shannon formulation where the effective width is either calculated based on the standard deviation of end points or using the error rate with the assumption that the movement end points are normally distributed [2] (error rate is defined as the percentage of erroneous clicks within a block of trials). The effective width is equal to the original width when 96% of the end points fall within the target width while moving "as fast as possible." "As fast as possible" indicates that there are no pauses; therefore, according to Soukoreff and Mackenzie [2] the movement time should be normally distributed. If the error rate is greater than 4%, the effective width is greater than the original width and vice versa. The effective width is computed by $4.133 * SD$, where SD is the standard deviation of the experimentally obtained end-point coordinates. The Shannon formulation of the index of difficulty (ID) for Fitts's law is given by

$$\begin{aligned} MT &= a + b * ID \\ IDe &= \log_2\left(\frac{Ae}{We} + 1\right) \end{aligned} \tag{1}$$

where a and b are experimentally derived constants specific to an individual participant, MT is movement time, ID is the index of difficulty (bits), A is movement amplitude, and W is target width.

Some motion-impaired users have spastic movements, which result in error rates beyond 4% and lead to longer pauses during movement correction; therefore, the spatially constrained movement theory might not be obeyed. Moreover, Fitts's law assumes that movements are visually guided, which is seemingly the case for Fitts IDs greater than 3. Gan and Hoffmann [11] stated that for an *ID* less than 3, the movement is a nonvisual guided corrective movement (ballistic movement). However, this testing was only conducted by typically developed individuals. Individuals with cerebral palsy have different access approaches and needs [12], thus a better model is required.

In a study of 22 children (aged 5–16 years) with congenital spastic hemiplegia (CSH), Smith-Englesman *et al.* [13] found that children with CSH adhere to Fitts's law in visually guided tapping tasks (Fitts ID ranges from 2 to 4 bits). However, in an earlier study of eight participants with cerebral palsy, CP (aged 28–60 years, seven with moderate to severe spastic quadriplegia and one with mild CP), Gump *et al.* [14] found that pointing task movements conducted by adults with CSH did not adhere to Fitts's law (ID ranges from 2.19 to 6.00 bits), but they obeyed the ballistic factor [15]. On the other hand, Gump *et al.* [14] did find that one of the participants adhered to both Fitts's law and the ballistic factor law. However, they explained that noncompliance with Fitts's law might have been caused by visual problems, especially for severely impaired participants who may not have used visual feedback to control their movement.

We have found that for participants with CP, the ability to conduct computer point and click tasks is limited to an index of difficulty of 2. Computer tasks become too difficult for this population for IDs greater than this [12].

Analysis of discrete submovement components supplies additional information that may provide a larger picture of point-and-click computer tasks. Fitts's law and the ballistic movement law are bounded by movement amplitude and target width parameters. Combining these has led to the development of the initial impulse model that accounts for discrete submovements and can be used for graphical interface design for motion-impaired users [8], [16], [17]. The optimized initial impulse model is a form that includes both spatial and temporal movement tasks.

Fitts's law has already been augmented to provide a better picture of human motor functionality during point-and-click computer tasks. Wobbrock *et al.* [18] attempted to reverse Fitts's law to develop an error model for point-and-click computer tasks [18], [19]. They concluded that the error prediction model based on a reversed Fitts's law provides predictions with a strong similarity to observed error rates for movements with experimentally controlled movement times (using a metronome-based time-matching study). On the other hand, the probability of success, P_h (= 1-error rate), has been added as an independent variable in Fitts's law to establish the system-human model (SH model). The SH model is an example of an augmented Fitts's law that includes both the system and human effects [1]. The SH model equations are as follows:

$$\begin{aligned} MT &= e^a * SI_s^b * SI_h^c \\ SI_s &= \log_2\left(\frac{A}{W} + \lambda + 1\right) \\ SI_h &= \log_2\left(\frac{1}{P_h}\right) \\ P_h &= \frac{n+1}{m+2} \end{aligned} \tag{2}$$

where *a, b,* and *c* are constants, λ is an estimated parameter from the minimum Akaike information criterion (AIC), n is the total number of clicks inside the target, and m is the total number of trials (click attempts), SI_s is system effect, SI_h is human effect, and P_h is the probability of success.

III. Proposed Model

The fundamental idea behind our proposed model was to join the Shannon formulation of index of difficulty [(1)] of Fitts's law with the most important path evaluation measures as listed below to formulate an equation to predict movement time (MT). Our model is based on the inclusion of both system influence and human influences; similar to the SH model [1]. System influence is evaluated by the pointing task condition (the amplitude between targets and the target width). The number of erroneous clicks is an example of human behavior affecting task performance. In previous research [20]–[30], 40 different path evaluation measures were identified as possible contributors to movement and submovement times. The most important path evaluation measures that relate to movement time were determined using an automatic linear modeling technique on collected data (experiment design is discussed in detail in next section). We found that the best indicators of human error that significantly affect movement time were the number of erroneous clicks (EC), the number of submovements (NS), the curvature index (CI), the number of slips-off (NSO), and average speed (AS). These were used in the development of the new model. These parameters are defined as follows.

A. Number of Erroneous Clicks (EC)

The number of nontarget clicks within a trial. Nontarget clicks require movement correction; therefore, movement time is expected to increase as the number of nontarget clicks increases. This number is unit-free.

B. Number of Submovements (NS)

The number of discrete movements separated by pauses defined as a zero cursor speed. It is unit-free. A high number of submovements indicate more movement correction, resulting in an increase in movement time. Hwang *et al.* [4], [9] found that typically developed users completed 90% of point-and-click trials in less than seven submovements, while 90% of trials of motion-impaired users required more than seven submovements. In our experiment, the definition of a pause was conservatively set to a cursor speed of zero because it is difficult to specifically define a submovement [3].

C. Curvature Index (CI)

The ratio of the total distance traveled to the straight-line distance between the start and end points. A value of 1 indicates the cursor path follows a straight line toward the target, and a larger value shows increasing deviations [23]. It is expected that involuntary movement in an unintended direction increases as the degree of impairment increases; therefore, the distance travelled and hence the movement time increases [31]. It too is unit-free.

D. Number of Slips-Off (NSO)

A slip-off is defined as the submovement that starts inside the target and ends outside the target. Note that this means the cursor had stopped inside the target before moving away. The number of slips-offs is a count of the number of in-out target submovements within a trial [4]. It is unit-free. Hwang *et al.* [4], [9] found that typically developed users rarely slip off, and motion-impaired users slip off more frequently than typically developed users.

E. Average Speed (AS)

The average value of speeds sampled within a given trial. It is expected that the degree of impairment has an influence on average speed. The unit is pixels/millisecond.

These measures were used in the development of a general new model (the unit of movement time is milliseconds)

$$MT = a + b * SE + c * EC + d * NS + e * NSO + f * CI + g * AS. \quad (3)$$

F. SE

ID (for Fitts based models), or A (for Ballistic based models).

where a, b, c, d, e, f, and g are time factor constants, and SE is system effects.

Note that most of these variables can only be obtained post-hoc. Also note that multicollinearity is analyzed later under the Results and Analysis section.

IV. Empirical Validation of the Proposed Model

It was important to validate the model by carrying out a controlled experiment using standard discrete pointing tasks. This section covers three aspects of the experiments, including participants, apparatus, and experimental design.

A. Subjects

1) Twelve typically developed (TD) participants (eight males and four females, aged 18–32, all right-handed) took part in the experiment.
2) Eleven participants (aged 13–22) with cerebral palsy (CP) (eight MACS[1] I and three MACS II) [32] took part in the point-and-click tasks. Inclusion criteria: able to use the mouse. Mouse experience: the participants uses the computer during computer teaching sessions in rehabilitation centres.

B. Apparatus

1) Typically Developed Participants: Participants were seated comfortably on a desk chair in a normally lit room whilst they completed computer mouse pointing tasks at a desk. The experiment was conducted on a Dell desktop machine with a 2.4 GHz Intel Core 2 Quad CPU with 2 GB of RAM running 64-bit Windows 7 Enterprise. The pointer speed (control and display gain) was set to 10 as normal. The screen used was at a resolution of 1280×1024 pixels (51×33 cm) with a refresh rate of 60 Hz. The pointing device type was a standard USB optical mouse. The resolution of the pointing was 96 pixels per inch (DPI). The average horizontal distance between the screen and a participant's face ranged between 50 and 60 cm.

[1]MACS (Manual Ability Classification System): is used to classify the level of upper limb ability in children with CP; widely ranging from MACS I (handles objects easily and successfully) to MACS V (does not handle objects and has severe impairment that require assistance to carry out simple actions).

TABLE I
SUMMARY OF EXPERIMENT CONFIGURATION

Quasi-random target directions	Eight directions (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°)
Number of trials per block of A&W combination	40 trials (five in each direction)
TargetA&Wcombinations	Eight combinations(six amplitudes [100, 150, 200, 250, 300, 350 pixels] with a target size of 50 pixels andtwo amplitudes [200 and 300 pixels] with a target size of 100 pixels)

2) Individuals With CP: Participants sat at a desk (some of them in a wheelchair) and completed pointing tasks with a computer mouse under normal lighting conditions. The experiment was conducted on an HP laptop machine with a 2.2 GHz AMD Turion X2 Ultra Dual-Core Mobile ZM-82 with 3 GB of RAM running 32-bit Windows 7 Enterprise. The pointer speed (control and display gain) was set to 10 as normal. The screen used was at a resolution of 1280×800 pixels (35×24 cm) with a refresh rate of 60 Hz. The pointing device type was a standard USB optical mouse (manufactured by Dell). The resolution of the pointing was 96 pixels per inch (DPI). The average distance between the screen and participants ranged between 50 and 60 cm.

C. Experimental Design

A multidirectional discrete pointing task was undertaken by each participant to evaluate the cursor movement between two targets with different sizes and center-to-center amplitudes. The software was developed in C# with a sampling interval of 15 ms. A single trial was defined as the cursor traveling from a home square, located at the center of the screen, to a target square, which was visible prior to trial start. A trial started (and movement time is counted) from when the user clicked on the home square and ended when the user clicked on the target square. Next, the user returned the cursor to the home square to initiate a new trial. Trials were conducted in blocks of 40 with roughly half to one minute breaks in between. In each block, the amplitude and width was consistent whilst the target direction was varied quasi-randomly between eight compass directions. The eight combinations of amplitude and width are summarized in Table I along with the possible target directions.

The typically developed (TD) participants undertook two sets of the eight blocks of combinations; while the youths with CP did only one set to diminish issues with fatigue. The total number of trials for each set (A-B-A-B) of the experiment was 320 (8×40). Participants were instructed to take breaks whenever they wanted (not mid-trial; they can stop whenever they click on the target object). The total number of trials across the 12 TD participants was 7680, and the 11 participants with CP completed a combined total of 3520 trials.

V. RESULTS AND ANALYSIS

To show the need to develop a better model for point-and-click computer tasks, it was necessary to investigate the effect of impairment on pause time (the time interval when the cursor travels at zero speed), since Fitts's law depends on there being none, or at least very little. Fig. 1 shows the average pause time grouped by successful trials (with no erroneous clicks) and unsuccessful trials (with erroneous clicks) across TD, MACS I, and MACS II participants. Fig. 1 shows that the average pause time during point-and-click computer tasks conducted by youths with CP (MACS I [575 ms successful, 1409 ms unsuccessful] and MACS II [501 ms successful, 1032 unsuccessful]) is more than double the average pause time of typically developed users (195 ms successful, 380 ms unsuccessful).

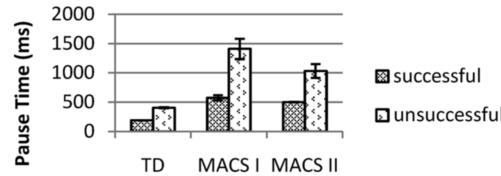

Fig. 1. Average pause time.

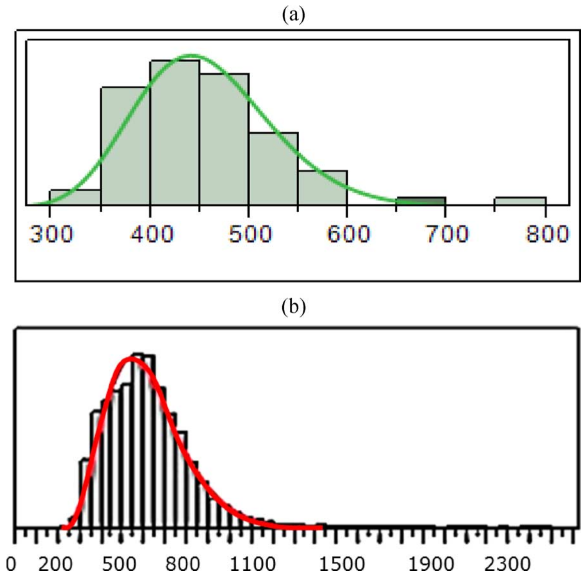

Fig. 2. (a) Log distribution of movement time (TD participant 1, A: 100 pixels, W: 50 pixels (ms). (b) Log distribution of overall movement time for TD participants.

Whereas Fitts's law is based on a selective normal distribution of data, the analysis of experimental data for movement times in our point-and-click tasks showed a non-normal distribution (positively skewed). The best-fitting distribution (as required for statistical analysis) was found to be a log distribution (natural log, Fig. 2). Thus, a better model must represent the components based on the natural log. For example, the number of erroneous clicks can be represented as

$$\ln(1 + EC). \tag{4}$$

If the number of erroneous clicks is 0, the result of [(4)] is zero; the EC would only contribute to the model if, in fact, EC actually occurred. The same applies to NSO and NS. Therefore, the log-transformed model is given by

$$\begin{aligned}\ln(MT) = a + b * \ln(SE) + c * \ln(1 + EC) + d * \ln(1 + NS)\\ + e * \ln(1 + NSO) + f * \ln(CI) + g * \ln(AS). \end{aligned} \tag{5}$$

Equation (5) can be transformed nonlinearly (natural exponentiation) as the following:

$$MT = \exp^{a} * SE^{b} * (EC+1)^{c} \\ *(NS+1)^{d} * (NSO+1)^{e} * CI^{f} * AS^{g}. \quad (6)$$

The proposed model without the human effect is given by

$$\ln(MT) = a + b * \ln(SE) \\ MT = \exp^{a} SE^{b}. \quad (7)$$

A. Validation of Models

To further validate the model, it was formulated with Fitts-like and ballistic-like system effects, and with [(5)] and without [(7)] human effects. It was also tested against Fitts's model [(1)] (with original and effective width), and the SH model [$\lambda = 0$, (2)]. The effective width is calculated based on Mackenzie's equation for the error rate [2]. Outliers of movement time or movement amplitude beyond three standard deviations were removed from analysis based on Fitts's law. The movement time and amplitude used for Fitts's law (effective width) is recorded from start to the first click (either target or erroneous click to compensate for end-point scattering).

The analysis of collected data was conducted using multiple linear regressions [note that the linearization of a nonlinear equation allows linear regression; linearization of (6) to (5)]. Seven different models—Fitts's law (with original width and effective width), SH, Fitts-like (with and without the human effect), and ballistic-like (with and without the human effect)—were compared. Using analysis of variance on movement times (A and W Combination $\times$ Direction) direction was not found to be significant ($p > 0.05$) nor to interact significantly ($p > 0.05$) with A and W combination for either typically developed individuals or youths with CP. As such, it was not used as a factor in regression modeling. Participants and blocks were considered as random effects in regression modeling.

Three criteria were used to validate the model: the Akaike information criterion (AIC), multicollinearity of independent variables, and homoscedasticity. The AIC allowed the selection of the best model among the seven models. After that, the best selected model is diagnosed by the multicollinearity of independent variables to ensure that each variable is really making an independent contribution to the movement time and, finally, homoscedasticity. The homoscedasticity test is to ensure constant variance of the dependent variable for all data.

B. The Akaike Information Criterion

The main goal of statistical modeling is to develop a model with robust prediction features given that the independent variables are accurately known. This allows us to compare the effectiveness of different models. The traditional method (coefficient of determination, R^2) of model comparison and evaluation is not sufficiently powerful as it cannot represent the model's prediction ability and is limited only to linear models. One of the shortcomings of R^2 is that it does not become smaller as the number of independent variables increases; therefore, adjusted R^2 compensates for the increase of independent variables (adjusted R^2 is less than or equal to R^2). The Akaike information criterion has gained a strong reputation in model selection as it can be applied to linear and nonlinear models. Furthermore, it can characterize the prediction features of the model based on maximum log likelihood and the number of parameters. The selection of a robust predictive model of those compared is based on the lowest AIC value among the compared models [1], [33]–[38]. AIC is defined as follows:

$$AIC = -2M + 2k \quad (8)$$

where M is maximum log likelihood of the model, and k is the number of estimated parameters, including intercept and error terms in the model.

C. Regression Analysis

The regression of the models is based on the original data of each $A \times W$ block rather than the average of each combination. The average of each combination removes the effect of variation in regression. In addition, according to statistical theory, estimation of results is more robust when using the original data to develop a model; therefore, we implement model regression using the original data. For example, the regression of the SH model is conducted by calculating the error rate of each $A \times W$ combination and reprinting the error rate in each trial within each $A \times W$ combination. A similar method is conducted for the calculation of effective width.

D. Statistical Analysis to Interpret the Development of the Final Model

Table II shows the AIC for each model. The lowest two AIC values for the experiment conducted by TD, MACS I, and MACS II, respectively, fits with the models that include human factors.

The evaluation of each independent variable's contribution to constructing the model is based on the F-ratio value (a high value indicates higher contribution to the model; F-ratio value is used to add or remove an independent variable to/from the model, where a high value indicates it should be added and a low one indicates it could be deleted) [39], [40]. Table III shows the contribution of each independent variable to the lowest AIC models; Fitts-like and ballistic-like + human effects.

1) Homoscedasticity (Constant Variance) : To be valid, the regression model must have a constant variance over predicted values of the dependent variable. If it has a changing variance, it is called heteroscedastic. The presence of heteroscedasticity requires further correction of the model, such as applying a better mathematical transformation [38]. The examination can be made visually and numerically using the root-mean-square error (RMSE). The homoscedasticity can be visually examined by predicted plot versus actual plot and residual versus actual plot (see Figs. 3 and 4).

The homoscedasticity may not be related to human factors. To clarify this issue, the Fitts-like and ballistic-like proposed models have been compared with [Fig. 3(a) and (b)] and without human effects (Fig. 4), respectively in Table IV.

TABLE II
AIC AND R^2 VALUES FOR THE SEVEN MODELS FOR TD, MACS I, AND MACS II

Model	AIC			R^2		
	TD	MACS I	MACS II	TD	MACS I	MACS II
Fitts's Law (OW)	127494	39228	14065	0.56	0.43	0.55
Fitts's Law (EW)	129774	39377	14235	0.46	0.4	0.46
SH	−2698	1190	223	0.53	0.64	0.62
Fitts-like (+)	−12143	−2139	−790	0.81	0.9	0.87
Fitts-like (−)	−2685	1233	217	0.53	0.63	0.62
Ballistic-like (+)	−21109	−4806	−1420	0.92	0.97	0.93
Ballistic-like (−)	−82	1565	500	0.4	0.58	0.49

OW: Original width, EW: Effective width.
(+): With human effect, Equation 5.
(−): Without human effect, Equation 7.

TABLE III
F-RATIO VALUES FOR EACH INDEPENDENT VARIABLE OF LOWEST AIC MODEL (ALL F VALUES ARE SIGNIFICANT)

Independent Variable	Fitts-like (ID)			Ballistic-like (A)		
	TD	MACS I	MACS II	TD	MACS I	MACS II
System Effect	17770	2277	917	55704	11346	2715
$ln(1+EC)$	1639	236	72	150	40	21
$ln(1+NS)$	515	149	132	114	67	97
$ln(1+NSO)$	90	62	8	8	7	10
$ln(CI)$	3081	1702	528	17393	9501	2262
$ln(AS)$	2228	873	205	32290	8600	1700

2) Multicollinearity of Independent Variables: A high correlation between independent variables is an indication of multicollinearity. Multicollinearity is tested by the variance interactive factor (VIF). The threshold value of VIF is 10. A value greater than 10 indicates the existence of multicollinearity between one independent variable with another independent variable or a combination of other independent variables [38]. The VIF values for both Fitts-like and ballistic-like models ranged from 1.1 to 3.5 (TD) and 1.1 to 2.3 (MACS I &MACS II) indicating the absence of multicollinearity.

3) Model Constants: The ballistic-like model has a lower AIC than the Fitts-like model. The values of constants (a, b, c, d, e, f) are obtained using linear regression under the Fit Model option in JMP software (participants and blocks are added as random factors). Therefore, the reformatted model is given as the following.

Typically developed

$$MT = \exp^{0.34} * A^{0.94} * (EC+1)^{0.07} *(NS+1)^{0.02} * (NSO+1)^{0.04} * CI^{0.94} * AS^{-0.86}. \quad (9)$$

MACS I

$$MT = \exp^{0.63} * A^{0.91} * (EC+1)^{0.07} *(NS+1)^{0.04} * (NSO+1)^{0.04} * CI^{0.90} * AS^{-0.86}. \quad (10)$$

MACS II

$$MT = \exp^{1.2} * A^{0.83} * (EC+1)^{0.11} *(NS+1)^{0.09} * (NSO+1)^{0.08} * CI^{0.73} * AS^{-0.75}. \quad (11)$$

VI. DISCUSSION

The ballistic-like proposed model has the lowest AIC of those compared within each subject group; therefore, it is the best model. However, further diagnosis of model validity was conducted, which involved homoscedasticity, R^2, and VIF.

A visual examination of homoscedasticity appears in the predicted plot versus actual plot for TD, MACS I, and MACS II (see Fig. 3). This suggests that the proposed model works effectively for predicting the movement time. Fig. 3 shows the homoscedasticity of the log-transformed movement time model, which has horizontal residual ranges from -0.65 to 0.70 for TD, -0.5 to 0.9 for MACS I, and -1.80 to 0.25 for MACS II (no tendencies to be positive or negative). Fig. 3 also shows that the predicted and actual movement time has a linear relationship with increasing variations at higher movement times. According to the diagnosis of a prototypical residuals plot, the model is homoscedastic; therefore, the model does not require additional correction and transformation of independent variables.

Table III shows that the F-value of the system effect *(ID)* is higher than the F-values of the human effects *(EC, NS, NSO, CI and AS)*. A comparison of the proposed model with human effects [(5)] and without human effects [(7)] shows that the proposed model with human effects has a lower AIC and higher R^2 than without human effects (see Table II). In addition, Table IV shows that the addition of the human factors homogenates the variance, thereby reducing the root-mean-square error. Fig. 4(b) shows that there is no linear relationship between predicted and actual movement time for typically developed users in comparison to the linear trend presented in Fig. 3(b).

R^2 is a measure of the independent variables' contribution to the linear model, and the model variations are explained by $1-R^2$. Of the TD-based, MACS I–based, and MACS II–based models, 92%, 97%, and 93% of the respective variations are explained by the given independent variables, which are *EC*, *NS*, *NSO*, *CI*, and *AS*. Compared to previous studies [41], we found R^2 values that were poor in comparison (OW:0.55 , EW:0.46). This is because the regression included all data rather than the average of each A $*$ W combinations. This was based on consultation with a statistician who insisted that the data not be averaged as variation especially evident for youths with cerebral palsy is eliminated by doing so.

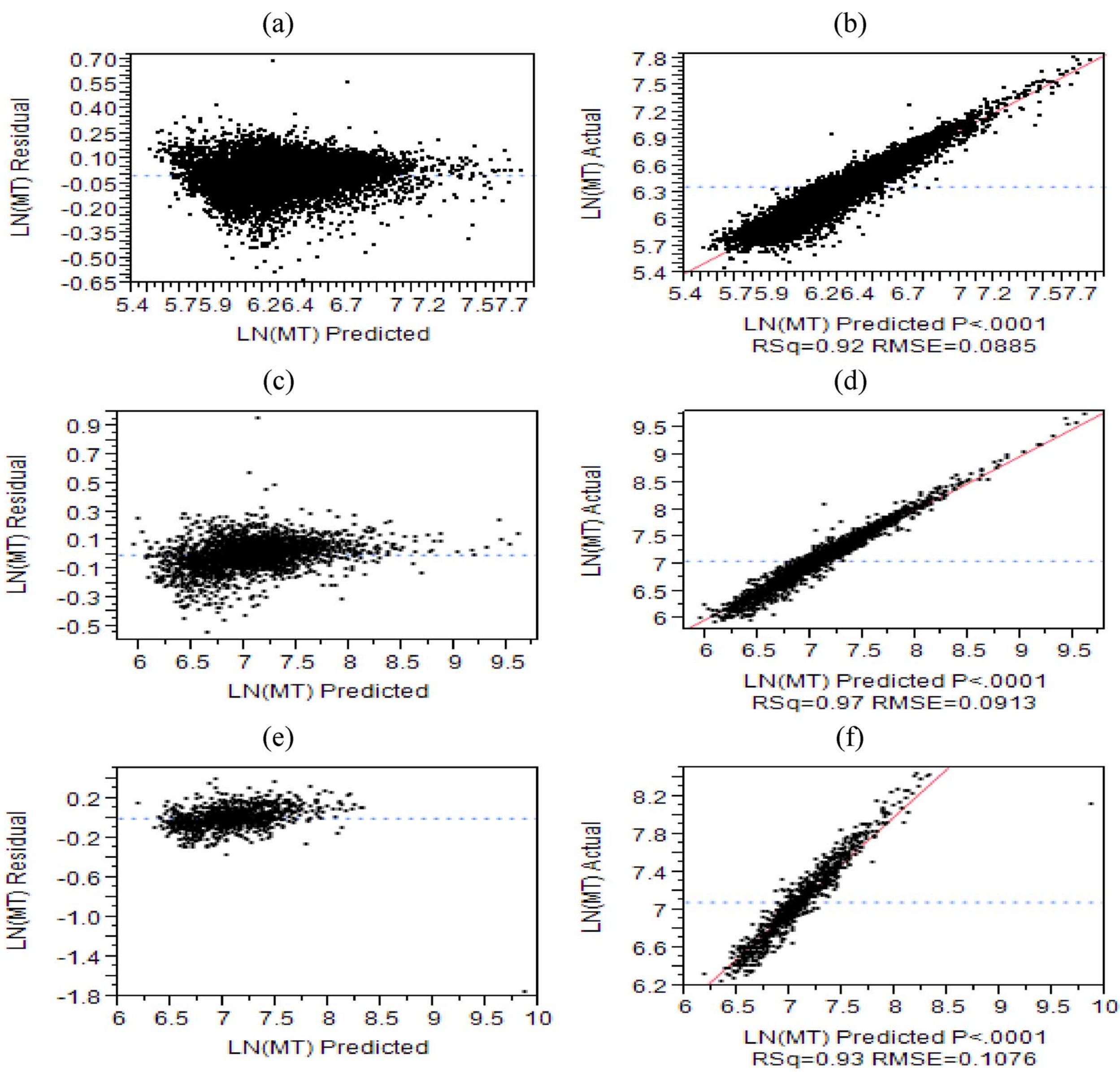

Fig. 3. (a), (c), and (e) Residual of predicted log-transformed movement time of the ballistic-like model with human effects. (b), (d), and (f) Distribution of actual versus predicted movement time of the ballistic-like model with human effects. Both (a) and (b) represent typically developed participants, (c) and (d) represent MACS I, and (e) and (f) represent MACS II. (a) TD. (b) TD. (c) MACS I. (d) MACS I. (e) MACS II. (f) MACS II.

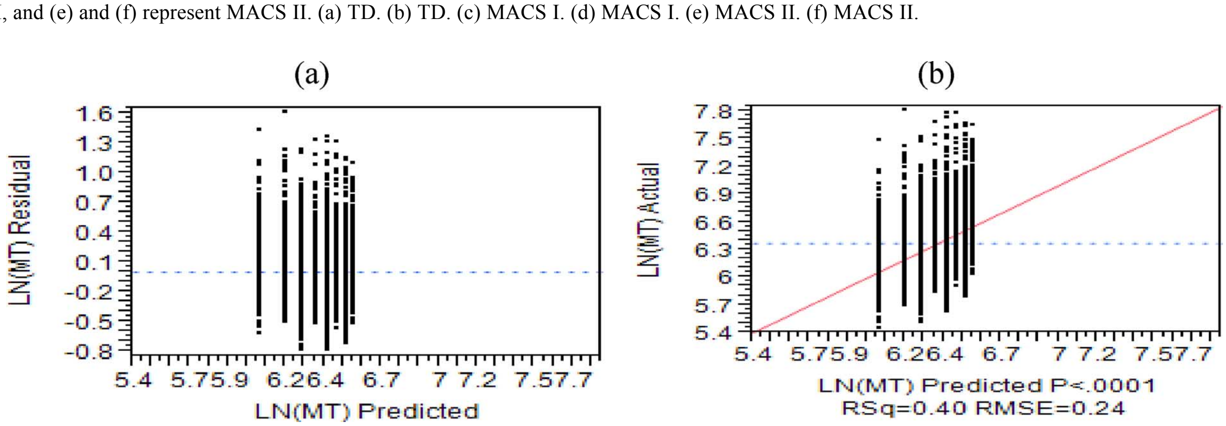

Fig. 4. (a) Residual of predicted log-transformed movement time of the ballistic-like model without human effects. (b) Distribution of actual versus predicted movement time of the ballistic-like model without human effects. Both (a) and (b) represent typically developed participants.

The VIF values for experiments of TD, MACS I, and MACS II range from 1 to 2 and indicate the absence of multicollinearity.

Table III shows the system effect contributors to the task performance for all TD, MACS I, and MACS II groups. The

TABLE IV
COMPARISONS OF HOMOSCEDASTICITY OF THE PROPOSED MODEL WITH/WITHOUT HUMAN FACTORS USING RMSE

	Fitts-like			Ballistic-like		
	TD	MACS I	MACS II	TD	MACS I	MACS II
With Human Factor	0.14	0.16	0.15	0.09	0.09	0.11
Without Human Factor	0.21	0.3	0.27	0.24	0.58	0.49

curvature index and average speed were found to be the biggest contributor of human effects on the task performance for all TD, MACS I, and MACS II groups. Previous research study with a different population of individuals with CP (29 individuals range from MACS I to MACS IV) showed that average speed was significantly correlated with both Index of Difficulty (system effect) and MACS level [11]. That study (which did not include submovement analysis) also showed the CI was significantly correlated with ID (system effect) and had a good correlation with MT for typically developed individuals. In this paper, we combined the system effect (ID or A) with human effect to model the movement time, we found that average speed and CI are not only the main human effects, but also significant correlated with of MT in both Fitts-like and ballistic-like models. The number of slip-offs is the lowest contributor of human effects on the performance task for all TD, MACS I, and MACS II groups of the five chosen human effects.

Equations (9), (10), and (11) show that all independent variables correlate positively with movement time except average speed (negative power, -0.86 and -0.86 and -0.75, respectively). Simply, a higher number of submovements, erroneous clicks, and slip-offs and a larger curvature index increase the movement time and vice versa for higher average speed.

Previous studies have compared task performance discretely based on path evaluation measures. Hwang *et al.* [4], [9], [26] compared the task performance for each subject and each path evaluation measure independently; however, a model representing all participants and measures was not developed. Thus, Hwang *et al.* [9] failed to account for the effect of human factors to efficiently evaluate task performance. This type of nonlinear modeling can potentially augment Fitts's law or the ballistic movement model to predict the movement time or to evaluate pointing devices because it better includes the human influence. Connelly [42] concluded his study by saying that nonlinear or higher-order-control models account for varying coefficients along the trajectory can be developed to describe task performance. This study has provided a nonlinear model that account for trajectory variables such as submovements.

In an ideal case, when the user moves in a straight line from target to target (curvature index becomes 1) and produces no erroneous clicks, submovements, or slip-offs, the movement time model is reduced to two independent variables, which are reciprocal average speed (negative power) and system effect (index of difficulty or movement amplitude).

Fitts's law itself cannot apply to participants with motion control issues because the movement time distribution must be normal, with no midtrial pauses [18], [19], which only occurs in environmentally controlled experiments. Chapuis *et al.* [3] argued against the success of Fitts's law in the real world as users are not forced to move rapidly. Their analysis indicated the collapse of Fitts's law beyond a specific range of movement time data [3]. They augmented Fitts's law by adding a mathematically transformed curvature index (called the length-distance index) as an independent variable. Our results support Chapuis's model in terms of using CI as an independent contributor to movement time.

A potential application of this model is to compare different pointing input devices and algorithms by varying one independent variable and fixing others, similar to the SH model theory. This may result in a more detailed evaluation process of the user friendliness of devices. For example, the contribution of erroneous clicks to the total movement time may be lower for a certain device, possibly indicating that it is easier to correct.

Furthermore, since this model indicates that average speed and curvature index significantly affect movement time, it suggests that adjusting control-display gain and potentially the cursor's resistance to change in direction based on the curvature index and average speed (calculated in sets of trajectory samples) could enhance the performance of point-and-click tasks for motion-impaired users.

It should be reiterated that the immediate purpose of this model is not for predicting movement times. To achieve this, statistical information about the probability of events occurring, such as slip-offs, would be required.

VII. CONCLUSION AND FUTURE WORK

The proposed model in this research has been validated against the conventional Fitts's model and ballistic movement model. It shows better prediction of movement time compared to Fitts's law (assuming that the appropriate independent variables are known).

The model proposed in this research is nonlinear, including the system and human influences together. Unlike Hwang *et al.*'s approach, this model expresses task performance with a single equation. The curvature index was found to be the biggest contributor of human effects to task performance.

Future work will include a validation of the proposed model with different types of point-and-click tasks, such as one without prior knowledge of target locations for both typically developed individuals and individuals with motion impairment.

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