Examining Fitts' and FFitts' Law Models for Children's Pointing Tasks on Touchscreens

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ABSTRACT

Fitts' law has accurately modeled both children's and adults' pointing movements, but it is not as precise for modeling movement to small targets. To address this issue, prior work presented FFitts' law, which is more exact than Fitts' law for modeling adults' finger input on touchscreens. Since children's touch interactions are more variable than adults, it is unclear if FFitts' law should be applied to children. We conducted a 2D target acquisition task with 54 children (ages 5-10) to examine if FFitts' law can accurately model children's touchscreen movement time. We found that Fitts' law using nominal target widths is more accurate, with a R^2 value of 0.93, than FFitts' law for modeling children's finger input on touchscreens. Our work contributes new understanding of how to accurately predict children's finger touch performance on touchscreens.

CCS CONCEPTS

• Human-centered computing → HCI theory, concepts and models

KEYWORDS

Fitts' law, FFitts' law, children, touchscreen, finger input

ACM Reference format:

Julia Woodward, Jahelle Cato, Jesse Smith, Isaac Wang, Brett Benda, Lisa Anthony, and Jaime Ruiz. 2020. Examining Fitts' and FFitts' Law Models for Children's Pointing Tasks on Touchscreens. In *Proceedings of the 2020 International Conference on Advanced Visual Interfaces (AVI'20).* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3399715.3399844

1 Introduction

Children are an important group to consider when designing touchscreen devices due to how often they interact with these devices for education and entertainment [16,21]. However, prior work has shown that interacting with touchscreen devices poses challenges for children (e.g., lower accuracy [2,3,30], and slower response times [34,35]), especially for small targets. Fitts' law is a model that predicts movement time in target acquisition based on target size and distance [10]. It is an accurate predictor of pointing performance in real space and with computer mice for both children and adults [7,14,17,19,26]. However, Fitts' law is not as precise for small-target acquisition (e.g., ≤ 4 mm) [9,33]. This makes using Fitts' law to examine pointing performance on mobile touchscreen devices problematic, since small targets are commonly used (e.g., around 4 mm [22]) and finger input is not as precise as mouse pointing (i.e., fat finger problem) [1,12,13].

To address Fitts' law being imprecise for small targets, Bi et al. [5] presented FFitts' law. FFitts' law takes into account the imprecision of finger touch input when calculating the difficulty of the pointing task. Bi et al. proved that FFitts' law is more exact than Fitts' law for small-target acquisition with finger input on touchscreens for adults. However, since children's touch interactions are less accurate [3,30] and more variable [29,30], it is unclear whether Fitts' law or FFitts' law would be the better model for children for small-target acquisition on touchscreens.

We conducted a study of a 2D target acquisition task on a smartphone with 54 children (ages 5-10). Children in this age range are of particular interest because of the rapid cognitive

Figure 1. Screenshots from our Bubble Pop application used for 2D Fitts' task: (a) start screen, (b) start bubble, and (c) bubble target example.

AVI '20, September 28-October 2, 2020, Salerno, Italy

ACM ISBN 978-1-4503-7535-1/20/09…$15.00
https://doi.org/10.1145/3399715.3399844

and motor development that occurs [23,27]. To gamify the task for children, we developed a Bubble Pop application (Figure 1). Incorporating gamification elements in empirical studies has been shown to increase completion rates for children [6].

We analyzed the data using Fitts' law, both nominal and effective width [19], and FFitts' law [5]. We found that Fitts' law, using nominal width, is more accurate than FFitts' law for modeling children's finger input on touchscreens. Fitts' law using effective target width performed the worst. The contributions of this work are: (1) collection of touch data from 54 children (ages 5-10) in a 2D target acquisition task; and (2) comparison of Fitts' law, using nominal and effective target widths, and FFitts' law for modeling children's finger input on touchscreens. Our findings contribute new understanding of how to more accurately predict children's finger touch performance on touchscreens. Understanding which model to apply has a wide range of implications, such as evaluating new input devices for children, calibrating difficulty for children's mobile games, and assessing children's fine motor control.

2 Background and Related Work

Fitts' law (Eq. 1) is a model that predicts movement time in target acquisition based on target size and distance [10]. Fitts' law has been used to evaluate the throughput of different input devices and interaction techniques [7,19,24].

$$MT = a + b \cdot ID \qquad (1)$$

$$ID = \log_2\left(\frac{A}{W} + 1\right) \qquad (2)$$

In Equation 1, *MT* is movement time, *ID* is the index of difficulty (measured in bits), and a and b are empirically determined constants. The index of difficulty (*ID*) represents the difficulty of the task (Eq. 2). In Equation 2, A is target amplitude (i.e., distance from starting location to center of target) and W is the width of the target. Fitts' law reveals a speed-accuracy tradeoff in target acquisition, i.e., the less precise the task, such as acquiring a larger target over a shorter distance, the faster it is to accomplish, and vice versa. Previous work has also proposed using effective target width (W_e), which aims to normalize the target width by modifying the width based on the distribution of touchpoints (σ) from all of the users [19]. The underlying assumption is that, if there is a high variability in the touchpoint distribution, then the user chose to be faster rather than accurate; therefore, the effective width increases to compensate for the faster movement time. Likewise, if the touchpoint distribution is smaller, then the user focused more on accuracy, resulting in a smaller effective target width. The Fitts' law effective width equation replaces W with $W_e = \sqrt{2\pi e}\sigma$, in which σ is the standard deviation of the distribution of touchpoints.

Bi et al. [5] proposed FFitts' law, which interprets the variability in the distribution of touchpoints from finger input as a result of the relative precision governed by the speed-accuracy tradeoff and the absolute precision of finger touch input. FFitts' law modifies effective width by replacing W_e with $\sqrt{2\pi e(\sigma^2 - \sigma_a^2)}$; σ_a reflects the absolute precision of the input finger, which is used to compensate for the natural variability in finger input. Bi et al. found that FFitts' law was more accurate than Fitts' law for modeling adults' finger input on smartphones. However, since Bi et al. only examined FFitts' law with adults, it is unclear if it would be accurate in modeling children's finger input for small targets on touchscreens.

Previous studies have shown that Fitts' law can model children's pointing movements both in real space [17,25,26,31] and with computer mice [14,15], and that younger children perform worse than older children and adults [14,25,26,31]. Hourcade et al. [14] conducted a study examining pointing task performance for small targets using computer mice with young children (ages 4 and 5) and adults. They found that Fitts' law modeled children well only when they first entered the target, compared to when pressing or releasing the target. Also, they found higher correlation coefficients when using nominal target width compared to effective width. Prior work has also applied Fitts' law to examining children's performance on touchscreens [8,28]. Chang et al. [8] analyzed touchscreen touch interactions from children (ages 11-14), adults (ages 20-28), and older adults (ages 65-84). They found that the older adults' and children's performance was worse than adults. We go beyond Chang et al. by comparing three different models: Fitts' law using nominal widths, effective widths, and FFitts' law. Our study, to the best of our knowledge, is the first study to examine Fitts' law using effective widths and FFitts' law with children and touchscreens.

3 Method and Design

In our study, each child performed a 2D Fitts' law target acquisition task. We created a Bubble Pop application in Unity [36], in which different sized bubbles (i.e., targets) would appear on the screen in different locations (Figure 1c). The bubbles were solid circles that would "pop" (i.e., disappear) when touched. We instructed the children to hold the phone with their non-dominant hand and touch the bubbles with a finger on their dominant hand. We did not constrain the children to a specific finger, allowing them to interact with the smartphone naturally; the majority used their index finger. The children were awarded a small prize (e.g., stickers) after completing the study, which took five to ten minutes. Our protocol was approved by our Institutional Review Board. The application was run on a Samsung Galaxy S9 smartphone running Android OS.

Our application had seven different levels, described below. At the beginning of each level, a 15 mm diameter bubble labeled "start" would appear in the center of the screen (Figure 1b). The start bubble was not used for analysis, instead it was used to control the location of the first touch position. Once a bubble was successfully touched the current bubble would disappear and the next bubble would appear in a different location, which is consistent with prior Fitts' law studies [18,20]. If the bubble was not touched successfully the application would not move on until the bubble was successfully acquired in order to control the amplitude of the next target. The study included 6 amplitude (A) × width (W) conditions, with 2 levels of A (40, 60 mm) and 3 levels of W (4.8, 9.6, 14.4 mm), resulting in an *ID* ranging from 1.92 to 3.75 bits (Eq. 2) (consistent with Bi et al.'s study [5]). W

was the diameter of the bubble, and *A* was the distance measured from the center of the previous bubble to the center of the current bubble. Each level had a total of 12 bubbles, not including the start bubble.

Level 1 was used as training for the children to get familiar with the task and was not used for analysis. *W* remained at 14.4 mm, and *A* varied between 40 mm and 60 mm. *Level 2* was used to calculate the absolute precision of finger input (σ_a) for FFitts' law [5]. *W* remained at the smallest value (4.8 mm) to be consistent with Bi et al.'s study [5]. The children were instructed to lift their finger off the screen after touching a bubble, rest it for approximately 1 second on the table, and then touch the next bubble. This allowed for the calibration to not be influenced by the speed-accuracy tradeoff and is consistent with Bi et al.'s task procedure with adults. *Levels 3 to 7* are consistent with 2D Fitts' tasks. Each *A* × *W* combination appeared ten times, twice per level, resulting in a mix of *A* and *W* per level. The order of *A* × *W* combinations was randomized, and then the same order was used for every child. However, if the children missed a bubble on their first attempt, the current bubble condition (*A* × *W*) would appear again. We had the children redo the bubble conditions that were missed on the first try because children naturally have high error rates [34] and we wanted to ensure that all the children had the same number of successful touches when comparing the models. The children were instructed to touch the bubbles as quickly and as accurately as they could.

3.1 Participants

The participants in our study included 54 children, ages 5 to 10 (M = 7.26, SD = 1.48): 6 five-year-olds, 13 six-year-olds, 14 seven-year-olds, 7 eight-year-olds, 10 nine-year-olds, and 4 ten-year-olds. Thirty children (56%) were female, 9 were left-handed and 2 were ambidextrous. The children were recruited at the Florida Museum of Natural History, where the study was also run.

4 Data Analysis and Results

We analyzed the data from the touch interactions using Fitts' law, both nominal (Eq. 2) and effective target width versions, and FFitts' law. Due to children dragging their touches [29,35], we used the touch-down position as the default touch point, instead of the take-off position used in Bi et al.'s study [5].

We only examined the touch points from the children's *first touch attempt* on a target, whether they touched the target or missed. We labeled touch points that were more than 11 mm from the center of the target as outliers and did not include them in analysis. The 11 mm value was determined by examining the pattern of distribution for touch distances across all children. We removed 204 touch events as outliers (4.5%), leaving a total of 4,365 touch events. Out of the total amount, 623 were from *Level 2* and were used to calculate the absolute finger precision (σ_a). The touch points from *Levels 3 to 7* were used to calculate error rate, movement time, and touchpoint distribution (σ).

4.1 Error Rate and Dispersion of Touch Points

The children missed on the first try 32.7% of the time for the finger calibration task (*Level 2*), and 13.9% for the 2D Fitts' tasks (*Levels 3 to 7*). The higher error rate for the finger calibration task is most likely due to only including the smallest target size (4.8 mm). Table 1 shows the error rates per *A* × *W* combination. The error rates were higher for the smallest target size, and the highest error rate occurred for the smallest target that was furthest away (33%), which is consistent with prior work [5,14].

We also investigated the dispersion of touch points (Table 1). We computed σ by calculating the standard deviation (*SD*) of the distance, in mm, between the target center and the touch point. The *SD* for the finger calibration task (σ_a) was 1.590148 mm. The differences between σ and $\sqrt{(\sigma^2 - \sigma_a^2)}$ varied regardless of target size, which is *inconsistent* with prior work [5].

4.2 Fitts' Law and FFitts' Law

We computed movement time (*MT*) as the time, in ms, it took the child to touch the screen after the target appeared. We only examined successful target acquisitions when computing *MT*. Touch points that were more than three *SD*s away from the mean of *MT* were marked as outliers and removed from analysis (35 touch points). While 40 mm × 9.6 mm and 60 mm × 14.4 mm result in the same *ID* (Table 1), we did not average the *MT*s to avoid confounds [11]. We calculated regression results with the six conditions to be consistent with Bi et al. [5]. Figure 2 shows the regression results for: Fitts' law using nominal target widths (ID_n), effective target widths (ID_e), and FFitts' law (ID_f). The R2 values were: ID_n 92.8%, ID_e 7.6%, and ID_f 21.3%. The ID_n model had the strongest fit for children's finger input on touchscreens, and the ID_e model was the worst.

We analyzed the *ID* values across the three models per *A* × *W*

A × W (mm)	σ	$\sqrt{(\sigma^2 - \sigma_a^2)}$	**Error Rate**	**ID_n**	**$W_e = \sqrt{2\pi e}\sigma$**	**ID_e**	$\sqrt{2\pi e(\sigma^2 - \sigma_a^2)}$	**ID_f**	**Time (ms) [SD]**
40 × 4.8	1.591275	0.059879	26.7%	3.22	6.57	2.82	0.25	7.35	745.31 [94.87]
60 × 4.8	1.712747	0.636342	33%	3.76	7.07	3.24	2.64	4.57	787.88 [100.63]
40 × 9.6	1.747563	0.724849	5.3%	2.37	7.23	2.71	2.98	3.84	678.81 [82.36]
60 × 9.6	1.605135	0.218833	4.4%	2.86	6.65	3.33	0.91	6.07	686.45 [82.66]
40 × 14.4	1.815423	0.875894	0.92%	1.92	7.52	2.66	3.64	3.59	642.35 [69.64]
60 × 14.4	1.750543	0.732004	0.37%	2.37	7.23	3.22	3.02	4.38	648.70 [70.77]

Table 1. Touch point dispersion, error rate, and index of difficulty (ID) per amplitude (A) × width (W). Fitts' law using nominal target widths (ID_n), Fitts' law using effective target widths (ID_e), and FFitts' law (ID_f).

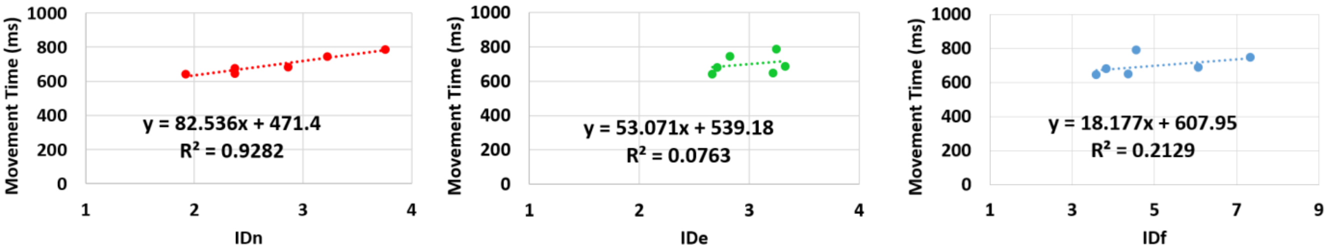

Figure 2. Regression Results for Movement Time (ms) vs ID_n (left), MT vs ID_e (middle), and MT vs ID_f (right).

combination in Table 1. The ID_f values were higher than the ID_n and ID_e values for every $A \times W$ condition. Also, the ID_n values consistently decreased as the target sizes increased (i.e., lower index of difficulty for larger targets), but the ID_e and ID_f values did not. For example, the index of difficulty for 60 mm × 9.6 mm (6.07 bits) was higher than 60 mm × 4.8 mm (4.57 bits) for ID_f.

5 Discussion

Our results with children and Fitts' law are consistent with the speed-accuracy tradeoff when examining movement time; the smallest target over the longest distance had the slowest movement time (788 ms), while the largest target over the shortest distance had the fastest movement time (642 ms). However, the index of difficulty was lower for the smallest targets when examining ID_e and ID_f (Table 1). Having a lower index of difficulty and slower movement time does not follow Fitts' law, which states that smaller targets are more difficult and take longer to acquire. Therefore, the difficulty of the task was not accurately reflected by ID_e and ID_f in our study.

Effective target width aims to normalize the target width by modifying the width based on the distribution of touchpoints (σ) from all of the users [19,32]. For effective width to accurately normalize the target width based on performance, the conditions with faster movement times need to have a larger touchpoint distribution, which will increase the effective width (i.e., lower index of difficulty). However, we did not see that occur. The faster movement times did not correspond to the largest σ values. For example, 60 mm × 4.8 mm had a higher distribution (1.71) than 60 mm × 9.6 mm (1.61), but slower movement time. In Bi et al. [5], the σ values consistently increased as target sizes increased; however, our σ values varied between target sizes. Since children's touch interactions are more variable [29,30] than adults a higher touchpoint distribution does not inherently mean that the children were prioritizing being faster than accurate, which is the underlying assumption behind effective width.

Similar to effective width, FFitts' law did not have the highest index of difficulty for the smallest target over the longest distance. FFitts' law modifies the effective width equation by considering finger touch precision (σ_a) when examining the distribution of touchpoints. Our σ_a for children (1.59 mm) was similar to Bi et al.'s result of 1.5 mm for the 2D Fitts' task for adults, which shows that the children had a similar precision level with larger targets (4.8 mm) as the adults did with smaller targets (2.4 mm). Even though the σ_a values were close between adults and children, our high variability in σ values lowered the regression result for FFitts' law and for effective width.

The variability in σ may be due to the children's motor development. The children in our age range (ages 5 to 10) are still undergoing rapid motor development [27], which may have caused more variation in performance. Prior work in children's touchscreen input behaviors has shown that children have slower response times [34,35], lower accuracy [2,3], and higher touch-offset [29,30]. Therefore, the variability in σ is most likely a product of the children's motor development affecting touchscreen input behavior. Understanding which model to apply to children's touchscreen performance has implications in evaluating input devices and interaction techniques for children and assessing children's fine motor control. Fitts' law using nominal target widths is the most accurate predictor of children's pointing performance on touchscreens.

6 Limitations and Future Work

While our work contributes new understanding on modeling children's finger input on touchscreens, there are limitations. We only conducted a 2D target acquisition task, while Bi et al. [5] examined FFitts' law in a 1D and 2D target acquisition task and a touchscreen keyboard typing task. Children's touchpoint distribution could have less variability between target sizes during a different Fitts' task. Future work should examine FFitts' law with children in different tasks, as well as replicate our study with adults to compare against Bi et al.'s study. Also, we only compared three models. Future work can investigate other models for children, such as models that consider the cost of errors [4]. Our study points to new investigations into when the three different Fitts' law models should be applied.

7 Conclusion

We conducted a 2D target acquisition task with 54 children (ages 5-10) on a smartphone. We analyzed the touch data using Fitts' law using nominal target widths, effective target widths, and FFitts' law. We compared how the different models predicted movement time for children's finger input on touchscreens and found that Fitts' law using nominal widths was the most accurate. Fitts' law using effective widths performed the worst. Our work contributes new understanding of how to accurately predict children's finger touch performance on touchscreens.

REFERENCES

[1] Pär-Anders Albinsson and Shumin Zhai. 2003. High Precision Touch Screen Interaction. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'03)*, 105–112. DOI:https://doi.org/10.1145/642611.642631

[2] Lisa Anthony, Quincy Brown, Jaye Nias, Berthel Tate, and Shreya Mohan. 2012. Interaction and Recognition Challenges in Interpreting Children's Touch and Gesture Input on Mobile Devices. In *Proceedings of the ACM Interational Conference on Interactive Tabletops and Surfaces (ITS'12)*, 225–234. DOI:https://doi.org/10.1145/2396636.2396671

[3] Lisa Anthony, Quincy Brown, Berthel Tate, Jaye Nias, Robin Brewer, and Germaine Irwin. 2014. Designing Smarter Touch-based Interfaces for Educational Contexts. *Pers. Ubiquitous Comput.* 18, 6 (August 2014), 1471–1483. DOI:https://doi.org/10.1007/s00779-013-0749-9

[4] Nikola Banovic, Tovi Grossman, and George Fitzmaurice. 2013. The Effect of Time-Based Cost of Error in Target-Directed Pointing Tasks. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'13)*, 1373–1382. DOI:https://doi.org/10.1145/2470654.2466181

[5] Xiaojun Bi, Yang Li, and Shumin Zhai. 2013. FFitts Law: Modeling Finger Touch with Fitts' Law. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'13)*, 1363–1372. DOI:https://doi.org/10.1145/2470654.2466180

[6] Robin Brewer, Lisa Anthony, Quincy Brown, Germaine Irwin, Jaye Nias, and Berthel Tate. 2013. Using Gamification to Motivate Children to Complete Empirical Studies in Lab Environments. In *Proceedings of the International Conference on Interaction Design and Children (IDC'13)*, 388–391. DOI:https://doi.org/10.1145/2485760.2485816

[7] Stuart K. Card, William K. English, and Betty J. Burr. 1978. Evaluation of Mouse, Rate-Controlled Isometric Joystick, Step Keys, and Text Keys for Text Selection on a CRT. *Ergonomics* 21, 8 (August 1978), 601–613. DOI:https://doi.org/10.1080/00140137808931762

[8] Hsien-Tsung Chang, Tsai-Hsuan Tsai, Ya-Ching Chang, and Yi-Min Chang. 2014. Touch Panel Usability of Elderly and Children. *Comput. Human Behav.* 37, (August 2014), 258–269. DOI:https://doi.org/10.1016/J.CHB.2014.04.050

[9] Olivier Chapuis and Pierre Dragicevic. 2011. Effects of Motor Scale, Visual Scale, and Quantization on Small Target Acquisition Difficulty. *ACM Trans. Comput. Interact.* 18, 3 (July 2011), 1–32. DOI:https://doi.org/10.1145/1993060.1993063

[10] Paul M. Fitts. 1954. The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement. *J. Exp. Psychol.* 47, 6 (1954), 381–391. DOI:https://doi.org/10.1037/h0055392

[11] Julien Gori, Olivier Rioul, Yves Guiard, and Michel Beaudouin-Lafon. 2018. The Perils of Confounding Factors: How Fitts' law Experiments can Lead to False Conclusions. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'18)*, Paper No. 196. DOI:https://doi.org/10.1145/3173574.3173770

[12] Christian Holz and Patrick Baudisch. 2010. The Generalized Perceived Input Point Model and How to Double Touch Accuracy by Extracting Fingerprints. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'10)*, 581–590. DOI:https://doi.org/10.1145/1753326.1753413

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

[14] Juan Pablo Hourcade, Benjamin B. Bederson, Allison Druin, and François Guimbretière. 2004. Differences in Pointing Task Performance Between Preschool Children and Adults Using Mice. *ACM Trans. Comput. Interact.* 11, 4 (2004), 357–386. DOI:https://doi.org/10.1145/1035575.1035577

[15] Juan Pablo Hourcade, Michael Crowther, and Lisa Hunt. 2007. Does Mouse Size Affect Study and Evaluation Results? A Study Comparing Preschool Children's Performance with Small and Regular-Sized Mice. In *Proceedings of the International Conference on Interaction Design and Children (IDC'07)*, 109–116. DOI:https://doi.org/10.1145/1297277.1297300

[16] Hilda K. Kabali, Matilde M. Irigoyen, Rosemary Nunez-Davis, Jennifer G. Budacki, Sweta H. Mohanty, Kristin P. Leister, and Robert L. Bonner Jr. 2015. Exposure and Use of Mobile Media Devices by Young Children. *Pediatrics* 136, 6 (December 2015), 1044–1050. DOI:https://doi.org/10.1542/peds.2015-2151

[17] Robert Kerr. 1975. Movement Control and Maturation in Elementary-Grade Children. *Percept. Mot. Skills* 41, 1 (August 1975), 151–154. DOI:https://doi.org/10.2466/pms.1975.41.1.151

[18] Edward Lank, Yi-Chun Nikko Cheng, and Jaime Ruiz. 2007. Endpoint Prediction Using Motion Kinematics. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'07)*, 637–646.

[19] I. Scott MacKenzie. 1992. Fitts' Law as a Research and Design Tool in Human-Computer Interaction. *Human–Computer Interact.* 7, 1 (March 1992), 91–139. DOI:https://doi.org/10.1207/s15327051hci0701_3

[20] Michael McGuffin and Ravin Balakrishnan. 2002. Acquisition of Expanding Targets. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'02)*, 57–64. DOI:https://doi.org/10.1145/503376.503388

[21] Cathleen Norris and Elliot Soloway. 2004. Envisioning the Handheld-Centric Classroom. *J. Educ. Comput. Res.* 30, 4 (June 2004), 281–294. DOI:https://doi.org/10.2190/MBPJ-L35D-C4K6-AQB8

[22] Tom Page. 2013. Usability of Text Input Interfaces in Smartphones. *J. Des. Res.* 11, 1 (2013), 39. DOI:https://doi.org/10.1504/JDR.2013.054065

[23] Jean Piaget. 1983. Piaget's Theory. In *Handbook of Child Psychology*, P. Mussen (ed.). Wiley & Sons, New York, NY, USA. DOI:https://doi.org/10.1007/978-3-642-46323-5_2

[24] Adrian Ramcharitar and Robert J. Teather. 2017. A Fitts' Law Evaluation of Video Game Controllers: Thumbstick, Touchpad and Gyrosensor. In *Extended Abstracts of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'17)*, 2860–2866. DOI:https://doi.org/10.1145/3027063.3053213

[25] Alan W. Salmoni and John S. McIlwain. 1979. Fitts' Reciprocal Tapping Task, a Measure of Motor Capacity? *Percept. Mot. Skills* 49, 2 (December 1979), 403–413. DOI:https://doi.org/10.2466/pms.1979.49.2.403

[26] David A. Sugden. 1980. Movement Speed in Children. *J. Mot. Behav.* 12, 2 (June 1980), 125–132. DOI:https://doi.org/10.1080/00222895.1980.10735212

[27] Jerry R. Thomas. 1980. Acquisition of Motor Skills: Information Processing Differences between Children and Adults. *Res. Q. Exerc. Sport* 51, 1 (March 1980), 158–173. DOI:https://doi.org/10.1080/02701367.1980.10609281

[28] Tsai-Hsuan Tsai, Kevin C. Tseng, and Yung-Sheng Chang. 2017. Testing the Usability of Smartphone Surface Gestures on Different Sizes of Smartphones by Different Age Groups of Users. *Comput. Human Behav.* 75, (October 2017), 103–116. DOI:https://doi.org/10.1016/J.CHB.2017.05.013

[29] 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 International Conference on Human-Computer Interaction (INTERACT'15)*, pp.1-9. DOI:https://doi.org/10.1007/978-3-319-22723-8_1

[30] Radu-Daniel Vatavu, Gabriel Cramariuc, and Doina Maria Schipor. 2015. Touch interaction for children aged 3 to 6 years: Experimental findings and relationship to motor skills. *Int. J. Hum. Comput. Stud.* 74, (February 2015), 54–76. DOI:https://doi.org/10.1016/J.IJHCS.2014.10.007

[31] Stephen A. Wallace, Karl M. Newell, and Michael G. Wade. 1978. Decision and Response Times as a Function of Movement Difficulty in Preschool Children. *Child Dev.* 49, 2 (June 1978), 509–512. DOI:https://doi.org/10.2307/1128718

[32] Alan T. Welford. 1968. *Fundamentals of Skill.* Methuen.

[33] Alan T. Welford, Arthur H. Norris, and Nathan W. Shock. 1969. Speed and Accuracy of Movement and Their Changes with Age. *Acta Psychol. (Amst).* 30, (January 1969), 3–15. DOI:https://doi.org/10.1016/0001-6918(69)90034-1

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

[35] Julia Woodward, Alex Shaw, Aishat Aloba, Ayushi Jain, Jaime Ruiz, and Lisa Anthony. 2017. Tablets, Tabletops, and Smartphones: Cross-Platform Comparisons of Children's Touchscreen Interactions. In *Proceedings of the ACM International Conference on Multimodal Interaction (ICMI'17)*, 5–14. DOI:https://doi.org/10.1145/3136755.3136762

[36] 2018. Unity. *Unity Technologies*. Retrieved from https://unity3d.com/