Children adapt drawing actions to their own motor variability and to the motivational context of action

Shukri, Siti Rohkmah Mohd; Howes, Andrew

DOI:
10.1016/j.ijhcs.2019.06.004

Children Adapt Drawing Actions to Their Own Motor Variability and to the Motivational Context of Action.

Siti Rohkmah Mohd Shukri[a,*], Andrew Howes[a]

[a]*School of Computer Science, University of Birmingham, B15 2TT, UK*

Abstract

Children like to draw, but how easy is it for them to draw on a touch screen device? More specically, how do children adapt the way they draw to the device and to their own motor limitations? To answer this question, we conducted empirical studies on children taking part in drawing tasks to examine how they adapt drawing actions to their own motor variability and to extrinsic motivation (rewards). Our study consisted of drawing tasks that tested the application of the Model of Movement Planning based on Bayesian Decision Theory. The model predicts shifts in subjects' drawing actions in response to changes of reward and penalty structures within the drawing environment and to subjects' own motor uncertainty during rapid drawing movement. Our results show that children make near optimal adaptation to the reward signals and to their own motor performance variability. This suggests a viability of exciting new way to model children's interaction with technology.

Keywords:
Children's drawing; drawing strategies; motor variability; Bayesian decision theory.

1. Introduction

Children make increasing use of touchscreen devices not only for entertainment but also for learning (Chiong and Shuler, 2010; Kang, 2013;

*Please address correspondence to Author1. Author1 was with Universiti Teknologi PETRONAS, Malaysia at the point of submission.

Email addresses: rohkmah@gmail.com (Siti Rohkmah Mohd Shukri), a.howes@bham.ac.uk (Andrew Howes)

Crescenzi et al., 2014). Due to the rapid growth in younger users, researchers and developers have given more serious attention in touch interaction design specifically for children (Kim et al., 2013; Anthony et al., 2014; Vatavu et al., 2015a; Woodward et al., 2016). Recent work has focused on touch gesture (McKnight and Fitton, 2010; Aziz, 2013; Nacher et al., 2015), touch accuracy (Wang et al., 2013; Anthony et al., 2014; Vatavu et al., 2015a) and touch feedback (Zhai et al., 2012; Anthony et al., 2013; Nacher and Jaen, 2015) to understand children's touch behaviour better. Among others, they made comparison between adults' and children's touch interaction (e.g., Anthony et al., 2013, 2014; Woodward et al., 2016). These studies have also reported on children's limitations concerning their perceptual and motor skills during touch interaction. For example, children often face difficulties in trying to maintain contact with the screen. They tend to miss a greater proportion of onscreen targets compared to adults when only single touch action is required (Brown and Anthony, 2012; Anthony et al., 2012; Vatavu et al., 2015b) and they make unintentional touches with trailing fingers and thumbs (McKnight and Fitton, 2010). These problems could possibly be due to their smaller fingers, less fine motor control and less experience with technology (Anthony et al., 2012) which also affect children's motor variability. Therefore, by understanding the potentials and constraints imposed by children's touch interaction, we could possibly inform an effective way to use touch application for early learning environment.

A review of extant literature reveals limited research that investigates children's adaptation to interactive technology. Most recent work mentioned earlier study children's touch behaviour on a simple environment. In practice, many touch applications for children are built within a complex environment that requires multimodal interaction. A recent study by Woodward et al. (2016) examined how interface complexity might impact touchscreen interactions of children aged 5 to 10 years old. Even though they mentioned that most interfaces did not optimize children interaction, they did not suggest a way to optimize them. They also regard their interfaces of only one target onscreen at a time as complex environment, which seem to depict more of simple environment. This has motivated us to investigate further. How can we know whether children are adapting to a complex touchscreen environment? Since drawing is a natural task that children seem to enjoy very much, our work looked into this from the perspective of drawing action as touch gesture. In order to explain the emergence of touch drawing action in children, the psychology of how drawing is enabled by the cognitive system

should be understood. According to Van Sommers (1984), the components of the cognitive system; motor output, imagery, memory, meaning, perception and aesthetics constrain the strategy adopted. Therefore, to examine children's drawing performance, our work looks into children's perceptual and motor skill in their touch accuracy. Our work also proposed a motivational reward for children's context of action as touch feedback in their meaning making drawing. Following Shukri and Howes (2017), children altered their drawing actions according to the reward conditions introduced. The work provided encouraging evidence that children between the age of 4 to 12 years old do adapt to extrinsic motivation (reward) when drawing on touch screens; and the question here is: to what extent do children adapt strategies to their own internal cognitive constraints?

Drawing is a product of movement control of motor and cognitive processes. Their motivation to draw are normally driven from the cognitive aspect. Children find it rewarding to see their aesthetic drawing progress from meaningless and abstract scribbles to meaningful and detailed graphical representations (Matthews, 2003). Basic forms such as circles and rectangles that are constructed from drawing are intrinsically attractive for them (Kellogg, 1970). Children can be intrinsically motivated in order to perform a task that they like. Drawing itself is intrinsically motivating for children. However, in order to improve children's motor efficiency in their drawing skills or performance, this could be achieved by having a reward effect as their extrinsic motivation. As drawing development becomes the statistic property of motor control, our work looks into the Model of Movement Planning by Trommershäuser et al. (2003b) to study children's motor efficiency. The model is used to examine human's ideal performance for action under risk among adults. Our study extends this work to children in order to explain how they plan their drawing strategies to the extrinsic reward within constraints (as risks) in the environment. What if besides gaining higher rewards there are also penalty effects nearby? What can be observed if a time limit is introduced in the tasks making the drawing task more challenging? How would children plan their drawing actions to gain higher rewards within the limitations imposed? The idea here was to see how children act as ideal drawing planners when choosing movement trajectories on touch surfaces with regions carrying rewards and penalties. The study focused on understanding of how children adapt drawing close to the proximity of penalty regions when under time pressure.

2. Related Work

In the introduction of this paper, we highlighted the three components of touch gesture, touch accuracy and touch feedback within the domain of children's touch interaction. We further describe these in the following subsections. The first one, Touch Gesture is perceived in the context of touch drawing actions. The second one, Touch Accuracy, discusses on recent work of children's touch performance, followed by the fundamental of pointing task for accuracy. The last section, Touch Feedback, discusses on the importance of feedback for optimal movement.

2.1. Touch Gesture

Drawing is a task that many children under the age of 12 like to do (Toomela, 2002; Einarsdottir et al., 2009). It is also a task that may increasingly be done by children on a tablet rather than on paper, reflecting a broader digitisation of both child and adult activities. Current research suggests that children's drawings on touch screen convey far quicker and richer information than often claimed in the past (McKnight and Fitton, 2010; Zhai et al., 2012). Drawing traces and marks left on screen can be quantified more accurately than drawing on paper, providing a theoretical and empirical understanding of children's motor process (Lin et al., 2015; Tu et al., 2015) and drawing strategies (Tabatabaey-Mashadi et al., 2013; Price et al., 2015). Crescenzi et al. (2014) for example, has found that children tend to make more complex and longer sequences of continuous touch actions when drawing on iPad compared to when drawing on physical paper. In contrast, a similar quantitative comparison by Picard et al. (2014) reported loss of details in finger drawing and that the mark making outcome from drawing on touchscreen was slightly poorer than on paper. Arguably, Lee et al. (2017) stated that direct manipulation movement enhanced the drawing result. Nonetheless, evidence from these work show that richer information can be claimed and understood from children's touch drawing action.

While drawing on paper seems like a natural task for children, how easy is it for them to draw on a touch screen device? Touch drawing devices do impose some limitation. According to Crescenzi et al. (2014), when drawing on a tablet, there are restriction on quantity and range of fingers, limited range of touch pressure and even lost of several sensory features (haptic and tactile). Nevertheless, drawing is still a task that may increasingly be done by children on a tablet (Lee et al., 2017). Therefore, how do children

adapt the way they draw to the device and to their own limitations? To answer this question, our work looked into children's cognitive and motor skill to examine their drawing strategies on a tablet. Kim et al. (2016) used sketch recognition techniques to classify fine motor skills based on children's drawings. Their work assisted children to draw basic shapes apart from informing the maturity of the children's fine motor skills according to age group, from their drawings. In doing so, they use tracing dots for children to form continuous strokes.

2.2. Touch Accuracy

Vatavu et al. (2015a) work focused on the build device adapted to user behaviour. They created an adaptive user interfaces where the interface can switch specifically for end user group that are children aged 3 to 6 years old and adult. Their work examined user touch accuracy by using Bayes' rule classifier that involves time and offset. The offset is the distance between the actual touch point where the user's finger is placed and the center of the touch target (offset-distance). In contrast, Anthony et al. (2014) work focused on how user can learn well to adapt to the device via target acquisition task. They built a foundation on how to build an application that can increase the success rate of touch accuracy. They used four different target sizes that were displayed uniformly across the interface to differentiate how well adult and child user (7 years old and beyond) performed. Children were set into different age groups according to their motor variance. Both work mentioned here look into children's motor variance and termination for adaptation but with less or no constraint. According to Payne and Howes (2013), for a person to make accurate movement in an interaction, the individual should be delineated by the experience and constraints of the task, motivated by what they find value on pursuing the task and driven by the cognitive capacities that allow them to process information altogether.

Pointing constitutes the basic act of hand movement that mostly studied under the motor development literature. They are the fundamental work for accuracy. The task is about the production of accurate rapid aimed movements toward a target. Prior work used Fitts' law to compare how children and adults acquire targets using pointing devices to study their hand motor performance (e.g., Jones, 1991; Hourcade et al., 2004; Donker and Reitsma, 2007). However, it did not consider task difficulty but rather counter balances between target's distance and width (Guiard, 2009). The amplitude movement is normally compensated by either increasing the aiming time or

becoming less accurate. According to Bertucco et al. (2013), this is beneficial at the level of motor planning but not at the corrections of on-going movements. Furthermore, it does not consider extrinsic cost in determinant to motor behaviour. Bayesian decision theory has also been used to investigate pointing tasks. The approach has been successfully applied to explain how people adapt pointing to their own internal noise (Trommershäuser et al., 2005; Wu et al., 2006; Maloney and Zhang, 2010; Hudson et al., 2012). Their work reported that the motor system is highly efficient in estimating both movement variability and uncertainty when pointing to a target position. Bayesian approach has shown that adult's performance in aim pointing is optimal.

2.3. Touch Feedback

Anthony et al. (2013) suggested that application built specifically for children should provide visual feedback. Their work shows that the younger the children, the more absence of visual feedback impacted their touch gestures and accuracy. Zhai et al. (2012) work reported that children show a smaller average size of touch gestures with the presence of visual feedback compared to when there is no show of visual feedback. With visual feedback, child user performed touch gestures faster that significantly reduce the completion time of overall touch action. Nacher and Jaen (2015) work also highlighted the importance of touch feedback among child user. They evaluated pre-kindergarden children's touch performance by using a boundary area as termination phase for rotate, drag and zooming. They suggested that when accuracy is required, a visual termination phase of touch gesture could help children to improve their motor skills development. These work mentioned here indicated that feedback from touch device can affect the cognitive and motor skill of children ability to correctly execute their movement control.

Trommershäuser et al. (2005) created a constrained environment to study optimal movement by embedding reward and losses as feedback in the motor task. Their series of work have shown that subjects can perform as well as they did and learned their own motor uncertainty without going through the learning phase. The uncertainty covers the sensory environment and stochastic information that represented in the motor and cognitive tasks. Subjects in their studies selected efficient strategies that maximized the expected gain that is the reward and losses introduced as feedback; given the costs of motor commands and benefits such as reward in the motor task. Examples of other work that use similar approach in their feedback

for optimal movement are such as; two penalty regions carrying different penalties (Wu et al., 2006), targets in two different shapes placed in different directions (Gepshtein et al., 2007), a bet placing to a rotating visual display (Landy et al., 2007), time penalty for slower and faster movements (Hudson et al., 2008) and movement task around virtual obstacle (Hudson et al., 2012). These studies although conducted to adult participants show that the importance of feedback in motor task for optimal performance.

3. The Experimental Study

The drawing task consists of a series of *Join-the-dots* drawing activities which require the child to connect the dots according to a numbered sequence. The task mimicked the conventional way of joining the dots on paper but with drawing constraints and feedback. The constraints imposed were penalty effect next to a reward condition and time limitation, while drawing feedback is the number of stars gained as drawing scores. This drawing application is an extension of the drawing tool in our previous study (Shukri and Howes, 2017) but with reward and penalty effects. The aim of the work here is to study children's adaptation not only to the reward signal but also to the limitations imposed according to their own motor variability when drawing on touch surfaces. We aim to answer the following research questions:

1. How do children adapt their drawing strategies according to their own motor abilities and to the limitations of drawing tools and devices?
2. How does a child adapt to the drawing actions according to his or her own motor variability?

3.1. The Model of Movement Planning

The model of motor planning concerns the movement planning that addresses the problem of defining and finding the optimal sequence of motor commands given a pre-specied goal. In planning a goal-directed movement, the motor system is required to make rapid and good motor decisions to pick one of many possible motor programs. This motor program is a strategy that includes a choice of goal bound trajectory with ongoing visual feedback during the movement. During this planned movement, the motor program takes into account the consequences of possible motor errors (Wu et al., 2006) that resulted from sensory uncertainty (Trommershäuser et al., 2005). When executed under a tight time constraint, the motor responses are varied (Fitts

and Peterson, 1964; Meyer et al., 1988). This outcome of movement planning is called a visuo-motor strategy.

If we take the situation where a subject is limited to a set of possible choices in reaching an object, how does the subject plan to attain the intended goal? There are several possible movement plans or strategies that the brain must select in planning this movement. Statistical and Bayesian decision theory can be utilised to find the best possible choice of movement plan. First, the subject needs to have prior information of the object location and obtain accurate sensory information of the environment such as whether there is any obstacle to avoid. Second, the motor plan needs to specify intended properties of movement for the arm and body to reach the object such as direction, velocity and other movement properties estimated from the sensory information acquired. While the accuracy is determined by velocity of movement (Fitts and Peterson, 1964), the subject can accurately control their own movement depending on how fast or slow the movement is. Thus, faster movements would require a larger control signal and are more varied in the motor outcome, resulting in a well-known speed-accuracy trade-off (Harris and Wolpert, 1998). At the end, the success or failure of the movement takes into account the sensory information obtained, possible gains and losses associated with possible motor outcomes and the error in executing a motor response (Tassinari et al., 2006; Dean et al., 2007).

The goal of movement planning is to select a movement trajectory that optimises the visuo-motor movement strategy. Equation 1 (Trommershäuser et al., 2008) is the optimal visuo-motor strategy S that is used to maximise the subject's expected gain G. The Gain is the total of reward and penalty points. This movement strategy is a visual motor strategy that forms a sequence of motor commands involving intermediate goal in space and time. The probability $P(R_i|S)$ is used to define the choice of strategy S with reaching region R_i before the time limit ends (t=timeout). If the task is completed beyond the time limit, a penalty $G_{timeout}$ is given. For this study, timeout incurs no reward. $P(timeout|S)$ occurs as a probability of a visuo-motor strategy S that leads to a timeout.

$$\Gamma(S) = \sum_{i=1}^{4} G_i P(R_i|S) + G_{timeout} P(timeout|S) \tag{1}$$

3.1.1. A Plan for Drawing Movement

The drawing movement plan consisted of a visual motor strategy, S, where S is selected based on the mean end-point of drawing movements within time. For any time t, the drawing movement trajectory, $\tau(T)$ is a result of a fingertip contact point or position in time and 2-dimensional drawing space with $\tau{:}t \rightarrow [x(t),\ y(t)]$. When motor strategy is executed, it imposes a probability density, $P(\tau|S)$ that is a possible drawing movement trajectory on a 2-dimensional drawing space. This probability density $P(\tau|S)$ of drawing movement is likely to be affected by the interactivity of the drawing task itself from the goal of drawing and visual drawing feedback; experiences from performing the drawing trials and intrinsic uncertainties embedded in the motor system (Trommershäuser et al., 2003a). The drawing task environment contains regions that carry penalty or reward points that are explicitly known to the subject. The term gain, G_i, $i = 0,....N$ refer to both rewards and penalties point incurred from different regions, R_i, $i = 0,...,N$. The optimal of visual-motor strategy S occurred when subject maximised the expected gain $\Gamma(S)$ on any drawing trials.

In the drawing task, each subject is required to draw a line from a starting point towards a target region within a time limit. On every trial, there is a penalty region placed near to the proximity of the target of reward region. The penalty region is located either overlapping the reward region or next to it. Each drawing action that is completed within the time limit has four possible outcomes of reward and penalty value represented as gains, G:

- **The non-overlapping target is hit**. If region R_0 is hit, the subject receives a high reward of G_0 stars ($R_0 > 0$).
- **The non-overlapping penalty region is hit**. If region R_1 is hit, the subject receives a penalty of low reward of G_1 stars ($R_0 > R_1 > 0$).
- **The overlapping target and penalty region is hit**. If region R_2 is hit, the subject receives a medium reward of G_2 stars ($R_0 > R_2 > R_1$).
- **The outside region is hit**. If region R_3 is hit, the subject does not receive any reward ($G_3 = 0$).

Late responses or failure to complete the drawing action within the time limit incurs no score. The possible visual-motor strategies S is denoted by the resulting mean end point (x,y) of the contact point on the touch screen.

This is yielded as the *aim point* of the subject. In order to predict the optimal *aim point* of a drawing movement, the drawing end point should maximise the expected gain function as shown in equation 2 below.

$$\begin{aligned} L(x,y) = {} & G_0 P(R_0 \mid x,y) + G_1 P(R_1 \mid x,y) \\ & + G_2 P(R_2 \mid x,y) + G_3 P(R_3 \mid x,y) \end{aligned} \tag{2}$$

We can ignore the constant G_3, the outside region which gives a 0 point.

$$\begin{aligned} L(x,y) = {} & G_0 P(R_0 \mid x,y) + G_1 P(R_1 \mid x,y) \\ & + G_2 P(R_2 \mid x,y) \end{aligned} \tag{3}$$

The movement goal as in equation 3 is used when the reward and penalty region is reached within the time limit. The penalty and reward points are determined based on the position of the end-point when the subject lifts their pen/finger off the target area. Strategy S is identified as the aim point resulting from the plane ($\overline{x}$,$\overline{y}$) which resulted in a particular choice of strategy S of mean end points. When there is no penalty imposed, the maximum expected gain of *aim point* (the mean end point) is at the center of the target region. When the penalty is imposed or set as non-zero, the maximum expected gain of aim point shifts away from the penalty region, hence away from the center of the target region. The optimal shift occurs when the magnitudes of motor variability is largest, the penalty region is at the closest distance to the target and with greater penalties imposed (Todorov, 2004; Trommershäuser et al., 2005; Tassinari et al., 2006).

For the childrens drawing task, the focus was only on the penalty conditions of their distance to the reward region. Therefore, the hypothesis of the study is derived;

- *The subject makes the largest shift when the penalty region is closest, moderate shift when penalty region is less close and least shift when the penalty region is least close.*

The study also investigates the effect of drawing input (*finger* versus *pen*), towards the drawing performance. According to Tu et al. (2015), drawing smaller and intricate objects or tasks with a pen would yield better accuracy than drawing using a finger on touch surfaces. Therefore, the second hypothesis is derived;

- *The subject who draws using a pen rather than drawing with their finger is more accurate in their drawing.*

a: The first ant.

b: The second ant.

Figure 1: *Join-the-dots* drawing pictures with red dots (penalty regions) placed on different sides (left/right) of black dots (reward regions).

3.2. Apparatus

The experimental setup used was an iPad Air tablet device with 10.1-inch wide screen connected to an Apple MacBook-Pro 13-inch laptop via a USB cable. The drawing application was loaded by Safari web browser onto the tablet device via a stable internet connection. All input data of subject's touch interactions from the tablet were extracted using Safari web inspector development tool.

3.2.1. Stimulus

A drawing application of *Join-the-dots* was developed using HTML5 and JavaScript. There are 20 drawing tasks comprised of vehicles and animal shapes that are displayed randomly. These drawing shapes were motivated from a collection of drawing pictures from various children's books and depicted children's representational drawing (Arnheim, 1954; Maitin et al., 1968). The drawing tasks consisted of 10 drawing pictures, each repeated twice but with different features. Each drawing picture consisted of single black dots and pairs of red and black dots. The single black dot serves as a target dot but without any points and therefore is one unit size smaller than the pair dots with points and size of 20 radius. The point given is shown in number of stars. The stars were chosen to acommodate younger children who may be more motivated with figures points rather than numbers. The black pairing dot serves as a reward dot while the red serves as a penalty dot. Similar to Trommershäuser et al. (2003b) design, these red dots are placed in three different proximities from the black dots. The first red dot is placed closest to the black dot (0 unit CSS pixel of radius) labelled as *close*,

a: The red dots on the left side of the black dots, each in *close*, *medium* and *far* distance.

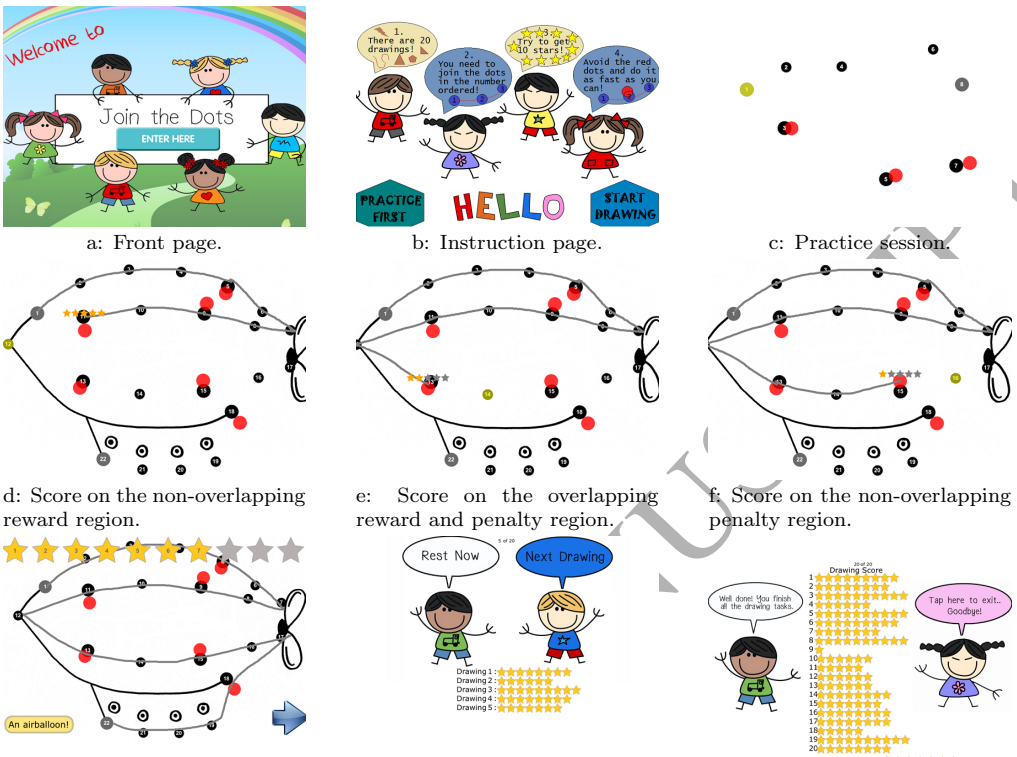
b: The red dots on the right side of black dots, each in *close*, *medium* and *far* distance.

Figure 2: The red and black dots act as penalty and reward regions used in *Join-the-dots* drawing tasks adapted from Trommershauser et al., 2003. Hitting the black dot (non-overlapping reward region) gives 5 stars, red dot (non-overlapping penalty region) gives 1 star, maroon area between black and red dots (overlapping reward and penalty region) gives 2 stars and outside area (background) yields 0 star.

the second red dot is placed less close to the black dot (0.5 unit CSS pixel of radius) labelled as *medium* and the third red dot is placed the furthest to the black dot (1 unit CSS pixel of radius) labelled as *far* (see Figure 2). There are six red dots, all in the order of the length, *close*, *medium* and *far* paired to the black dots in each drawing picture. The red dots are randomly placed either at the left or right side of the black dots. Since each drawing picture is repeated twice, the location of the red dots (left/right) toward the black dots are changed to the other side (right/left) in the second drawing of the same picture. For example, in Figure 1a, the red dots are on one side of the black dots but in Figure 1b, the red dots are placed on the opposite side of the black dots.

3.3. Procedure

The drawing application started with a main page (Figure 3a) followed by a simple instruction page (Figure 3b). A *Start Drawing* button is placed at the bottom-right hand corner of the instruction page which, if tapped, loads the first drawing task. There is also a *Practice First* button at the bottom-left hand corner of the same page. Users are required to go through the practice session first (Figure 3c). Once the practice session is completed and the user is ready, the main drawing task is started (Figure 3d, 3e and 3f). In each drawing task, the first dot is highlighted yellow to enable the user to easily identify where to initially place their finger or pen to start drawing. There will be no traces of strokes if the pen or finger is placed elsewhere other than the area of the first dot. Once the first dot is touched, the yellow highlight on the current dot (first dot) will disappear and the next target dot (black dot) will be highlighted. The purpose of highlighting the



a: Front page. b: Instruction page. c: Practice session.

d: Score on the non-overlapping reward region. e: Score on the overlapping reward and penalty region. f: Score on the non-overlapping penalty region.

g: The overall score for airballoon drawing task. h: Rest page with current score board. i: Final score board.

Figure 3: Drawing application *Join-the-dots* with reward and penalty effects.

dots is to conveniently guide users to find the next target dot. If the next target is a pair of red and black dots, five tiny fading yellow stars will start to appear once the user has touched the current dot. The fading stars effect is an indication that the time has started for the user to draw and reach the target dot in time. The time set is 1500 millisecond (ms). If the user's touch reached the non-overlapping black dot pairing with a red dot within time, the user gains five stars (Figure 3d). If the user's touch reached the overlapping black and red dots within time, the user gain two stars (Figure 3e). If the user reached the non-overlapping red dot pairing with a black dot, only one star is gained (Figure 3f). If the user's touch reached outside the region from the pair dots or failed to reach the dots within time, no star is gained. Each score of user's hitting the pairing red and black dots area is accumulated and calculated up to ten yellow stars and the full score is shown

at the top of the page (Figure 3g). An arrow button will then be visible for the user to proceed to the next page that led to a rest page (Figure 3h). The rest page is alternated with a drawing task page until all 20 drawing tasks are completed. The purpose of the rest page is for children to pause before continuing to the next task whenever they are ready. At the end of the session, a page detailing the score for every drawing task and an overall score will be shown (Figure 3i). The last page is a "thank you" page to user for their participation.

3.4. Experimental Design

The experiment was within-participant design for penalty condition (*close*, *medium* and *far*) and between-participant design for drawing input (*finger* or *pen*). There were two experimental groups; one group drawing with a *finger* and the other using a *pen*. Participants were put in alternate order for each drawing input group regardless of age. For example, the first participant drew using finger while the second one drew using a pen and this was alternately done throughout. Other than that, all participants from both groups went through the same drawing tasks. The experiment was a one data point per participant, a three-by-two analysis of whether user's drawing action was affected by the penalty conditions and/or drawing input. The drawing inputs and the penalty conditions are the independent variables while the number of stars as the scoring system is the dependent variable. On average, the experiment lasted about 40 minutes to 1 hour per participant.

3.5. Subjects

There were 40 children participants (18 boys and 22 girls) with ages ranging from 4 to 12 years old. 4 children's participant data were discarded from the analysis due to not following the instruction. Therefore, 36 children participants were used with a mean age of 7.44 years (SD=2.5 years). Half of the participants draw with their finger and the other half used a pen (refer Figure 4). There was a mixed background (nationalities/races) of children, and all attended nurseries and primary schools in Birmingham, UK. These child participants on average had 2 hours of touchscreen exposure per day.

3.6. Instruction

All parents had given their informed consent to allow their children to participate in the study, verbally and in writing prior to their child's sessions. In the beginning of the session, each child participant expressed their interest

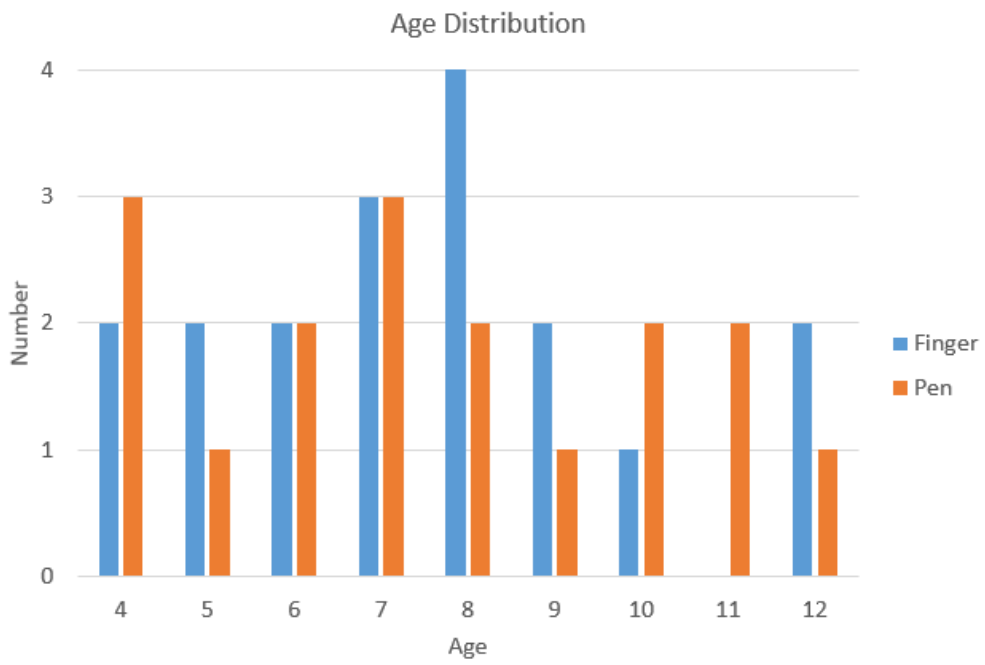


Figure 4: Age distribution of children participants.

to participate in the session, again verbally and in writing. Each participant was briefly informed about the task before they did a warm-up practice session using the tablet. The purpose of the practice session was to ensure that participants were familiar with the numbering order and understood the task. Each participant was assigned to one of the two groups based on the order of the participants. The first participant was assigned to group 1, drawing using touch *finger*; the second participant to group 2, drawing with a *pen* stylus. The order of the group continued, following the alternate method for the following participants described above. All were unaware of the hypotheses of the tests. Once the participants completed the task, they were each given a form to fill in their background information and a survey on their exposure of drawing on paper and tablets. At the end of the sessions, they were given a small gift bag as a token of appreciation.

3.7. Pilot Study

A pilot study was conducted on four children participants, two boys and two girls aged 5, 6, 8 and 10. The purpose of the pilot study was to ensure whether they understood the task. The size of the dots were tested so that younger and older children could manage to complete the task with good accuracy. Based upon observations made in the pilot study, the time limit of 850 (ms) was deemed too short for the children to be able to draw towards the target region within the set time. Therefore, the time limit was adjusted to 1500 (ms) to make it sufficiently challenging for child users to aim the target on time. A second pilot study was conducted with the same child participants to test the new time set. Subsequent to the two studies, the drawing application was deemed ready for experimental work.

3.8. Data Analysis

There were 452 dots in 20 drawing tasks with 120 data points. Dots from the red (penalty) and black (reward) dots were used for data analysis. The *endpoint* location of the drawing lines that reached the target areas on time were recorded together with number of stars gained and drawing time. All tasks completed beyond the time limit were omitted from the analysis. The normality of continuous data was assessed. Any noise that contributed to the faulty of the data was removed such as not following the order number of the dots.

3.8.1. Calculation for End Point

The *endpoint* position (x^d_{ij}, y^d_{ij}) was recorded relative to the center of target region for each penalty distance i(i=1,2,3), displacement condition j(j=1,2) and drawing task d(d=1,...,n_{ij}). The penalty distances were *close*(1), *medium*(2) and *far*(3). The displacement condition is represented by the penalty distance at the left or right side of the target regions. The unit of penalty distances from target region are $x_{red,i}$=-0.5,-0.25,0,0,0.25,0.5 unit and $y_{red,i}$=0. The endpoint relative to the target center was calculated: $|x_{ij}|=X_{ij}$ - X^{target}_j in all conditions. The mean *end point* for each subject and each condition X_{ij} and Y_{ij} were averaged across replications p = 1,...,n_{ij}. A value of $|\ x_i\ |>0$ indicated that the recorded *end point* was on the right side of the target center. The *aim point* is the mean distribution for all *endpoints* according to the penalty distances per subject.

3.8.2. Predictions of Optimal Aim Point

The model predicts a shift of *aim point* in horizontal directions. Equation 1 is used to form the maximum expected gain (*meg*) for each penalty condition. When the penalty region is zero, the *aim point* maximising expected gain, ($X^{meg}_{ij}, Y^{meg}_{ij}$) is the center of target region, ($X^{target}_j, Y^{target}_j$) with ($X^{meg}_{ij}$=$X^{target}_j, Y^{meg}_{ij}$=$Y^{target}_j$) (Trommershäuser et al., 2003a). When the penalty is non-zero, the *aim point* maximising expected gain shifts away from the penalty region and thereof, away from the center of target region.

3.8.3. Predictions of Performance

To find the subjects' individual score compared to optimal performance, the mean and variance distribution of optimal performance predicted by the model using equation 3 was computed. This was computed for every penalty condition for each subject individually. The estimation of a subjects' motor variance were performed around 60 trials in each penalty condition. This estimation was to see whether a subjects' performance is significantly different from optimal.

3.8.4. Predictions of Efficiency

The efficiency is the comparison between a subjects' performance and optimal performance. It is defined by taking the observed point as a percentage of the optimal point. The observed point is the actual average score for a subject while the optimal point is the maximum expected gain calculated for that subject. The efficiency was also computed for each subject in each

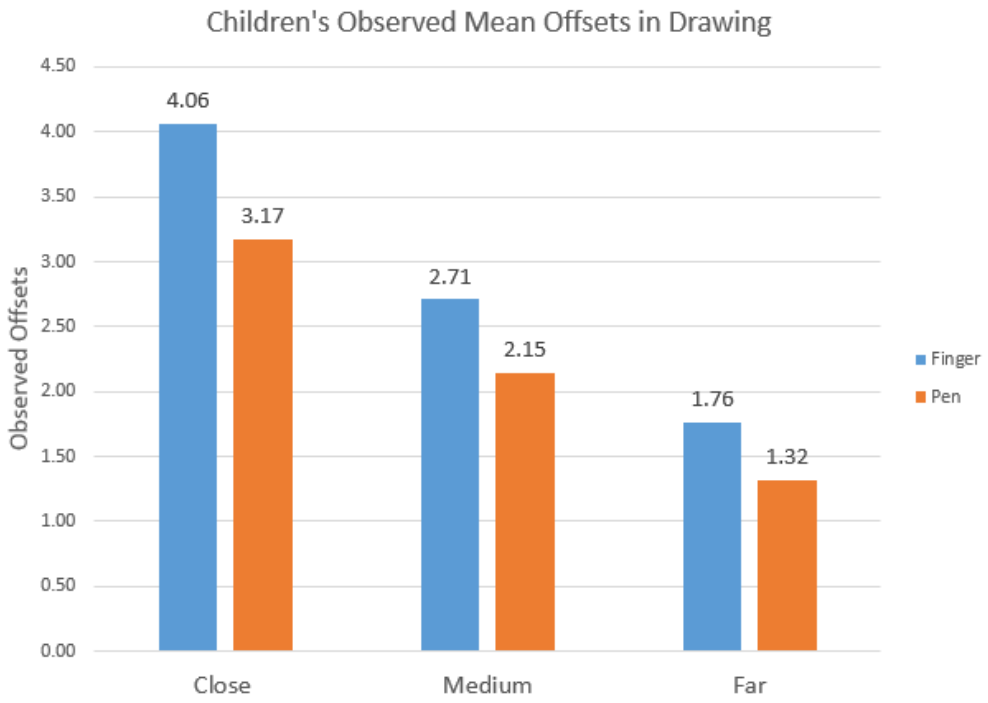


Figure 5: Children's observed mean offsets (px) based on penalty conditions *close*, *medium* and *far* for drawing input *finger* and *pen*. The offset is the distance between the actual touch point where the user's finger is placed and the center of the touch target (offset-distance).

condition. From there, the average efficiency for all subjects was computed within all conditions to see whether a subject's overall performance correlated with the optimal performance predictions.

4. Result

There are n=36 data of child participants used in the analysis. A mixed between-within subjects analysis of variance was conducted to assess the impact of penalty conditions (*close*, *medium* and *far*) with drawing input (*finger* and *pen*) on a subject's drawing performance. The result is discussed according to the research question of the study.

Table 1: Descriptive Statistics

Penalty Conditions	Medium	Mean (observed points)	Std. Deviation	N
close	finger	4.06	3.08	18
	pen	3.17	3.49	18
	Total	3.62	3.28	36
medium	finger	2.71	2.69	18
	pen	2.15	3.06	18
	Total	2.43	2.86	36
far	finger	1.76	2.91	18
	pen	1.32	1.67	18
	Total	1.54	2.35	36

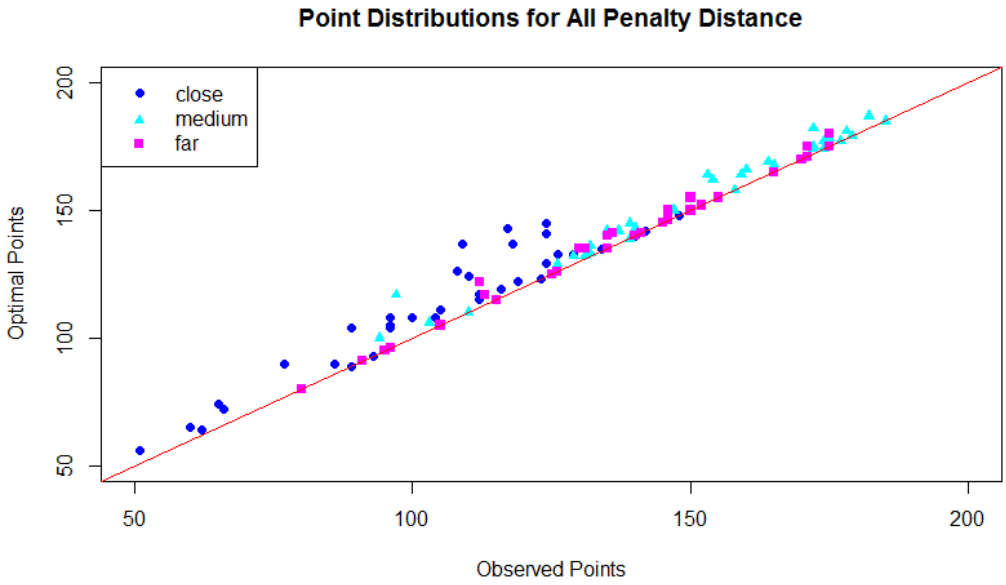


Figure 6: The observed and optimal points of all penalty conditions (*close*, *medium* and *far*) for all children participants. These are the gain points accumulated from the reward and penalty regions. The points were computed using equation 3 based on a subject's mean *aim point* yielding the observed point. The observed point was compared with the highest point from the estimation of a subject's motor variance which gives the optimal point.

4.1. How do children adapt their drawing strategies according to their own motor abilities and to the limitations of drawing tool and devices?

Based on the analysis performed, our results showed that there was a substantial main effect for penalty conditions (*close*, *medium* and *far*) towards the drawing performance given, *Wilks' Lambda*=.645, $F(2,33)$=9.068, p <.001 with *partial eta squared*=.355 for both groups (refer Figure 5). However, there was no significant interaction effects between penalty conditions and drawing inputs towards drawing performance. This suggested that whether child participants were drawing using a finger or a pen with these penalty conditions, it did not alter the drawing performance. We performed an Independent-Samples T-Test to examine whether there is a statistical significant different between drawing input on participants' observed points. The result from the analysis still showed that there was no effect of drawing input on the drawing performance. However, participants who drew using their fingers performed slightly better by gaining higher points than those who drew with a pen stylus as shown in Figure 5 and Table 1.

To examine whether there was a gap between participants' drawing movements and optimal performance, the graph in Figure 6 showed that there is a strong positive significant correlations between the observed points and optimal points for all penalty conditions; *close*, r=.955; *medium*, r=.988 and *far*, r=.995 given p <.001. The illustrated graph in Figure 6 showed that optimal strategy is a good predictor of participant performance. All points shown in the graph are above the diagonal lines indicating that they could not go further than the optimal points. The efficiency of the overall participants' performance was 96.42% which deviate about 4% to the optimal performance resulting a near-optimal adaptation to the ideal drawing movement.

To find out whether participants' drawing actions were according to the hypothesis predicted, the graph in Figure 7 portrayed that the *aim points* in blue showed larger shift, *aim points* in cyan showed moderate shift and *aim points* in pink showed the least shift respective to the distance of the penalty conditions *close*, *medium* and *far*. The observed offsets are subjects' mean *aim point* from the centre of the reward region while the optimal offsets are based on subjects' optimal points derived from equation 3. The result is in agreement to the predicted shift suggesting that child participants make the largest shift when the penalty region is closest (*close*), a moderate shift when the penalty region is less close (*medium*) and less shift when the penalty region is least close (*far*). As shown in Figure 7, the relative offsets for participants' mean of observed *aim point* and optimal *aim points* were

taken for all penalty conditions and average offsets were computed per child participant to examine the correlations from the pooled data. The graph showed that there is a positive significant correlation between the two given r=.914 and p <.001; suggesting that the subject's aiming points were close to optimal.

Our results suggested that child participants were making a predicted shift based on the predictions of the model but how do we know whether they were truly making an optimal adaptation? Perhaps they were aiming at what was remaining at the middle area of the target if in the case they were adapting less. Would this suggest that they were aiming at the centre of non-overlapping reward regions, rather than optimising? To investigate this further, we made an additional analysis to define child participants' *aim points* relative to the centre of non-overlapping reward regions. We plotted the optimal *aim points* versus observed *aim points* for all penalty conditions relative to the centre of non-overlapping reward region (see Figure 8). Although the graph showed a weak positive non-significant correlation given r=.292, p=.08; the overall scatterplots did not revolved around the centre of non-overlapping reward region but rather shifted away from it. However, since the penalty region has higher value than the outside region (background), the scatterplots seemed to shift nearer towards the penalty region rather than the background. Therefore, in response to the question: *Were participants not just aiming at the centre?* The analysis displayed in Figure 8 showed that this was not the case. Subjects showing near-optimal adaptation offered a better explanation.

4.2. How does a child adapt to the drawing actions according to his or her own motor variability?

Younger children tended to have higher motor variance than older children. Therefore, we predicted that they would compensate for this by extending their drawing time in order to gain higher rewards. This was true based on our results which showed a strong negative significant correlation between age of participants and *drawing time*; r=-.694, p <.001. This suggested that younger child users spent more time to complete the tasks than older child users (see Figure 9a). Given that they spent more time, they may have had the tendency to miss the time limit frequently and/or it may have affected their drawing scores. There was a positive significant moderate correlation between age of participants with the number of *stars*; r=.506, p <.001. This revealed that older child users scored higher than

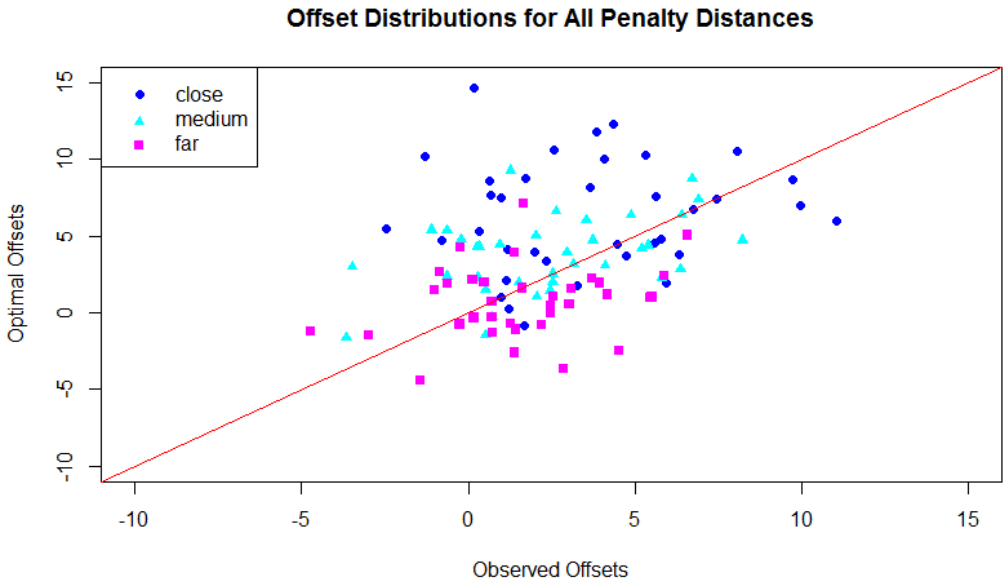


Figure 7: The observed and optimal offsets of all penalty conditions (*close*, *medium* and *far*) for all child participants relative to the centre of the reward region.

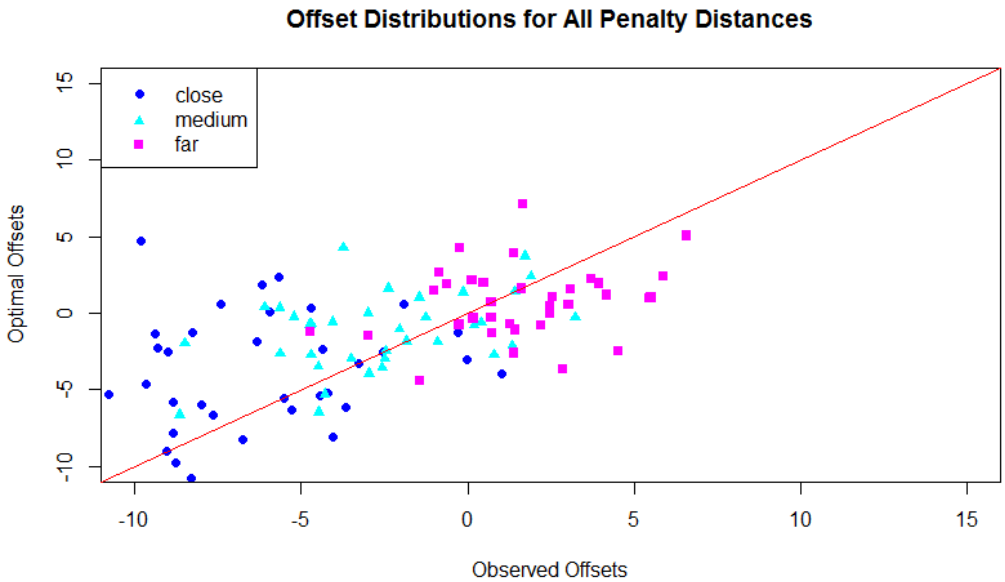
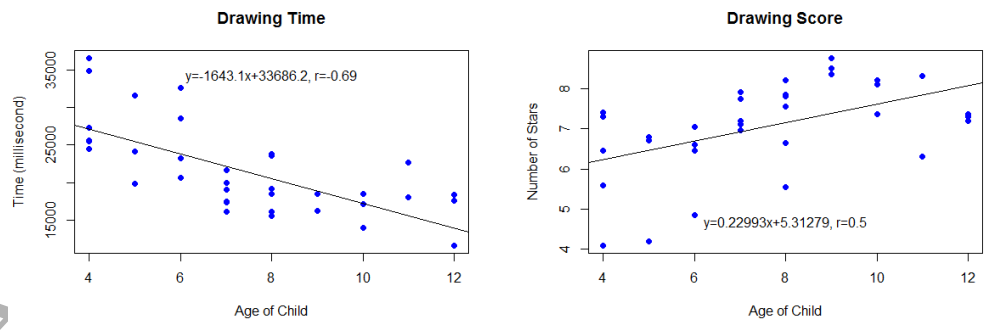


Figure 8: The observed and optimal offsets of all penalty conditions (*close*, *medium* and *far*) for all child participants relative to the centre of the non overlapping reward region.



a: Drawing time.

b: Drawing scores.

Figure 9: Children's drawing actions based on age distributions.

younger child users (see Figure 9b). The graphs provide information about the participating children's motor variability.

Figure 10 and 11 illustrate six child participants as examples of *aim point* distributions predicted at different offsets of margin 1 for the two groups (*finger* and *pen*), respectively. The experimental data were chosen based on the three highest number of data points for both groups. The *aim points* of the small circle dots have score points that maximised the expected gain from all possibilities regions, predicted by equation 3 based from the child's observed *aim point*. The child's observed *aim point* is marked based on the blue dashed line as the observed offset. These drawing *aim points* are distributed around the observed mean end-point (*aim point*) according to a bivariate Gaussian distribution. The coloured bar lines in both of the figures show the region boundaries as explained in detail in the captions for both figures. The highest plot point is the optimal *aim point* with the highest score. We made a direct comparison of the prediction values of *aim points* with the optimal *aim points* in the figures. As there was significant correlation between observed and optimal *aim points* shown earlier in Figure 7, this suggested that both *aim points* for every child participant were not far away from each other as shown in Figures 10 and 11. The graphs represent an example of how every child participant adapted their drawing actions according to his or her own motor variability when drawing either with their finger or using a pen. The graphs show a left-skewed due to the higher points on the penalty region than the outside region. Nevertheless, the graphs in these figures indicated that each child adapts to the drawing actions according to his or her own motor variability.

Figure 12 displays a random set of children participants' drawing samples from the experimental study. The data taken from the drawing samples were only the children's mark touches input on the touchscreen. The red and black dots were excluded from the drawings. These were among the drawings that did not achieved higher marks due to mistakes the children participants' made. Among those were trailing in drawing due to fat finger problems (refer to the first two rows of drawings), making double or multiple lines to make corrections in the drawing (refer to the third and fourth rows of drawings), not following the numbers ordered in completing the drawing figures (refer to the fifth and sixth rows of drawings) and loss in the details of the drawings (refer to the last row). Although the children participants were receiving low marks in some of their drawings, they were still enjoying and persisting to completing all the 20 drawing tasks given. Some of them even requested to

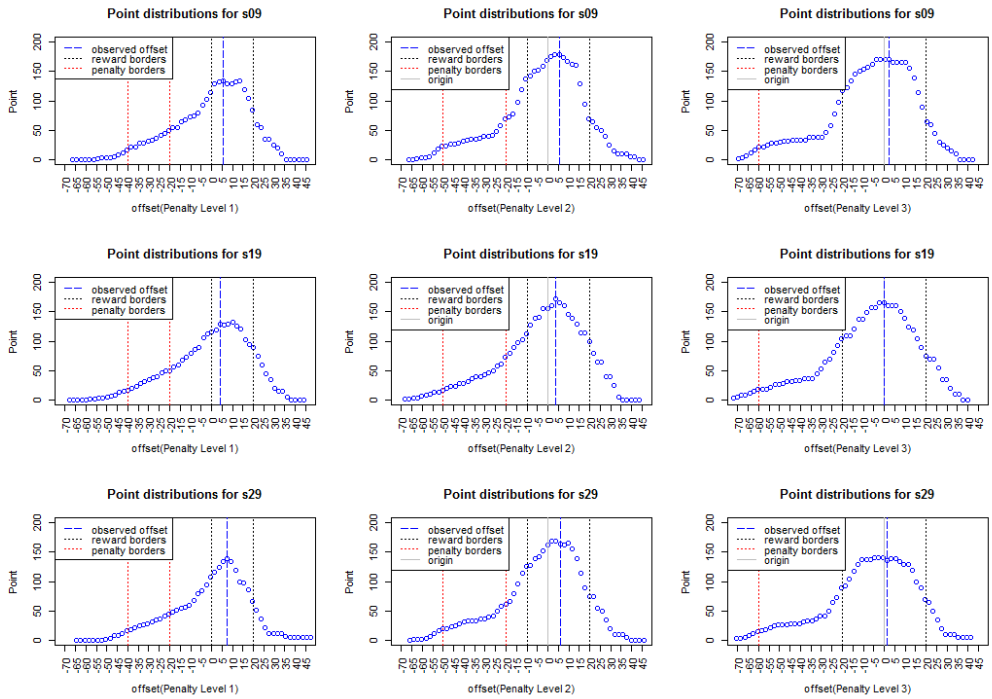


Figure 10: Experimental data of *aim point* distributions for child participant s09 (9 years old), s19 (7 years old) and s29 (8 years old) that performed the drawing task with their finger. The rows represent subjects and columns represent penalty conditions *close* (Penalty Level 1), *medium* (Penalty Level 2) and *far* (Penalty Level 3). The coloured bar lines show region boundaries. The grey bar is the centre of reward region at offset 0 as shown in Penalty Level 2 and 3. For Penalty Level 1, the grey bar is overshadowed by the black bar (one of the reward borders). The non-overlapping reward region boundaries span between the two black bars. The non-overlapping penalty region boundaries span between the two red bars. The range between the black and the red bars is the overlapping reward and penalty region. Penalty Level 3 does not have overlapping regions. The blue bar is the child's observed *aim point* offset.

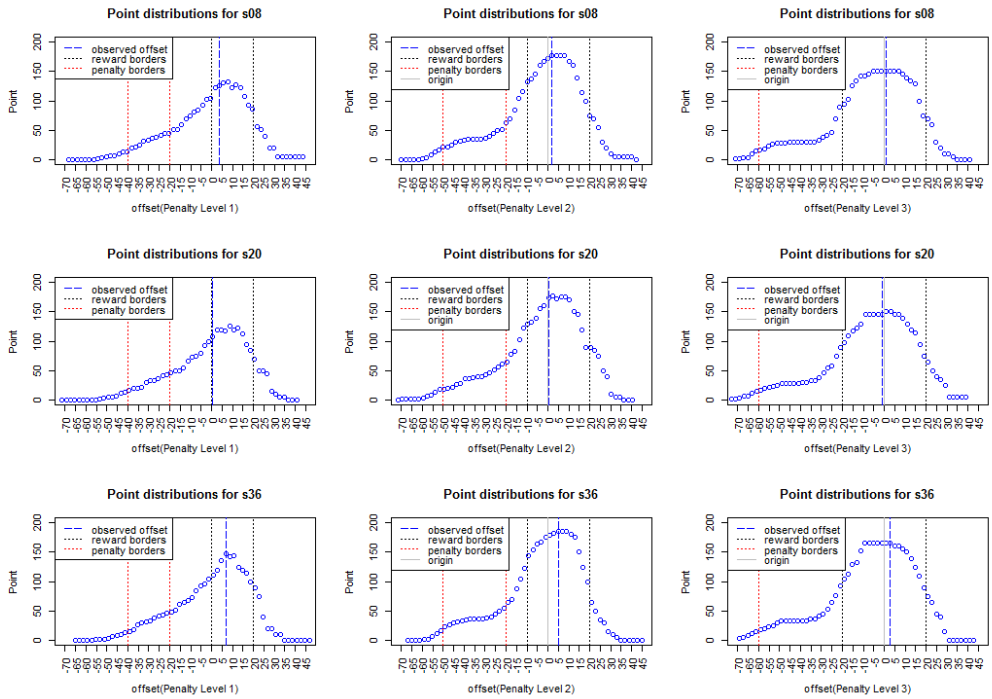


Figure 11: Experimental data of *aim point* distributions for child participant s08 (10 years old), s20 (7 years old) and s36 (9 years old) that performed the drawing task using a pen. The rows represent subjects and columns represent penalty conditions *close* (Penalty Level 1), *medium* (Penalty Level 2) and *far* (Penalty Level 3). The coloured bar lines show region boundaries. The grey bar is the centre of reward region at offset 0 as shown in Penalty Level 2 and 3. For Penalty Level 1, the grey bar is overshadowed by the black bar (one of the reward borders). The non-overlapping reward region boundaries span between the two black bars. The non-overlapping penalty region boundaries span between the two red bars. The range between the black and the red bars is the overlapping reward and penalty region. Penalty Level 3 does not have overlapping regions. The blue bar is the child's observed *aim point* offset.

attempt all the drawing tasks again after the experiment ended. We could probably say that when children are intrinsically motivated to pursue a task that are challenging but rewarding, they would pursue the task as well as they could and even for longer and more.

5. Discussion

In essence, our study aimed at exploring how children respond to variability in the outcome of drawing movement with reward and penalty effects. The results of the study suggested that children are able to adjust how they aim to the motivating reward signals (stars) and to their own motor performance variability. Given that children are known to have less established motor skills, our study shows that child participants were able to adjust their drawing movements to achieve the desired goals within their motor limitations and challenges imposed by the drawing tools and touch screen devices. In addition, the ability of children to adapt to the constraints was not affected by whether they used a pen or their finger to draw. The effect of penalty distance was the same regardless of the drawing method. Most importantly, child participants in this study showed near optimal adaptation to drawing on touch surfaces according to the Bayesian Model of Movement Planning.

Beyond drawing, graphical production is a theoretical construct in the work of the motor or manual control of the hand. Articulation in drawing is less demanding with respect to motor performance in younger children but becomes important later to children when their fine-motor skills become significant. Since drawing itself is an intrinsically motivating task that excites children to see the transformation from what is absent in a piece of paper to something that is meaningful to the drawer, children would tend to do well despite of their own limitations. To make it more fun, we embedded the drawing task with rewards and penalties as a form of play. The purpose was to make children engaged longer in all the twenty tasks given. Children's natural need to develop a mastery of play can be exhibited the same way to mastery in drawing (Wood and Hall, 2011). Children participants in our study, regardless of age, have seen to perform as really well as they could to meet their goals in all the drawing tasks. In particular, they adapt their drawing actions to their own motor variability and to the motivational context for action.

Drawing activity such as joining the dots resembles closely to pointing task activity that has been used extensively to study hand motor perfor-

mance. Drawing on touch surfaces has its advantages on the rewarding effect as touch feedback. The model that we used is to understand children's drawing strategies given limits and reward feedback. In the Bayesian approach, the aims were adjusted so as to maximize the motivating reward (stars) given the penalty region placed nearby the reward region in different proximities. This approach has been used before to predict adult performance in ballistic movement tasks but not to predict children moving fingers along a tablet surface. Previous studies suggested that adults choose near-optimal strategies when planning speed movement under risk (Trommershäuser et al., 2003b, 2005, 2006; Gepshtein et al., 2007; Dean et al., 2007; Maloney and Zhang, 2010). The results of our study extend these results to children but in a substantially more complex environment. Child users in our study shifted their aiming points away from the centre of the reward region when there was a penalty region nearby. When the penalty region was placed closest to the reward region, they made the largest shift; when the penalty region was placed less close to the reward region, they made a moderate shift; and when the penalty region was placed least close to the reward region, they made the least shift. The overall performance was correlated with the optimal rate suggesting that children were making near optimal adaptations. Our results also suggested that viability is a new way to model childrens interaction with technology that derives from the Bayesian decision theoretic approach. Our study shows the importance of understanding children's motor variability when developing a tool used for skill (e.g., Greer and Lockman, 1998; Hourcade et al., 2004).

This paper contributes to a growing body of literature in the area of children-computer interaction by providing evidence that children can adapt well on a touchscreen despite their motor variability and their own limitations and limitations imposed by touch-based devices. Specifically, children adapt drawing strategies to their own motor variability and to motivational context of action. When a child is intrinsically motivated to perform a task and be extrinsically rewarded, this leads to a motivational context of action for them to make optimal movement and decision even when there were risks and uncertainties. The findings can confirm that, child participants can learn really well when there are higher rewards and losses gain altogether in a complex environment. Therefore, designers of future touch based applications for these specific users should consider building an interface of a playful learning or activity with rewarding effects and risks in order for children to adapt at their best. As decision theory can apply to conditions of certainty, risk, or

uncertainty, the idea can help to understand how children adapt strategies to the risks and perceived costs of drawing errors, slips and mistakes. This can also be applied to other children touch interaction activities.

6. Future Work

The study however does have limitations. Although all child participants seemed to enjoy and were engaged in completing the 20 drawing tasks, a few of them, regardless of age, were not able to pursue the task exactly as instructed in certain conditions. A few children were seen to have tendencies to draw toward other dots before realising their mistake, resulting in them traversing back their drawing movements toward the correct target dots. Data that occurred due to this were discarded from the analysis. This is not a motor issue but a cognitive problem in drawing. These children would perceive the drawing outcomes even before the start of the task due to the overall dot that formed an indication of a drawing figure. Instead of following the number order to form the drawing picture, child participants may use their own ordering based on the mental image processed in their cognitive system. Trommershäuser et al. (2003b) used a single target at one time in their ballistic aiming task. In contrast, due to the nature of the *Join-the-dot* task, other sequence targets need to be shown altogether in one single drawing task making the task cognitively more demanding than Trommershäuser et al. (2003b)'s task. We plan to investigate these cognitive aspects of drawing in future work.

The Bayesian theoretical framing of this work opens-up a number of research opportunities in understanding childrens touch interaction. One possible area is to extend to basic shapes such as circles, squares or apex. How and why do children make a certain choice of preference strokes of a shape? How are they influenced by motor variability and reward? A free form drawing where the goal is to achieve a desired drawing figure should also be explored. The work can be extended to study the whole motion of drawing trajectory using the Steering Law (Accot and Zhai, 1997). The question then is, is it possible that such tasks can be understood through the lens of Bayesian decision theory?

7. Conclusion

A child can perform well in a task if we put a bit of a fun. Even if it is challenging enough to get the reward. A child's intention to try his/her best

is embedded as intrinsic motivation while the desire to give the best comes from the benefit of extrinsic motivation. These two added together would allow a child to give their optimal performance in a task that becomes the statistic property of motivational context for action. The work reported here shows how it is possible that a child's strategies for drawing on a tablet can be understood as a Bayesian adaptation to movement variability, motivation and the limitations of the device surface. This perspective offer a promising means of understanding children's drawing strategies and their touch behaviour interaction.

8. Acknowledgments

We would like to express our appreciation for all parents who gave consent for their children to take part in this study. We also wish to thank all the children for their valuable participation.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

9. References

References

Accot, J., Zhai, S., 1997. Beyond fitts' law: models for trajectory-based hci tasks. In: Proceedings of the ACM SIGCHI Conference on Human factors in computing systems. ACM, pp. 295–302.

Anthony, L., Brown, Q., Nias, J., Tate, B., 2013. Examining the need for visual feedback during gesture interaction on mobile touchscreen devices for kids. In: Proceedings of the 12th International Conference on Interaction Design and Children. ACM, pp. 157–164.

Anthony, L., Brown, Q., Nias, J., Tate, B., Mohan, S., 2012. Interaction and recognition challenges in interpreting children's touch and gesture input on mobile devices. In: Proceedings of the 2012 ACM international conference on Interactive tabletops and surfaces. ACM, pp. 225–234.

Anthony, L., Brown, Q., Tate, B., Nias, J., Brewer, R., Irwin, G., 2014. Designing smarter touch-based interfaces for educational contexts. Personal and Ubiquitous Computing 18 (6), 1471–1483.

Arnheim, R., 1954. Art and visual perception: A psychology of the creative eye. Univ of California Press.

Aziz, N. A. A., 2013. Children's interaction with tablet applications: Gestures and interface design. Children 2 (3), 447–450.

Bertucco, M., Cesari, P., Latash, M., 2013. Fitts law in early postural adjustments. Neuroscience 231, 61–69.

Brown, Q., Anthony, L., 2012. Toward comparing the touchscreen interaction patterns of kids and adults. In: ACM SIGCHI EIST workshop.

Chiong, C., Shuler, C., 2010. Learning: Is there an app for that. In: Investigations of young children's usage and learning with mobile devices and apps. New York: The Joan Ganz Cooney Center at Sesame Workshop. pp. 13–20.

Crescenzi, L., Jewitt, C., Price, S., 2014. The role of touch in preschool children's learning using ipad versus paper interaction. Australian Journal of Language & Literacy 37 (2), 86–95.

Dean, M., Wu, S.-W., Maloney, L. T., 2007. Trading off speed and accuracy in rapid, goal-directed movements. Journal of Vision 7 (5), 10.

Donker, A., Reitsma, P., 2007. Aiming and clicking in young children's use of the computer mouse. Computers in Human Behavior 23 (6), 2863–2874.

Einarsdottir, J., Dockett, S., Perry, B., 2009. Making meaning: Children's perspectives expressed through drawings. Early child development and care 179 (2), 217–232.

Fitts, P. M., Peterson, J. R., 1964. Information capacity of discrete motor responses. Journal of experimental psychology 67 (2), 103.

Gepshtein, S., Seydell, A., Trommershäuser, J., 2007. Optimality of human movement under natural variations of visual–motor uncertainty. Journal of Vision 7 (5), 13.

Greer, T., Lockman, J. J., 1998. Using writing instruments: Invariances in young children and adults. Child Development 69 (4), 888–902.

Guiard, Y., 2009. The problem of consistency in the design of fitts' law experiments: Consider either target distance and width or movement form and scale. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, pp. 1809–1818.

Harris, C. M., Wolpert, D. M., 1998. Signal-dependent noise determines motor planning. Nature 394 (6695), 780–784.

Hourcade, J. P., Bederson, B. B., Druin, A., Guimbretière, F., 2004. Differences in pointing task performance between preschool children and adults using mice. ACM Transactions on Computer-Human Interaction (TOCHI) 11 (4), 357–386.

Hudson, T. E., Maloney, L. T., Landy, M. S., 2008. Optimal compensation for temporal uncertainty in movement planning. PLoS Comput Biol 4 (7), e1000130.

Hudson, T. E., Wolfe, U., Maloney, L. T., 2012. Speeded reaching movements around invisible obstacles. PLoS Comput Biol 8 (9), e1002676.

Jones, T., 1991. An empirical study of children's use of computer pointing devices. Journal of Educational Computing Research 7 (1), 61–76.

Kang, C., 2013. Survey: For young children, mobile devices such as tablets, smartphones now a mainstay. The Washington Post.

Kellogg, R., 1970. Analyzing children's art. Mayfield Palo Alto, CA.

Kim, H.-h., Taele, P., Seo, J., Liew, J., Hammond, T., 2016. Easysketch 2: a novel sketch-based interface for improving children's fine motor skills and school readiness. In: Proceedings of the Joint Symposium on Computational Aesthetics and Sketch Based Interfaces and Modeling and Non-Photorealistic Animation and Rendering. Eurographics Association, pp. 69–78.

Kim, H.-h., Taele, P., Valentine, S., McTigue, E., Hammond, T., 2013. Kimchi: a sketch-based developmental skill classifier to enhance pen-driven educational interfaces for children. In: Proceedings of the International Symposium on Sketch-Based Interfaces and Modeling. ACM, pp. 33–42.

Landy, M. S., Goutcher, R., Trommershäuser, J., Mamassian, P., 2007. Visual estimation under risk. Journal of vision 7 (6), 4–4.

Lee, T.-H., Wu, F.-G., Chen, H.-T., 2017. Innovation & evaluation of tangible direct manipulation digital drawing pens for children. Applied ergonomics 60, 207–219.

Lin, Q., Luo, J., Wu, Z., Shen, F., Sun, Z., 2015. Characterization of fine motor development: Dynamic analysis of children's drawing movements. Human movement science 40, 163–175.

Maitin, S., Lark-Horovitz, B., Lewis, H. P., Luca, M., 1968. Understanding children's art for better teaching.

Maloney, L. T., Zhang, H., 2010. Decision-theoretic models of visual perception and action. Vision research 50 (23), 2362–2374.

Matthews, J., 2003. Drawing and painting: Children and visual representation. Sage.

McKnight, L., Fitton, D., 2010. Touch-screen technology for children: giving the right instructions and getting the right responses. In: Proceedings of the 9th International Conference on Interaction Design and Children. ACM, pp. 238–241.

Meyer, D. E., Abrams, R. A., Kornblum, S., Wright, C. E., Keith Smith, J., 1988. Optimality in human motor performance: ideal control of rapid aimed movements. Psychological review 95 (3), 340.

Nacher, V., Jaen, J., 2015. Evaluating the accuracy of pre-kindergarten children multi-touch interaction. In: Human-Computer Interaction. Springer, pp. 549–556.

Nacher, V., Jaen, J., Navarro, E., Catala, A., González, P., 2015. Multi-touch gestures for pre-kindergarten children. International Journal of Human-Computer Studies 73, 37–51.

Payne, S. J., Howes, A., 2013. Adaptive interaction: A utility maximization approach to understanding human interaction with technology. Synthesis Lectures on Human-Centered Informatics 6 (1), 1–111.

Picard, D., Martin, P., Tsao, R., 2014. ipads at school? a quantitative comparison of elementary school children's pen-on-paper versus finger-on-screen drawing skills. Journal of Educational Computing Research 50 (2), 203–212.

Price, S., Jewitt, C., Crescenzi, L., 2015. The role of ipads in pre-school children's mark making development. Computers & Education 87, 131–141.

Shukri, S. R. M., Howes, A., 2017. Reward conditions modify children's drawing behaviour. In: International Visual Informatics Conference. Springer, pp. 455–465.

Tabatabaey-Mashadi, N., Sudirman, R., Khalid, P. I., 2013. An evaluation of children's structural drawing strategies. Jurnal Teknologi 61 (2).

Tassinari, H., Hudson, T. E., Landy, M. S., 2006. Combining priors and noisy visual cues in a rapid pointing task. The Journal of neuroscience 26 (40), 10154–10163.

Todorov, E., 2004. Optimality principles in sensorimotor control. Nature neuroscience 7 (9), 907–915.

Toomela, A., 2002. Drawing as a verbally mediated activity: A study of relationships between verbal, motor, and visuospatial skills and drawing in children. International Journal of Behavioral Development 26 (3), 234–247.

Trommershäuser, J., Gepshtein, S., Maloney, L. T., Landy, M. S., Banks, M. S., 2005. Optimal compensation for changes in task-relevant movement variability. The Journal of Neuroscience 25 (31), 7169–7178.

Trommershäuser, J., Landy, M. S., Maloney, L. T., 2006. Humans rapidly estimate expected gain in movement planning. Psychological Science 17 (11), 981–988.

Trommershäuser, J., Maloney, L. T., Landy, M. S., 2003a. Statistical decision theory and the selection of rapid, goal-directed movements. JOSA A 20 (7), 1419–1433.

Trommershäuser, J., Maloney, L. T., Landy, M. S., 2003b. Statistical decision theory and trade-offs in the control of motor response. Spatial vision 16 (3), 255–275.

Trommershäuser, J., Maloney, L. T., Landy, M. S., 2008. The expected utility of movement. Neuroeconomics: Decision Making and the Brain, PW Glimcher, CF Camerer, E. Fehr, and RA Poldrack, eds.(Elsevier, 2009), 95–111.

Tu, H., Ren, X., Zhai, S., 2015. Differences and similarities between finger and pen stroke gestures on stationary and mobile devices. ACM Transactions on Computer-Human Interaction (TOCHI) 22 (5), 22.

Van Sommers, P., 1984. Drawing and cognition: Descriptive and experimental studies of graphic production processes. Cambridge University Press.

Vatavu, R.-D., Anthony, L., Brown, Q., 2015a. Child or adult? inferring smartphone users age group from touch measurements alone. In: Human-Computer Interaction. Springer, pp. 1–9.

Vatavu, R.-D., Cramariuc, G., Schipor, D. M., 2015b. Touch interaction for children aged 3 to 6 years: Experimental findings and relationship to motor skills. International Journal of Human-Computer Studies 74, 54–76.

Wang, Y., Yu, C., Liu, J., Shi, Y., 2013. Understanding performance of eyes-free, absolute position control on touchable mobile phones. In: Proceedings of the 15th international conference on Human-computer interaction with mobile devices and services. ACM, pp. 79–88.

Wood, E., Hall, E., 2011. Drawings as spaces for intellectual play. International Journal of Early Years Education 19 (3-4), 267–281.

Woodward, J., Shaw, A., Luc, A., Craig, B., Das, J., Hall Jr, P., Holla, A., Irwin, G., Sikich, D., Brown, Q., et al., 2016. Characterizing how interface complexity affects children's touchscreen interactions. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. ACM, pp. 1921–1933.

Wu, S.-W., Trommershäuser, J., Maloney, L. T., Landy, M. S., 2006. Limits to human movement planning in tasks with asymmetric gain landscapes. Journal of Vision 6 (1), 5–5.

Zhai, S., Kristensson, P. O., Appert, C., Andersen, T. H., Cao, X., 2012. Foundational issues in touch-screen stroke gesture design-an integrative review. Foundations and Trends in Human-Computer Interaction 5 (2), 97–205.

Authors

Dr. Siti Rohkmah Mohd Shukri was a lecturer of Computer Science at Universiti Teknologi PETRONAS, Malaysia. Her research interest area are Computer Graphics, Computer Animation and Human Computer Interaction where she did her master at George Washington University, Washington D.C. After embarking her PhD at University of Birmingham in Computer Science, her research interest has now focus more on children interaction through technology. She has numerous experience working with children in the UK and currently now working with children in Malaysia for her research work.

Professor Andrew Howes is Professor of Computer Science at University of Birmingham and Marshall Weinberg visiting professor at the University of Michigan. He has previously held academic posts at the University of Manchester, Cardiff University, Carnegie-Mellon University and the Medical Research Council, Cambridge. He is known for his work in Cognitive Science and Human-Computer Interaction and he focuses on computational rationality, that is in computational models of human behaviour that adapt to human cognitive capacities, as well as to the statistical structure of the environment. His recent book offers a general integrative framework for understanding human interaction with technology (Payne and Howes, 2013). Professor Howes is an Associate Editor at the International Journal of Human-Computer Studies and Cognitive Science journal. He has been an Associate Chair for ACM SIGCHI for a number of years and he is program chair for the Annual Meeting of the Cognitive Science Society (2017).

Conflict of Interest

This research did not receive any specific grant from funding agencies in the public, commercial, or not for profit sectors. There is no conflict of

interest regarding the work of this research.

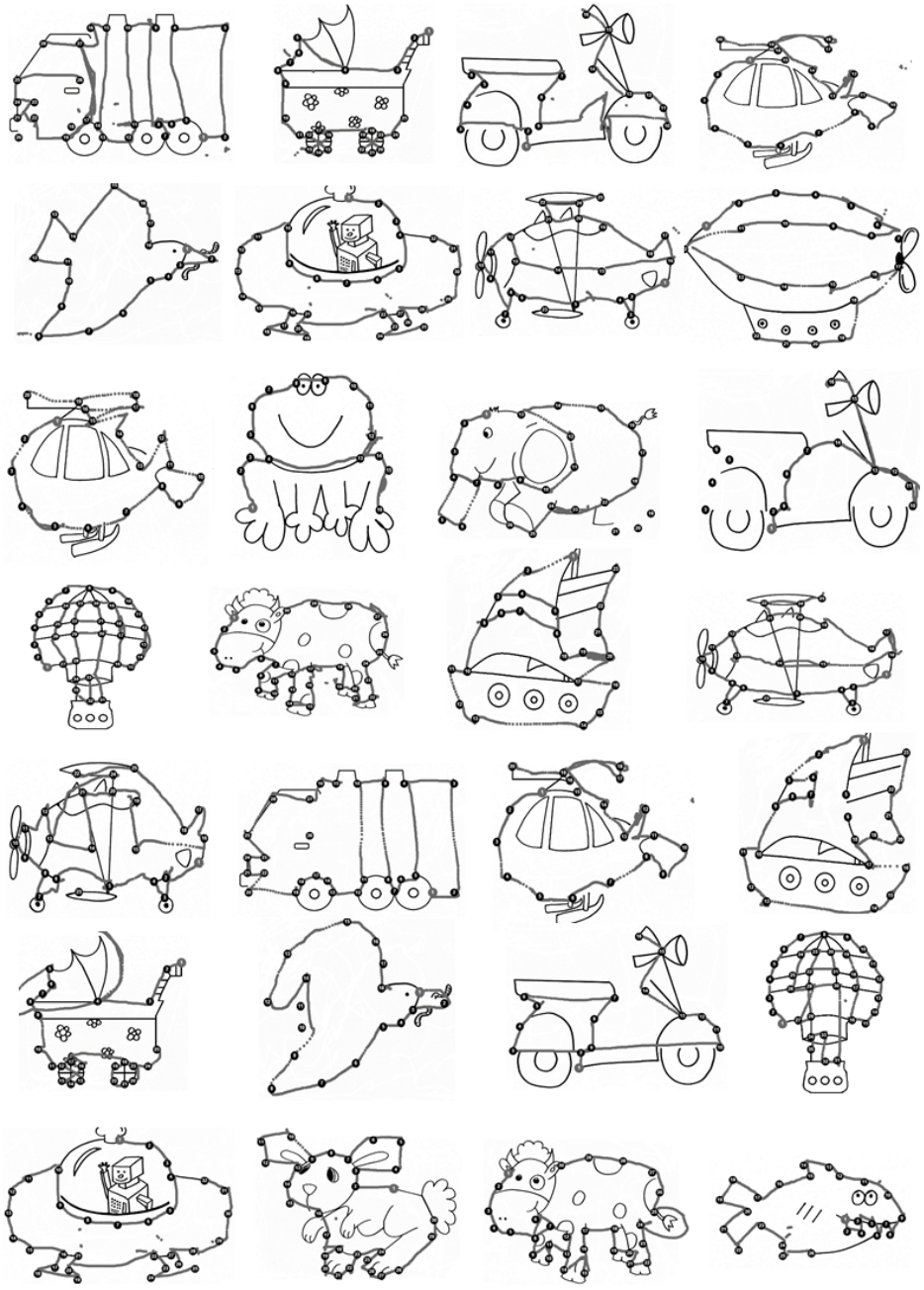


Figure 12: Samples of children participants' drawing outcome from the experimental study.