Article

U-Shape by Quadratic Equation: A Best-fit for Modelling Hemodynamic Changes in the DCCS Task

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Abstract: General Linear Modelling (GLM) has been widely employed to estimate the hemodynamic changes evoked by cognitive processing, which are more likely to be nonlinear than linear. First, this study re-analyzed the fNIRS data (N = 38, M_{age} = 5.0 years, SD = 0.69 years, 17 girls) collected in the *Mixed-Order Design Dimensional Change Card Sort* (DCCS) task. The results indicated that the quadratic equation was better than GLM to model HbO changes in this task. Second, analysis of a new set of data indicated that the Habit-DisHabit design of DCCS was more effective in identifying the neural correlates of cognitive shifting than the Mixed-Order Design. Third, this study found that the Non-users were more attentive and engaged than the Heavy-users, with a slower but more steady increase of brain activation in BA8 and BA9.

Keywords: Pad use; Executive Function; fNIRS Evidence; *Dimensional Change Card Sort Task* (*DCCS*) task; Preschoolers

1. Introduction

The functional near-infrared spectroscopy (fNIRS) technology is a portable and comfortable way to measure the hemodynamic changes in targeted brain areas [1−3]. It can generate time-sensitive data that could be analyzed using general linear modeling (GLM) to estimate the oxygenated hemoglobin (HbO) changes between the task and baseline. For instance, Li et al. examined the effect of heavy tablet use on preschoolers' executive function during the *Dimensional Change Card Sort* (DCCS) task using fNIRS [4]. They conducted t-tests and GLM to compare the hemodynamic changes in the Non-user and the Heavy-user groups and found a significant difference between the two groups in activating the prefrontal cortex (BA 9). The 'Non-user' activation pattern was ‘normal and healthy’, whereas the 'Heavy-user' pattern was ‘not normal thus needs further exploration’ [4]. However, they presented no further statistical evidence to demonstrate how ‘abnormal’ the ‘Heavy-user’ pattern was. In addition, the hemodynamic changes over time in brain areas are a nonlinear rather than linear relationship; thus, the GLM analysis conducted by Li et al. [4] might not be appropriate or accurate. Therefore, this study aims to re-analyze the same data with a quadratic or cubic equation to identify the best-fit way to model the hemodynamic responses in the DCCS task. In addition, a set of data with a new design DCCS task was also collected and analyzed with a quadratic equation.

1.1. Modeling Hemodynamic Changes with GLM

The fNIRS technology allows us to monitor brain activation by measuring hemodynamic changes such as the concentration of oxy-hemoglobin (*HbO*) and deoxy-hemoglobin (*HbR*) in targeted brain areas. The *HbO* and *HbR* data are dynamic and changing over time; thus, careful and advanced statistical analyses are needed to examine this type of

 doi:10.20944/preprints202107.0417.v1

time-sensitive data [1-3]. However, no systematic and standardized approaches were established in the first decade of this millennium; thus, fNIRS scientists had the liberty to choose the statistical methods they believed to be appropriate and adequate. Later, Schroeter et al. [5] proposed employing the general linear modeling (GLM) as the standard statistical approach for fNIRS data. Accordingly, Pouliot et al. [6] adopted GLM as the standard hemodynamic response function to examine the fNIRS data for spikes and seizures. They concluded that GLM could be used to analyze the fNIRS data for posterior epileptic activity. In 2014, Tak and Ye [7] systematically reviewed the commonly used fNIRS statistics such as principal component analysis, independent component analysis, false discovery rate, in addition to the inference statistics such as the standard t-test, F-test, analysis of variance, and statistical parameter mapping framework. Eventually, they proposed adopting GLM mixed-effect model with restricted maximum likelihood variance estimation [7].

Since then, employing GLM to estimate the hemodynamic changes has become the standard inference statistics in fNIRS studies. GLM empowers scientists to estimate the subject, channel, and task-specific evoked hemodynamic responses and robustly separate the evoked brain activity from systemic physiological interference using independent measures of nuisance regressors [1-3]. In addition, GLM can significantly enhance the contrast to noise ratio of the brain signal, improve feature separability, and ultimately lead to better classification accuracy. Recently, von Lühmann et al. [8] found that GLM could provide better single-trial estimates of brain activity as well as a new feature type, such as the weight of the individual and channel-specific hemodynamic response function regressor. Therefore, GLM has become the well-established and well-accepted method for fNIRS data analysis.

1.2. Modeling Hemodynamic Changes in the DCCS Task

The DCCS task asks children to sort a set of two-dimensional (i.e., color and shape) test cards according to two target cards that match the former in one dimension but not the other. Normally, a set of white paper cards (3.5 x 7.0 cm) is used as the stimuli, which have two dimensions: shape and color. Children are asked to sort the test cards according to one dimension that matches the target card (e.g., red/blue, boat/rabbit). And the rule for matching is changed according to the experimenter's instruction. Initially, Morriguchi and his colleagues [9] conducted fNIRS studies on the DCCS task. They conducted t-tests and correlation analyses to compare *HbO* changes between the task and baseline conditions. Even recently, Moriguchi & Lertladaluck [10] and Xie et al. [11] conducted the same t-tests and correlation analysis of the *HbO* changes for the same DCCS task. But the results were contradictory: Moriguchi & Lertladaluck [10] found no significant relationship between prefrontal activations and English proficiency, whereas Xie et al. [11] found a significant correlation. This inconsistency indicated that either the data analysis or the DCCS task paradigm employed by the two teams might not be rigorous or sensitive enough to identify the specific neural correlates responsible for the cognitive shifting of the DCCS task.

Therefore, Li et al. [12] developed the "habituation–dishabituation paradigm of DCCS task" ("Habit-Dishabit Design" hereafter) and proposed a more direct and critical indicator – the "V shape of General Linear Modelling" to identify the cognitive shifting. This paradigm has improved the arrangement of testing items to maximize the chances of habituation and dishabituation in the participating children. In the pre-switch period (20'), the children were asked to sort six or more cards using the same rule thus tended to be habituated before. Then, they were asked to use the other rule to sort another six cards in the pos-switch period (20'). And the three sessions followed the same sorting rule of the second period of the previous session: Session 1: color (6 cards) → shape (6 cards); Session 2: shape (6 cards) → color (6 cards); and Session 3: color (6 cards) → shape (6 cards). The children tended to be habituated when they knew the second round of sorting cards should follow the same rule. In another word, this paradigm has helped to trigger

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the occurrence of habituation and dishabituation. Accordingly, Li et al. (2020) proposed a pair of GLMs to estimate HbO changes (ΔHbO) for the pre- and post- switch periods, using the same regression formula: $Y_{\Delta HbO} = aX_{time} + b + \varepsilon$. If $a_{pre\text{-}switch}$ is negative (-a), whereas $a_{post\text{-}switch}$ is positive (+a), and both models are significant, a perfect V shape could be verified. The corresponding channel was identified as the neural correlate of 'cognitive shifting' [12]. Using this new paradigm, they found V shape in BA 6, BA8, BA 9, BA 10, BA 40, and BA 44, which should be regarded as the neural correlations of cognitive shifting during the DCCS task.

1.3. The Context of This Study

Recently, Li et al. [4] adopted the Mixed-order design DCCS and GLM by Moriguchi & Lertladaluck [10] and Xie et al. [11] to examine the impact of tablet use on preschoolers' executive function. They found that the Non-users outperformed the Heavy-users with a significantly higher correct rate in the DCCS task. And the two groups differed significantly in the activation of BA9 (ch 16), indicating that the Non-user pattern was 'normal and healthy' [4]. In contrast, the Heavy-user pattern was 'not normal and needs further exploration'. However, the hemodynamic changes in each channel should be a kind of nonlinear relationship [1-3]; thus, polynomial regression via quadratic function might be more appropriate for estimating the HbO changes in targeted brain areas. Accordingly, in this study, we proposed a quadratic function for better modeling the hemodynamic changes: [$\boldsymbol{Y_{\Delta HbO} = aX_{time}^2 + bX_{time} + c + \varepsilon(error\ term)}$]. If a > 0, the curve is a typical U shape; if a = 0, the quadratic function does not exist, indicating a linear relationship that GLM could model; if a < 0, the curve is a kind of reversed U shape. We hypothesized that this U-shape curve by quadratic function might be more statistically appropriate for modeling hemodynamic changes in the DCCS task than the V-shape by GLM [12]. In addition, we also hypothesized that the "Habit-DisHabit Design" might be more appropriate for identifying the neural correlates of cognitive shifting. Accordingly, this study dedicated to addressing the following questions:

1. GLM, quadratic, or cubic equations, which is the best fit for estimating the hemodynamic changes in the DCCS task?

2. Mixed-Order Design versus Habit-DisHabit design, which is more effective in identifying the neural correlates of cognitive shifting in the DCCS task?

3. What are the significant differences in brain activation between the heavy-users and non-users evidenced by fNIRS?

2. Materials and Methods

2.1. Participants

Li et al. [4] reported that 38 children (ages 4 to 6.3 years, M_{age} = 5.0 years, SD = 0.69 years, 17 girls, 21 boys) completed this experiment. The parents of 38 participating children completed the survey to identify the heavy-users or non-users. Eight children never used tablets; thus were included in the 'Non-user' group (2 girls, 6 boys). About 16 (12 girls, 4 boys) were classified into the 'Heavy-user' group as their daily screen time was more than the mean level, and their use was neither controlled nor limited [4].

2.2. Measures

2.2.1. The Mixed-Order Design DCCS Task

This task included two target cards and 24 test cards, each different in shape and color. One pair of target trays was used for the three consecutive test sessions, and each session consisted of a rest (20 s) phase and mix (25 s) phase. During the rest phase, children were asked to be still, doing nothing. As shown in Figure 1, during the mix phase, the

 doi:10.20944/preprints202107.0417.v1

children were asked to sort the cards according to the instructed rule (color or shape). In each phase, the children were given the rule before each trial. In each block, the rule order was fixed and mixed: shape, shape, color, shape, shape, color, shape, shape (totally 8 cards per block). This fixed-order was applied to all the participants, resulting in more color-to-shape switches in total [4].

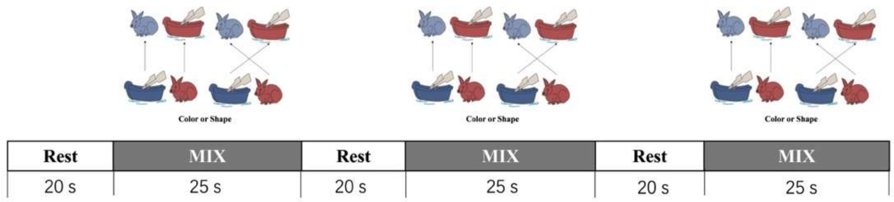

Figure 1. The Mixed-Order Design DCCS Tasks (Li, et al., 2021)

2.2.2. The Habit-DisHabit Design DCCS Task

This task is different from the Mixed-order design. As shown in Figure 2, the children were asked to sort eight to twelve cards using the same rule within the pre-switch period (20s). Then, they were asked to use the other rule to sort another eight to twelve cards within the pos-switch period (20s). And the three sessions followed the same sorting rule of the second period of the previous session: Session 1: color (20s) → shape (20s); Session 2: shape (20s) → color (20s); and Session 3: color (20s) → shape (20s). This design was very inductive to cognitive habituation and dishabituation [12].

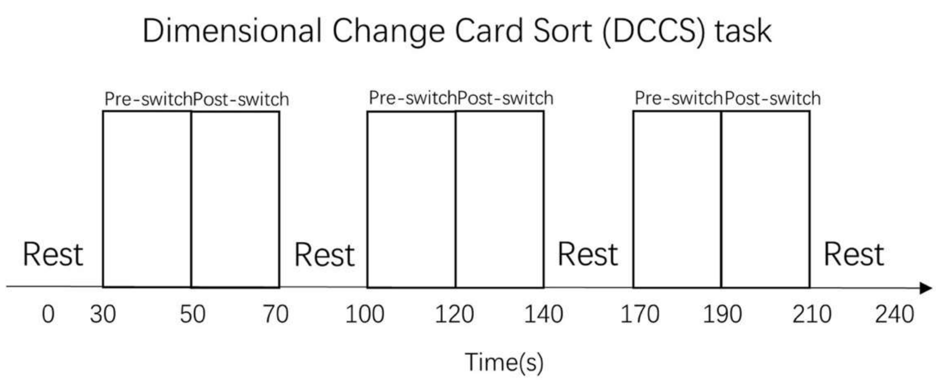

Figure 2. The Habit-DisHabit Design DCCS Task (Li, et al., 2020)

2.2.3. The fNIRS Examination and Data Analysis

In Li et al. study [4] and this study, the same multiple-channel fNIRS system (Oxymon Mk III, Artinis, The Netherlands) and child caps were used to simultaneously measure the concentration changes of oxygenated hemoglobin (*HbO*), deoxygenated hemoglobin (*HbR*), and total hemoglobin (*HbT*) in the participants. The region of interest (ROI) was located at Brodmann Areas (BAs) 6/8/9/10/40/44 [4]. In particular, channels 1 & 9 were located in BA 6, channels 13, 15, 17 were located in BA 10, channel 10 was located in BA 8, channels 11, 12, 14, 16 were located in BA 9, channel 4 was located in BA 40, and channels 2, 3, 5, 6, 7 and 8 were located in the right IFC (BA 44).

In Li et al. [4], the mean of z-scores (*HbO* & *HbR*) was calculated for each DCCS task block separately for each participant. Then, the mean of z-scores (*HbO* & *HbR*) was calculated by averaging across the three task blocks for each participant. Finally, the mean of z-scores (*HbO* & *HbR*) across all channels were compared using t-tests between 'Non-user'

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and 'Heavy-user' groups using SPSS. Li et al. [4] conducted GLM analysis predicting z-scores (*HbO* & *HbR*) in channel 16 in R ($Y_{\Delta HbO} = aX_{time} + b + \varepsilon$). This study explored two sets of polynomial regression to better fit the nonlinear relationship between hemodynamic changes and time. The first set was quadratic equation using R [$Y_{\Delta HbO} = aX_{time}^2 + bX_{time} + c + \varepsilon(error\ term)$]. If a > 0, the curve is a typical U shape; if a = 0, the quadratic function does not exist, indicating a GLM linear relationship; if a < 0, the curve is a kind of reversed U shape. The second set was cubic equation analysis using R [$Y_{\Delta HbO} = aX_{time}^3 + bX_{time}^2 + cX_{time} + d + \varepsilon(error\ term)$]. If a = 0, the cubic function does not exist, indicating a quadratic equation or GLM (if b = 0) should be considered.

3. Results

3.1. Re-Analysis of Li et al. [4] Data with Quadratic and Cubit Equations

First, as shown in Table 1, the quadratic regression results for the Non-user group indicated that: (1) a U-shaped curve (a > 0) was observed in 9 channels (ch 1, 2, 5, 6,7,8, 9, 11, & 14), the quadratic predictor (time) could significantly explained 7.5% to 94.3% of the variance (HbO), R^2s > .075, *F*s > 5.94, *p*s < .001; (2) the quadratic function does not exist in channels 3 and 4 (a = 0), R^2s >. 66, *F*s = 145.65, *p*s < .001; and (3) a reversed U-shaped curve (a < 0) was observed in channels 10, 12, 13, 15, 16, & 17, R^2s > .27, *F*s > 27.27, *p*s < .001. These findings indicated that the U-shaped curve was found for BA6 (ch 1 & 9), BA9 (ch11 & 14), and BA 44 (ch 2, 5, 6, 7, & 8), which were involved in the cognitive shifting. Only two channels (ch 3 & 4) could not be estimated by this quadratic equation.

Table 1. *Re-analyzing the HbO Changes in the Non-User Group (Li et al., 2021) with Quadratic Equation*

	Model Summary			Regression Estimates			Quadratic
	R^2	*F*	Sig.	*c*	*b*	*a*	
Ch 1	0.566	96.041	0.000	-0.107	-0.108	0.004	√
Ch 2	0.943	1217.460	0.000	0.219	-0.271	0.011	√
Ch 3	0.846	405.072	0.000	-0.465	-0.033	0.000	GLM
Ch 4	0.665	145.654	0.000	-1.149	0.065	0.000	GLM
Ch 5	0.358	41.019	0.000	-0.574	0.000	0.001	√
Ch 6	0.353	40.048	0.000	-0.185	-0.049	0.002	√
Ch 7	0.729	198.044	0.000	-0.492	-0.076	0.004	√
Ch 8	0.832	363.664	0.000	-0.652	-0.121	0.005	√
Ch 9	0.075	5.941	0.003	-0.158	-0.037	0.001	√
Ch 10	0.636	128.357	0.000	-0.050	0.080	-0.003	√
Ch 11	0.358	40.957	0.000	-0.211	0.008	0.001	√
Ch 12	0.352	39.980	0.000	0.320	0.028	-0.001	√
Ch 13	0.271	27.279	0.000	0.027	0.114	-0.004	√
Ch 14	0.807	307.870	0.000	0.357	-0.097	0.001	√
Ch 15	0.624	121.910	0.000	0.424	0.027	-0.001	√
Ch 16	0.919	830.919	0.000	0.506	0.057	-0.001	√
Ch 17	0.562	94.382	0.000	-0.230	0.057	-0.001	√

Note: $Y_{HbO\ change} = ax^2+bx+c$.

Second, as shown in Table 2, the quadratic regression results for the Heavy-user group indicated that: (1) a U-shaped curve (a > 0) was observed in channels 2-5, 8, 12, 16 and 17, the quadratic predictor (time) could significantly explain 37.1% to 92.3% of the *HbO* changes, R^2s > .037, *F*s > 43.25, *p*s < .001; (2) the quadratic function does not exist in

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channels 1, 6, 7, and 13 (a = 0), R^2s > .059, Fs > 4.68, ps < .011; and (3) a reversed U-shaped curve (a < 0) was observed in channels 9-11 and 14-5, R^2s > .117, Fs > 9.87, ps < .001. These findings indicated that the U-shaped curve was found in BA9 (12 &16), BA10 (17), BA40 (ch 4), and BA 44 (ch 2, 3, 5, & 8). Four channels (ch 1, 6, 7, & 13) could not be estimated by this quadratic equation (See Table 2).

Table 2. Re-analyzing the HbO Changes in the Heavy-User Group (Li et al., 2021) with Quadratic Equation.

	Model Summary			Regression Estimates			
	R^2	F	**Sig.**	c	b	a	*Quadratic*
Ch 1	0.060	4.687	0.011	-0.397	0.014	0.000	GLM
Ch 2	0.727	196.141	0.000	0.769	-0.133	0.004	√
Ch 3	0.887	576.348	0.000	0.332	-0.148	0.003	√
Ch 4	0.595	107.839	0.000	0.356	-0.043	0.001	√
Ch 5	0.371	43.260	0.000	0.446	-0.082	0.002	√
Ch 6	0.432	56.0120	0.000	-0.142	-0.002	0.000	GLM
Ch 7	0.092	7.469	0.001	0.232	-0.007	0.000	GLM
Ch 8	0.923	880.189	0.000	0.534	-0.129	0.003	√
Ch 9	0.118	9.880	0.000	-0.142	0.022	-0.001	√
Ch 10	0.816	325.979	0.000	0.025	0.075	-0.003	√
Ch 11	0.568	96.717	0.000	0.399	0.071	-0.003	√
Ch 12	0.669	148.690	0.000	0.547	-0.114	0.004	√
Ch 13	0.521	79.901	0.000	0.078	0.025	0.000	GLM
Ch 14	0.475	66.407	0.000	0.097	-0.003	-0.001	√
Ch 15	0.477	67.002	0.000	-0.439	0.062	-0.002	√
Ch 16	0.668	147.668	0.000	0.719	-0.180	0.005	√
Ch 17	0.683	158.110	0.000	0.633	-0.104	0.003	√

Note: $Y_{HbO\ change} = ax^2+bx+c$.

Third, two sets of cubic equation analyses were conducted for the Non-user and Heavy-user groups, separately, with X^3 as the cubic term in addition to X^2 as the quadratic term and X as the linear term. However, the results for the Non-user group indicated that only two channels (ch 11 & 13) could apply to the cubic regression (a ≠ 0). In contrast, all the other channels should be modeled with a quadratic equation (a = 0). Similarly, the results for the Heavy-user group indicated that no channels could be estimated by the cubic regression, as a = 0. Therefore, we adopted a quadratic equation to analyze the new data collected in this study.

Last, we calculated the local maximum of *HbO* and *HbR* changes and the estimated time for the Heavy-user and Non-user groups separately and compared the between-group differences in the estimated time using t-tests. As shown in Table 3, the results indicated a significant between-group difference in the estimated time for channels 10 and 11. The Non-user group was significantly slower than the Heavy-user group to achieve the local maximum of *HbO* changes for channels 10 [$M_{difference}$ = 10.47 (second), t = -2.825, p < .05] and 11 [$M_{difference}$ = 9.66 (second), t = -3.337, p < .05].

Table 3. Comparison of the Local Maximum and Estimated Time for the HbO Changes between Non-user and Heavy-user Groups (Li et al., 2021).

	Local Maximum			Estimated Time		
	Heavy User	**Non-user**	***T test***	Heavy User	Non-user	*T test*
Ch 1	0.979	1.136	-0.223	16.662	15.768	0.178
Ch 2	1.542	0.547	1.257	14.655	15.198	-0.104
Ch 3	0.816	0.320	0.673	13.491	11.564	0.375

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Ch 4	1.460	1.461	-0.002	15.947	21.874	-1.412
Ch 5	1.383	1.070	0.442	13.691	15.613	-0.370
Ch 6	0.386	0.229	0.455	16.724	18.000	-0.313
Ch 7	1.662	1.950	-0.381	15.129	17.848	-0.549
Ch 8	0.854	0.309	0.671	8.584	14.772	-1.368
Ch 9	0.433	0.208	0.812	13.597	11.192	0.588
Ch 10	1.128	1.697	-0.745	10.495	20.961	-2.825*
Ch 11	1.655	0.922	1.523	15.327	24.987	-3.337*
Ch 12	1.928	1.934	-0.004	19.467	13.262	1.324
Ch 13	1.389	2.381	-0.928	17.935	15,519	0.615
Ch 14	1.271	0.722	0.772	15.351	10.622	1.031
Ch 15	1.040	1.541	-0.642	16.933	16.121	0.185
Ch 16	1.108	2.563	-0.204	18.366	15.959	0.456
Ch 17	1.379	1.531	-0.277	17.959	18.383	-0.099

Note: $Y_{HbO\ change} = ax^3+bx^2+cx+d$. *. $p < .05$.

3.2. Quadratic Regression Modelling New DCCS Data

First, we compared the behavioral performance in the Habit-DisHabit design DCCS task with *t*-test and found no significant differences between the 'Non-user' ($M_{correct\ rate}$ = .989, *SD* = .017) and 'Heavy-user' ($M_{correct\ rate}$ = .979, *SD* = .045) groups, $t = -.587$, $p > .562$. Then, a set of independent-samples *t*-tests with FDR correction was conducted to determine whether there were significant differences in *HbO* increases in the 17 channels between the 'Non-user' and 'Heavy-user' groups. However, no significant differences were found in 17 channels between the Non-user and the Heavy-user, *t*s < 0.44, *p*s > .05. These results jointly indicated that the two groups had the same behavioral performance and total *HbO* changes during the DCCS task.

Second, as shown in Table 4, the quadratic regression results for the Non-user group indicated that: (1) a U-shaped curve (a > 0) was observed in 14 channels (ch 1, 2, 4, 5,7, 8, 9, 11-17), and the quadratic predictor (time) could explained 48.1% to 96.3% of the variance (HbO), R^2s > .48, *F*s > 91.16, *p*s < .001; (2) the quadratic function does not exist in channels 3 and 6 (a = 0), R^2s >.050, *F*s = 5.39, *p*s < .005; and (3) a reversed U-shaped curve (a < 0) was observed in channels 10, $R^2 = .570$, $F = 130.73$, $p < .001$. These findings indicated that the U-shaped curve was found for BA6 (ch 1 & 9), BA9 (ch11,12 ,14 & 16), BA40 (ch 4), and BA 44 (ch 5, 7, & 8), which were involved in the cognitive shifting. Only two channels (ch 3 & 6) could not be estimated by this quadratic equation.

Table 4. Quadratic Regression Predicting HbO Changes for the Non-user group in the DCCS Habit-DisHabit Design Task.

	Model Summary			Parameter Estimates			U Shape
	R^2	***F***	***Sig.***	*c*	*b*	*a*	
Ch 1	0.762	315.838	0.000	0.068	-0.128	0.003	√
Ch 2	0.963	2586.161	0.000	0.960	-0.232	0.004	√
Ch 3	0.076	8.130	0.000	0.390	0.000	0.000	GLM
Ch 4	0.590	141.630	0.000	-0.559	-0.108	0.002	√
Ch 5	0.862	616.488	0.000	0.232	-0.178	0.005	√
Ch 6	0.052	5.391	0.005	-0.007	0.017	0.000	GLM
Ch 7	0.798	388.446	0.000	0.256	-0.104	0.002	√
Ch 8	0.895	841.443	0.000	-0.477	-0.207	0.006	√
Ch 9	0.608	152.895	0.000	-0.383	-0.006	0.001	√
Ch 10	0.570	130.726	0.000	0.669	0.116	-0.003	reversed
Ch 11	0.685	213.853	0.000	0.532	-0.157	0.003	√

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Ch 12	0.844	5321.266	0.000	0.318	-0.218	0.005	√
Ch 13	0.541	115.909	0.000	0.489	-0.092	0.002	√
Ch 14	0.497	97.300	0.000	1.501	-0.163	0.004	√
Ch 15	0.827	469.602	0.000	1.201	-0.123	0.002	√
Ch 16	0.784	356.732	0.000	0.374	-0.155	0.002	√
Ch 17	0.481	91.169	0.000	-0.384	-0.019	0.001	√

Note: $Y_{HbO\ change} = ax^2+bx+c$.

Third, as shown in Table 5, the quadratic regression results for the Heavy-user group indicated that: (1) a U-shaped curve (a > 0) was observed in channels 1, 2, 4, 8, 9, 11, 12, 14, and 16, the quadratic predictor (time) could significantly explain 23.3% to 80.3% of *HbO* changes, R^2s > .233, *F*s > 29.95, *p*s < .001; (2) the quadratic function does not exist in channels 3, 5-7, 10, 13, 15, and 17 (a = 0), R^2s > .028, *F*s > 2.92, *p*s < .05; and (3) no reversed U-shaped curve (a < 0) was observed. These findings indicated that the U-shaped curve was found in BA 6 (ch 1 & 9), BA9 (11, 12, 14 &16), BA40 (ch 4), and BA 44 (ch 2 &8). Eight channels (ch 3, 5, 6, 7, 10, 13, 15, & 17) could not be estimated by this quadratic equation.

4. Discussion

4.1. Quadratic: The Best-fit Modelling

Li et al. [4] conducted GLM analysis to model the *HbO* changes in channel 16 and found significant between-group differences in a set of *t*-tests. The GLM results could only demonstrate a significant *HbO* increase for the Non-user group and a significant decrease for the Heavy-user group. However, *HbO* changes evoked by cognitive shifting are not a linear function of time; instead, there is a nonlinear relationship [1-3]. Therefore, first, a set of quadratic equation analyses was conducted to re-analyze Li et al. [4] data. The Non-user group results indicated that 15 channels could be perfectly modeled, whereas only two channels (ch 3 & 4) were suitable for GLM. The Heavy-user group results indicated that 13 channels could be perfectly modeled by the quadratic equation, whereas only four channels (ch 1, 6, 7, & 13) should be modeled by GLM. Second, a set of cubic equation analyses was conducted to re-analyze Li et al. [4] data. However, the results indicated that the cubic equation could model only channels 11 and 13 for the Non-user. In addition, all the other channels for both groups were not suitable for this cubic equation. This finding implies that the cubic equation might not be appropriate for modeling the *HbO* changes in the DCCS mixed-order design task. Thus, these results jointly indicated that the quadratic equation might be the best-fit modeling for the *HbO* changes in the DCCS tasks.

Table 5. Quadratic Regression Predicting HbO Changes for the Heavy-user group in the DCCS Habit-DisHabit Design Task.

	Model Summary			Parameter Estimates			U Shape
	R^2	*F*	*Sig.*	*c*	*b*	*a*	
Ch 1	0.803	400.535	0.000	-0.358	-0.124	0.004	√
Ch 2	0.755	304.194	0.000	0.493	-0.108	0.002	√
Ch 3	0.029	2.924	0.056	-0.815	-0.001	0.000	GLM
Ch 4	0.414	69.509	0.000	-0.555	-0.096	0.003	√
Ch 5	0.484	92.488	0.000	0.447	-0.043	0.000	GLM
Ch 6	0.123	13.867	0.000	-0.276	0.012	0.000	GLM
Ch 7	0.040	4.107	0.018	-0.196	-0.012	0.000	GLM
Ch 8	0.473	88.232	0.000	-0.412	-0.066	0.002	√
Ch 9	0.233	29.960	0.000	0.151	-0.021	0.001	√
Ch 10	0.740	280.658	0.000	0.231	0.050	0.000	GLM
Ch 11	0.747	290.877	0.000	0.512	-0.097	0.002	√
Ch 12	0.631	168.348	0.000	-0.284	-0.124	0.003	√
Ch 13	0.381	60.718	0.000	-0.036	-0.005	0.000	GLM

Ch 14	0.274	37.205	0.000	-0.273	-0.048	0.001	√
Ch 15	0.160	18.810	0.000	-0.287	0.000	0.000	GLM
Ch 16	0.523	108.047	0.000	-0.119	-0.103	0.003	√
Ch 17	0.540	115.509	0.000	0.160	-0.045	0.000	GLM

Note: $Y_{HbO\ change} = ax^2+bx+c$.

4.2. Habit-DisHabit design: More Effective for Identifying the Cognitive Shifting

This study first re-analyzed Li et al. [4] data with quadratic equation and identified U-shape in 9 channels for the Non-user group. Then, analysis of the new Habit-DisHabit design data found a U-shape in 14 channels. Similarly, within the Heavy-user group, the re-analysis identified U-shape in 8 channels, whereas the new design data demonstrated it in 9 channels. The within-group increases in the U-shape indicated that the Habit-DisHabit design could help identify more neural correlates of the cognitive shifting in the DCCS task. In addition, within the Non-user group, the Mixed-Order Design data indicated that six channels had a reversed U-shape, indicating that the *HbO* changes increased over time for the corresponding channels. In contrast, the Habit-DisHabit design data indicated only one channel (ch 10) had a reversed U-shape. Therefore, this accumulative increase cannot reflect the rise and fall of *HbO* over time corresponding to the cognitive shifting. For the Heavy-user group, the Mixed-Order Design data indicated that five channels had a reversed U-shape, indicating that the *HbO* changes increased over time. In contrast, the Habit-DisHabit design data indicated no channel had a reversed U-shape, indicating a tendency of decreasing *HbO* in all the channels. This tendency might reflect the unique brain activation pattern for the Heavy-user, which will be discussed in the next section.

In particular, Li et al. [4] employed linear GLM analyses to model the *HbO* changes in BA 9 (ch 16) and found a significant increase for the Non-user group. In contrast, a significant decrease was found for the Heavy-user group, which demonstrated a significant increase after the 12th second. Thus, they concluded that BA 9 was significantly activated only in the Non-user group during the DCCS task [4]. However, we believe that this contrast might indicate a U-shape (fall and rise) of *HbO* changes in channel 16. Re-analyzing Li et al. [4] data and analyzing the U-shape data with quadratic equation have jointly indicated a U-shape in channel 16 for the Heavy-user group (See Table 2). In contrast, re-analysis found a reversed U-shape in channel 16 for the Non-user group (See Table 1), whereas the new analysis of Habit-DisHabit design found a U-shape in this channel. Therefore, this study has proved that the Habit-DisHabit design DCCS by the quadratic equation could effectively identify the neural correlates of cognitive shifting.

4.3. Two Brain Activation Patterns: Heavy-user Vs. Non-User

First, Li et al. [4] found that the Non-users group outperformed the Heavy-users with a significantly higher correct rate in the Mixed-Order Design DCCS task. This study found no significant between-group differences in the behavioral performance using the Habit-DisHabit design DCCS tasks. The two designs differed in the arrangement of changing rules: Habit-DisHabit design followed a simple pattern of changing the sorting rules thus was more likely to cause habituation, whereas the Mixed-Order Design had no pattern of changing rules; thus, the children had to be highly attentive. In this study, both groups completed the Habit-DisHabit design with almost the same success rate, indicating that they shared the same level of cognitive shifting. But the Heavy-user group had a significantly lower rate in completing the Mixed-Order Design, indicating that they might not be so attentive to the frequently changing rules thus made more mistakes in sorting the cards. Therefore, the first conclusion is that the Non-users tend to be more attentive than the Heavy-users.

Second, the analyses of HbO changes found that a quadratic equation could perfectly model 15 channels, and only two channels were found fit for GLM linear analysis in both

 doi:10.20944/preprints202107.0417.v1

mixed- and Habit-DisHabit designs. Thus, the Heavy-user group had 13 or 9 channels perfectly modeled by a quadratic equation in the Mixed-order and Habit-DisHabit designs, respectively. Meanwhile, four or eight channels should be modeled by GLM for the Mixed-order and Habit-DisHabit designs, respectively. This contrast indicated that the Non-user group had more channels engaged in the cognitive shifting in both Mixed- and Habit-DisHabit designs. Therefore, the second conclusion is that the Non-users tend to be more engaged in the DCCS task than the Heavy-users.

Third, this study found that the Non-user group was significantly later to achieve the local maximum *HbO* changes for BA8 (ch 10) and BA9 (ch 11) than the Heavy-user group. To the contrary, the Heavy-users achieved the local maximum of *HbO* changes very early, followed by a significant decrease in the following period. This finding implies that the Non-users tend to respond to the DCCS tasks slower but more steadily than the Heavy-users, whose *HbO* achieved the maximum very early but dropped very quickly. Therefore, the third conclusion is that the Non-users tend to be more slowly and steadily increasing their hemodynamic responses than the Heavy-users. As it is widely accepted that *HbO* increase reflects the enhancement of brain activation thus is the most sensitive indicator in NIRS measurements [1-3]. These findings suggest that the Non-users are more attentive and engaged than the Heavy-users, with a slower but steady increase of brain activation in BA8 and BA9.

5. Conclusions, Limitations, and Implications

First, this study found that the quadratic equation might be the best-fit statistics for modeling the *HbO* changes in the DCCS tasks, by re-analyzing Li et al. [4] data and analyzing new data. Second, this study has proved that the Habit-DisHabit design DCCS in conjunction with the quadratic equation effectively identified the neural correlates of cognitive shifting. Third, this study found that the Non-users were more attentive and engaged than the Heavy-users, with a slower but steady increase of brain activation in BA8 and BA9. However, these results must be interpreted with caution, as the sample size was very small. The unexpected COVID-19 lockdown in China has stopped the experiment in late January 2020. Thus, only 38 cases were included in this study. A post hoc power analysis on G*Power 3.1 (https://www.psychologie.hhu.de) with effect size as d = 0.50 and an alpha of 0.05 was conducted. And the result indicated a power of 0.32, which might have compromised the significance of the statistical comparisons in this study.

Nevertheless, the findings have some implications for future study and practical improvement. First, the quadratic equation should be considered a standard nonlinear model to estimate hemodynamic changes in the DCCS tasks. Second, the Habit-DisHabit design DCCS could be widely used and further developed to better identify the neural correlates of cognitive shifting. Third, the finding that Non-users were more attentive and engaged than Heavy-users implies that we should consider limiting and regulating young children's tablet use.

Author Contributions: Conceptualization, H.L. and D.W.; methodology, C.C., J.Y., D.W.; formal analysis, J.Y., H.L.; investigation, D.W., J.Y., J.L., S.X.; resources, C.C., S.X.; data curation, J.Y.; writing—original draft preparation, J.Y, W.D.; writing—review and editing, H.L., W.D., S.X.; visualization, J.Y.; supervision, H.L.; project administration, D.W.; funding acquisition, C.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (61971289), Shenzhen Fundamental Research Project (JCYJ20170412111316339), and Shenzhen-Hong Kong Institute of Brain Science-Shenzhen Fundamental Research Institutions. The APC was funded by Macquarie University, Australia.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Shenzhen University (No.2018005; Jan 2018).

 doi:10.20944/preprints202107.0417.v1

Informed Consent Statement: Informed consent was obtained from all the participating parents involved in the study.

Data Availability Statement: All the data for this study will be available upon request.

Acknowledgments: The authors are incredibly grateful to Madam WANG Weili and Mr. WANG Xiuhong, and all the teachers, parents and children of Shenzhen No. 8 Kindergarten, China.

Conflicts of Interest: The authors declare no conflict of interest.

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