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Detection of Dyslexic Children Using Machine Learning and Multimodal Hindi Language Eye-Gaze Assisted Learning System

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***Abstract*—Children with dyslexia need specific instructions for spelling and word analysis from an early age. It is important to provide appropriate tools using technology for writing aids to such children that can help them to input text, while providing multiple feedback. However, it is unclear how children with dyslexia can efficiently use a gaze-based virtual keyboard. In this study, we propose to use the typing performance of a multimodal Hindi language eye-gaze assisted learning system based on a virtual keyboard to help in the reduction of tracking errors for people with writing and reading deficiencies and to detect children with dyslexia. Performance was assessed at three levels: eye-tracker, eye-tracker with soft-switch, and touchscreen as a baseline modality using a predefined copy-typing task. The system was validated through a series of experiments with 32 children (16 dyslexic and 16 control). The results show that the workload and the usability of the system are substantially different for children with dyslexia. Children with dyslexia have a lower typing performance when using the touchscreen modality or the eye-tracker only. The detection of children with dyslexia from others was assessed with seven different types of classifiers using the typing speed on different words (AUC>0.9). These results highlight the need to have fully inclusive virtual keyboards. This work demonstrates the superior use of a multimodal system with participants having unique neuropsychological conditions and that the proposed system can be used to detect children with dyslexia.**

***Index Terms*—Eye tracking, Multimodal Interaction and Interfaces, Eye-Gaze Assisted Learning System, Virtual Keyboard, Dyslexia, Machine Learning**

I. Introduction

Dyslexia occurs worldwide with a prevalence of at least 10% of any given populace. The prevalence depends on the orthographic system, type and degree of dyslexia, reading age assessed, and sampling methods used [1]. Dyslexia impacts the gaining knowledge of procedures concerned with studying (reading), spelling or writing (or an aggregate). Reading and writing require coordination of lower-stage oculomotor (e.g., model, accommodation, and vergence) and higher-level cognitive tactics (e.g., attention, memory, and language processing). The imbalance in these components could create a variety of learning problems such as dyslexia. The outcomes of such a disorder include deficiency in the speed of processing, issues with sense modalities, sequencing, and motor skills. Therefore, dyslexia should be taken into consideration when designing input modalities for user interfaces (e.g., virtual keyboards (VKs)) that may be used in educational settings.

Despite the fact that the exact etiology of dyslexia is unknown, a deficiency in phonological awareness and poor phonological encoding represents one of the most accepted theories about the cause of dyslexia. There is also evidence of visual and oculomotor abnormalities in dyslexia [2]. It affects at least 5% of school-age children and is more prevalent in boys than in girls [3]. It is worth noting that dyslexia is a problem with language, not with vision. Yet, studies have suggested that vision therapy may help with certain vision problems that can affect a child's ability to see (e.g., convergence insufficiency) [4]. A study reported that dyslexia is a neuro-developmental condition and not a serious mental health condition or chronic physical condition [5]. Also, the user's performance with VK is not a proxy of mental or physical health. Yet, the relationship between mental and physical health is evident in the area of lifelong conditions such as dyslexia. There exist multiple associations between physical and mental health. For instance, poor mental health is a risk factor for chronic physical conditions. Moreover, people with serious mental health conditions are at high risk of experiencing chronic physical conditions. Children with dyslexia have difficulty with correct and fluent recognition of words and are poor at spelling. They might not be affected by reading development due to the absence of sensory impairment. However, the disruption in age-specific reading and writing skills is a substantial impediment to their education and future employment [6].

The different cognitive abilities and the strength of these abilities affect the quality and rate of learning [7], [8]. Processing speed is certainly one of them, it encompasses the speed of thinking ability on simple visual or auditory tasks. Testing and training around auditory and visual processing have been reported to improve phonological deficits in children with dyslexia. Furthermore, a textual content presentation has a bearing on the reading performance of children with dyslexia [9]. The significance of eye movement during reading as an indicator of deficiencies is observed in dyslexia [10]. In addition, it is unclear how the writing system influences reading performance because the Hindi language written in the Devanagari script uses glyphs with various levels of perceptual complexity (e.g., mirrored glyphs with different meanings ** ञ ज, ब व, भ म **). Specifically, restrained studies are adopt-

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ing those techniques in the use of Hindi (2-3 mirror characters) language as findings concerning oculomotor deficits in children with dyslexia are based on English, Spanish, German, and other languages, but not the Hindi language. Dyslexic readers of the Hindi language have a complication in developing high-quality, segmentally organized phonological representations of words and display poor blending skills [11]. While a pilot study suggested the possibility to enhance the awareness of a child with dyslexia through an adaptive multimodal interface using eye-tracking [12], this trend needs to be demonstrated rigorously with a collection of children with dyslexia and a control group, as proposed in this paper.

Previous research studies demonstrated the importance of multimodal interfaces that engage in natural behaviours [13]. A multimodal interface typically includes several distinct tools for input and output data interactions. For instance, a multimodal VK interface applied to assistive technology used a two-stage selection process, where pointing to the letter is performed through electrooculogram (EOG)-based eye-gaze control, and then click to select the letter is achieved through electromyogram (EMG) activation through eyebrow muscle activity [14], [15]. Different multimodal systems with improved performances by developing effective user interfaces and techniques have been proposed [16], [17], [18], [19], [20]. However, most of the systems are implemented for partially locked-in patients and it is shown that eye-tracking provides a higher performance compared to systems using electroencephalography (EEG) signals as inputs. Likewise, an eye-tracker combined with haptic feedback in virtual reality-based games is proposed for learning-based games [21]. Multimodal systems are advanced for communique functions, combining eye-tracking, gesture, and contact-and-voice input [22], [23], [24], [25], however, they did not consider potential end users in their studies. Also, it is unclear how the choice of the modality can impact the performance, especially if children with dyslexia have a different performance. Answering these questions is important for making user interfaces more accessible to children with disabilities.

Multiple studies have investigated the detection of dyslexia using machine learning. These approaches include game-based techniques, reading and writing tests, facial image capture and analysis, eye tracking [26], magnetic reasoning imaging (MRI) and EEG scans [27]. In this paper, we propose the use of the typing speed of different words of various complexity. This paper addresses the above-mentioned challenges with the following contributions: 1) assessing and quantifying the difference in performance across three modalities: touchscreen, eye-tracker using a dwell time, and eye-tracker using a soft-switch, between children with and without dyslexia, with a VK in copy spelling mode with auditory and visual feedback; 2) detecting children with dyslexia from other children using machine learning with features based on the VK performance; and 3) estimating the difference of performance existing with children with dyslexia at different levels: typing speed, system usability, workload, and psychological assessment.

The rest of the paper is organized as follows. Section II describes the multimodal Hindi language assisting learning system. The experimental protocol is detailed in Section III and methods are explained in Section IV, with the results presented in Section V. Their implications are discussed in Section VI and finally summarized in Section VII.

II. System Overview

A. Description

The proposed personalised assistive learning system consists of three main components: (1) a graphical user interface (GUI) representing a Hindi language VK (adapted from Meena et. al., [28]); (2) a multimodal textual content entry input that consists of 3 extraordinary input modalities: a touchscreen, an eye-tracker, and a soft-switch (adapted from Meena et. al., [22]); (3) a new multimodal feedback where two different multimodal feedback (auditory and visual) [8]. Two types of visual positive (for intended item selection) and negative feedback (for accidental item selection) with GUI. This is represented by a change in the colour of the button border, from silver to green (positive feedback) or red (negative feedback) depending upon maintenance of gaze; and 4) a novel typing task and intrinsic motivation for children. The VK comprises the ten possible direct commands that can be selected by the user; output text display (character, letters, words, tasks, messages); and multimodal feedback (auditory and visual) are presented in Fig. 2. The hierarchical structure and typed characters and letters of an experimental task are presented in Fig. 1.

The letters are organized in alphabetical order, the use of a script-specific association layout, due to the fact the alphabetical arrangement is simpler to examine and recall, specifically for complicated established languages inclusive of Hindi [28]. The 10 command buttons are located at the edges of the screen while the second component, the output textbox, is placed in the centre of the screen (see Fig. 2). The VK-GUI is organized on a multi-level menu choice along with ten commands at each level. This technique may be useful whilst the display length is small [29], [28] such as with 14-inch screen laptops, and tablets, taking into account potential confusions that may arise with gaze detection whilst commands are close to each other. The GUI tree-based structure permits the users to type forty-five Hindi language letters, seventeen Matras (diacritics) and Halants (killer strokes), fourteen punctuation marks and special characters, and ten digits (0 to nine). Normal editing capabilities, e.g., “delete”, “delete all”, “new line”, “space”, and “go back” commands for corrections are present in the list of available actions.

The first level of the GUI includes 10 commands. Every command is composed of a set of 10 characters. Character selection requires the user to enter two commands by following two steps. During the first step, the user has to choose a command box (at the primary level of the GUI) in which the desired character is located. The successful selection of a command box changes the content of the buttons of the GUI to the second level, where the ten commands at the display are assigned to the 10 characters which belong to the chosen command box on the preceding level. During the second step, the user can see the desired character in a unique command box, and eventually select it to write it in the output

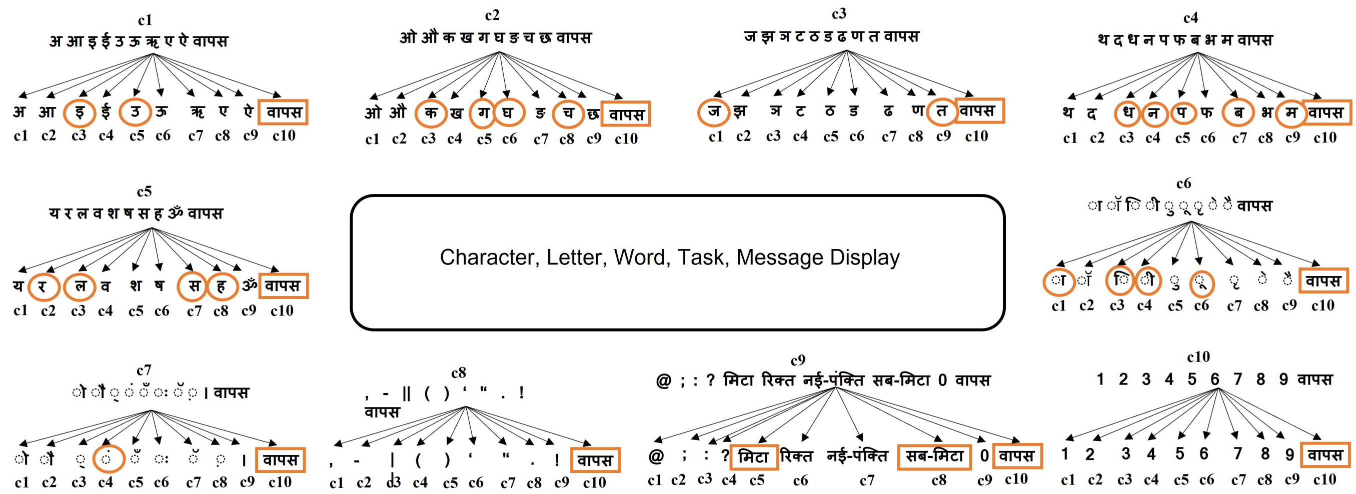


Fig. 1. Hierarchical structure showing the sequence of commands (c1 to c10) for letter selection. The selected characters/letters are highlighted with an oval shape and the commands that are used for correction are highlighted with a rectangle shape. The box in the center depicts the typed characters/letters, words, and tasks. Based on children typing performance, the system displayed feedback messages as well-done/well-tried at the end of each task to better engage the participants.

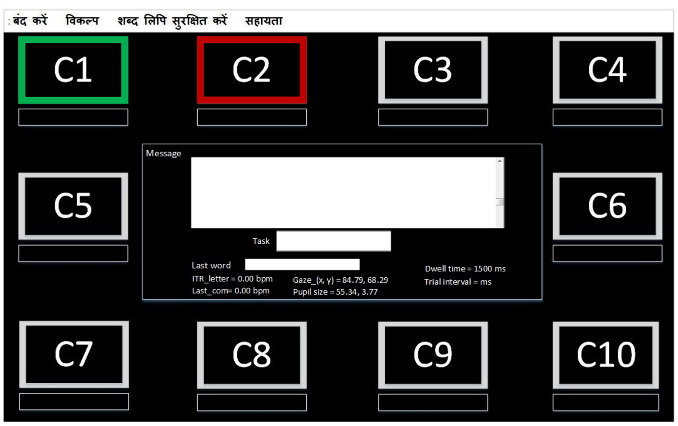


Fig. 2. Positions of 10 commands (c1-c10) in the Hindi language virtual keyboard. Two types of visual positive (for intended item selection) and negative feedback (for accidental item selection) are shown in commands C1 and C2, respectively.

text display. After the selection of a character at the second level, the GUI goes back to the preliminary level (i.e., first level) to facilitate the next character selection. The system is designed to write all the Hindi language letters including half-letter scripts and required punctuation marks. Besides, the Nukta and Halant-based techniques are adapted from previous research works for designing a VK application for the Hindi language [22].

B. Modalities

The VK application includes three non-invasive human-computer interaction (HCI) modalities: touchscreen (TS), eye-tracker with dwell time Δt=1.5 s) (ET), and eye-tracker with a soft-switch (ETSS). In the ETSS modality, the eye-tracker was used for pointing to the item that can be then selected by pressing the soft-switch. HCI modalities include two visual (positive and negative feedback) and one auditory feedback (beep after successful execution of each command) [12]. In the gaze-based VK application, efficient feedback is necessary for the user so that the intended command box/character was selected to avoid errors in copy spelling and increase efficiency [22].

III. Experimental protocol

A. Participants

64 children were screened during a systematic field study in multiple schools, 16 of which were diagnosed as dyslexic children. A total of 32 volunteers participated in the experiment, 16 children with dyslexia (age range of 10–13 years (11.05 ± 1.09)) were part of the dyslexic group; 16 children (age range of 10–14 years (12.43 ± 1.03)) were part of the control group (see Table I). A healthy school-going child with the diagnosis of dyslexia but no other medical condition was the inclusion criteria for the experimental group. Age-matched normal healthy school-going with no specific learning disability was the inclusion criteria for the control group. The presence of any other condition was the exclusion criteria. In both groups, two participants completed the experiments with vision correction. All participants were new to using the input modalities with the VK application. Prior to the study participants were informed about the purpose of the study, its procedure, and the nature of the work. No financial aid was given to the individuals for their participation in the study. This study followed the Helsinki Declaration of 2000 to conduct the experiments.

B. Multimodal input devices

This study includes two input devices: a portable eye-tracker for determining the eye-gaze, and a soft-switch device as a single-input tool (see Fig. 3) [22].

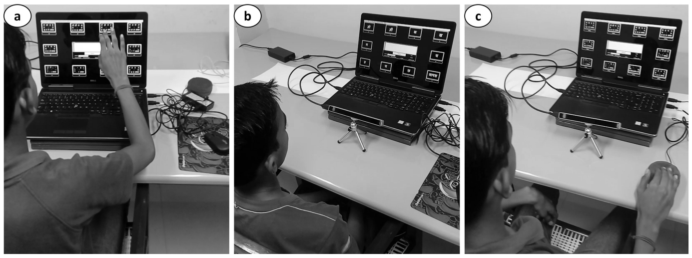


Fig. 3. Experimental setup for eye-gaze recording during the typing task. The participant sits in a relaxed chair in front of the PC display screen. The eye-tracking and soft-switch devices were connected to the PC through a USB port. Blocks a-c present three experimental conditions where participants complete the typing task. a) with the touchscreen (TS) modality condition, b) with the eye-tracking (ET) modality condition, and c) with the eye-tracking and soft-switch (ETSS) modality condition.

C. Data acquisition

The eye-gaze signals using the eye-tracker device have been recorded at 30 Hz. It involves binocular infrared illumination with a spatial resolution (0.1 roots mean square (RMS)) that records the (x, y) coordinates of gaze, and pupil diameter for both eyes (in mm). The soft-switch device was used to select a command as a single input. Throughout the experiments, participants were requested to sit down in a relaxed chair in front of the PC display screen ((DELL, 15.6 inches, 60 Hz refresh rate, optimum resolution 1920 $\times$ 1080, touchscreen). The distance between the PC display screen and the participant was approximately 80 cm. The horizontal and vertical visual angles were measured at approximately 36 and 21 degrees, respectively.

D. Experimental paradigm

The typing task involves 10 predefined Hindi words in increasing order of difficulty, based on the number of letters (two to six: घर, नमक, बचपन, जलमहल, इधरउधर) and the number of letters with one extra matra (diacritic: राम, इमली, तरबूज, किसतरह, संगमरमर). The details of the different words including the number of letters, diacritics (i.e., matra in Hindi), and commands are given in Table II. The transliteration of the task words in English is Ghar, Namak, Bachapan, Jal Mahal, Idhar Udhar, Ram, Imalee, Tarabooz, Kistarah, Sangamaramar and the direct translation in English is House, Salt, Childhood, Water Palace, Here and There, Ram, Tamarind, Watermelon, How, Marble. Participants were asked to write (i.e., type) these predefined words (i.e., copy spelling). The typed words are displayed within the output textbox if they match with one of the predefined words. If there are errors, they are saved in a log file and are not displayed on the screen. Participants were asked to look at the word while typing. The maximum duration given to the participants for the first five words are 40 s, 60 s, 80 s, 100 s and 120 s, respectively; it was 60 s, 80 s, 100 s, 120 s and 140 s, respectively, for the last five words. The maximum duration was chosen as 20 s per character (letter or matra). Each word was displayed at the bottom of the screen one by one during these particular periods. If the participant completed the task within the predicted time length, then a message "बहुत बढ़िया (i.e., "well-done") displayed, otherwise "अच्छा प्रयास" (i.e., "well-tried") appeared in the message box.

TABLE I
DEMOGRAPHIC INFORMATION FOR PARTICIPANTS IN STUDY

Group	Age	Gender	Handed	Vision Correction
Dyslexic (n=16)	11.05 (1.09)	9 M, 7 F	13 R, 3 L	15 N, 1 Y
Control (n=16)	12.43 (1.03)	12 M, 4 F	14 R, 2 L	13 N, 3 Y

n= sample size; Age= mean (standard deviation); M=Male, F=Female; R=right-handed, L=left-handed; N= no vision correction, Y=vision correction (wear eyeglasses)

TABLE II
OVERVIEW OF THE DIFFERENT WORDS.

Index	Hindi word	# letters	# diacritics	# commands
1	घर	2	0	4
2	नमक	3	0	6
3	बचपन	4	0	8
4	जलमहल	5	0	10
5	इधरउधर	6	0	12
6	राम	3	1	6
7	इमली	4	1	8
8	तरबूज	5	1	10
9	किसतरह	6	1	12
10	संगमरमर	7	1	14
Total	-	38	5	76

Both groups of participants (i.e., children with dyslexia and control groups) performed the task by using the three HCI modalities: 1) a touchscreen; 2) an eye-tracker; and 3) an eye-tracker along with a soft-switch. Each input modality corresponds to an experimental condition (see Fig. 3). In this study, the touchscreen modality is used as a baseline to measure the change in performance from a touchscreen switching to another modality that can include visual feedback. The touchscreen represents a common input method for electronic gadgets that is recognizable to the participants (e.g., phone, tablet). For each experimental condition, only the correctly spelled characters are displayed inside the output text display window. But incorrectly spelled characters aren't displayed however stored in a log file for post hoc analysis purposes. At the end of the experiment, the usability and workload were measured for each HCI modality for both groups of participants.

IV. METHODS

A. Typing performance metrics

Performance was assessed through the computation of the text entry rate (the number of letters spelled out per minute, without any error in the input text), the information transfer rate (ITR) adopting the methods from previous research works [22], [28]. The ITR at command and letter level were measured as $ITR_{com} = log_2(M_{com}) \cdot \frac{N_{com}}{T}$ and $ITR_{letter} = log_2(M_{letter}) \cdot \frac{N_{letter}}{T}$, respectively. Where N_{com} is the total number of commands produced by the user to type N_{letter} characters. T is total time to produce N_{com} or type all the N_{letter}. The number of commands is 10 ($M_{com} = 10$); the number of commands at the letter level is 88 ($M_{letter} = 88$). The "delete", "clear-all", and "go-back" buttons were used as special commands to correct the errors. The ITR assumes that all the different commands and letters are equiprobable and without misspelling.

B. Feature selection and classification

The classification between children with and without dyslexia is assessed with 7 state-of-the-art classifiers. It is performed using linear discriminant analysis (LDA) [30] and its variations: Bayesian LDA (BLDA) and stepwise LDA (SLDA) [31]. SLDA begins with an initial model and then takes successive steps to modify the model by adding or removing features. At each step, the p-value of an F-statistic is computed to test models with and without a potential feature. We also considered the weighted k-nearest neighbor (k-NN) approach where the confidence value for the binary classification is determined by the probability to belong to one of the two classes based on the k neighbors. The confidence value of k-NN is set to negative for class 1 and positive for class 2. We considered a multi-layer perceptron (MLP) classifier with 50 hidden units, rectified linear unit (ReLU) activation function, and Broydon - Fletcher - Goldfarb - Shanno (BFGS) as an optimization function; Extreme Learning Machine (ELM) [32] with 200 hidden units using a sigmoid activation function; Tree Bagger (TB) with 50 trees, which generates in-bag samples by oversampling classes with large misclassification costs and undersampling classes with small misclassification costs. Therefore, out-of-bag samples have fewer observations from classes with large misclassification costs and more observations from classes with small misclassification costs.

The performance is assessed with the area under the ROC curve (AUC) using a leave one out cross validation [33]; so, we have 31 children for training and one child for the test, using both groups, and we assess the 32 possibilities by reporting the results across the 32 evaluations. We consider the speed (commands per minute) for the 10 words that are spelled out as input features. For each child in the dataset, the 10 features are normalized by removing the mean across the 10 words.

C. Dyslexia screening test and behavioral tool

Dyslexia screening test [34] was administered to screen the children for dyslexia and the records were made available to the researchers. The Wechsler Intelligence Scale (WISC-IV) for Children [35] was administered to assess verbal comprehension index (VCI: similarities, vocabulary, comprehension, information and word reasoning) and perceptual reasoning index (PRI: block design, picture concept, matrix reasoning and picture completion).

D. Subjective evaluation

The system usability scale (SUS) outcomes are used to understand the participant's performance about the system usability level [36]. The NASA Task Load Index (NASA-TLX) is considered to assess the participant's workload during the experimental tasks. The workload experienced by the user during the interaction with the VK application is based on the intellectual demand, physical call for, temporal demand, overall performance, attempt, and frustration [37].

V. RESULTS

The general overall performance assessment of machine learning approaches, multimodal virtual keyboard interface, and feedback was undertaken based on the effects gathered from the typing experiment. The corrected error rate was assessed for each condition without considering the special commands as an error. The corrected errors are typing errors made by the user however they were corrected at some stage in the text entry [38]. The Wilcoxon signed rank test was conducted using the false discovery rate (FDR) correction method for multiple comparisons on several performance measurements across diverse conditions. Two-sample t-test and Wilcoxon rank sum test were executed to compare the children with dyslexia and the control groups' performances.

A. Typing performance

We evaluated the multimodal VK interface with multimodal feedback for all three conditions across the ten words with the control and dyslexic group of participants. Each experimental condition was associated with one or more than one feedback. First, the touchscreen (TS) modality condition included auditory feedback. Second, the eye-tracking (ET) modality condition involved both auditory and visual feedback. Third, the eye-tracking and soft-switch (ETSS) modality condition also provided both auditory and visual feedback. The typing performance is presented in Tables III, IV, and V for the three conditions and for both control and dyslexic groups.

TS: The average text entry rate, ITR_{com}, ITR_{letter} with the control group were 10.97 ± 1.75 letters/min, 61.58 ± 6.09 bits/ min, and 18.05 ± 12.14 bits/min, respectively, whereas the average text entry rate, ITR_{com}, ITR_{letter} with the dyslexic group were 9.06 ± 1.75 letters/min, 52.49 ± 3.44 bits/ min, and 17.62 ± 15.60 bits/min, respectively.

ET: The average text entry rate, ITR_{com}, ITR_{letter} with the control group were 9.52 ± 1.34 letters/min, 58.58 ± 3.48 bits/ min, and 17.81 ± 13.37 bits/min, respectively, whereas the average text entry rate, ITR_{com}, ITR_{letter} with the dyslexic group were 7.49 ± 1.50 letters/min, 53.68 ± 3.04 bits/ min, and 15.21 ± 13.02 bits/min, respectively.

ETSS: The average text entry rate, ITR_{com}, ITR_{letter} with the control group were calculated as 12.43 ± 1.16 letters/min, 73.70 ± 8.49 bits/ min, and 21.37 ± 14.07 bits/min, respectively, whereas the average text entry rate, ITR_{com}, ITR_{letter} with the dyslexic group were 11.22 ± 1.17 letters/min, 68.92 ± 9.19 bits/ min, and 20.58 ± 12.77 bits/min, respectively.

We compared the performance measurement between the conditions and found that the ETSS leads to a greater text entry rate, ITR_{com}, ITR_{letter} than the touchscreen and eye-tracking for both groups ($p<0.05$, FDR corrected).

Average typing error: We measured the number of errors based on records in the log file across the words for each condition. The participant received a message "well-done" across the words for each condition when they completed the task within the predefined time. The "go-back" function of the VK application is considered as the error (i.e., the go-back command was used while completing the task). We estimated errors made by participants during the task with both groups

TABLE III
TYPING PERFORMANCE FOR THE TOUCHSCREEN (TS).

Word	Control Group Speed (letter/min)	Control Group ITR (com)	Control Group ITR (letter)	Dyslexic Group Speed (letter/min)	Dyslexic Group ITR (com)	Dyslexic Group ITR (letter)
1	11.63	46.54	43.60	11.84	57.69	56.04
2	11.98	60.81	33.07	7.50	51.80	31.68
3	8.97	59.19	23.46	7.48	50.63	20.88
4	8.60	58.96	18.67	5.87	45.67	14.79
5	11.53	61.48	16.99	9.15	49.87	13.53
6	12.95	63.48	7.41	10.35	51.67	6.98
7	13.87	66.96	8.99	10.01	53.15	7.14
8	9.17	65.95	9.34	8.44	53.23	7.91
9	10.33	65.89	9.46	9.99	54.79	7.95
10	10.71	66.49	9.52	9.96	56.40	9.26
Mean	10.97	61.58	18.05	9.06	52.49	17.62
Std	1.75	6.09	12.14	1.75	3.44	15.60

TABLE IV
TYPING PERFORMANCE FOR THE EYE-TRACKING (ET).

Word	Control Group Speed (letter/min)	Control Group ITR (com)	Control Group ITR (letter)	Dyslexic Group Speed (letter/min)	Dyslexic Group ITR (com)	Dyslexic Group ITR (letter)
1	12.27	49.28	47.63	10.22	45.95	44.63
2	11.51	58.20	32.50	9.03	54.95	29.36
3	9.13	57.30	23.09	5.79	51.55	18.39
4	8.43	59.08	18.53	6.32	53.32	18.39
5	8.99	59.00	15.67	6.64	54.97	11.24
6	8.80	60.17	6.83	9.12	55.75	4.94
7	9.95	61.00	8.11	7.22	56.24	5.76
8	8.68	60.40	8.48	7.26	55.20	6.22
9	9.04	60.67	8.65	7.46	55.18	6.84
10	8.36	60.70	8.59	5.85	53.71	6.33
Mean	9.52	58.58	17.81	7.49	53.68	15.21
Std	1.34	3.48	13.37	1.50	3.04	13.02

across each word. The average errors are presented in Fig. 4 for both control and dyslexic groups.

TS: The average errors for the 10 words: घर (1), नमक (2), बचपन (3), जलमहल (4), इधरउधर (5), राम (6), इमली (7), तरबूज (8), किसतरह (9), and संगमरमर (10) with touchscreen in the control group were calculated as 0.06, 0.25, 0.13, 0.31, 0.44, 0.00, 0.13, 0.69, 0.38, and 0.69, respectively whereas the

TABLE V
TYPING PERFORMANCE FOR THE EYE-TRACKING WITH SOFT SWITCH (ETSS)

Word	Control Group Speed (letter/min)	Control Group ITR (com)	Control Group ITR (letter)	Dyslexic Group Speed (letter/min)	Dyslexic Group ITR (com)	Dyslexic Group ITR (letter)
1	12.54	54.91	51.58	9.66	49.34	47.93
2	11.92	65.62	36.46	10.78	57.74	33.65
3	11.54	70.28	29.62	11.25	64.17	27.70
4	10.58	70.56	22.46	10.29	68.78	22.66
5	12.59	75.32	20.08	13.51	71.99	20.26
6	14.77	78.60	9.74	12.90	73.45	9.03
7	13.78	80.20	10.50	11.42	74.70	10.32
8	12.19	80.62	11.01	11.05	75.98	12.23
9	11.93	80.38	11.17	10.54	76.28	11.54
10	12.43	80.56	11.07	10.78	76.80	10.47
Mean	12.43	73.70	21.37	11.22	68.92	20.58
Std	1.16	8.49	14.07	1.17	9.19	12.77

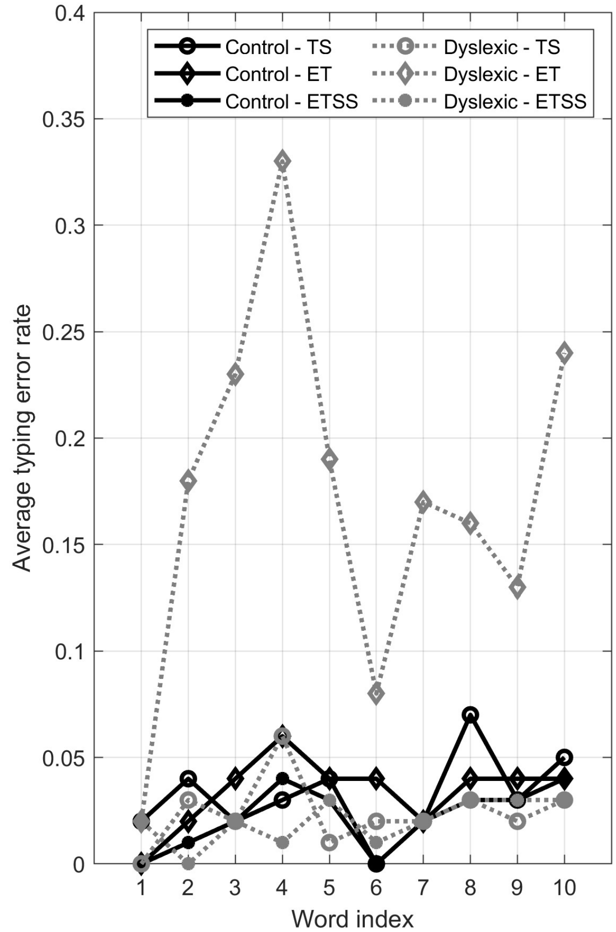


Fig. 4. Average typing error across difficulty levels for each condition (TS: touchscreen, ET: eye-tracker, ETSS: eye-tracker with soft-switch).

average errors in the dyslexic group were found as 0.00, 0.19, 0.13, 0.56, 0.06, 0.13, 0.13, 0.25, 0.25, and 0.44, respectively.

ET: The average errors for the 10 words: घर (1), नमक (2), बचपन (3), जलमहल (4), इधरउधर (5), राम (6), इमली (7), तरबूज (8), किसतरह (9), and संगमरमर (10) with eye-tracking in the control group were calculated as 0.00, 0.13, 0.31, 0.56, 0.50, 0.25, 0.19, 0.38, 0.44, and 0.50, respectively whereas the average errors in the dyslexic group were found as 0.06, 1.06, 1.81, 3.31, 2.25, 0.50, 1.38, 1.56, 1.56, and 3.31, respectively.

ETSS: The average errors for the 10 words: घर (1), नमक (2), बचपन (3), जलमहल (4), इधरउधर (5), राम (6), इमली (7), तरबूज (8), किसतरह (9), and संगमरमर (10) with eye-tracking and soft-switch in the control group were calculated as 0.00, 0.06, 0.19, 0.38, 0.38, 0.00, 0.13, 0.31, 0.38, and 0.63, respectively whereas the average errors in the dyslexic group were found as 0.06, 0.00, 0.13, 0.13, 0.38, 0.06, 0.19, 0.31, 0.31, and 0.44, respectively.

In Fig. 4, we can observe that the error rate decreases due to the change in word type and the difficulty level. Starting with the word index 6, the number of letters increases with simple ा matra, which is usually very easy to read and write compared to other Matras in index 7 (ी), 8 (ू), 9 (ि), 10 (ं). For this reason, a user completes word index 6 quickly without any errors in the TS and ETSS conditions. However, there were a few errors with the ET condition for both groups.

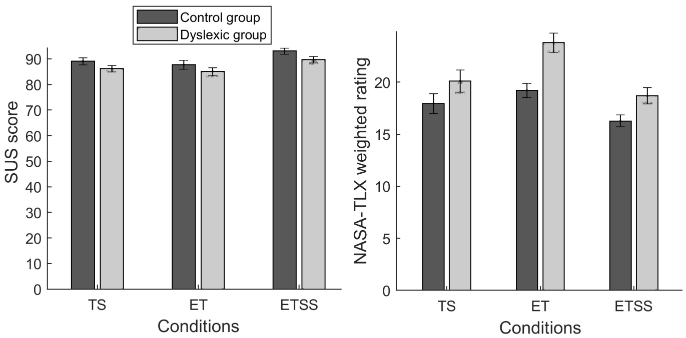


Fig. 5. SUS and NASA-TLX score for TS, ET, and ETSS conditions with the control and dyslexic groups of participants. The error bars represent standard error across participants.

Among the different words, we observe that the maximum error rate is achieved with a word index of 4 "Jal Mahal" for both groups. The results suggest that the average error rate varies depending on the characters contained in the word. Looking at the performance of a single word can be deceiving as there is a substantial variation across the different words. The trend between ET and the other modalities is consistent across the different words. However, the error rate is low for the control group, with a different pattern of performance across modalities for the different words.

B. Typing performance over VCI and PRI indices

The verbal comprehension index (VCI) and perceptual reasoning index (PRI) scores are given as percentile rank with their descriptive classification. We further estimated the performance of participants for each descriptive classification across all conditions. The typing performance with VCI and PRI are presented in Tables VI and VII. These typing performances are obtained with psychological assessment metrics. We administered WISC-IV to measure VCI and PRI for descriptive classification, and calculated the average typing performances for children with dyslexia in each classification.

The performance of eye-tracking and soft-switch with a low average (12.98 ± 1.43 letters/min), borderline (10.87 ± 1.39 letters/min), intellectual disability (9.49 ± 1.57 letters/min) in VCI found greater than both eye-tracking and touchscreen ($p<0.05$, FDR corrected). In addition, we found eye-tracking and soft-switch with a low average were superior to borderline and intellectual disability ($p<0.05$).

The performance of eye-tracking and soft-switch with average (12.21 ± 2.58 letters/min), low average (11.92 ± 2.13 letters/min), borderline (9.72 ± 1.16 letters/min), intellectual disability (10.78 ± 1.14 letters/min) in PRI was found greater than both eye-tracking and touchscreen ($p<0.05$, FDR corrected). However, we found eye-tracking and soft-switch with an average descriptive classification of PRI was superior to low average, borderline, and intellectual disability but not statistically significant ($p>0.05$).

C. Detection of children with dyslexia

The Area under the ROC curve (AUC) for the classification between children with and without dyslexia is presented in Table VIII. We report the mean and standard deviation values across 20 runs to account for the stochastic aspect of some of the algorithms. The standard deviation is not null for MLP, ELM, and TB due to the random initialization in these approaches. Fig. 6 depicts the ROC curves for a single run. For all the conditions, the AUC is superior to 0.5 (random decision). The best performance is obtained with LDA for the ET condition with an AUC=0.910. Across the 3 conditions, the MLP provided the best results (AUC=0.825). For the TS condition, the best performance is obtained with BLDA with AUC=0.838. With the condition ETSS, the best AUC is reached with K-NN (k=5), AUC=0.799. Across classifiers, the AUC is the highest with the ET condition and the lowest with the ETSS condition. The worst performance is provided by the ETSS condition with AUC<0.7.

D. System usability scale

The results from the system usability scale (SUS) test are presented in Fig. 5 (Left) with each input condition for both groups of participants. The average SUS score with eye-tracker and soft-switch in the control group was 93.91 ± 3.98 and was found superior to eye-tracker (87.03 ± 4.85) and touchscreen (89.84 ± 6.22). The average SUS score with eye-tracker and soft-switch indicates the best imaginable grade on the adjective rating scale [39]. Likewise, the average SUS score achieved with eye-tracker and soft-switch in the dyslexic group was (89.53 ± 4.49) around 90%, indicating the best possible performance grade on the adjective rating scale [39] and found greater than eye-tracker (85.16 ± 3.82) and touchscreen (86.25 ± 4.18). The SUS score was significantly higher for the control group compared to the group of children with dyslexia ($p<0.05$).

E. NASA Task Load Index

The NASA Task Load Index (NASA-TLX) scores for each condition are depicted in Fig. 5 (Right). The system achieved an average NASA-TLX score with the ETSS condition (16.07 ± 2.02), which was lower than ET (19.80 ± 2.15) and TS (17.91 ± 2.10) conditions in the control group. The same pattern of performance was observed where a low workload was found with ETSS condition (18.51 ± 2.33) than ET (23.82 ± 2.29) and TS (20.18 ± 2.14) in the dyslexic group. The NASA-TLX score was significantly higher for the group of children with dyslexia compared to the control group ($p<0.05$).

F. Correlations

We assess the correlation between the different measurements of the 3 conditions. We consider the BLDA classifier for the detection of dyslexic children due to its high performance and stable results across conditions. The correlation between VCI and the BLDA score is -0.675, -0.262, and -0.511 for conditions TS, ET, and ETSS, respectively. It shows a moderate

TABLE VI
PERCENTILE RANK AND DESCRIPTIVE CLASSIFICATION OF VCI INDEX WITH TYPING PERFORMANCE FOR CHILDREN WITH DYSLEXIA.

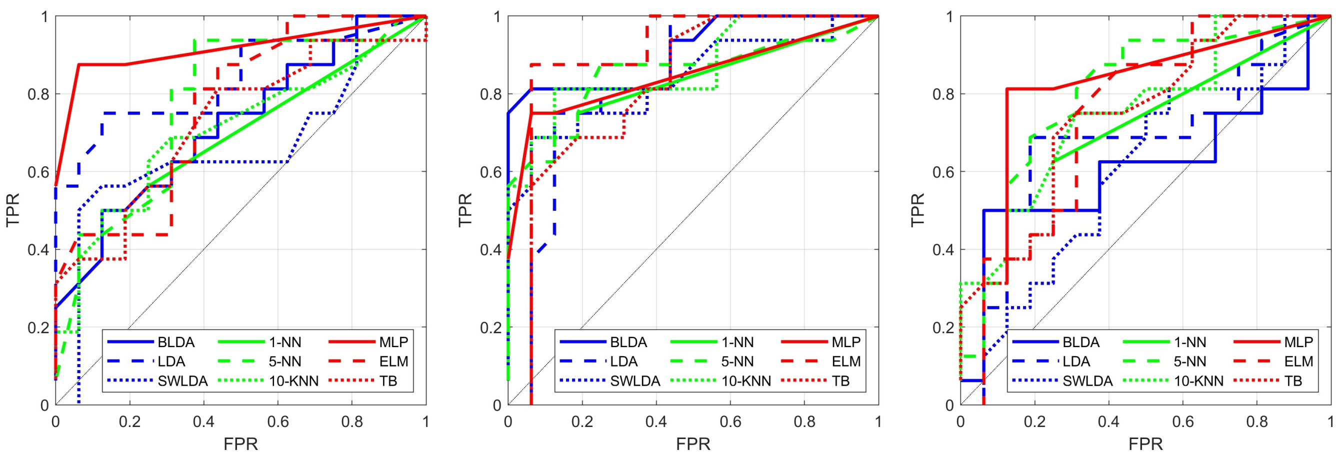
VCI Percentile Rank	Descriptive Classification	Group Sample	Speed (letter/min) TS		ET		ETSS	
			Mean	Std.	Mean	Std.	Mean	Std.
9-23	Low Average	n=8	10.61	1.25	7.42	0.48	12.98	1.43
2-8	Borderline	n=5	9.21	1.03	7.33	0.33	10.87	1.39
0.01-2	Intellectual Disability	n=3	7.28	1.32	6.89	0.61	9.49	1.57

TABLE VII
PERCENTILE RANK AND DESCRIPTIVE CLASSIFICATION OF PRI INDEX WITH TYPING PERFORMANCE FOR CHILDREN WITH DYSLEXIA.

PRI Percentile Rank	Descriptive Classification	Group Sample	Speed (letter/min) TS		ET		ETSS	
			Mean	Std.	Mean	Std.	Mean	Std.
25-73	Average	n=6	10.96	2.70	8.23	1.47	12.21	2.58
9-23	Low Average	n=3	10.06	1.46	7.17	0.75	11.92	2.13
2-8	Borderline	n=3	7.43	1.15	6.48	0.09	9.72	1.16
0.01-2	Intellectual Disability	n=4	7.66	0.75	5.57	0.89	10.78	1.14

TABLE VIII
AUC FOR EACH CONDITION (TS: TOUCHSCREEN, ET: EYE-TRACKER, ETSS: EYE-TRACKER WITH SOFT-SWITCH).

Condition	LDA	BLDA	SWLDA	1-NN	5-NN	10-NN	MLP	ELM	TB
TS	0.721	0.838	0.666	0.586	0.775	0.701	0.870 ± 0.031	0.780 ± 0.043	0.766 ± 0.029
ET	0.910	0.834	0.838	0.711	0.852	0.869	0.845 ± 0.035	0.835 ± 0.044	0.800 ± 0.026
ETSS	0.613	0.678	0.605	0.609	0.799	0.758	0.762 ± 0.033	0.765 ± 0.032	0.758 ± 0.019



Touchscreen Eye-tracker Eye-tracker with soft-switch

Fig. 6. ROC curve for each condition for the detection of dyslexic children based on the typing speed.

correlation between conditions TS and ETSS. The correlation between PRI and the BLDA score is -0.407, -0.378, and -0.393, for conditions TS, ET, and ETSS, respectively. They indicate weak relationships between PRI and the classifier output. The correlation between NASA-TLX and the BLDA score is 0.081, 0.399, and 0.110 for conditions TS, ET, and ETSS, respectively. It indicates a weak relationship with condition ET. Finally, all the correlations between SUS and BLDA scores are below 0.2 in absolute value.

VI. DISCUSSION

Creating fully inclusive virtual keyboards should be a priority to include a large range of users, including children with disabilities such as dyslexia. Virtual keyboards using eye-tracking as an input modality can have multiple purposes: they can be used for communication as a primary purpose, they can be used to record and analyze the gaze of the users, they can provide a typing aid through the feedback that is assigned to the commands, and they can be used to detect children with dyslexia.

This work proposes a multimodal virtual keyboard as an assisted learning system that can be used as a writing aid for children with dyslexia. Dyslexia can impact mental health in multiple ways: education, career, financial, physical well-being, social and community connections, and psychological and emotional well-being. Altogether, it indicates a close relationship between mental and physical long-term conditions, which should be taken into account for designing multimodal VKs. The system was compared using two groups of children with a similar age range (about 11 years old). While most studies focus on the Latin script, the Hindi script has particular features: Hindi has a consistent symbol-sound mapping with an extensive list of complex graphemes. In this study, a virtual keyboard using an eye-tracker is used as a direct means of communication, i.e., for command selection and the detection of children with dyslexia through the analysis of the typing performance. However, virtual keyboards using eye-tracking can be used for providing an alternative means of communication for people with severe disabilities, including stroke patients in rehabilitation [28]. Virtual keyboards using eye-tracking can also be used to assess visual and oculomotor abnormalities through the gaze path.

Multiple evaluation metrics such as typing performance, usability, and workload are proposed to assess the differences across modalities and between the control group and the group of children with dyslexia. The results show that the SUS score is lower for the dyslexia group and the NASA-TLX score is higher. The usability has a better score for the control group, suggesting additional efforts should be made to improve the usability of the proposed system. Likewise, the workload is higher for children with dyslexia. These results highlight how a different population of participants can impact performance estimation. In all these cases, we observed differences between the control group and children with dyslexia. The differences can be used in two ways. First, the best modality can be directly suggested by default to a child with dyslexia. Second, the difference in performance could be used to better diagnose dyslexia through the direct comparison of performance between multiple modalities, and the type of encountered errors. The difference in performance that occurs between children without and with dyslexia can be found at the subject level using machine learning when considering the typing speed across 10 words. Different classifiers are assessed and it was possible to reach an AUC superior to 0.9. These results indicate that the proposed approach can be used for different purposes, and it could be used to track the progress of children with dyslexia. The moderate correlation between the verbal comprehension index (VCI) and the classifier score with the touchscreen (TS) condition suggests the possibility to use the classifier, which is based on features related to typing speed, to assess verbal comprehension.

The proposed system could also benefit from multiple technological aids that are available commercially to help dyslexic individuals to overcome their reading, spelling, or writing challenges. Some promising examples are novel text-to-speech software and custom user interface for dyslexic individuals to help in reading [40], [41]. Word processing tools can check spelling, grammar, and highlight errors automatically. Predictive text approaches are considered to provide the most likely upcoming words to be typed. These approaches help to reduce the number of keystrokes and time and improve spelling. Voice recognition software tools and programs enable users to dictate text to computers. These approaches are proven effective for writing, correcting, formatting, and editing on computers. The proposed system could directly benefit from word completion procedures [42] and time-based adaptive approaches [22] for increasing the typing speed.

The current findings are based on the virtual keyboard interface for complex structure language (i.e., Hindi language) that is also read from left to right, it has peculiar characteristics such as the usage of diacritics (Matras) and killer strokes (Halants). The Hindi language can be used by 490 million speakers. It would be interesting to compare the proposed design approach with other language interfaces. Further work will include an evaluation of other natural languages and other types of learning disabilities. Dyslexia Assessment for Languages of India (DALI) contains two screening tools for dyslexia: the Junior Screening Tool (JST) and the Middle Screening Tool (MST) in four languages, Hindi, Marathi, Kannada and English. The evaluation of these languages would provide more evidence about how the proposed system can be deployed in clinical settings.

While we have shown how the pattern of performance changes between children with dyslexia and non-dyslexia with typing tasks of different difficulty levels, it is unclear how the performance would evolve during treatment, if some training with the user interface would decrease the performance gap with the control group. Further studies with analyses across sessions, with free typing, with children from different locations, would provide key insight into how typing performance can evolve with children with different types of dyslexia. Dyslexia has three sources: a grapho-phonemic deficit, a graphemic deficit, and an audio-phonemic deficit [43]. Future work should be carried out to discriminate the core deficits in dyslexia.

This study highlights the need for multimodal interfaces, interactions, feedback, and machine-learning techniques for developing efficient rehabilitation tools. Typical rehabilitation and communication devices do not take into account the mental capacity of the users. The performance gap and different typing speeds for each modality show the need to focus on the target population for assessing a user interface such as a gaze-based VK. This study stresses the need to test a system on the target users (e.g., children with dyslexia) for obtaining reliable results that can represent what would happen outside of the lab. However, the performances obtained with the eye-tracking modalities show that it is possible to detect children with dyslexia without any physical contact between them and the system. Therefore, this work could transfer to the use of systems that require users to touch a device, e.g., an ATM keypad, which can be limited for hygiene reasons in a time when there is a global pandemic.

VII. Conclusion

Dyslexic children can be detected using machine learning when typing 10 words using an adapted virtual keyboard, and the modality with eye-tracking provides the best performance. The results suggest that for writing aids, 1) an eye tracker with a soft switch provides an effective input modality for children with dyslexia; 2) traditional input modalities such as touchscreen and mouse are not the most suitable for children with dyslexia. The implementation of positive and negative feedback could be further enhanced to overcome the error rate and oculomotor deficits of children with dyslexia.

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