DysVis: A User-Centred Data Visualization System for Dyslexia Pre-screening

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Abstract

Dyslexia is a common neurobiological learning disorder significantly impacting reading, writing, and spelling worldwide. Early identification and intervention are essential, but most pre-screening tools focus on Latin languages, leaving Chinese-speaking students underserved. To address this gap, we conduct semi-structured interviews with special education (special-ed) teachers to gather their needs for dyslexia pre-screening tailored to Chinese contexts. Using their insights, we have developed *DysVis*, a user-centered data visualization system that combines handwriting analysis, body movement keypoint conversion, and a comprehensive visualization interface. *DysVis* provides teachers with multi-level visualizations, such as performance overviews, task analyses, handwriting observations, and behavioural insights, enabling them to identify the root causes of learning difficulties. Our evaluations, including case studies, a user study, and expert interviews, demonstrate that *DysVis* is user-friendly and effective in quickly identifying at-risk students, ultimately enhancing learning outcomes for Chinese-speaking students with dyslexia.

CCS Concepts

• **Human-centered computing → Visualization systems and tools**; **Interactive systems and tools**; *Web-based interaction.*

Keywords

Data Visualization System, User-centred Design, Data-driven Technology-enabled Analytics, Dyslexia Pre-screening

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1 Introduction

Dyslexia is a prevalent neurobiological learning disorder that significantly influences a person's reading, writing, and spelling skills [10]. It is characterized by challenges in word recognition, spelling, and decoding, often linked to deficiencies in the phonological aspect of language [33, 63]. These challenges can severely affect students' academic performance, self-esteem, and lifelong development [59]. Early intervention is essential to help students with dyslexia overcome challenges and reach their potential [77]. Through timely support, special education (special-ed) teachers can provide tailored instruction and personalized learning experiences to meet each student's unique needs.

To support early identification, previous research has explored various pre-screening methods to assist educators in recognizing dyslexia. For example, Chan et al. [16] developed a behaviour checklist to screen dyslexia. In contrast, Hou et al. [44] created a tool that utilizes multiple checklists, including parent reports and intelligence assessments. Although these behavioural assessments provide valuable insights, they may not fully capture the complexities of dyslexia in diverse linguistic contexts [1, 11]. This limitation is particularly pronounced in non-Latin language contexts, such as Chinese, where linguistic variation can complicate the assessment and intervention for those with dyslexia [62]. For example, in Hong Kong, where Cantonese is the primary language, students often switch between formal and informal speech in their daily communication.

Furthermore, compared to Latin languages that are syllabic-aware with prominent sound-script correspondence, there is no strong correlation between the sound and script of Chinese because Chinese writing is logographic [20, 42, 67]. Thus, indicators such as morphological awareness, Chinese handwriting stroke order, and handwriting gestures are crucial for Chinese dyslexia pre-screening [45, 51, 68, 84]. For example, although various resources are available for identifying and supporting students with dyslexia, such as Ghotit Real Writer & Reader [61], QS Dyslexia Tests [56], Amira [21], and Realize Reports [60], they mainly focused on phonological awareness [85], letter positions [49], letter combinations [86], and letter sequences [52], due to the limited number of characters and the horizontal writing format of the English language. These characteristics are not available in Chinese. As a result, different predictors for assessing dyslexia in China are necessary.

To this end, educational visualization systems are considered more effective and promising in delivering users detailed analytics [4, 25, 40, 72]. For example, Herodotou et al. [40] implemented predictive learning analytics to identify at-risk students based on quantitative metrics such as submission status and grades. Despite these advancements, these tools only provide special-ed teachers with the final pre-screening results without comprehensively analyzing students' learning process. As a result, many students may struggle with their learning without effective pre-screening tools tailored to their learning needs. This lack of support can result in long-term academic challenges. Consequently, students' confidence may diminish, further hindering their educational progress. Thus, addressing these gaps is essential for improving educational outcomes for students with dyslexia in Chinese-speaking contexts.

This work has aimed to design and develop a pre-screening system for special-ed teachers to provide early intervention for at-risk students with Chinese dyslexia. To understand the needs of special-ed teachers in conducting pre-screening, we conducted semi-structured interviews with 13 teachers, based on which we distilled design requirements. Specifically, teachers emphasized the importance of evaluating overall student performance to transition from general assessments to individualized support for at-risk students with dyslexia. They highlighted the need for quickly identifying specific learning challenges and thoroughly analyzing students' approaches to sub-questions to uncover root causes, ultimately leading to more effective and personalized interventions.

In response to the identified requirements, we propose a data visualization system for dyslexia pre-screening, *DysVis*, designed to enhance the pre-screening process for special-ed teachers by improving *usability* and *effectiveness* [1]. Inspired by previous research [47, 55, 58], our approach integrates open-pose techniques to enable quick, convenient, and detailed pre-screening. Specifically, our system integrates three key components: (1) handwriting data analysis, (2) body movement keypoint conversion, and (3) a user-centered visualization interface to assess and support students at-risk of dyslexia comprehensively. Specifically, we first analyze real-time handwriting animations alongside body movement data. We collect writing data, convert it into SVG format, and illustrate the writing strokes sequentially based on the student's writing performance. Then, we convert videos into keypoints for body movement data to represent the student's skeletal structure. Key features indicating impatience, such as abnormal head and hand movements (e.g., unusual head rotations and vigorous hand motions), are highlighted for analysis. Lastly, we design a user-centered interface to facilitate the discovery of marginal cases among students with dyslexia at four levels of detail: *Student Overview Panel* provides special-ed teachers with a summary of pre-screening performance. *Task Overview Panel* allows teachers to analyze student performance and quickly pinpoint which testing tasks require further investigation; *Sub-question Panel* enables teachers to examine sub-questions within each category and observe students' handwriting through animations; *Student Behaviour Panel* offers detailed insights into the behaviours of students exhibiting dyslexia symptoms. It helps identify the underlying reasons for their difficulties in those areas. Our contributions are:

- We have constructed the design requirements for dyslexia pre-screening by collaborating with domain experts, such as special-ed teachers, and reviewing existing research.
- We propose a user-centered data visualization system, *DysVis*, which integrates real-time handwriting analysis and body movement data to quickly identify specific learning challenges and assess individual student difficulties, equipping special-ed teachers with systems for early intervention in at-risk students and enabling rapid identification, comprehensive insights, and reliable assessments to uncover the root causes of students' difficulties.
- We have conducted a comprehensive evaluation and encompassed two case studies, a thoughtfully crafted user study,

[1]The University's Institutional Review Board (IRB) approved the experimental protocol.

and expert interviews to exemplify the effectiveness and usability of the advanced method.

2 Related Work

Our paper's related work can be divided into four sections: support for reading and writing disabilities in Human-Computer Interaction (HCI), existing dyslexia pre-screening methods, the behaviour of students with dyslexia, and existing assessment methods.

2.1 Support for Reading and Writing Disabilities in HCI

In the HCI context, various systems have been developed to support individuals with reading and writing disabilities, particularly dyslexia [36, 41]. These systems utilized user-centered design to improve the educational experience by offering personalized interventions that respond to the specific challenges encountered by students. For example, automatic speech recognition (ASR) systems require users to listen to questions and content, thereby improving their reading fluency and comprehension [78]. In addition, interactive platforms that incorporate gamification elements can motivate students to engage in reading and writing tasks while providing immediate feedback on their performance [35, 38]. These systems often utilized HCI principles to create user-friendly interfaces accommodating diverse learning preferences. By leveraging these principles, our system supports reading and writing, enhancing overall learning experiences through thoughtful HCI design.

2.2 Dyslexia in Chinese

Students with dyslexia encounter significant challenges when learning Chinese, primarily due to the unique logographic writing system of the language [23]. Unlike alphabetic languages, students need to memorize specific radicals and components of characters, which do not have a direct link to pronunciation [57]. This lack of grapheme-phoneme correspondence hampers their ability to predict spelling, further complicating the learning process [79]. Therefore, it is challenging to pre-screen at-risk students with dyslexia.

To effectively assess at-risk students with dyslexia, educators often employ various methods for pre-screening. One common approach involves requiring students to read 180 words, classifying those who make mistakes in ten consecutive words as high-risk cases of dyslexia [30, 36, 37]. However, a young student's vocabulary size can be influenced by factors such as family background, demographics, and the quality of kindergarten education [2, 66]. Also, the timing of the evaluations (i.e., at the beginning or end of the academic year) can lead to varying test results.

In addition to reading assessments, special-ed teachers focus on writing-related aspects such as component ratios, stroke order, and writing consistency [27]. The student is often considered high-risk if specific writing issues are frequently observed. It is essential to recognize that young students may have underdeveloped motor skills, which can result in poor handwriting [3, 24]. While existing research primarily focuses on reading disabilities [82, 83], dyslexia encompasses both reading and writing challenges. Given the multifaceted nature of dyslexia, our work aims to provide a comprehensive pre-screening process. This process enables special education teachers to assess students' linguistic abilities, literacy, handwriting, and behavioural factors cohesively, ensuring more accurately identifying at-risk students.

2.3 Behaviour of Students with Dyslexia

Teachers observe students' behaviours while writing Chinese characters for several purposes. First, they assess writing techniques, including stroke order and overall proficiency [51]. Second, they identify common character formation errors and misunderstandings [74]. Third, they evaluate how students approach writing tasks and apply learned concepts [48]. In addition, teachers monitor attention and sensory processing [50], noting that students with dyslexia may struggle to remain still, often showing restlessness through body movements or shaking of the legs as expressions of impatience.

To assess dyslexia symptoms, special-ed teachers and parents are encouraged to utilize behavioural checklists, such as the Hong Kong Dyslexia Behaviour Scale for Primary School Students (Second Edition) [2] and the Parental Behavioural Checklist [3]. Students are required to complete nine questionnaires. Although each questionnaire is relatively brief, students often experience fatigue after a full day of lessons, sometimes needing two to three days to complete all assessments. Furthermore, some teachers report challenges in understanding certain parts of the questionnaires, complicating their ability to make informed decisions. Consequently, many teachers rely on personal experience to evaluate students' behaviour, which can lead to oversight of individual performance and misjudgments. Therefore, one of the objectives of this work is to establish a standardized procedure and objective measurements to enhance the accuracy of dyslexia pre-screening.

2.4 Existing Assessment Methods

In this section, we discuss the existing assessment methods for dyslexia assessment.

Standardized Assessment: The standardized assessment was developed by the Department of Health in Hong Kong [70]. This approach offers various metrics for identifying dyslexia symptoms, including reading and writing abilities, reported behaviours at home and school, and communication skills. Conducted by registered professionals such as educational psychologists, this structured assessment provides a systematic approach to diagnosing reading and writing disabilities. However, it may overlook nuanced behaviours and contextual factors that significantly influencing student performance. In addition, private assessments are expensive (e.g., HK $15,000 per assessment), and most families may not be able to afford the price.

Observation Method: Another pre-screening method involves observing student behaviours, classwork, and interactions in the classroom. This approach can provide valuable information on the individual learning process and challenges faced by at-risk students with dyslexia. However, although it allows for a more holistic understanding of student needs, it can be subjective and heavily depends on teachers' experience with possible biases [17].

[2] https://hksld.eduhk.hk/
[3] https://www.eoc.org.hk/EOC/Upload/UserFiles/Image/Barrier-freeLife/SLD.pdf

Furthermore, the time-consuming nature of this method may hinder its practical implementation in busy classroom settings.

Biological Integration: Dyslexia arises from variations in language processing within certain brain regions. Some researchers explored insights into brain behaviour through electroencephalography (EEG) signals [19]. Participants are required to wear an EEG headset to enable analysis of neural activities. While EEG sensors may facilitate the exploration of significant information by assessing brain electrical activity, it is difficult to collect data from users, particularly with young children [75, 76]. This work proposes a more accessible method to gather data for dyslexia pre-screening.

Visualization System: Visualization systems present comprehensive data in an accessible format, allowing educators to make informed decisions [91]. These systems [9, 14, 40] are especially useful in learning analytics (LA), enabling educators to monitor student performance, identify at-risk students with dyslexia, and adjust teaching strategies accordingly [90]. For example, Dyckhoff et al. [25] developed the Learning Analytics Toolkit (eLAT) to examine the relationships between student behaviours, characteristics, and assessment results. However, existing systems were not designed to meet the specific needs of special-ed teachers, such as a user-centered dyslexia pre-screening system [46].

Current systems can generally be improved in several aspects, such as data processing, analysis techniques, and integrating valuable attributes into one unified system [95]. For example, the effectiveness of visualization systems can be improved by integrating user-centered design principles, which prioritize the needs and preferences of the intended audience [69]. Therefore, we developed *DysVis* – a user-centered data visualization system for dyslexia pre-screening, incorporating strengths from various methodologies while addressing their limitations. By an iterative design based on a thorough analysis of existing methods [28], *DysVis* enhances the accuracy and reliability of dyslexia identification, satisfying the unique needs of students and educators.

3 Formative Study

To better understand the unique needs of special-ed teachers, we conducted a formative study and derived design requirements in pre-screening students with dyslexia.

3.1 Methods

The formative study consisted of an online survey and interviews to understand special-ed teachers' perceptions, experiences, challenges, and needs in pre-screening students with dyslexia. We began with the **survey** to have a broad understanding of special-ed teachers' pre-screening procedures, user experience, and feedback. To deepen our understanding of the challenges and needs of the teachers, we conducted **individual interviews** with the participants (Table 1). We narrowed down the interview questions based on the survey results. Based on the interview feedback, we derived the **design requirements**.

3.1.1 Survey. We sent out an online survey (Appendix A) via Qualtrics [4] to different teacher groups to recruit participants. Special-ed teachers or those with experience using pre-screening and/or assessment systems were selected. Our study included eight participants (P1 - P7, P9; Age: 20 – 60; 5 females) with an average of 15.25 years in special-ed (SD=11.82, MAX=33, MIN=1). After collecting the survey responses, the first author performed a thematic analysis [13] of the data with another author.

Survey results. Most respondents used various pre-screening methods, including robot-assisted pre-screening tools, reading vocabulary assessments, checklists, and pre-screening kits. One-third of the respondents focused on students' handwriting performance, while others evaluated vocabulary size or reading abilities. Most respondents expressed a desire to understand students' overall performance, behaviours, and the difficulties they encountered. However, due to the non-standardized nature of these methods, many respondents found existing assessment and pre-screening techniques challenging, leading to concerns about the reliability of the results. By consolidating the survey results, we designed more specific questions for the individual interviews, which can be found in Appendix B.

3.1.2 Interview. Five participants were recruited by a purposive sampling method, including four special-ed teachers (P8, P11, P12, P23) and one expert (P10) participants (Age: 20 – 50; 4 females) with an average of 15.4 years in special-ed (SD=10.43, MAX=30, MIN=4). P10 was a senior lecturer specializing in special learning disabilities and educational psychology at a university. P8, P11, P12, and P23 were special-ed teachers with teaching experience of 7, 4, 30, and 16 years, respectively. The interviews were held for one hour. After obtaining consent from participants, we introduced the study's objective. We recorded the details for each interview session via Zoom [5]. We asked the participants different questions (Appendix B) to explore special-ed teachers' current practices and challenges when utilizing data visualization systems for dyslexia pre-screening. The first author used Zoom's auto-transcription function to transcribe all content and conducted a thematic analysis with another author. The first author performed the initial coding to generate preliminary codes. Subsequently, two rounds of discussions were performed to group and refine these codes, ensuring a comprehensive understanding of the feedback received.

3.2 Design Requirements

Based on our survey and interview study, we have distilled the following four design requirements (DRs).

DR1: Transition from general to individualized student focus. Special-ed teachers serve approximately 1,000 students and employ a four-step approach to identify those at-risk of dyslexia. In Step 1, they screen students who underperform in homework and tests. Step 2 involves assessing overall performance, including in-class behaviour and handwriting, for significant gaps, after which at-risk students are referred to Special Education Needs Coordinators (SENCOs) for further evaluation. Step 3 requires gathering data on test scores, exam results, handwriting proficiency, and classroom observations. Finally, Step 4 shifts from a general performance

[4] https://www.qualtrics.com/
[5] https://www.zoom.com/

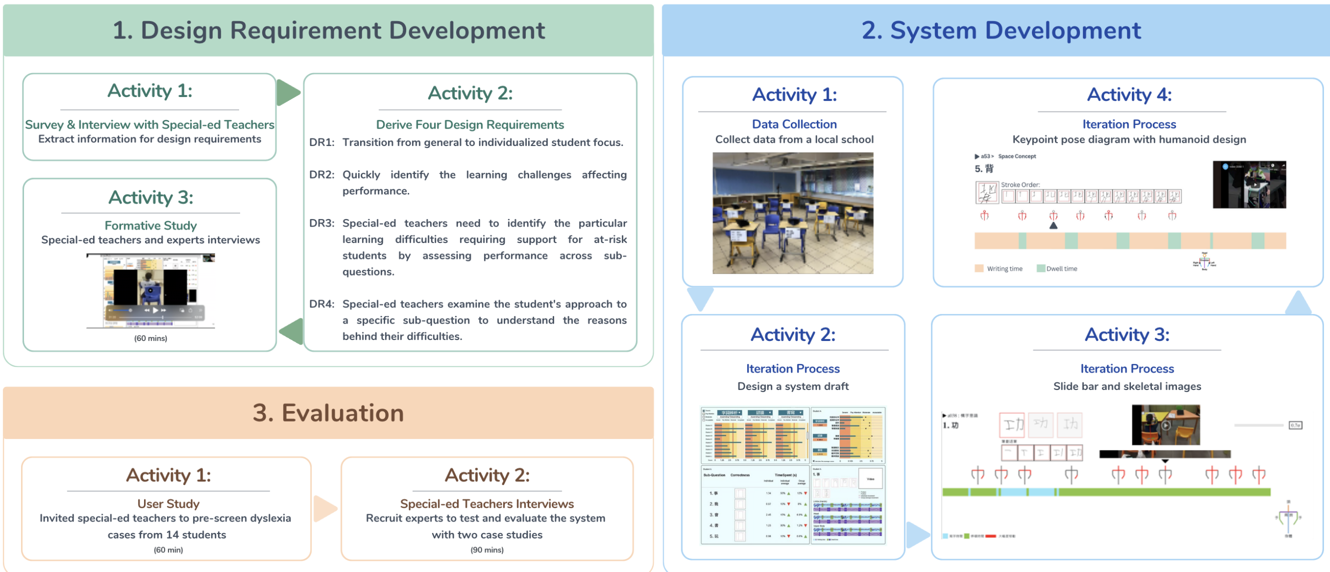

Figure 1: The whole research flow: (1) developed design requirements via survey, interviews, and formative study, (2) developed the system with data collection and iterations, and (3) conducted formal study through interviews. The translation of Traditional Chinese characters: Appendix E.

Table 1: Expert background (P1 – P26). The last three columns annotate participants’ involvement in the formative survey (Section 3.1.1), interviews (Section 3.1.2), and evaluation (Section 6).

ID	Age Range	Gender	Teaching Degree	Teaching (years)	Certificate/Study	Formative Survey	Formative Interview	Evaluation
P1	31-35	F	Degree	10	Special-ed	Y	N	N
P2	51-55	M	Degree	27	Special-ed	Y	N	N
P3	20-25	F	Degree	1	Special-ed	Y	N	N
P4	36-40	F	Degree	11	Special-ed	Y	N	N
P5	26-30	M	Degree	2	Special-ed	Y	N	N
P6	36-40	M	Degree	13	Special-ed	Y	N	N
P7	56-60	F	Degree	33	Special-ed	Y	N	N
P8	26-30	F	Certificate	7	Special-ed	N	Y	Y
P9	51-55	F	Certificate	25	Special-ed	Y	N	Y
P10	46-50	F	Degree	20	Special-ed	N	Y	N
P11	51-55	M	Certificate	30	Special-ed	N	Y	Y
P12	20-25	F	Degree	4	Inclusive	N	Y	Y
P13	20-25	M	Degree	1.5	Special-ed	N	N	Y
P14	20-25	F	Certificate	3	Special-ed	N	N	Y
P15	26-30	F	Degree	5	Special-ed	N	N	Y
P16	26-30	F	Certificate	2	Special-ed	N	N	Y
P17	20-25	F	Certificate	1	Special-ed	N	N	Y
P18	36-40	F	Certificate	11	Special-ed	N	N	Y
P19	26-30	F	NA	5	Special-ed	N	N	Y
P20	46-50	F	NA	3	Special-ed	N	N	Y
P21	31-35	F	Degree	8	Inclusive	N	N	Y
P22	31-35	F	Degree	3	Inclusive	N	N	Y
P23	41-45	F	Degree	16	Special-ed	N	Y	N
P24	20-25	M	Degree	1	Inclusive	N	N	Y
P25	26-30	F	Degree	6	Special-ed	N	N	Y
P26	41-45	F	Degree	25	Special-ed	N	N	Y

overview to detailed observations of student behaviour. Teachers preferred initially assessing collective performance before identifying potential dyslexia cases, particularly severe and marginal ones. Monitoring progress and identifying areas for improvement is crucial [94]. Performance data enables special-ed teachers to make informed decisions for better student support [92]. P3 emphasized, "This step is very important because it helps us understand the situation of the person being evaluated." P10 elaborated, "It proves advantageous in understanding the circumstances and requirements of students."

An overview of overall performance is beneficial before focusing on specific weaknesses. If students show poor performance, teachers evaluate individual potential issues. P5 noted, "The categories of the paper-based assessment tool encompass vocabulary, literacy, reading ability, speaking skills, and handwriting." P11 added, "Sorting makes categorization and clarity more accessible, enhancing convenience. Including categories for reading and writing difficulties tailored for students with dyslexia is highly beneficial." P8 remarked, "Narrowing down offers preliminary numerical evidence regarding students' reading and writing challenges, aiding in pinpointing areas of weakness." However, some teachers noted that many students fell into marginal cases that were difficult to identify early, potentially missing early intervention and impacting academic performance, motivation, and self-esteem [32, 34]. Preliminary data can help special-ed teachers estimate whether a student has a higher risk for dyslexia.

DR2: Quickly identify the learning challenges affecting performance. Special-ed teachers aim to identify the root causes of poor performance by assessing individual results across different question types, pinpointing specific learning issues tied to low scores, and comparing performance to average benchmarks. A snapshot of students' progress on specific tasks has been found to help teachers identify areas needing attention [5]. P2 noted, "Some areas are uncertain and difficult to navigate. We can only roughly understand the characteristics of reading and writing difficulties, aiding in grasping students' situations and needs." Teachers noted that consistent incorrect answers on specific question types usually prompt an investigation into the underlying reasons (P10). They emphasized the importance of quickly outlining students' fundamental language abilities and clarifying their strengths and weaknesses to support educators in developing personalized intervention plans (P5). Additionally, some teachers suggested that highlighting the bar graphs would be more effective for severe cases, as they illustrated the performance gap compared to average scores and provided various references, such as total scores (P11). However, some teachers may find interpreting bar charts challenging.

DR3: Special-ed teachers need to identify the particular learning difficulties requiring support for at-risk students by assessing performance across sub-questions. Special-ed teachers analyze student performance to identify specific questions where students struggle rather than relying solely on category scores. They aim to understand the reasons behind these difficulties, whether due to lack of attention or comprehension issues. By examining individual sub-question performance, teachers can uncover misconceptions and weaknesses, guiding them on which areas to investigate further [7, 65]. This process requires teacher input, as noted by P4 "Relying solely on personal judgment may not always be accurate." To enhance pre-screening accuracy, P11 suggested that comparing questions helps assess the impact of complexity on student performance. If students struggle with simple questions, this may indicate significant reading and writing challenges. Teachers also need to gauge how far behind a student is compared to peers, as slower but accurate responses may signal cognitive difficulties. P8 added that comparing similar questions can reveal if a student's slow response time is due to distractions, aiding teacher observations.

Time taken to complete tasks is another crucial indicator for pre-screening dyslexia. P11 stated that if a student spends considerable time on a question but completes it, it provides insights into their processing abilities for future assessments. P8 noted that extended task completion times often indicate reading and writing challenges, emphasizing that including time as a factor can improve pre-screening effectiveness. Handwriting proficiency is also vital for identifying dyslexia risk. P11 explained that demonstrating stroke order can reveal symptoms and spatial awareness issues, providing insights into reading and writing difficulties. P12 noted that for dyslexia, interpreting text resembles deciphering symbols rather than forming words. P8 emphasized that showing the handwriting process can highlight issues like spacing problems or poor hand-eye coordination, indicating a higher likelihood of dyslexia.

DR4: Special-ed teachers examine the student's approach to a specific sub-question to understand the reasons behind their difficulties. Special-ed teachers seek a deeper understanding of student performance by examining how they approach specific sub-questions, including their behaviours, postures, and handwriting styles [53, 81]. Environmental factors significantly influence student performance during pre-screening. P12 emphasized, "Considering environmental factors is crucial. A student's slowness may not indicate reading and writing difficulties; question difficulty, individual abilities, and the student's overall state must also be considered." P4 added, "A significant challenge is students' susceptibility to external distractions, which impacts their focus on answering questions."

P11 emphasized that assessing students' concentration levels offers valuable insights into their engagement, which aids in evaluating their performance and focus; by considering their state on a given day, teachers can better understand the circumstances surrounding any hesitance to participate or poor scores. Additionally, students' psychological well-being can impact their performance during pre-screening. As P12 pointed out, those with dyslexia may avoid writing and display restlessness, suggesting possible avoidance of participation. P8 added that observing videos or postures can help differentiate between concentration issues and dyslexia, providing further context. This holistic approach allows teachers to assess student needs more effectively and tailor interventions accordingly.

4 Data Collection

As shown in Figure 1, to enable the effective pre-screening of students with dyslexia, we propose using a specialized dyslexia pre-screening application complemented by video recordings taken during the pre-screening test. This approach aims to provide special-ed teachers with comprehensive evidence. During the pre-screening test, we recorded students' body movements, including head and hand. Previous studies have examined handwriting features as indicators for pre-screening students with dyslexia [51, 87]. However, given that students with dyslexia often face challenges related to both reading and writing, particularly when dysgraphia is also present, our strategy involves collecting a variety of interaction data. Our approach is to collect different data, such as the correctness rate, answer time, handwriting processes during reading and word recognition, and time spent on each task. When combined with video data, this additional evidence can help elucidate the reasons behind students' underperformance on specific test tasks.

4.1 Data Collection Set-up

We gathered data from a local school using an automated dyslexia pre-screening tool [37] designed for Chinese (Cantonese) in Traditional Chinese, as no public data are available for dyslexia pre-screening. The data collected includes accuracy rates, response times, handwriting processes, and videos of students engaging with the touchscreen.

Participants and Apparatus. In this data visualization system, we randomly selected 14 students' data (5 females and 9 males) aged from 6 to 8 years old ($\bar{M}$= 7.87-year-old, σ= 0.61-year-old) from a local primary school in Hong Kong. Four students were diagnosed with dyslexia, while ten students were non-dyslexia. To participate in this study, students needed to meet the following criteria: (1) be in grades 1 or 2; (2) be able to read and write Traditional Chinese characters and speak Cantonese; and (3) have no medical or physical disabilities that could affect their handwriting and reading aloud skills. Additionally, all students were familiar with using tablets. We obtained informed consent from the parents prior to beginning the experiment. Participation was completely voluntary and contingent on consent. The University's Institutional Review Board (IRB) approved the experimental protocol. The preliminary study took place in a classroom setting.

Furthermore, we sanitized and cleaned all tablets prior to testing. As shown in Figs. 2, (a) and (b), three cameras were used for the video recordings in a classroom. Two Olympus E-M-10 cameras were in front of and at the back of the classroom. One Insta 360 camera was put in the middle of the classroom. This setting could capture all students' front and back views. To ensure high-quality input, we assigned at least one instructor to provide immediate support for every two students. However, the instructors did not provide any hints to the students on the pre-screening tests.

Procedure. We set the classroom before the pre-screening tests (Figure 2, b). After being seated, we turned on the camera and said, "Start". Students could press the "start" button to initiate the pre-screening test. Students played an instructional demo game to learn each question type. Students could complete the pre-screening test at their own pace within 30 minutes.

4.2 Collected Data

Table 2 shows the basic statistics of the collected data: video, data outputs, and test data.

Video Data. In the pre-screening recordings, we collected 48 videos with 24 FPS (Olympus E-M-10 cameras) and 30 FPS (Insta 360 camera) with 960 x 540 resolution. The videos lasted 15 to 24 minutes, as some students finished earlier.

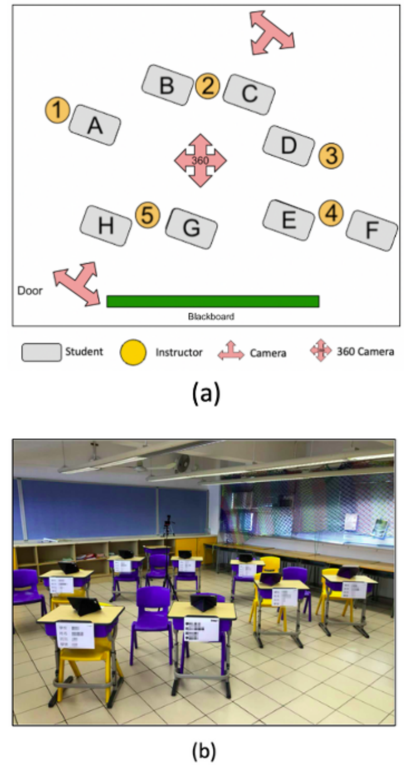

Figure 2: (a) The seating plan of the video recordings. (b) The classroom setting during recordings.

Table 2: Statistics of collected data for 14 student participants.

Number of Participants	14
Number of Confirmed Cases of Dyslexia	4
Number of Students without Dyslexia	10
Number of Videos	48
Number of Videos (Cut)	278
Length of Videos:	2h 4m 44s
Number of Test Data	3,786
Word Recognition	1,595
Reading Data	396
Handwriting Data	1,795

Data Outputs. We drew the humanoid posture using Adobe Illustrator, exported it as SVG, and converted SVG to HTML. We used open poses to output video data points. After post-processing the videos, we cut one sub-question per video. We then calculated the SDs and displayed the top 10 postures with substantial movement. The threshold value compared all pre-screening test students. Teachers were able to adjust the threshold slider. We also outputted the videos with posture denotes and blurred students' faces to preserve their anonymity.

Test Data. The game prototype logged all interactions of students during the pre-screening test, including the running time (i.e., time to press "start" button and time to press "exit" button), interaction with the touchscreen on iPads (i.e., start time and end time of each click on the screen), handwriting images (i.e., each writing path and writing grid size), and game answer inputs (i.e., true, false, and null (participants who did not answer the sub-question)).

5 *DysVis* System

In this section, we introduce the system design and details of our visualization system for pre-screening students with dyslexia.

Procedure. We co-designed the system with several iterations. In each iteration, we collaborated with special-ed teachers through the following process. First, we obtained participants' consent to record the entire co-design process. Next, we comprehensively explained the study's scope, design objectives, and functionalities to ensure participants understood how to interact with the system. Following this, we asked them to freely explore the system for 30 minutes, where they could modify the design. Finally, we conducted interviews (Appendix C and D) to solicit their feedback on potential modifications of the design, including additions, deletions, or adjustments of the user-interface designs and functions based on their interactions.

Interview and Analysis. We recorded the interviews and the modifications made by the participants and took detailed notes on the participants' suggestions. The first author transcribed all interviews, performed the initial coding to generate preliminary codes, and then discussed the codes with another author in the group and refined them.

5.1 System Overview

We designed *DysVis* to fulfill the design requirements discussed in Section 5. Figure 3 shows a screenshot of the user interface. *DysVis* consists of four panels: the student overview panel, which allows teachers to overview students' performance for comparison purposes, the task overview panel allowing teachers to quickly identify tasks requiring further investigation, the sub-question panel, which addresses teachers' needs by presenting various student data for each sub-question, the student behaviour panel helps teachers gather evidence of dyslexia characteristics.

5.2 Student Overview Panel (DR1)

Panel 1 (Figure 3, 1) allows teachers to narrow down students from mass to specific **(DR1)**. The panel offers teachers a summary of pre-screening performance in *overview*, *word recognition*, *writing*, and *reading*. Teachers can filter student records by selecting from four learning difficulty levels: $0 = Severe \leq 25\%$, $25\% < Moderate \leq 50\%$, $50\% < Mild \leq 75\%$ and $75\% < Acceptable \leq 100\%$. A bar chart with gradient colour-enhanced contrast helps teachers quickly identify students needing attention. Additionally, the average score of all students is annotated by a red line, enabling teachers to compare a student's performance to that of the average student.

5.3 Task Overview Panel (DR2)

Panel 2 (Figure 3, 2) allows teachers to analyze student performance and quickly identify which testing tasks warrant further investigation **(DR2)**. The panel displays a student's overall and sub-task scores. Teachers can filter student records by selecting from four learning difficulty levels: $0 = Severe \leq 25\%$, $25\% < Moderate \leq 50\%$, $50\% < Mild \leq 75\%$ and $75\% < Acceptable \leq 100\%$. *Word Recognition* includes six question types: (1) Stroke Addition, (2) Confusion of Similar Sound and Font, (3) Similar Word and Vocabulary Formation, (4) Vocabulary Meaning Paring, (5) Morphological Awareness, and (6) Word Meaning Confusion. *Writing* includes four question types: (1) Word Formation, (2) Stroke Concept, (3) Word Dictation, and (4) Space Concept. *Reading* includes three question types: (1) Confusion of Same Pronunciation Characters, (2) Phonetic Matching, and (3) Word Pronunciation Leads to Confusion. This panel also indicates how much a student needs to catch up to each task's average performance, total questions, correct questions, and a red warning phrase for below-threshold performance.

5.4 Sub-question Panel (DR3)

Panel 3 (Figure 3, 3) enables teachers to examine sub-questions in each category and observe students' handwriting using animation **(DR3)**. The panel focuses on teachers' needs by providing student data for each sub-question. The panel includes game UIs (Panel 3.2), accuracy rates (correct, incorrect, and unanswered), time consumption on each student's sub-questions, average time consumed on all sub-questions within the same task, and the average time all students consumed on a particular sub-question. Additionally, we created a new handwriting animation that allows the playback of the handwriting process (Panel 3.1). We collected input data on handwriting animation and displayed it in SVG and HTML. The animation records students' real-time writing performance, which allows special-ed teachers to understand students' spacing issues and eye-hand coordination. A red colour frame indicates the writing border. When teachers press the handwriting image under *Writing Performance*, a handwriting animation enlarges, and the animation is auto-played. Teachers can press the animation to stop or replay.

5.5 Student Behaviour Panel (DR4)

Panel 4 (Figure 3, 4) allows teachers to examine how students approach specific sub-problems, including their behaviour, posture, and handwriting or speaking abilities, to ascertain the underlying reasons for their difficulties in those areas **(DR4)**. The panel is designed to reduce special-ed teachers' time to review the detailed performance of at-risk students with dyslexia. Panel 4.1 shows the static handwriting stroke display. Panel 4.2 demonstrates the timeline of students answering a sub-question with green for dwell time and blue for writing time. We transformed the screen interaction data and calculated the difference between the start and end times.

A key point pose diagram demonstrating students' movement data is illustrated in Panel 4.3. OpenPose AI model [15] processes student actions, emphasizing the diagram's heads, arms, and hands. Hovering over and clicking on the diagram shows the video recording of the student's movements in Panel 4.4.

Iteration process. As shown in Figure 4, Panel 4 underwent **three rounds of iterations**. Figure 4, (1) depicts the **first design**.

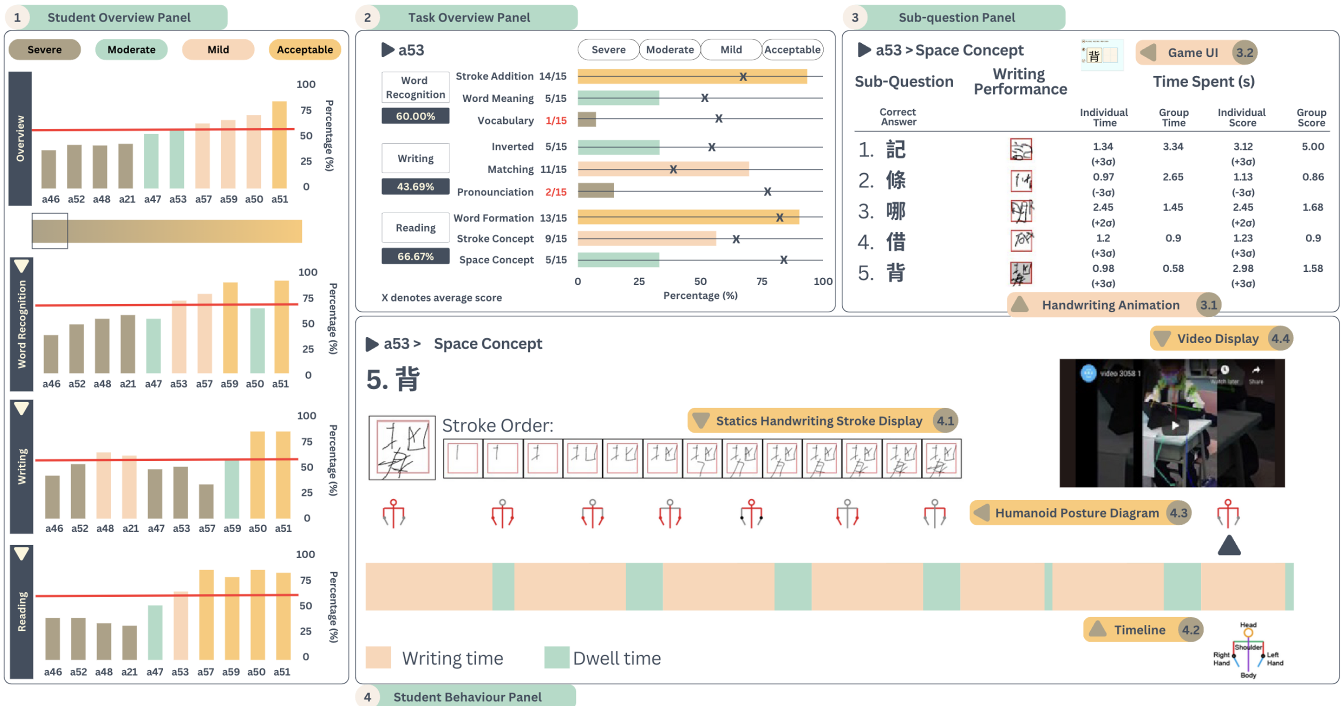

Figure 3: The user interface of the *DysVis* system for dyslexia pre-screening. The translation of Traditional Chinese characters: Appendix E.

Area A shows the static handwriting stroke display. *Area B* shows students answering a sub-question timeline. The line charts (circled in red colour) demonstrated the visualization of the movement data and the comparison between individual and average movement. *Area C* displayed the full video recording of the student movement.

All teachers appreciated the visualization of the static handwriting stroke display in *Area A*. P8 mentioned, *"It is very good. The teacher can see the strokes one by one."* P4 added, *"Stroke order is very important in writing Chinese characters. I can replay and watch the entire group of writing performance"* P15 further explained, *"I can understand students' thinking process and know how each stroke is written, especially the writing direction."* P17 indicated, *"In a large class, teachers have no time to understand students' writing. So, this is very useful for teachers."* P19 mentioned, *"I can know where students make mistakes. So,* DysVis *can also assist in teaching. For example, I can point out common problems to students in class."*

Regarding *Area B*, some teachers agreed that the line could provide more information about students' performance and save them time watching the entire video. P12 mentioned, *"The line charts allow me to compare students' performance. It can save my time. I will first look for fluctuations, then look for flat lines, and compare the two. I especially look at what happens when the fluctuations begin."* P8 added, "I want to want more with a large amplitude. It is good to pop videos automatically, which will save time. It makes it easier for teachers to look at a chart. However, if you can add a red line to indicate the video progress, it will be more convenient." However, special-ed teachers found that the line chart was considered complicated. P8 explained, *"The video makes it easier to understand the situation of the students. However, the line charts are somewhat complicated. The green one is a bit better."* P11 added further, *"P11: This line needs to change a lot to be noticeable."* Some teachers suggested displaying videos, handwriting, and timelines simultaneously. P8 explained, *"If the videos, handwriting, and timeline can be seen at the same time, we can know more clearly the students' learning results and writing status."* P23 further clarified, *"P23: It would be better if both the stroke order and the video could be shown. Because students may look left and right in the middle of writing, now there is a line, and I cannot estimate what students were present at that time. That is fine if I can press it and see that moment."*

Inspired by the participants, we devised a **second iteration**, as shown in Figure 4, (2). Our new design separated the timeline and simultaneously displayed short videos, writing, and movement for a clearer view of students' learning and writing status. *Area D* shows a timeline of answering the sub-questions, with green for dwell time and blue for writing time. In *Area E*, skeletal images were shown to visualize students' movement. The red colour indicated a more vigorous movement, while grey was less. The benchmark was based on students' self-comparison. Teachers could see that moment when they hovered over the skeletal images in *Area D*. Special-ed teachers generally mentioned that the timeline was useful as it gave them more information on students' task completion patterns. P14 told us, *"Because the pause time was long, I clicked in to watch. I mainly look to see if students get distracted because they cannot do it, and then the pauses get longer."* However, some teachers mentioned that skeletal images in *Area E* were not intuitive. They needed a longer time to understand how it worked. P17 told us, *"I could not*

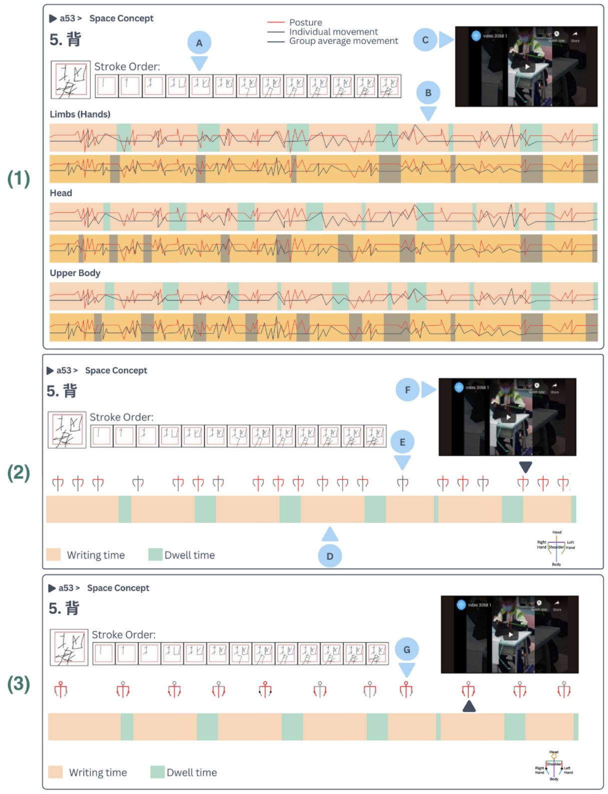

Figure 4: The three-iteration process of Panel 4 – *Student Behaviour Panel.* (1) The x-axis represents the timeline, while the y-axis indicates the range of movement. For the limbs, the horizontal axis is set to zero, with upward movements considered positive and downward movements considered negative. The midpoint is zero for the head and upper body, with movements to the left as negative and movements to the right as positive. The translation of Traditional Chinese characters: Appendix E.

understand it when I first used it. I have been using it for a while, and I think it is okay." P19 explained further, *"When I first looked at it, I thought it was the Chinese character for* towel, 巾. *I do not feel like this is a skeletal image. A humanoid design would be appropriate and intuitive, such as a head, hands, body, and neck."*

Most participants agreed that the timeline provided objective information. They also understood how the skeletal images worked. However, they preferred a more intuitive posture design than the current design, such as emphasizing heads, arms, and hands. Inspired by the participants, we devised a **third design**, highlighting the skeletal images' iteration. As shown in Figure 4, (3), we designed a keypoint pose diagram with a humanoid design (Area G). The diagram consisted of a head with eyes and a mouth, a neck, two shoulders, two upper/lower arms, two palms, and a body. The red colour indicated a more vigorous movement, while white was less. The benchmark was based on students' self-comparison.

6 Evaluation

We utilize three methods to evaluate the effectiveness of *DysVis*, including user scenarios, user study, and interview.

6.1 Usage Scenarios

This section presents two usage scenarios to illustrate how the proposed data visualization system enhances the pre-screening process for teachers assessing students with dyslexia.

6.1.1 Scenario 1: A Confirmed Case. In this scenario, we outlined the entire workflow for identifying a confirmed case of a student with dyslexia by observing the performance of different pre-screening categories.

First, we analyzed Panel 1 to classify students based on their performance. Next, we examined the overview session to identify below-average students. A046 was found to be below average in all three categories, as shown in Figure 5 (a) **(DR1)**. To assess whether this student had dyslexia, we pinpointed specific underperforming tasks, such as incorrect stroke orders (Figure 5, c) and confusion with similarly shaped words (Figure 5, d) in Panel 2 **(DR2)**. We selected the Similar Word and Vocabulary Formation to determine which sub-question to investigate. A046 answered all questions incorrectly in a relatively short time **(DR3)**, prompting us to explore whether A046's challenges stemmed from dyslexia or distractions. To further verify this, we examined A046's movements while answering the sub-questions in Panel 4 **(DR4)**. A046 exhibited significant head and body movement, a common characteristic of students with dyslexia. Video observations confirmed that A046 was attentive during the pre-screening session but rushed to submit answers without thoughtful consideration.

Next, we clicked on the Word Dictation bar, as A046 received a zero score in this sub-category **(DR2)**. A046 incorrectly dictated all words **(DR3)** Figure 5, b) and appeared to be copying rather than dictating. We investigated further, noting that A046's dwell time significantly exceeded writing time **(DR4)**. This suggests that A046 spent little time contemplating the dictation tasks instead of copying words stroke by stroke, indicating dyslexia. Ultimately, we believe that A046 has experienced challenges in both the Word Recognition and Writing categories, aligning with characteristics of dyslexia in our data visualization system. This scenario illustrated how *DysVis* effectively aids teachers in pre-screening students for dyslexia while providing comprehensive evidence to validate confirmed cases.

6.1.2 Scenario 2: A Marginal Case. This scenario presented a marginal case identified through a detailed movement and handwriting performance analysis. The overview revealed that A053 had just met the average performance level (Figure 5, a). However, A053's writing performance was found to be below average. In comparison to other sub-questions, A053 demonstrated moderate skills in Stroke Concept and Space Concept but struggled severely in Word Dictation (Panel 2) **(DR2)**. In the Stroke Concept section (Panel 3), A053 successfully wrote most of the components **(DR3)** (Fig 6, a). However, upon reviewing the video, we noticed that A053's dwell time (Fig 6, b) was relatively long, accompanied by noticeable movement **(DR4)**. In the Space Concept, A053's performance in Group 2 writing was notably better than in Group 1 **(DR3)**. Panel

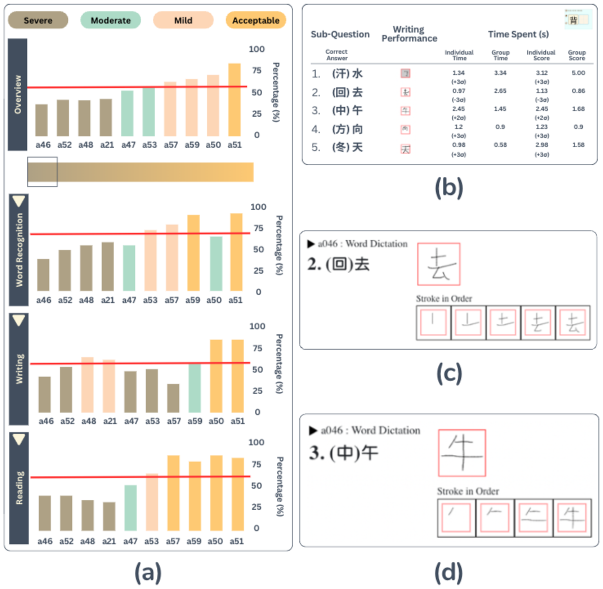

Figure 5: A046's overall performance was below average, and A046 struggled to dictate words correctly, often copying them inaccurately. (a) A046's pre-screening results in all three categories were below average. (b) A046 incorrectly dictated all words and spent excessive time on the Word Dictation task. (c) A046 demonstrated incorrect stroke orders. (d) A046 also confused words with similar shapes. The translation of Traditional Chinese characters: Appendix E.

4 shows that A053's dwell time exceeded the writing time **(DR4)**, and A053's movements while writing Group 1 were more vigorous than those in Group 2 (Figs 6 c and d). This raised questions about whether the sudden change in performance was related to learning proficiency or potential dyslexia issues. A053 could not dictate any word correctly **(DR3)**. A053 either dictated a wrong word or copied the given word once. Also, the dwell time was relatively longer than the writing time **(DR4)**, which reflected A053's weak memory retrieval ability. Thus, we may consider this a marginal case and forward A053 to special-ed teachers for further assessment.

6.2 User Study

A user study was conducted to evaluate the efficiency and effectiveness of our approach in identifying and confirming potential cases of dyslexia.

Datasets and Tasks. Our user study involved 14 students (the detail was discussed in Section 4), utilizing a dataset comprising video clips and performance data from four students with dyslexia, one marginal case, and nine without dyslexia. The dataset included over 10,000 data points across word recognition, writing, reading, video recordings, and posture analysis. *Task 1* is to screen students with dyslexia. *Task 2* is to identify the UserID of those students with dyslexia. *Task 3* is to find out which students are underperforming, not because of dyslexia. *Task 4* refers to the factors teachers consider when special-ed teachers judge those students with dyslexia.

Interview. Our user study employed purposive sampling to recruit 17 special-ed teachers (P8 – P9, P11 – P26; Age: 20 – 55; 14 females). They reported an average age of 8.26 in special-ed (SD=9.22, MAX=30, MIN=1). All participants either had a professional diploma or a special-education bachelor's degree. We conducted 1.5-hour evaluations with participants individually over Zoom. The process involved introductions, consent for anonymous data use, instructions on *DysVis* features, 20 minutes of *DysVis* exploration, a user experience interview, and a usability/effectiveness questionnaire (Appendix C). The first author transcribed all the content and collaborated with another author to perform a thematic analysis. The first author performed the initial coding to develop preliminary codes. Subsequently, two rounds of discussions were conducted to group and refine these codes, ensuring a comprehensive understanding of the feedback received.

Based on the user-centered design process, we interviewed special-ed teachers regarding usability, learnability, effectiveness, data sources, visualization types, and functionality [80]. The questionnaires are shown in Appendix D. The interview questions focused on understanding the usability and effectiveness of the *DysVis* system for dyslexia pre-screening. Teachers were asked to evaluate the ease of understanding and learning for each panel, identify the most and least useful panels and justify their choices, assess the sufficiency of the provided data and suggest additional data points, provide feedback on the system's layout, and propose additional features to enhance *DysVis*'s functionality.

The questionnaire (Appendix C) used a five-point scale (1=most negative, 5=most positive) to evaluate *DysVis*'s usability (part one) and effectiveness (part two).

6.2.1 Results. We asked participants to perform four tasks sequentially in our user study. They are: *Task 1* is to screen students with dyslexia, *Task 2* is to identify the UserID of those students with dyslexia, *Task 3* is to find which students are underperforming, not because of dyslexia and *Task 4* refers to the factors teachers consider when special-ed teachers judge students with dyslexia.

Results of Task 1 and Task 2. Eight teachers selected a different number of students with dyslexia (Figure 7), from a "not sure" case to six "confirmed" cases. This variation stemmed from the differing focus on dyslexia symptoms. Some teachers prioritized video observation to ensure student attention during pre-screening. In contrast, others relied more heavily on handwriting or overview results. Eight participants (P8, P11-12, P15, P21-22, P24-25) identified students at-risk for dyslexia based on their experience. They first checked the students' handwriting and compared their writing between sets. In addition, they also checked the movement of students while writing characters. P11 told us: "If the student's writing is particularly substandard, it may be due to other factors. This is because his dictation score is higher than the average score. Although there was a little movement in the video, his overall performance is quite stable." The other nine participants utilized our system to identify at-risk students with dyslexia. They pre-screened at-risk students with dyslexia based on the red line (average score). They paid attention to those cases that were below average or borderline among different categories. For example, P9 viewed the overview in Panel 1 and dug deeper into the reading category and the relevant performance of the task.

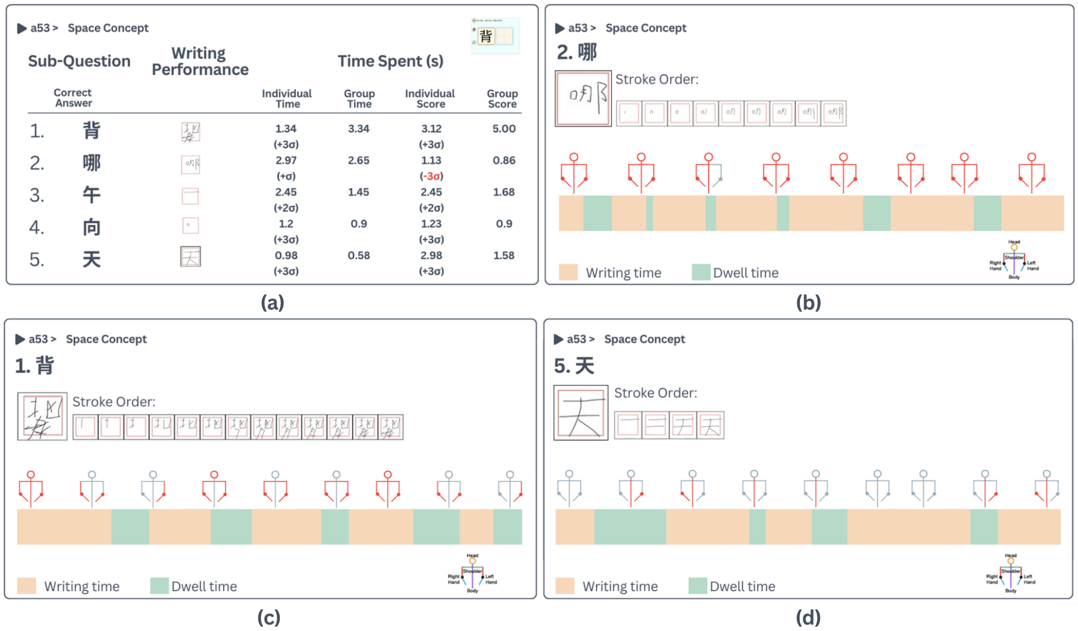

Figure 6: The writing and posture performance of A053. (a) In the Stroke Concept from Panel 3, A053 could write most components. (b) A053's dwell time was relatively longer than writing time. (c) A053 had less vigorous movements when writing Group 2's Chinese characters. (d) A053 had less vigorous movements when writing Group 2's Chinese characters. The translation of Traditional Chinese characters: Appendix E.

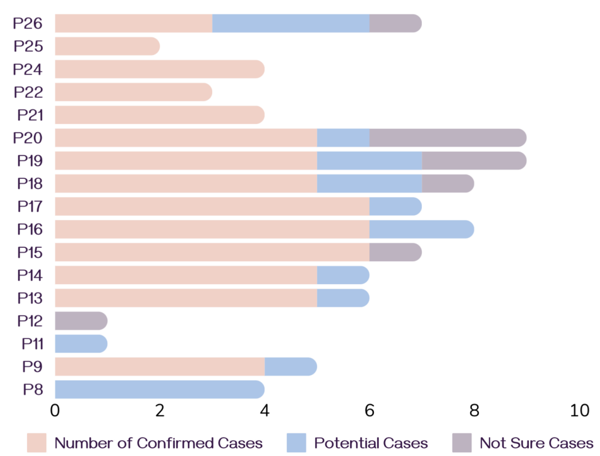

Figure 7: The special-ed teachers screened out different numbers of students with dyslexia. The x-axis represents the total number of cases found, while the y-axis indicates the number of teachers participating in the evaluation.

Results of Task 3. Teachers had various interpretations of student performance. For example, P8 questioned a student's potential diagnosis of dyslexia based on inconsistent writing and dictation skills, stating, "A057's writing is particularly substandard. However, A057's dictation is above average." Meanwhile, P11 and P24 emphasized that writing speed and occasional errors alone should not be considered conclusive indicators of dyslexia.

Results of Task 4. Participants primarily assessed students based on writing and reading performance, focusing on writing speed, adherence to writing grids, and stroke formation. For example, P8 and P21 noted that difficulty writing within the lines and slow writing speed were indicators of dyslexia. P22, on the other hand, focused on student behaviour observed in the videos, noting that "weaker students have a larger movement range".

6.3 Special-ed Teachers' Interviews

A small-scale study [73] using questionnaires and interviews evaluated *DysVis*'s ease of use and support for accurate decision-making for special-ed teachers. The following section summarizes their feedback. Overall, the vast majority of respondents (15 out of 17) found the information provided by *DysVis* sufficient for identifying students at-risk for dyslexia. Teachers highly valued *DysVis*'s handwriting analysis feature and praised its ability to provide in-depth information crucial for supporting students' literacy development.

User-friendly design and one-click access to essential information for dyslexia pre-screening. *DysVis* was well-received for its ease of use, with most respondents (13 out of 17) finding the visualization easy to understand, especially Panels 1-3. The "one-click" access to inter-related information was particularly appreciated. However, some users suggested dividing the content into separate pages for smoother navigation. While Panels 1-3 were generally praised for their clarity, Panels 2 and 3 were perceived as overwhelming by some users due to the density of information presented. Suggestions included incorporating visual cues like icons, labels, and colour-coding to enhance navigation and highlight key information. Panel 4 received specific feedback regarding the timeline and keypoint pose diagram, with suggestions for simplification and resizing to reduce visual overload (P8, P11, P16, P21), which could enhance user interaction with the system [22]. The questionnaire, adapted from a study by Li et al. [55], assessed the usability and effectiveness of *DysVis* from the perspective of special-ed teachers. A standard 5-point Likert scale was used, with higher scores indicating stronger agreement with positive statements about the system's usability and effectiveness. *DysVis* received positive feedback on usability, with an initial ease of use rating of 3.24 (SD = 1.03) that increased to 4.12 (SD = 0.70) after guidance.

Handwriting animation and stroke order visualization enhance teachers' understanding of students' writing behaviours. Teachers found that *DysVis*'s handwriting analysis feature is valuable for identifying potential dyslexia indicators and informing targeted instruction. The dynamic visualization of stroke sequences offered insights into student thinking and writing difficulties, as highlighted in previous research [31, 37]. As one teacher mentioned, "It is useful to show how to write because they can see the stroke order of students' writing" (P17). Respondents appreciated the ability to replay the writing process, which revealed important information about challenges faced by students. For instance, P20 expressed a desire to understand gestures that may lead to poor performance. At the same time, P8 observed, "I can spot students' minor actions, like shaking their bodies during tasks." Previous research indicated that students with dyslexia exhibit greater body movement than their peers [8].

7 Discussion

Building on research highlighting the benefits of typing interventions for students with dyslexia [89]. The need for theory-driven insights for educators [54], we developed *DysVis*, a user-centered system for special-ed teachers. Informed by research on self-regulated learning [96], our system incorporates student behavioural data and teacher feedback. While existing research on learning analytics feedback emphasizes the need for context-aware design, practical support for interpretation, and a deeper understanding of its impact on learners [88], *DysVis* addresses these gaps by systematically incorporating user feedback throughout its development. The following sections detail these design choices and user feedback.

DysVis's handwriting animation feature enhances dyslexia identification and literacy outcomes through insights into stroke order and student thought processes. The handwriting animation feature, praised for its potential to improve learning outcomes, offers several key advantages: (1) insights into stroke order, crucial for identifying dyslexia; (2) understanding student thought processes during writing; (3) pinpointing areas for targeted instruction; (4) efficient analysis of multiple students' writing; and (5) evidence-based support for literacy development [6, 39]. This versatile feature, applicable across languages, empowers educators to effectively address writing challenges and promote literacy, particularly for students with dyslexia. By illustrating the intricacies of handwriting, *DysVis* enhances teachers' pre-screening capabilities and fosters a deeper understanding of student learning behaviours, ultimately enabling more personalized and effective interventions. The human-centric design of *DysVis* emphasizes the importance of aligning educational technology with educators' needs, enhancing usability and effectiveness. Insights from special-ed teachers informed its development, providing a framework for future UI/UX practitioners to create supportive tools for educators and learners. Using data visualization techniques, *DysVis* enables teachers to make informed, data-driven decisions for more effective interventions for students at-risk of dyslexia. Its adaptable design principles pave the way for future educational tools to address a broader range of learning challenges, fostering inclusivity. Future research could integrate machine learning algorithms to improve predictive capabilities, aiding educators in accurately identifying at-risk students. This collaborative, user-centered approach can inspire innovative solutions that cater to the diverse needs of learners and educators.

An intuitive design and user-centered approach. A user-friendly interface is essential for effective system use [18]. In *DysVis*, we implemented gradient-coloured bar charts in Panels 1 and 2 to facilitate quick identification of dyslexia [12]. Panel 3 features a table and handwriting animation for comprehensive evaluation, allowing educators to visualize student performance dynamically. Enhancing the keypoint pose diagram by incorporating facial expressions, standardizing posture accuracy, and integrating multiple modalities will further support special-ed teachers in pre-screening dyslexia and assisting students [29]. This multi-faceted approach improves usability and enriches the data available to educators, enabling them to make more informed, nuanced decisions in their interventions. The user-centered design prioritizes teacher involvement in developing educational tools, vital for improving user experience and fostering knowledge creation [43]. Teachers provide essential insights into their needs, preferences, and challenges [71]. While current systems for students with dyslexia offer high-level statistics, teachers require explanations for difficulties and support strategies. Therefore, the design of *DysVis* incorporates a user-centered approach, actively involving end-users in the development process. This collaboration ensures that the tool meets the practical demands of teachers and empowers them to utilize the system more effectively. By integrating teacher feedback, *DysVis* enhances its relevance and usability, ultimately leading to better support for students with dyslexia and improved educational outcomes. Such an approach underscores the importance of bridging the gap between technology and classroom realities, fostering a more responsive and effective educational environment.

Granularity of studying dyslexia and addressing privacy concerns. Efficient communication is essential for *DysVis*, addressing the needs of special-ed teachers and incorporating their insights. In-depth data analysis enables informed decisions regarding dyslexia risk. At the same time, the design emphasizes credibility and questions validity based on student performance [93]. By providing optimal information, including question types and detailed data, we have enhanced dyslexia pre-screening and support. This user-centered approach establishes a foundation for future tailored tools for special-ed teachers. Teachers recommended using close-up videos to record students holding pens, as those with dyslexia often struggle with fine motor skills. However, filming faces raises privacy concerns [64]. An alternative is using heat map cameras,

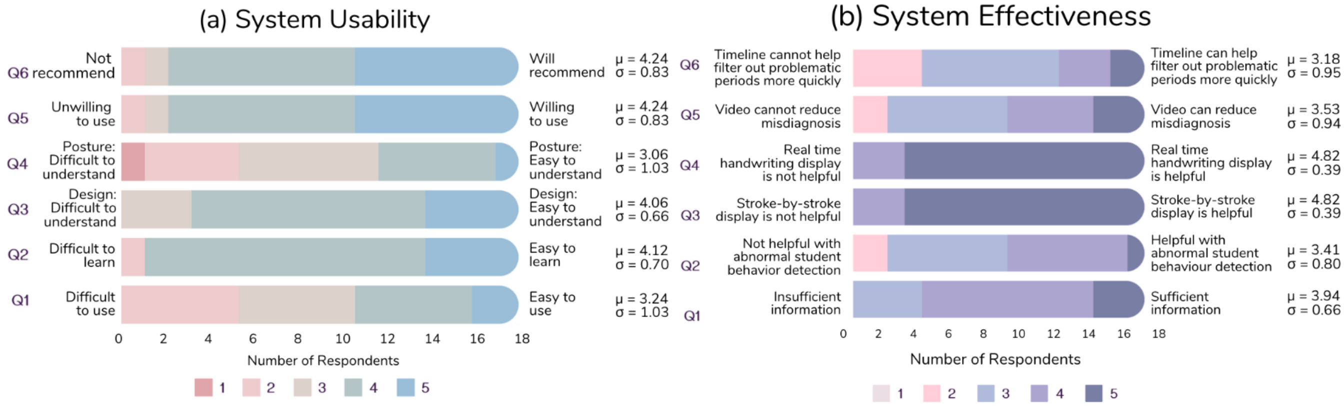

Figure 8: The results of Q1 – Q6 in our System Usability and System Effectiveness questionnaires, respectively. The scale from 1 to 5 represents "the most negative" to "the most positive". The number on each section shows the corresponding score. μ and σ denote the average score and standard deviation, respectively. (a) System Usability. (b) System Effectiveness. The questionnaires are shown in Appendix C.

which capture pen-holding strength with minimal privacy intrusion [26]. However, they tend to be relatively expensive.

Limitations. The study has several challenges, including privacy concerns, time limitations, population size, and resource constraints. To address privacy issues, videos were recorded from behind the students, balancing the need to preserve privacy with the need to facilitate pre-screening for at-risk students with dyslexia.

Regarding time constraints, special-ed teachers were given only 20 minutes to explore the system. Allowing a longer usage period, such as a week, could yield more comprehensive feedback. A responsive design would also enable compatibility with various devices, including computers, iPads, and mobile phones. It is desirable to gather a comprehensive range of data from students diagnosed with dyslexia, which necessitates collaboration with many schools, which is difficult to achieve. As a result, only four students identified as having dyslexia were included in the case study. However, we believe that this limited sample size does not compromise the reliability of our results. The insights gained from these four participants provide valuable information. However, we recognize the importance of a larger sample and plan to recruit additional cases of dyslexia to enhance the depth and validity of our study.

The dashboard was designed to function without a camera to tackle resource limitations, as Panels 1-3 provided sufficient evidence for dyslexia identification. Furthermore, Hong Kong's one-person-one-iPad initiative ensures that most schools have tablets available, allowing tablet cameras to capture handwriting, posture, and facial expressions during pre-screening assessments.

Moreover, students with dyslexia often encounter word recognition, writing, and reading challenges. A combination of evidence is necessary to effectively pre-screen at-risk students. Our work offers special-ed teachers a comprehensive assessment that evaluates multiple aspects of student performance rather than focusing solely on individual symptoms. We will assess how different system components influence user experience and outcomes in the upcoming stage.

8 Conclusion and Future Works

This paper proposes a user-centered system for teachers to pre-screen students with dyslexia in Traditional Chinese and Cantonese contexts. This visualization system transforms dyslexia pre-screening by integrating diverse data sources, such as handwriting performance, video, and posture detection, and offering user-friendly features for special-ed teachers. By prioritizing educators' input, the user-centered approach effectively addresses their needs and ensures tailored tools. This system advances dyslexia pre-screening by balancing comprehensive data assessment with privacy protection.

In Panel 3, we propose enhancing the current system by providing a concise report to special-ed teachers regarding students' writing symptoms, such as stroke addition and deletion. However, additional data is required to ensure the generalizability of our findings. Therefore, we plan to recruit more users to facilitate broader applications and gather further data for comprehensive analysis.

In Panel 4, we propose to expand our focus on gesture analysis to explore the relationship between writing symptoms and behaviours in relation to changes in gesture. However, to enable a thorough analysis, additional data is essential. Consequently, we plan to recruit more users to participate in various study sections to gather further data for a comprehensive evaluation.

Furthermore, *DysVis* will be expanded to analyze students' strengths and weaknesses, particularly in Chinese language subjects. It will provide a thorough understanding of students' reading and writing performance. Additionally, *DysVis* will be a valuable resource for educators to create customized training content for diverse learners. By offering insights into students' language competencies at the start of the academic year, *DysVis* will benefit native and non-native Chinese speakers.

Acknowledgments

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A Survey of Formative Study (Section 3)

(1) Do you have experience using dyslexia screening tools or assessments? If you answer "Yes", please proceed to questions (2) – (6).
(2) What is the procedure of pre-screening in schools?
(3) What kind of indicators would you pay attention to?
(4) Please describe your experience using dyslexia screening tools or assessments.
(5) In what ways do you find them helpful or challenging?
(6) What information or data do you find most useful?

B Interviews of Formative Study (Section 3)

(1) What factors do you think are effective in assessing dyslexia?
(2) How many categories of pre-screening performance should the system have to help you understand students' performance effectively? Why?
(3) What charts would help you quickly identify students with dyslexia?
(4) When you suspect that some students have dyslexia, how will you conduct assessments/quick tests for the students?
(5) What kinds of functions can help you quickly spot students with dyslexia? Why?
(6) When you see a report of a student with dyslexia, what part of the student's performance do you want to know? Why?
(7) Is it necessary to know the time required for students to answer the questions? Why? (If you answered "Yes", please proceed to questions 8–10. If you answer "No", please proceed to Question 11.)
(8) Is comparing the time required for the same students to answer similar questions necessary? Why?
(9) Is there a need to compare a student's required answer time across entire test cohorts? Why?
(10) Regarding the time required to answer the question, what method of expression do you think is more suitable for you?
(11) When a student completes a question, would you like to know the details of the student's answer? Why?
(12) What details would you like to know? Why?
(13) Do you have any suggestions for the design of the system?

C Questionnaires of Formal Study (Section 6)

- System Usability
  (1) This system is very easy to use.
  (2) This system is easy to learn how to use.
  (3) The visual design of *DysVis* is easy to understand.
  (4) The posture part in *DysVis* is easy to understand.
  (5) I am very willing to use this system to pre-screen students with dyslexia.
  (6) I would recommend this system to other special-ed teachers.
- System Effectiveness
  (1) The visual design of *DysVis* provides enough information to find students with potential dyslexia.
  (2) Posture can help teachers detect abnormal student behaviour (laziness/distraction).
  (3) Handwriting is displayed stroke-by-stroke to tell me which strokes a student writes poorly.
  (4) Handwriting lets me know how my students write in real-time.
  (5) Videos can reduce the chances of mis-pre-screening students with dyslexia more than traditional methods.
  (6) The timeline prominently marks the spacing between students' writing and pauses, which can help me filter out difficult periods more quickly.

D Interviews of Formal Study (Section 6)

(1) Student Overview Panel
  (a) Do you understand this panel?
  (b) How do you think the chart helps you quickly spot at-risk students with dyslexia?
  (c) Could categorize students' test performances into four categories more effectively assist you in reviewing their performance? Why?
  (d) How do you think the "classification" feature helps you quickly spot at-risk students with dyslexia?
  (e) How do you think the "increment/decrement" features help you quickly spot at-risk students with dyslexia?
  (f) What additional features would you like to see that would make it easier for you to review students' performance?
  (g) Do you have any other design suggestions?
(2) Task Overview Panel
  (a) Do you understand this panel?
  (b) Do you think the data on the panel can effectively assess dyslexia?
  (c) How do you think this chart can assist you in quickly identifying
  (d) students with dyslexia?
  (e) What additional features would you like to include to help analyze students' learning difficulties?
  (f) Do you have any other design suggestions?
(3) Sub-question Panel
  (a) Do you understand this panel?
  (b) Is Panel 3 useful for you in determining whether students have
  (c) dyslexia? How can it help you?
  (d) Is the handwriting animation a helpful function for you in determining whether students have dyslexia? How can it help you?
  (e) Do you have any other design suggestions?
(4) Student Behaviour Panel
  (a) Do you understand this panel?
  (b) Is Panel 4 useful for you to determine whether students have dyslexia? How can it help you?
  (c) The chart shows each student's writing time, posture, and answering conditions.
  (d) Do you think these features can help you more easily determine whether a student has dyslexia?
  (e) Is the handwriting sequence display helpful function for you in determining whether students have dyslexia? How can it help you?
  (f) Is the video helpful in determining whether students have dyslexia? How can it help you?
  (g) Do you have any other design suggestions?

(5) Follow-up questions
   (a) Among these students, how many have dyslexia?
   (b) What are their User IDs?
   (c) Which underperforming students are not affected by dyslexia?
   (d) What factors do you use to determine that these students have dyslexia?
   (e) Which part of the student's performance would you like to understand more deeply?
   (f) Which part can indicate whether a student might have dyslexia?
   (g) What content would you like to click into and view?
   (h) What do you think about the current design?
   (i) Are there any features you would like to add?

E Traditional Chinese characters

- Section 2, Figure 1
(1) 背 (Cantonese pronunciation: bui3; English meaning: Back)
(2) 功 (Cantonese pronunciation: gung 1; English meaning: Merit)
- Section 5, Figure 3
(1) 記 (Cantonese pronunciation: gei31; English meaning: Record)
(2) 條 (Cantonese pronunciation: tiu4; English meaning: Regulated)
(3) 哪 (Cantonese pronunciation: naa5; English meaning: Which)
(4) 借 (Cantonese pronunciation: ze3; English meaning: Borrow)
(5) 背 (Cantonese pronunciation: bui3; English meaning: Back)
- Section 5, Figure 4
(1) 背 (Cantonese pronunciation: bui3; English meaning: Back
- Section 6, Figure 5
(1) 汗水 (Cantonese pronunciation: hon4 seoi2; English meaning: Sweat)
(2) 回去 (Cantonese pronunciation: wui4 heoi3; English meaning: Return)
(3) 中午 (Cantonese pronunciation: zung 1 ng5; English meaning: Afternoon)
(4) 方向 (Cantonese pronunciation: fong1 hoeng3; English meaning: Direction)
(5) 冬天 (Cantonese pronunciation: dung1 tin1; English meaning: Winter)
(6) 去 (Cantonese pronunciation: heoi3; English meaning: Go)
(7) 牛 (Cantonese pronunciation: ngau4; English meaning: Cow)
- Section 6, Figure 6
(1) 哪 (Cantonese pronunciation: naa5; English meaning: Which)
(2) 背 (Cantonese pronunciation: bui3; English meaning: Back)
(3) 天 (Cantonese pronunciation: tin1; English meaning: Sky)