The Title of the Paper: Exploring the Impact of Sensory Profile and Environmental Factors on Behaviour and Attention of Children with ASD Using Sensors and Smart Devices

ABSTRACT

Difficulty with sensory processing is commonly observed in individuals with Autism Spectrum Disorder (ASD), which can affect their ability to react appropriately to sensory stimuli. Individuals with ASD also have unique patterns of sensory processing to sense the environment. We collected 21 ASD children's sensory processing patterns using Dunn's Sensory Profile. The impact of these sensory profiles combined with environmental factors was assessed, particularly on behaviour and attention. Each child completed 15 experiment sessions of attentional tasks within two months, while a prototype application was deployed to collect physiological and environmental data. The machine learning-based analysis identified that noise, temperature, humidity, and sensory profile affected children's attention significantly and differently. The performance of the machine learning models shows the feasibility of predicting the behaviour and attention with data collected by the prototype, which provides significant implications for subsequent development of a predictive sensory management application for ASD people.

CCS CONCEPTS • Social and professional topics • User characteristics • People with disabilities

Additional Keywords and Phrases: Autism Spectrum Disorder, Sensory Profile, Machine Learning, Mobile Application

1 INTRODUCTION

Autism Spectrum Disorder (ASD) refers to a group of neurodevelopmental disorders characterised by repetitive and restricted patterns of behaviour and difficulties with social and communication interaction [34]. ASD is a disorder with a high degree of co-morbidity, with more than 70% of individuals with ASD exhibiting one or more co-existing disorders such as social anxiety disorder, intellectual disability, oppositional defiant disorder and attention-deficit/hyperactivity disorder in their lifetime [38]. ASD impacts the whole family, as ASD children can place excessive demands on parents and high stress on the family unit. The core difficulties associated with ASD lead to challenges for parents, and prior research findings have highlighted challenges associated with parental well-being and adjustments [23].

For individuals with ASD, the ability to reflect on their own and other's thoughts and emotions is delayed. Consequently, this has a knock-on effect on their cognitive empathy and alters their perception of the world across their lifespan. As many as 90% of ASD individuals may have experienced atypical sensory responses in audition, vision, touch, taste and smell [28]. The behavioural output of atypical sensory responses in ASD can be very different across individuals, such as appearing to not listen when being spoken to, having difficulty paying attention, and having problems of distractibility and behaviour control [21, 43]. Atypical sensory responses are so idiosyncratic in individuals with ASD which would require highly customised and precise solutions. Capturing ASD individuals' sensation in different environments can provide a lens for understanding factors impacting on their sensory processing, which can further inform the design of technology-based approaches to facilitate their living. Although technologies have been shown to support ASD individuals effectively [45], there are very limited technological solutions focusing specifically on the sensory experiences of an ASD individual in real life [1, 3, 22].

In China, it was estimated that an astonishing number of 14 million children might have been affected by ASD [42]. However, it is believed that a large number of ASD children in China still remained underdiagnosed and unassisted [41]. The medical and caring cost of ASD children were higher than those of children without ASD [46]. The cost of receiving rehabilitation was around 20,000 RMB per person per year for individuals with ASD [46], and the cost of attending an 11-week training session at an ASD rehabilitation institution in Beijing was 6,500 RMB, which are considered to be prohibitively expensive and so mostly unaffordable for a rural family [40]. ASD is also associated with a lack of independence and an increased need for parents to give up employment to look after their children. Therefore, Chinese individuals with ASD have special demands on affordable assistive technologies to support their independent living [11].

The ultimate goal of the research is to create a phone-based system which can assist Chinese individuals with ASD's sensory management in varying environments and thus facilitate better, learning, comfort and wellbeing outcomes. Due to lack of Chinese-ASD specific research data for this exploratory study, we prototypically developed a measurement system using off-the-shelf devices to capture Chinese ASD individuals' responses in different environments. We also adopted a commonly used scale, Dunn's Sensory Profile [13], for sensory profiling. We then conducted a series of experiment sessions with ASD children to collect data for preliminary analyses. The machine learning-based analysis was conducted to explore the impact of sensory profile and environmental factors on children's behavioural and attentional responses.

Following the data analysis was a proposed design of the sensory management recommendation system for Chinese children with ASD.

2 RELATED WORK

2.1 Sensory Profile

Specifically for sensory profiling, Dunn [14] introduced four sensory patterns to describe a person's atypical sensory responses according to the individual's neurological thresholds: low registration, sensation seeking, sensory sensitivity and sensation avoiding. Dunn's model demonstrates a crucial link between neurological thresholds, self-regulation strategies and an individual's behavioural output in daily life (See Figure 1). Low registration and sensation seeking represent a high threshold to sensory experiences. People with low registration may fail to notice or detect changes in sensory events which others can easily detect. Individuals with sensation seeking pattern often act in a seeking manner to extend their sensory experiences. Conversely, sensory sensitivity and sensation avoiding patterns both represent a low threshold to sensory stimuli. People with the sensory sensitivity pattern are likely to be hyper-responsive to sensory stimulation, whilst those who present with the sensation avoiding pattern may go to the other extreme to avoid sensory stimulation.

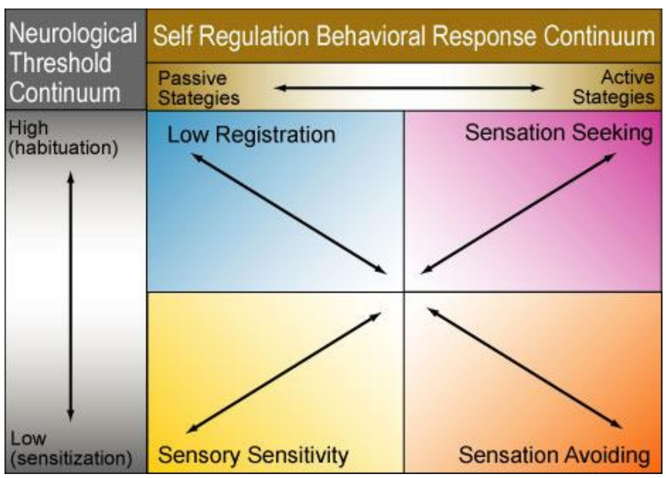


Figure 1: Dunn's model of four sensory profiles

Sensory Profile of Children 3 to 10 Years Caregiver Questionnaire [13] is a standardised test to determine how well the children processed sensory information in everyday situations and to profile their sensory patterns. It is caregivers of ASD children who complete the 125-question profile, reporting the frequency with which their child responds to various sensory experiences. The frequency of behaviours is determined from a Likert scale where an almost always (100% of the time) answer is scored with 1 point, frequently (at least 75% of the time) 2 points, occasionally (50%) 3 points, seldom (25%) 4 points, and almost never (0%) 5 points. Item scores are then interpreted into a classification of the sensory threshold and behavioural continuum (see Figure 2). Scores at the lower end of the scoring continuum indicate that the child displays disproportionately more behaviours for that particular section than most children of similar age. Larger scores are also indicative of a problem as the child displays less behaviours pertaining to that specific quadrant [16]. Figure 2 is an example of the Sensory Profile raw scores and classifications.

		←Less than Others				More than Others→
Quadrants	**Quadrant Raw Score Total**	**Definite Difference**	**Probable Difference**	**Typical Performance**	**Probable Difference**	**Definite Difference**
Registration	49/75	**	75------73	72------64	63-------59	58---X---15
Seeking	77/130	**	130------124	123-----103	102------92	91---X---26
Sensitivity	67/100	**	100------95	94-------81	80------73	72---X---20
Avoiding	102/145	145------141	140------134	133------113	112------103	102---X---29

**There can be no Definite Difference for this quadrant

Figure 2: An example of quadrant raw scores and classifications

2.2 Physiological Measurement

Wearable monitors can be worn on parts of the body, such as wrist (e.g. smart watch), chest, ankles, or head (e.g. headband), to gather information of physiological phenomena and movements [12]. Nowadays, physiological sensors such as heart rate sensors, thermometers and Galvanic Skin Response (GSR) sensors have been widely seen in many wearable monitors for stress detection and intervention in people with ASD. It is believed that when a person experiences stress or is aroused, moisture collects under the skin, changing the electrical conductance and temperature of skin and heart rate, which could be captured by these sensors [9]. For example, Reveal [2] is an application which uses a wearable band to monitor heart rate, body temperature and sweat levels. The user's physiological measurements can be viewed in the application installed on the phone. Caregivers are notified of changes to the user's physiological measurements. Additionally, electroencephalography (EEG) sensors have been used to infer attention level of individuals with ASD [47]. The Muse Headband is a lightweight headband that uses EEG sensors to monitor brain activity, which reflects attention level [20]. It uses seven precisely calibrated EEG sensors, two on the forehead, two behind the ear, and three reference sensors. However, it is noted that wearable monitors need physical contact with the body, which may cause aggressive behaviours for ASD individuals with tactile sensitivity [47].

Non-wearable monitors such as desktop-based eye trackers do not present a problem of physical touch for ASD individuals. Therefore, non-invasive eye trackers have been widely used to detect attention patterns relative to eyes. The iView X RED eye tracker [7] has been tested on individuals with ASD in a dark and isolated environment. Participants were provided with a small video as a visual stimulus and their gaze pattern was tracked by the device. However, such device is expensive and requires calibration for every subject in a laboratory setting. The subject must be facing the camera in order for the tracking to be successful. These problems restrict its application in real life for individuals with ASD [5, 47].

2.3 Environmental Measurement

Constructing explicit environmental conditions according to a person's sensory profile has the potential to support both the sensory responses and temperament [14]. Smart environment has become increasingly popular due to its benefits in making the sensory experiences more convenient, comfortable and secure. Industrial manufacturers and researchers have been working on efficient and affordable sensors to monitor and control lights, temperature, humidity and sound for a room or home [18]. Traditionally, people may use a hand-held sound level meter to measure the sound level in a room. Nowadays, smartphones would be more convenient than traditional devices for sound measurement [33]. For example, NIOSH [15] combines the features of noise dosimeters and high-accuracy sound level meters into a mobile application. The new Apple Watch released in 2019 has added a decibel monitor which allows developers to use the iOS device to detect noise levels [8].

Arduino board is a microcontroller board which has been widely applied in temperature and humidity detection, light level monitoring and controlling [18]. A number of off-the-shelf sensors can be directly interfaced to the board. Arduino board has the features of low cost, secure, ubiquitously accessible, auto-configurable, remotely controlled, making it a suitable platform for developers to create a number of do-it-yourself systems quickly and easily for environment monitoring.

Related work on sensory profiling, physiological and environmental measurements suggests the feasibility of combining several off-the-shelf technologies to obtain comprehensive information for the development of a novel sensory management recommendation system for children with ASD. To this end, we developed a prototype of a measurement application to collect preliminary data for understanding how ASD individuals' sensory profile combined with environmental factors, affect their responses in terms of behaviour and attention.

3 PROTOTYPE DEVELOPMENT AND EXPERIMENT DESIGN

In this research, a measurement application using off-the-shelf sensors, wearables and mobile devices was prototypically developed. We then conducted two experimental studies using the prototype to uncover the potential of this application to support sensory management for children with ASD in China. We firstly conducted a pilot study with few participants to assess the feasibility of the system and then improved the measurement application based on users' feedback from the pilot study. A formal experiment was carried out afterwards with a larger sample in a local special education institution in China. Physiological data and task performance were collected through the use of the prototype from the participants in response to controlled independent variables (i.e. temperature, noise level, and light intensity). These data were further analysed and assessed to understand the impact of a person's sensory pattern and response in relation to the changing environment on the attention and behaviour.

3.1 Development of Prototype

The prototype focuses on 1) environmental factors including light intensity, noise levels, temperature and humidity; 2) user's physiological measurements including heart rate, GSR, and hand movements; and 3) user's attention and stress levels. The prototype has the following parts and functions.

3.1.1 Arduino-Based Sensors

Sensors on Arduino board collect environmental data from external temperature and humidity, GSR, and light sensors. As shown in the Figure 3, from top to bottom the components are: Bluetooth module, temperature and humidity sensor, light sensor, and GSR sensor.

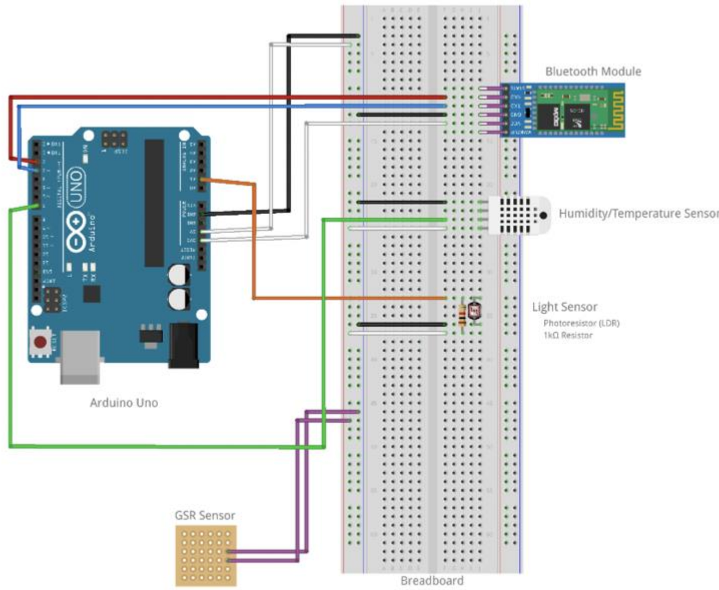


Figure 3: Arduino-based sensors

3.1.2 iPhone-Based Application

The application connects the Arduino-based sensors via Bluetooth and accesses all sensors available on an iPhone and Apple Watch devices to collect both physiological and environmental data (e.g. heart rate, hand movements, noise, and light intensity).The data collected will be visualised in the applications (see Figure 4), from which we are able to view the environmental and physiological changes.

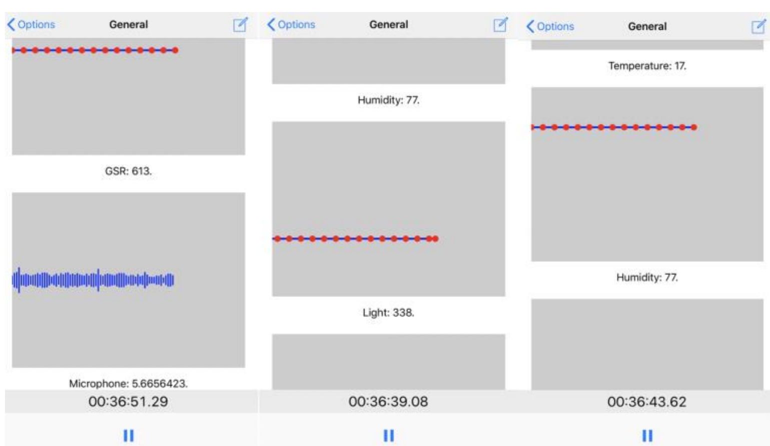


Figure 4: The interface of the measurement application

3.1.3 Attentional Tasks

The cognitive skills of children with ASD are typically affected by high level of stress [31]. To infer the attention and stress level of the participants, physiological sensors as well as attentional tasks were both used for measurement. For this study, three attentional tasks have been designed: Counting Task, Picture Matching Task, and Drawing Task. These tasks were contained in an application software for iOS. The Apple iPad has been used as an electronic platform that is believed to be the more attractive and preferred media in both ASD and non-ASD children [29]. In addition to measuring attention and stress data, the tasks have been designed also for the benefits of the participants, especially to improve memory, cognitive, and motor skills.

A. Counting Task. The counting task assesses the figure cognition and attention aspects, at which ASD children may not be as good as TD children of same age [32]. The task displays a number of apple(s), which the participant would count and select the correct quantity from a list (see Figure 5a).

B. Picture Matching Task. The picture matching task assesses the recognition and matching ability of the participant. This task displays an image on the left-hand side of the screen which the participant needs to match to a matching image from a collection of images on the right-hand side of the screen (see Figure 5b).

C. Drawing Task. In the drawing task, the participant will be presented with five images on the iPad and are required to trace the line in each image by using an Apple Pen (see Figure 5c). This task aims to help improving the eye gaze and motor skill of the participant. The participant's attention is assessed since they need to pay attention on the original line when tracing to get better result.

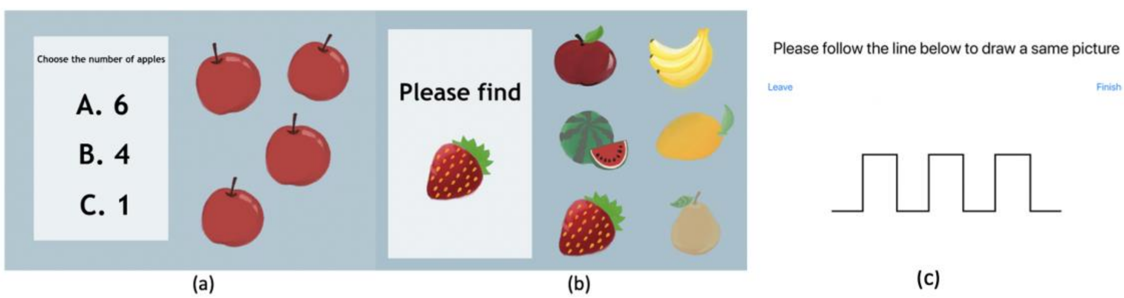


Figure 5: Counting task, picture matching task, and drawing task

Audio instructions were embedded in three tasks so that participants can complete the task as guided by the instruction. For the counting and picture matching task, the participant's choices were recorded, and data were extracted to identify the percentage of errors as an indicator of their performance. In the drawing task, the overlaps between the lines and touch position of the iPad Pen, along with the time required to complete each subtask were used to determine participants' performance.

3.2 Experimental Design

In order to know each participant's sensory responses in different settings, the study used the single subject design. Parents' informed consent and children's Sensory Profile questionnaire answers were obtained prior to the experiment. During the experiment, the prototype was placed in a testing room to record three aspects: environmental, physiological data, and task performance, where the three variables (i.e. light, temperature, and noise level) were controlled. Each of these variables has different settings from levels being low to high.

Each experiment session lasted about fifteen minutes and was divided into four phases. The first phase (first five minutes) was used for coaching three attentional tasks, equipping the device and getting the participant to adjust to experiment condition. Participants were required to wear the GSR sensor and Apple Watch on left wrist unless they used the left hand habitually. The first phase allowed us to help the participant become familiar with the tasks and to make sure that the participant was comfortable with the wearable devices. The next three phases were the actual experiment session. A flowchart for a single experiment session has been provided in the Figure 6. Each phase had time limits of three minutes. The participant should play the task until the completion of the task or the end of the three minutes whichever came first.

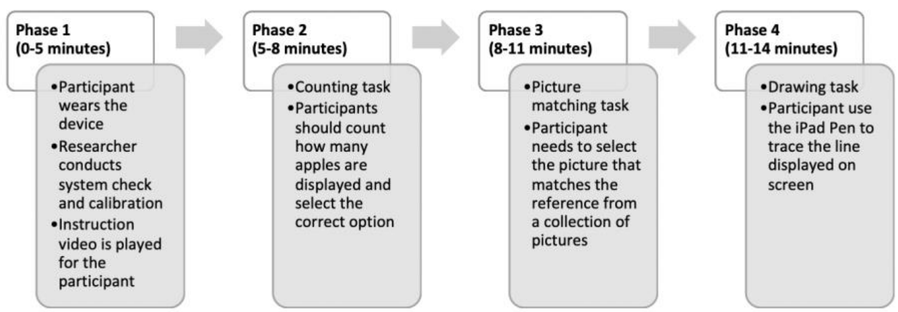


Figure 6: Experiment session flowchart

3.3 Pilot study

In the pilot study, the tolerance of devices, and levels of attention and stress associated with the changing environmental variables were assessed. Four children (all male, aged between 3 and 6) were recruited to complete the pilot study, consisting of one child formally diagnosed with ASD and three non-ASD children. Each participant completed nine experiment sessions within three weeks. A general experiment timeline for four children is shown in Figure 7. During the experiment sessions, two independent healthcare practitioners were asked to observe the participant's performance and rate the child's attention and stress level using 5-Scale Rating (from 1-5, where 1 being very low to 5 being very high) at seven time points as shown in Figure 8. Higher ratings on the attention scale means that the participant focused more on the task, while higher ratings on the stress scale means that the participant was more anxious.

Week	Controlled Variables	Day 1	Day 2	Day 3	Day 4	Day 5
Week 1	Temperature	Low	-	Moderate	-	High
Week 2	Noise	Low	-	Moderate	-	High
Week 3	Light intensity	Low	-	Moderate	-	High

* "-" = no session on the day

Figure 7: Experiment timeline of the pilot study

Time Point	Start of the experiment	Counting		Picture Matching		Drawing	
		Start	Finish	Start	Finish	Start	Finish
Attention Level							
Stress Level							

Figure 8: Healthcare practitioner and caregiver scoring sheet

The pilot study was conducted in a classroom of a local school in Ningbo City. In a classroom setting, environmental variables can be controlled at certain levels by using the air conditioner, white noise generator and lighting system. However, it is noticed that there was some unexpected outside noise because the school was having other classes next to the room during the experiment. The ambient noise level of each experiment was higher than the desired value but still within a reasonable range. Earphones were considered to be used in the subsequent formal experimental study to reduce the potential effect of outside noise.

We observed that the prototype was well tolerated by the participants in the pilot study. According to Figure 9, we found that ASD participant's performance was more variable to the environmental changes than non-ASD participants. Besides, both ASD and non-ASD children's sensory profile may have an impact on their attentional and behavioural changes. For instance, three children (one ASD child and two non-ASD children) performed poorly when the noise level went higher while the other one showed an opposite tendency in performance. This coincided with their sensory profiles that those who had difficulties in auditory processing were more distractible or inattentive in a noisy environment. It is also noteworthy that the performance of participants in the attentional tasks recorded by the prototype generally matched the health practitioners' rating on the attention and stress. The higher the accuracy, the higher the ${Attention}/{Stress}$ score. Overall, the pilot study provided evidence for the tolerability and feasibility of one such prototype and experimental design.

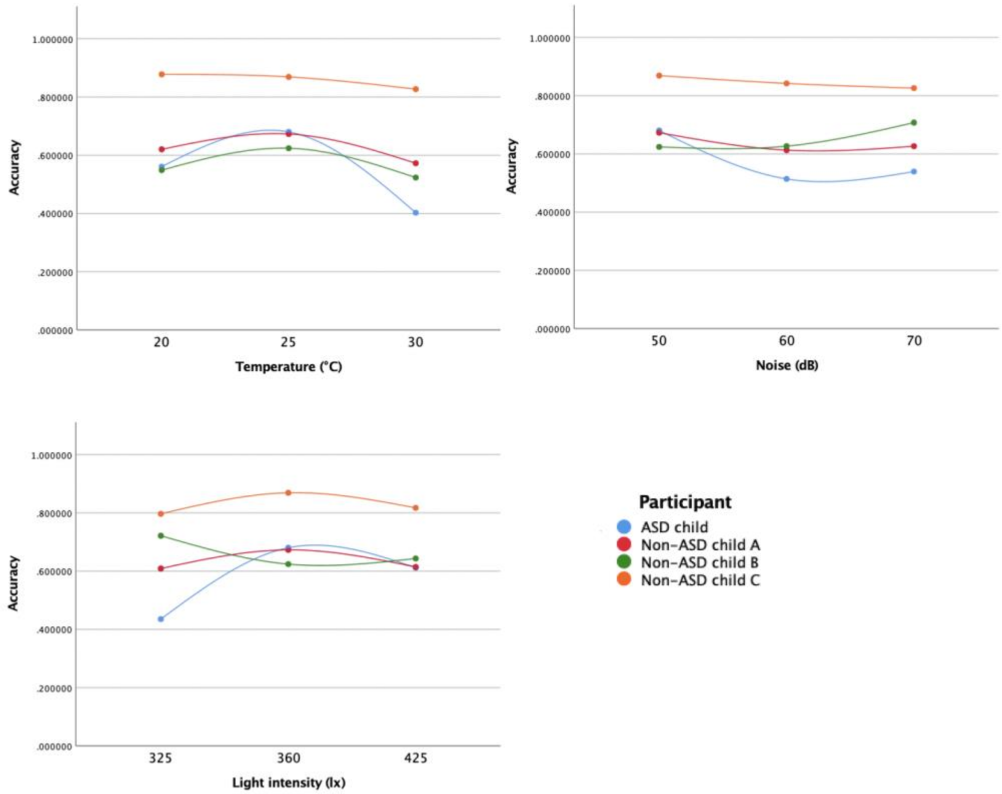


Figure 9: Performance changes of four participants in different settings

4 FORMAL EXPERIMENTAL STUDY

Following the primary findings of the pilot study, formal experimental study was conducted to collect more data to understand the impact of sensory profile and environmental factors on behaviour and attention of children with ASD. All data discussed in the Results section were collected in the formal experimental study.

4.1 Participants

The study was conducted in Elim Autism *(for anonymity check: none of the authors work for this institution)*, a special education institution in Ninghai County that caters specifically to children with ASD. A total of 21 Chinese children aged between 3 and 7 have been recruited from different classrooms. The diagnosis history of participants was confirmed by the institution that each child had been formally diagnosed with ASD by a medical professional. The demographic information of the participants has been summarised in the Table 1.

Table 1: Demographic information for the formal experimental study

Subject#	Gender	Age	Diagnosis	Rejection of wearables	Number of Sessions completed
1	M	6	ASD	Not observed	15
2	M	5	ASD	Not observed	15
3	M	4	ASD	Not observed	15
4	M	4	ASD	Not observed	15
5	F	7	ASD	Not observed	14 (could not complete high temperature session due to anxiety)
6	M	5	ASD	Not observed	15
7	M	7	ASD	Not observed	15
8	M	6	ASD	Not observed	15
9	M	4	ASD	Rejected to wear earphone	15
10	M	5	ASD	Not observed	15
11	M	4	ASD	Not observed	14 (could not complete low noise session due to distraction)
12	M	5	ASD	Not observed	15
13	M	5	ASD	Not observed	15
14	M	3	ASD	Not observed	15
15	F	4	ASD	Not observed	15
16	M	5	ASD	Not observed	15
17	M	6	ASD	Not observed	15
18	M	5	ASD	Not observed	15
19	M	5	ASD	Rejected to wear earphone	14 (could not complete high temperature session due to anxiety)
20	F	4	ASD	Not observed	15
21	M	6	ASD	Not observed	15

4.2 Experimental Setup

The experiment was carried out by the first author who is a qualified social worker. A reading room in Elim Autism, which equipped with air conditioner, study lamps, speakers, video recorder, table and chairs, was used as the experiment room. The participant was required to enter the room accompanied by their parent and sit beside the first author. Temperature, noise and light intensity were controlled in the room during the session. Each of these variables has five different settings, namely low level, low-moderate level, moderate level, moderate-high level and high level. Before each session started, one of the variables was adjusted to a desired level and the other two independent variables were controlled to be ‘moderate’. Details about controlled variables are provided in Table 2. Each participant was supposed to undergo 15 experiment sessions in total following experimental design as mentioned in section 3.2. According to the participant consent form, parents were able to decide not to continue the experiment for their child if they spot any uncomfortable feelings from the child. The number of sessions each participant completed and reasons for dropping from a session were recorded in Table 1.

Table 2: Controlled Variables

Variable	Values	Unit	Control method
Temperature	22, 24, 26, 28, 30	Celsius (°C)	Air Conditioning System will be set prior to each session to ensure desired temperature level is achieved for that session.
Noise level	40, 50, 60, 70, 80	Decibels (dB)	White noise is played during each session at constant volume level either through a speaker or earphones.
Light intensity	275, 325, 375, 425, 475	Lux (lx)	Study lamps with variable brightness settings are set and used for each session.

4.3 Data Acquisition

We stored all data collected by the prototype in a raw dataset. The raw dataset is comprised of several continuous features, such as Time, Temperature, Volume and Light, as well as raw sensory profile data of 21 participants. With raw sensory profile data, we evaluated the ASD children's sensory patterns and systematically categorised them into different subgroups according to their sensory profile. In this study, we focused on their audition, vision, touch and response threshold classifications and four sensory patterns (i.e. Registration, Seeking, Sensitivity and Avoiding). Descriptions of each feature can be referred to Table 3.

Table 3: Features in the raw dataset

Feature	Description
Time	Real local time (GMT+8)
Time_1	Number of seconds since experiment begins
Temperature	Environmental temperature
Humidity	Environmental humidity
Volume	Environmental noise level
Light	Environmental light intensity
Watch Accelerometer:x	Watch acceleration on the x axis
Watch Accelerometer:y	Watch acceleration on the y axis
Watch Accelerometer:z	Watch acceleration on the z axis
HeartRate	Heart rate BPM
GSR	Galvanic Skin Response
Task	Task the participant was playing
Question	Question or subtask the participant encountered in that task

Feature	Description
Correct_or_error	Response accuracy to that question or subtask
Accuracy_rate	Final accuracy score. For the counting task and picture matching task, this was obtained by multiplying percentage of correct answers by percentage of completed questions; for the drawing task, the accuracy rate was the matching rate of the drawn line on the original line.
Sensory profile	Classifications of four sections (i.e. Audition, Vision, Touch, Response threshold) and four sensory patterns (i.e. Registration, Seeking, Sensitivity and Avoiding). Three classifications are 'Typical Performance', 'Probable Difference' and 'Definite Difference'.

To obtain an overall insight into the relationship between sensory profile, environmental factors and attention of the children, we created a second dataset referred as merged dataset. In this dataset, we converted continuous physiological and environmental data into averaged data for each task and combined these data with sensory profile features. Physiological and environmental data have been derived from the average of the values 30 seconds before and when the task was played. For instance, the heart rate value for counting task was the average on the heart rate values in the range of 30 seconds before the task was started, until the end of the task, for the reason that the environmental factors and physiological signals before the task could also affect the performance. This dataset finally consisted of 312 tuples of experimental data obtained from 21 participants. In this dataset, we divided all the features into four subsets, namely environmental features (EF), sensory profile (SP), physiological features (PF) and personal characteristics (PC) as shown in Table 4.

Table 4: Subsets of features

Subset	Included Features
Environmental features (EF)	Temperature, Volume, Humidity, Light
Sensory profile (SP)	Audition, Vision, Touch, Response threshold, Registration, Seeking, Sensitivity, Avoiding
Physiological features (PF)	GSR, HeartRate, Watch Accelerometer:x, Watch Accelerometer:y, Watch Accelerometer:z
Personal characteristics (PC)	Gender, Age

4.4 Data analysis

Following data acquisition, there is a machine learning-based analysis phase, with comprehensive iterations of model training, testing and evaluation. Before the machine learning-based analysis, we also conducted a simple correlation analysis to assess the correlation between the target and features in the merged dataset.

We applied a neural network technique on the raw dataset to make connections between EF, SP features and behaviour. Neural network was chosen because it has the ability to fit all the functions desired in our study. However, a potential problem of this algorithm is overfitting [30]. One way to prevent this issue is applying a large dataset such as a data size of 10000. A study conducted by Kim [26] suggested that neural network could generate the best performance compared to linear regression and decision tree in the case of a large dataset (size=10000).

KerasRegressor is a neural network technique to solve regression problems [17]. It can be applied to build models for predicting continuous labels [24, 39]. The users are able to customise the number of neurons and layers within the network besides the basic parameter settings including number of epochs [10, 24, 39]. However, optimising might not be easy. This research has evaluated simple optimising strategies by tuning over different customising settings of the models based on KerasRegressor.

In this analysis, the target is participants' behaviour, which was quantified by measures of hand movements. We used data from 3-axis Apple Watch Accelerometer for hand movements. By averaging three absolute values, Watch Accelerate Average data were obtained. In order to link the hand movements with the environmental factors for children of various sensory processing patterns, we catergorised 21 participants into subgroups according to their sensory profile results. Those who displayed 'Probable Difference' or 'Definite Difference' in the specific section/quadrant were included in the corresponding group pertaining to that specific section/quadrant (see Table 5). The sizes of the raw dataset for the eight subgroups were 82936, 33626, 47728, 110989, 165558, 142159, 105045 and 60164 tuples respectively.

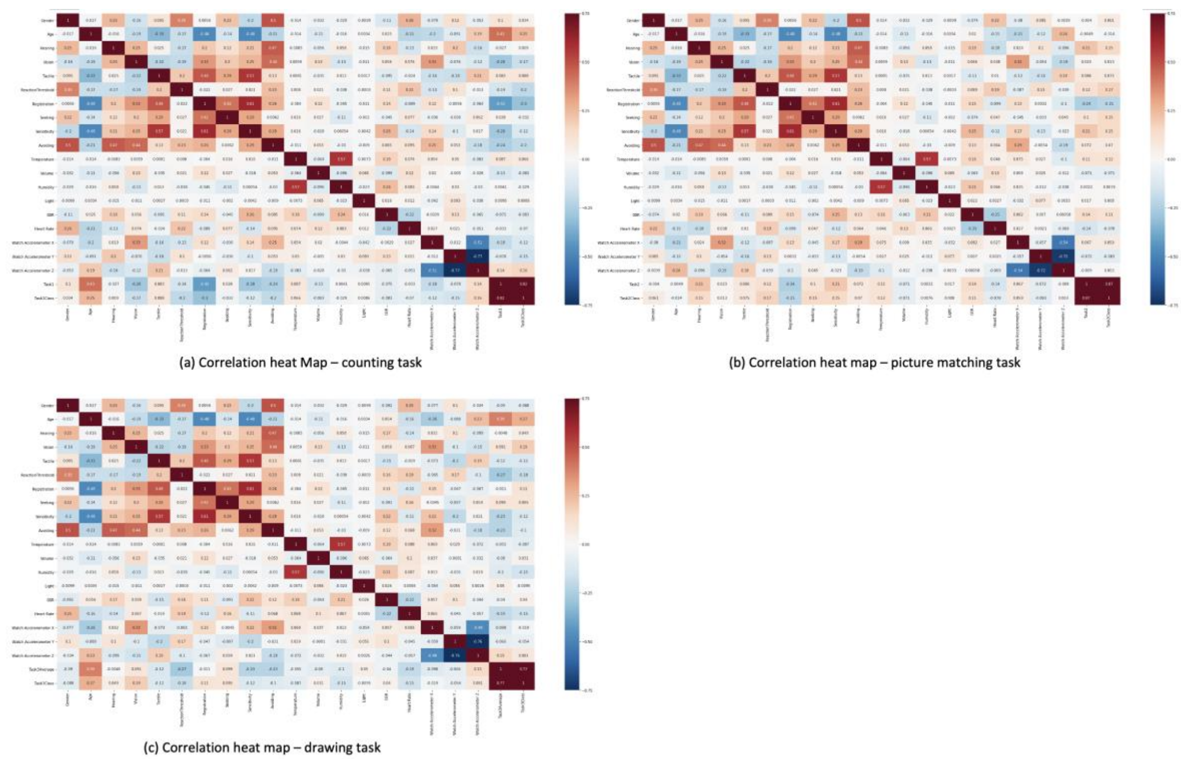
Table 5: Subgroups catergorised by participants' sensory profile

Subgroup	Included subject#
Audition	2, 3, 4, 5, 10, 12, 14, 18, 20, 21
Vision	3, 4, 7, 21
Touch	7, 8, 9, 10, 14, 15
Response threshold	3, 5, 6, 7, 8, 9, 11, 13, 14, 15, 18, 20, 21
Registration	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21
Seeking	3, 4, 5, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21
Sensitivity	1, 2, 3, 4, 7, 8, 9, 10, 11, 14, 15, 18, 21
Avoiding	3, 4, 5, 14, 15, 20, 21

For the merged dataset, we selected a K-nearest-neighbor (KNN) model for the classification analysis of the relationship between EF, SP, PF, PC features and attention. KNN is an algorithm widely applied in recommendation systems [36]. KNN identifies k objects closest to the object to be classified, then produces a prediction based on the label of the majority of neighbors. Choosing the appropriate set of input features is of great importance to a KNN model for a good performance. A KNN model with higher accuracy rate indicates that the input features are of relatively higher relevance to the target, so the importance of features could be identified by comparing the performance of KNN models on different sets of inputs [37]. The target of the analysis is attention, which was inferred by the accuracy rate of three attentional tasks (counting, picture matching and drawing). The accuracy rate data, as the target, were classified into two classes, namely Low (written as 1) and High (written as 2). An accuracy rate is classified Low if its value is more or equal to 0 and less than 0.5 and classified as High if the value is greater or equal 0.5 and less or equal 1.

5 RESULTS

The correlation heat maps in Figure 10 show that the features in the merged dataset in general has little correlation, suggesting that feature selection is needed to enable the machine learning algorithm to improve the precision of results based on the correct use of subset of features. Therefore, a feature selecting algorithm called Recursive Feature Elimination (RFE) [19] was used to effectively select features in the dataset that are more or most relevant in affecting and predicting the target variables.



(a) Correlation heat Map – counting task

(b) Correlation heat map – picture matching task

(c) Correlation heat map – drawing task

Figure 10: Correlation heat maps (see the Appendix A for full size figures)

The analysis based on KerasRegressor selected eight features from the raw dataset, including Time, Time_1, Light, Temperature, Humidity, GSR, Task and Question. Parameter n_features_to_select (number of features to select) was set to one, and Logistic Regression model was selected. Consistent with Kim's work [26], in this analysis, samples with 10000 tuples of each subgroup were extracted for the effectiveness of feature selection and further tunings.

Rankings for each feature with the target being Watch Accelerate Average (hand movements) for the subgroups are shown in Table 6. It is clear from the table that Time and Time_1, which refer to the real local time and time since the start of the experiment, play the most important roles in the hand movements of children with difficulties in audition or response threshold. Humidity has greater impact than other environmental features on hand movements. Besides, Question and Task are less useful for predicting the hand movements. The results imply that the three attentional tasks affect similarly to the children's hand movements, whereas real local time, duration of the tasks, noise, temperature and humidity of the environment affect their behavioural changes such as hand movements more significantly.

Table 6: Feature rankings

Subgroup	Rankings
Audition	Time > Time_1 > Humidity > Temperature > Volume > Question > Light > Task
Vision	Humidity > Time_1 > Temperature > Volume > Question > Light > Time > Task
Touch	Time_1 > Time > Humidity > Temperature > Volume > Question > Light > Task
Response threshold	Time > Time_1 > Humidity > Temperature > Volume > Light > Question > Task
Registration	Time > Time_1 > Humidity > Temperature > Volume > Question > Light > Task
Seeking	Time > Time_1 > Humidity > Temperature > Volume > Question > Light > Task
Sensitivity	Time_1 > Time > Humidity > Temperature > Volume > Question > Light > Task
Avoiding	Time > Time_1 > Humidity > Temperature > Volume > Light > Question > Task

An exhaustive search, tuning over all different feature combinations, was then applied to estimate the cross-validation scores. The feature ranked as 1 was first applied, one feature was added in each estimation until all features were selected. Mean mean-square errors (Mean MSEs) of the eight subgroups were stored and shown in Table 7a-h.

Table 7a: Feature estimation results for Watch Accelerate Average of Audition group

Features	Mean MSE
['Time']	-0.0323083596304059
['Time', 'Time_1']	-0.0322651389986277
['Time', 'Time_1', 'Humidity']	-0.0323741817846894
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0323391711339354
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0322483513504267
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.0322959581390023
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0324376633390784
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0322972785681486

Table 7b: Feature estimation results for Watch Accelerate Average of Vision group

Features	Mean MSE
['Humidity']	-0.0363270414993167
['Time_1', 'Humidity']	-0.0360331473872066
['Time_1', 'Temperature', 'Humidity']	-0.0359960975125432
['Time_1', 'Volume', 'Temperature', 'Humidity']	-0.035990415327251
['Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.0361510686576366
['Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0357790485024452
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0353085521608591
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0348079523071647

Table 7c: Feature estimation results for Watch Accelerate Average of Touch group

Features	Mean MSE
['Time_1']	-0.0288114234805107
['Time', 'Time_1']	-0.0287643071264029
['Time', 'Time_1', 'Humidity']	-0.0287750264629722
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.028402984701097
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0283701645210385
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.0283431719988584
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0280452366918325
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0282424036413431

Table 7d: Feature estimation results for Watch Accelerate Average of Response Threshold group

Features	Mean MSE
['Time']	-0.0326056849211454
['Time', 'Time_1']	-0.0327098179608583
['Time', 'Time_1', 'Humidity']	-0.0324831759557128
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0321773199364543
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0314998848363757
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity']	-0.0312852662056684
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.031047098338604
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0310242790728807

Table 7e: Feature estimation results for Watch Accelerate Average of Registration group

Features	Mean MSE
['Time']	-0.032451762445271
['Time', 'Time_1']	-0.032271428219974
['Time', 'Time_1', 'Humidity']	-0.0323711575940251
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0322748614475131
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0323064232245088
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.0323539439588785
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0324447762221098

Features	Mean MSE
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0322495305910706

Table 7f: Feature estimation results for Watch Accelerate Average of Seeking group

Features	Mean MSE
['Time']	-0.0340690638870001
['Time', 'Time_1']	-0.0340447975322604
['Time', 'Time_1', 'Humidity']	-0.0339012755081058
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0317323531955481
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0319025924429297
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.031680597923696
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0319065460935235
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0320369033142924

Table 7g: Feature estimation results for Watch Accelerate Average of Sensitivity group

Features	Mean MSE
['Time_1']	-0.0352699426934123
['Time', 'Time_1']	-0.03514074832201
['Time', 'Time_1', 'Humidity']	-0.0351300215348601
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0350238418206572
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0350048879161477
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity', 'Question']	-0.0352076698094606
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0350311364978552
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0350967701524496

Table 7h: Feature estimation results for Watch Accelerate Average of Avoiding group

Features	Mean MSE
['Time']	-0.0343345830217004
['Time', 'Time_1']	-0.0349205369129777
['Time', 'Time_1', 'Humidity']	-0.034100279957056
['Time', 'Time_1', 'Temperature', 'Humidity']	-0.0362884217873216
['Time', 'Time_1', 'Volume', 'Temperature', 'Humidity']	-0.0319142073392868
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity']	-0.0318511595949531
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Question']	-0.0318289501592517
['Time', 'Time_1', 'Volume', 'Light', 'Temperature', 'Humidity', 'Task', 'Question']	-0.0319091368466616

Pipeline from scikit learn was applied for the parameter tuning, with the three parameters including batch_size (the size of each batch), n_splits (number of folds) and epochs (number of iterations) to be adjusted. The Pipeline API can help estimate the cross-validation scores of all different parameter combinations by assembling several trainings with different parameter settings and evaluate their performance at the end of the pipeline [35].

Parameter selection was also based on exhaustive search: tuning over all different sets. Batch_size was selected from the list [3, 5, 10]; n_splits was picked from [5, 10, 20]; whereas epochs was from [30, 40, 50]. Feature combinations generating the best performance of each subgroup were applied for the tuning. Results in Table 8 shows the most optimising settings and the performances from the tuning of each subgroup, indicating the improvement on the accuracies compared to the ones before parameter tuning.

Table 8: Optimal parameter setting for each subgroup

Subgroup	Features	Epochs	Batch_size	N_splits	Mean MSE
Audition	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature']	40	3	10	-0.032046121545136
Vision	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Task', 'Question']	30	3	10	-0.0347844678908586
Touch	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Question']	30	5	5	-0.0278121016919613
Response Threshold	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Task', 'Question']	50	3	20	-0.0307071442715824
Registration	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Task', 'Question']	40	10	10	-0.0322269355878234
Seeking	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Question']	50	10	5	-0.0316184762865305
Sensitivity	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Task', 'Question']	40	10	10	-0.0322269355878234
Avoiding	['Time', 'Time_1', 'Volume', 'Humidity', 'Temperature', 'Light', 'Question']	40	3	20	-0.0315776719711721

The KNN-based analysis used different combinations of feature subsets mentioned in Table 4 and the results were presented in Table 9. It can be seen from the table that a relatively high accuracy was produced by using sensory profile features. EF and PF themselves alone produced a relatively low accuracy. When combining EF, SP, PF and PC features, the accuracy was largely increased compared to the situation of using each subset alone. However, the best accuracy did not always occur when all features were selected as input. Although the best feature combinations for each task differed, the combination of EF, SP, PF, PC features generated acceptable accuracies for all attentional tasks. This result indicates that sensory profile features have a critical impact on the attention level. When considering the impact of environmental changes on the person, the sensory profile of the person should not be neglected as the sensory profile and environmental features have cooperative effect on the attention level.

Table 9: Accuracy of KNN model on predicting attentional task performance

Input Features	Accuracy		
	Counting Task	Picture Matching Task	Drawing Task Average
EF	74.38%	94.23%	64.74%
SP	84.35%	98.10%	81.10%
PF	73.41%	94.23%	64.09%
EF, SP	84.35%	98.10%	81.70%
EF, PF	75.33%	94.23%	66.28%
EF, PC	76.30%	94.23%	67.02%

Input Features	Accuracy		
	Counting Task	Picture Matching Task	Drawing Task Average
SP, PF	84.35%	98.10%	79.81%
SP, PC	84.03%	98.10%	83.35%
EF, SP, PC	84.35%	98.10%	83.96%
EF, SP, PF	85.32%	98.10%	79.17%
EF, SP, PF, PC	85.32%	98.10%	82.38%

6 DISCUSSION

This preliminary research used a prototype of an application to collect data from Chinese ASD populations, which supports machine learning-bases analyses for exploring the relationships between sensory profile and individuals' responses to their environments. Attentional tasks that we designed were welcomed by children and their parents, providing educational benefits as well as attention level assessment for children with ASD. In general, all ASD participants presented high acceptance of devices worn on wrist and fingers in the study, although a few children with self-reported tactile sensitivity on ears displayed aversion to earphones. Two children did not complete the tasks in one extreme environmental condition due to anxiety; one child did not complete the tasks in low volume level setting because he seemed not to hear the instruction of the task and was distracted by the animation on the Apple Watch. Observing diverse sensory responses to different environments in ASD children increased our motivations to develop a sensory management recommendation system, which aims to help ASD individuals and their caregivers to respond to their variable environments.

6.1 Designing a Sensory Management Recommendation System

A therapeutic recommendation system which uses classified data based on the information of users to provide relevant recommendations can help users to improve health conditions and obtain better life quality [27]. Our research work has shown the feasibility of using non-invasive sensors to collect data streams and the potential of machine learning algorithms to learn user's specific patterns in physiological and behavioural data in response to changes in their immediate environment. On the basis of the prototype and algorithms presented in this study, we proposed to develop a sensory management recommendation system for people with ASD. The system uses sensory profile to identify the sensory processing patterns of its ASD user, correlating the user's measurable physiological parameters with information about their environment. The system can then notify the user group (caregivers and healthcare professionals) about potential atypical sensory responses, anxiety, or distraction of the ASD user, and recommend self-regulation strategies for them. For example, the system records the user's environment, physiological responses and sensory profiles, monitoring the user's behaviours, e.g. overexcited hand movements when the ambient noise level suddenly increases. By correlating these factors and behaviours, the system evaluates the neurological thresholds and predicts the user's potential behaviours. Once an individual user's neurological thresholds and preferred responses have been learnt, the system will recommend sensory management strategies in response to a detected sensory event, e.g. putting on their headphones for calming. Machine learning algorithms will be used to drive this predictive recommendation system. Since the smart home automation is becoming increasingly popular and common in the current era, the sensory management recommendation system can also be used in an environment equipped with a smart-home system, predicting possible sensory events and also automating adjustments as instructed by its user group.

6.2 Potential Use of Machine Learning Models in System Development

In this study, two machine learning models were used and evaluated on different targets. KerasRegressor was used to choose the features to predict hand movements indicated by Watch Accelerate Average with the environmental data recorded by sensors for children with different sensory profiles. The performance of the model showed the feasibility of predicting the hand movements and optimising the models with a simple approach. Although our prototype only measured the hand movements, according to previous studies [4, 44], hand movements can indicate the calmness or excitement of ASD children. Therefore, the model can be further used to predict potential behavioural issues such as overexcitement. In addition, KNN model was used to focus on the attention aspect. It is found that the prediction accuracy on attentional task performance using sensory profile, environmental data, physiological data, gender and age features was acceptable, coming out to 88.6% in average. It could be considered that both models have the potential to be used in the sensory management recommendation system to predict the performance of ASD children in different aspects and generate recommendations.

6.3 Limitations

Among 21 participants involved in the formal experimental study, there are 18 males and 3 females. The unbalanced ratio of the gender might have affected the accuracy of the model. Moreover, in the KerasRegressor-based analysis, participants were not evenly distributed into the subgroups of sensory profiles, leading to different input data sizes for training the models. Besides, there is an overlap of participants in the subgroups. Some groups have shared similar children data, leading to a low diversity of models among the subgroups.

The study initially proposed a balanced Latin-square design [48] for the formal experiments in which the order of experiment condition for participants can be randomised. By this way, each setting will be randomly repeated multiple times to obtain more unbiased data. However, the use of Latin-square design will greatly increase the number of experiment sessions, which prevents many parents from committing themselves to completing the study. Therefore, we have to limit the number of experiment sessions within 15 times in order to avoid losing many participants. In this case, participants only experienced a certain condition once, which is likely to cause bias due to occasional factors or learning effect.

7 CONCLUSION AND FUTURE WORK

This research identified that sensory profiles and environmental factors are a useful lens for predicting the attention and behaviour of ASD individuals. In this study, the prototype consisting of sensors and attentional tasks can successfully capture a range of physiological and environmental features. Machine learning algorithms were used to evaluate what are some of the key predictive features. Two models used in the study both show an acceptable accuracy in predicting hand movements and attention level of ASD children respectively with environmental and physiological data collected by the prototype. Therefore, we conclude that it is feasible to further develop a predictive sensory management recommendation system by integrating machine learning algorithms into the current prototype. The machine learning-driven system can be used in real life as a personalised tool to help ASD individuals and their caregivers to respond to their variable environments.

According to the most recent data released by Centres for Disease Control and Prevention [6], ASD is about 4.3 times more common among boys than girls. It is common that previous work on ASD were largely based on data from male participants [25]. Future work could examine the gender factors, the impact of which was considered to be still unclear in this study due to lack of female participants. This will require us to conduct a larger scale data collection, especially on girls with ASD, to obtain a better understanding of factors that have not been fully explored in this study. This will also help train a better model for the recommendation system. A prototype of the sensory management recommendation system can be expected in the foreseeable future. More efforts should be made to evaluate the effectiveness of the system.

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