# Developing An Effective Monitoring System Using Sensors and Artificial Intelligence for Sensory Regulation of Children with Autism Spectrum Disorders

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# *Abstract*

In the field of Autism Spectrum Disorder (ASD) intervention, there has been a growing need for technology-based methods to address atypical sensory responses, a core symptom experienced by most children with ASD. Atypical sensory responses lead to their difficulties in self-regulation in daily life. They may have difficulty paying attention or recovering from anxiety. Sensing technologies and artificial intelligence (AI) in collaboration represent a promising tool because they not only enable real-time monitoring of the sensory responses, but can also produce useful intervention strategies for assisting children with ASD. The aim of this research is to explore how to develop an effective and acceptable intelligent system, using reliable sensor and AI techniques, to facilitate sensory regulation of children with ASD. A monitoring system named *Roomie*, has been proposed and developed as a tool to explore the research questions. The research followed a user-centred principle and iterative process, which means that *Roomie* was developed with the help of ASD specialists and user groups, and had been constantly refined. Multiple sensors were used to collect environmental data and physiological data, in order to obtain a comprehensive understanding of a child's sensory responses in relation to their environment. A standardised sensory profiling tool was integrated in the system to obtain information about a child's sensory processing pattern. Machine learning algorithms were used to extract and analyse sensory-related data to detect the child's attention and stress levels. A fuzzy logic algorithm was employed to stimulate the strategy-making process of an ASD specialist based on the detected environmental stressors and abnormal states. Key modules such as data processing and feedback generating were integrated in a smartphone-based application, which make the system easier for children with ASD and their caregivers to access. The entire system has been tested in a series of evaluation sessions in a real-life setting. Overall, the results presented in this thesis suggest that the proposed sensor and AI-enabled

system can effectively address atypical sensory responses in children with ASD. At the end of the thesis, discussion on the further improvement and wider application of the system has been made. The work presented in this thesis has provided a solid foundation for future studies in which the proposed system and development framework can be used for creating a smart health home to implement the environmental control and sensory regulation strategies automatically without a continuous involvement of a human assistant.

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# Contents

# List of Abbreviations

| | |
|---|---|
| ABA | Applied Behavioural Analysis |
| ADHD | Attention Deficit Hyperactivity Disorder |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Networks |
| AQ-10 | Autism Spectrum Quotient 10 Items |
| ASD | Autism Spectrum Disorder |
| ASHRAE | American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| BLE | Bluetooth Low Energy |
| CNN | Conventional Neural Network |
| CPU | Central Processing Unit |
| CSV | Comma Separated Values |
| C-TRF | Caregiver-Teacher Report Form |
| DL | Deep Learning |
| DT | Decision Tree |
| DSM | Diagnostic and Statistical Manual of Mental Disorder |
| EEG | Electroencephalograms |
| FL | Fuzzy Logic |
| FN | False Negative |
| FP | False Positive |
| GBDT | Gradient Boosting Decision Tree |
| GSR | Galvanic Skin Response |
| HMD | Head-Mounted Display |

| | |
|---|---|
| HOG | Histograms of Oriented Gradients |
| IDE | Integrated Development Environment |
| IoT | Internet of Things |
| KNN | K-Nearest Neighbours |
| LOM | Largest of Maximum |
| LSTM | Long Short-Term Memory |
| MAV | Mean Absolute Value |
| ML | Machine Learning |
| NB | Naïve Bayes |
| NIOSH | National Institute for Occupational Safety and Health |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| RF | Random Forest |
| RFE | Recursive Feature Elimination |
| RNN | Recurrent Neural Network |
| RQ | Research Question |
| SCED | Single-Case Experimental Design |
| SD | Sensory Dataset |
| SKB | Strategy Knowledge Base |
| SMS | Short Message Service |
| SP | Sensory Profile |
| SUS | System Usability Scale |
| SVM | Support Vector Machines |
| TBI | Technology-Based Intervention |
| TD | Typically Developing |
| TN | True Negative |
| TP | True Positive |
| UI | User Interface |
| VR | Virtual Reality |

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# Chapter 1

# Introduction

This chapter provides a background that motivates this PhD research, beginning with an introduction to Autism Spectrum Disorder (ASD) and one of its core symptoms, atypical sensory responses. The chapter then briefly introduces the current development of technology-based interventions (TBIs) that are promising in the ASD field. Further, the aims of this PhD research and research questions are articulated. A summary of the scientific contributions of this work is presented. The actual work undertaken by the author is summarized. At the end of this chapter is an outline of this thesis.

## 1.1 Introduction to Autism Spectrum Disorder (ASD)

ASD refers to a neurodevelopmental disorder that can impact many aspects of a person's life, as shown in Figure 1.1.

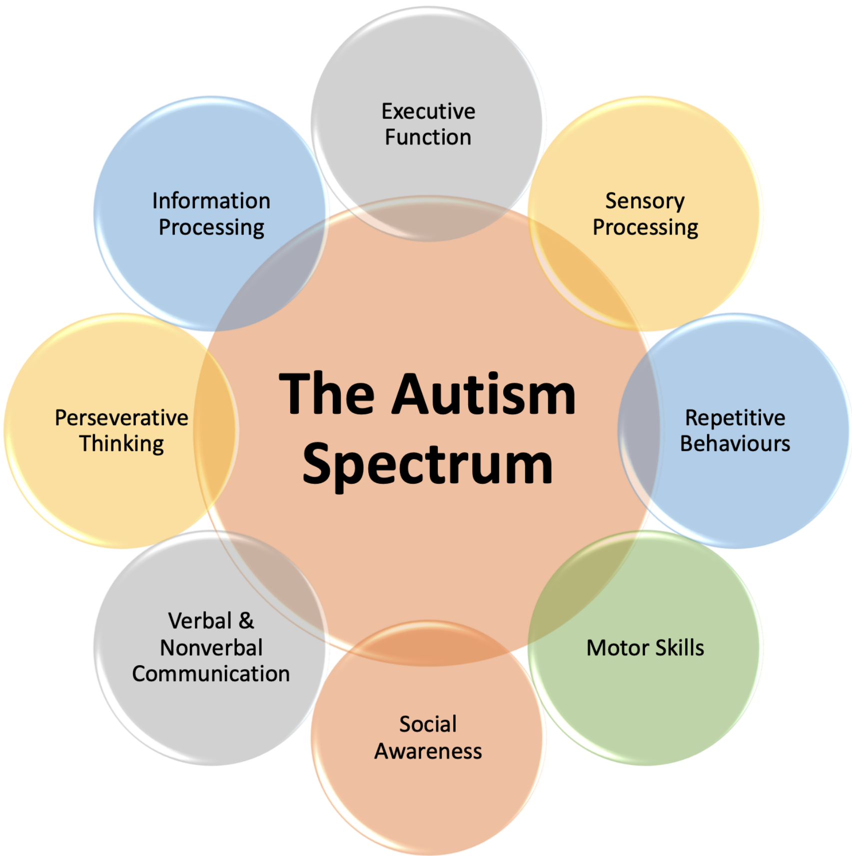



**Figure 1.1:** *Autism is a spectrum that impacts human functioning in each of these areas, adapted from AutismBC (2023)*

Individuals impacted by ASD may present non-verbal communication, stereotypical motor movements such as body-rocking and mouthing, and hypo- or hyper-reactivity to incoming sensory information (Benssassi et al., 2018). These symptoms can emerge very early in childhood and last throughout an individual's life (Levy, 2007), affecting the way individuals behaved and interacted in social and non-social contexts around them (Happé & Frith, 2020). ASD is also a disorder with a high degree of comorbidity, leading to high heterogeneity and complexity. The co-morbid psychiatric disorders include social anxiety disorder, attention-deficit/hyperactivity disorder, and depressive disorder (Simonoff et al., 2008). This has been shown to bring higher stress and a heavier raising burden for the families of children with

ASD compared to families of typically developing (TD) children[1] and children with other disabilities (Deng & Rattadilok, 2020).

Clinical diagnosis of ASD usually depends on qualified doctors' observation and assessment of the child's developmental history and behaviour (Hyman et al., 2020). In 2013, the Diagnostic and Statistical Manual of Mental Disorder (DSM), Fifth Edition established the latest criteria for ASD diagnosis (American Psychiatric Association, 2013). A variety of instruments validated based on the DSM criteria are used in many countries to provide structured data to facilitate the diagnosis (Constantino & Charman, 2016). They range from checklist questionnaires such as the Autism Spectrum Quotient 10 items (AQ-10) checklist (Baron-Cohen et al., 2000), to observational tools such as the Autism Diagnostic Observation Schedule (Lord et al., 2012).

The most up-to-date data estimates that over 28 million people are affected by ASD globally (Solmi et al., 2022). The mental health survey of National Health Service in the United Kingdom (UK) reported that the prevalence was around 1.5% in children of 5 to 10 years old (Franziska et al., 2018). This rate was higher among children aged 8 years in the United States, which was 2.3% in 2018 and 2.8% in 2020 (Maenner et al., 2021). In China, although the first case of ASD diagnosis was reported in the 1980s, ASD was officially listed as a mental disorder around two decades later in 2006 (Deng & Rattadilok, 2020; A. X. Huang et al., 2013). A meta-analysis study in 2018 estimated that the pooled prevalence of ASD in China was 0.4% (Wang et al., 2018). A recent nation-wide study estimated that the ASD prevalence rate among children aged 6 to 12 years in China was 0.7%, generally lower than estimates reported in other countries (Z. C. Zhang

[1] Typically developing children refers to children without an ASD or any other intellectual and developmental disabilities (Shivers et al., 2019).

& Han, 2020). The difference in prevalence rates between western countries and China suggests that many Chinese individuals with ASD may remain undiagnosed and unassisted (Deng & Rattadilok, 2020). Besides, the increase in the prevalence of ASD suggests that ASD is no longer a rare disorder but an important public health concern (Z. C. Zhang & Han, 2020; Zhou et al., 2020). Especially in China with around 1.4 billion people (The World Bank, 2021), if estimating the ASD population in China by applying the latest rate (0.7%), an astonishing 10 million people could have been affected by the condition.

To date, there is no known pharmacological treatment that can cure ASD (Lotufo Denucci et al., 2021). The goals of 'treatment' in ASD nowadays are only to minimise core deficits, maximise functional independence and prevent problematic behaviours (Hyman et al., 2020). This process should be more accurately described as psychosocial intervention[2] or psychoeducation. Autism is referred as a spectrum disorder because the symptom expression varies and the intervention that an individual needs is highly individualised depending on the condition (Deng & Rattadilok, 2020). Early intervention of children at young age has been shown to result in positive outcomes. The most evidence-based intervention is behavioural intervention, known as applied behavioural analysis (ABA) (Hyman et al., 2020). ABA intervention targets the development of specific skills (e.g., social engagement), and reinforces desired behaviours while discouraging undesired ones. Other mainstream interventions include speech and language program, sensory integration intervention, relationship development intervention and many more (Hyman et al., 2020).

[2]Unlike treatment which is used to cure the diseases, interventions are generally aimed at improving social functioning and reducing symptom distress and relapses. Interventions can be integrated in the treatment and facilitate the treatment. Compared to treatment, interventions can be applied more frequently and be administered by a wide range of media including computer programs, while treatment generally requires qualified therapists (Mueser et al., 2013).

## 1.2 Atypical sensory processing in ASD

Ability of sensory processing is established through neural development at the early stages of the life. ASD is a neurological and developmental disorder in which impairments in sensory processing are one of the most common issues observed (Case-Smith et al., 2015). The new diagnostic criteria in the DSM, Fifth Edition make changes from the Fourth Edition by adding the explicit recognition of atypical sensory responses within the domain of restricted, repetitive patterns of behaviours, interests or activities in ASD (American Psychiatric Association, 2000, 2013).

In general, sensory stimulation can arise from tactile, visual, auditory and a variety of other senses, such as the sense of smell (olfactory), the sense of taste (gustatory) and the sense of movement (vestibular and proprioceptive). However, individuals with ASD are known to respond to sensory stimulations differently from their TD counterparts in the daily life. According to the description in the DSM, specific atypical sensory responses, referred as hypo- or hyper- sensitiveness to sensory input or unusual interests in sensory aspects of the environment (American Psychiatric Association, 2013), will further lead to sensory regulation[3] issues. More specifically, individuals with ASD who are hypo-sensitive may fail to notice sensory events which TD peers can easily detect. For example, they can be indifferent to sound, having difficulty paying attention due to hypo-sensitiveness (Tomchek & Dunn, 2007). Contrariwise, hyper-sensitive people are more prone to suffer distress or have an excessive negative reaction to sensory stimuli. They may present adverse responses to specific sounds or physical touches (American Psychiatric Association, 2013). The distress caused

[3] Sensory regulation refers to a person's ability to take, modulate, and organise the information from senses, and in turn, making an appropriate behavioural adaptation to sensory stimuli (Harricharan et al., 2021).

by sensory stimuli may lead to self-injurious and aggressive behaviours (Javed et al., 2019). Individuals with unusual sensory interests may exhibit fascination with certain neutral or unpleasant stimuli, such as lights or movement (American Psychiatric Association, 2013). Sensory stimuli occur every day as part of human experience (Dunn, 2001). Any of the sense at any random time, may become hypo- or hyper-sensitive for individuals with ASD which can further trigger distraction or discomfort (Gomes et al., 2004; Talay-Ongan & Wood, 2000). In particular, atypical sensory processing is estimated to affect more than 90% of individuals with ASD (Marco et al., 2011; Robertson & Baron-Cohen, 2017).

Despite the overwhelming incidence of atypical sensory processing in ASD and its detrimental influence, related sensory regulation issues have received less attention than other developmental problems in ASD before the new diagnostic criteria were established in 2013 (Tomchek & Dunn, 2007). One potential impediment to addressing the issue is that sensory processing has been complex and idiosyncratic with unclear aetiology in individuals with ASD (Deng, Rattadilok, Hadian, & Liu, 2021). There is also a lack of evidence-based theories and interventions that have been standardised in the clinical practice. Identification and recognition of atypical sensory processing in ASD diagnostic criteria have encouraged empirical research, over the past decade, to lay emphases on the issue. Sensory assessment tools such as the Sensory Profile questionnaires are now commonly used to quantify sensory processing differences relative to smell, taste, vision, audition and touch (Hyman et al., 2020). In addition, recent studies have started collecting phenotypic and genetic information at scale in order to find biological explanations (Loth & Evans, 2019; Warrier et al., 2019). Exploring sensory processing patterns[4] with physiological measures and

[4]Sensory processing patterns refer to behavioural patterns relating to the child's atypical sensory responses according to Dunn's sensory processing framework (Tomchek et al.,

self-report questionnaires have been suggested to be important for future research in this area (Happé & Frith, 2020).

Evidence-based studies have identified some effective strategies to address atypical sensory processing and improve sensory regulation ability in ASD. Dominant interventions to help children with ASD reduce dysregulation in sensory processing include clinic-based sensory integration intervention, sensory regulation strategies, modification of environments and tasks in relation to their atypical sensory responses. A qualified specialist, usually an occupational therapist, is required to guide children to participate in these interventions, thereby supporting better regulation of their sensory responses. There are also alternative school-based, teacher-directed approaches, and home-based, parent-mediated approaches such as music intervention, ABA, and massage (Hyman et al., 2020; National Autism Centre, 2015). However, many conventional interventions necessarily involve human assistance to engage with a child to reinforce adaptive responses through play and sensory exercises (Hyman et al., 2020). They should be requested by caregivers of children with ASD through professional services (Deng, Rattadilok, Hadian, & Liu, 2021). However, in many areas in China, especially in remote regions, there are relatively few services to support the sensory processing issues in ASD (Deng & Rattadilok, 2020). Therefore, many researchers and practitioners have endeavoured to alter and enhance this circumstance by promoting collaborative development of inclusive smart interventions among technology developers, engineers, and different stakeholders in the ASD community (Deng, Rattadilok, Hadian, & Liu, 2021).

2015). Details regarding sensory processing patterns will be discussed in section 2.2.

## 1.3 Technologies for sensory regulation in ASD

Technologies for application in the ASD field have grown significantly in the past two decades. In most cases, technologies available to people with ASD can be categorised by the purpose of use, such as diagnosis, treatment, or intervention. However, there has been a lack of clear definition and classification for technologies providing specific interventions in ASD, for example, technologies targeting atypical sensory processing (National Autism Centre, 2009). Technologies for sensory regulation in ASD are of the larger intervention category, often known as technology-based interventions (TBIs), which are novel approaches that employed technology as a main medium of sensory strategy[5] delivery, or to assist sensory-based therapies within or outside clinical settings (Guan Lim et al., 2020). Among all the sensory-based interventions for ASD, TBIs can be more inclusive because they can offer sensorily cued instructions and trainings, which are consistent and repeatable, with less involvement of human assistance compared with other conventional interventions (Wilkes-Gillan & Joosten, 2016).

A TBI can be delivered via a computer, a robot, a wearable, a mobile device, or a mixture of these approaches. The last decade has witnessed a growing use of wearable and mobile devices in delivering sensory-based interventions for people with ASD. It has been suggested that portable mobile phones, tablets, smartwatches, and wireless sensors may be the ideal methods for addressing the needs of people with ASD, because they can be more easily accessed and more affordable than other devices such as robots.

[5]Sensory strategy, or sensory regulation strategy refers to the recommendation that a therapist usually make in sensory-based interventions to address the child's hyper-or hyposensitivity and support their self-regulation. For example, a single-sensory strategy can be a recommended modification to the child's environment which helps the child to fully participate in preferred sensory experiences. (Case-Smith et al., 2015)

Sensory feedback has also been possible because most successful wearable and mobile devices have already equipped with sensors to manage stress, anxiety and other sensory-related issues (Koumpouros & Kafazis, 2019).

At present days, wireless connectivity such as Bluetooth Low Energy and Wi-Fi has provided developers with an approach to integrate different types of devices in one system for delivering TBIs. The connection has enabled data transmission either between a sensor and a mobile phone, or between a device and a cloud server where a large scale of data management and computation can take place. Therefore, the wireless-enabled and Internet-connected devices can reduce the physical dimensions for a system, which shows their potential to be a contemporary trend in the development of TBI for people with certain impairments (Khullar et al., 2019). Benefiting from the network of devices, TBIs can take account of an individual's hypo- or hyper-sensitivity and idiosyncratic sensory interests to environmental factors (e.g., noise, brightness, and other features), to extract useful information from real-time data, and to provide customised interventions accordingly.

However, TBIs developed for individuals with ASD in China have been scarce (Tang, 2016). TBIs for sensory regulation in ASD are even rarer. Compared to western countries, TBIs in China have been more limited to the type of software applications (Apps) on mobile phones and tablets (Deng & Rattadilok, 2020). Maintream Chinese Apps aim to develop interactive platforms that allow users to share experience and information with others while receiving knowledge about symptoms, diagnosis, potential interventions and relevant services. This may be because that, in China, there is high penetration of mobile phones and a lack of access to ASD-related information and services, especially in rural regions. Moreover, the underdiagnosis of ASD in China implies that Chinese families of children with ASD usually opt to conceal the conditions from others due to their fear of judgments and stigma (D. Li et al., 2019). Stigma associated with disabilities and barriers to seeking TBIs can be reduced by using mobile devices, given that mobile devices are less obtrusive, which can successfully address the challenges of public exposure (Deng & Rattadilok, 2020; Morris & Aguilera, 2012). Apart from Apps, other types of TBIs have also emerged in China recently. For example, Tang et al. (2015) and Gao et al. (2018) have developed some plant-shape systems using tangible sensors for facilitating sensory experience or interaction in children with ASD.

## 1.4 Research aim and questions

This thesis presents an interdisciplinary PhD research covering computer science and healthcare. The author has been participating in a PhD program under supervision of a team involving professionals from areas of computer science, engineering, sociology, and psychology. The research has been carried out in China, an upper-middle-income country with a large ASD population as estimated (The World Bank, 2023). Motivated by the overwhelming prevalence of atypical sensory responses in ASD and low use of TBIs by people with ASD in China, this research aims to explore the development of an effective and innovative TBI to support the sensory regulation amongst children with ASD. With this broad aim, the thesis will address below specific research questions (RQs):

RQ1. What are the components and functionality of the system that match the needs of children with ASD?

RQ2. What AI algorithms can be embedded in such a system to better support monitoring of atypical sensory responses and to generate suitable sensory strategies?

RQ3. To what extent can the sensor and AI-enabled monitoring system developed for the purpose of this research effectively deliver those intervention strategies to support sensory regulation in children with ASD?

In this thesis, the author develops a system named *Roomie* as a tool to explore these RQs. Such a system is expected to play a role as a 'specialist' companion for children with ASD at home or at school. It monitors a user's environment, detects atypical sensory responses, and generates appropriate strategies to help the user regulate their responses. It uses affordable sensors, off-the-shelf devices, and AI techniques to achieve proposed functions of sensory environment monitoring, sensory processing pattern identification, atypical sensory responses detection, and sensory regulation strategy-making.

## 1.5 Summary of work done by the author

The aim of this thesis is to develop a TBI to support the sensory regulation for children with ASD. The author was responsible for all areas of development of *Roomie* with contributions also from student collaborators, caregivers of children with ASD, and ASD specialists. The following clarifies the actual work done by the author within this thesis and the work that has been done by others but used in this thesis.

1. Ideation – The initial requirements of the system and the interactions that the users would need were decided by the key stakeholders, including ASD specialists, and caregivers of children with ASD. The author and her PhD supervisors were involved in discussing how to

transform these ideas into a feasible, usable, and affordable system to aid children with ASD. The author investigated the cost, efficiency, and effectiveness of possible hardware and decided the focus of the prototype. The author also coordinated consultation meetings with key stakeholders after they used the prototype to obtain feedback and new suggestions for iterative development.

2. Data collection – The procedure of data collection was determined by the author through consultations with ASD specialists. With the help of ASD specialists, the author recruited participants and was involved in all sessions of data collection under close supervision of ASD specialists.

3. Design and programming – Based on the requirement specification, the author designed the interaction flow, system architecture, user interface, and data processor of the system. The author was the programmer of the main components of the system, with the initial interface to the system programmed by student collaborators. The author was the programmer of machine learning (ML) and rule-based models embedded in the system. Two student collaborators have devoted their time in the process of ML training. The author and student collaborators independently completed the training process as described in section 3.5 and cross-matched the results. The author also designed the attention task App described in section 3.4.1 with two student collaborators completing the programming.

4. Real-life evaluation – The author undertook the real-life evaluation of the system within the classroom with the help of caregivers and teachers. The procedure of formal evaluation on the overall system was designed and carried out by the author, under the oversight of one PhD supervisor from computer science and one PhD supervisor

from psychology.

5. Research – The author presented an independent and comprehensive piece of research work with clear clarifications of research questions, research process, ethical aspects, novelty, and potential future applications in this thesis. The author independently reflected upon knowledge from the field and described the scientific theories and methods on which this thesis has been based. The author conducted a scoping review of previous research with the help of two student collaborators to avoid the risk of bias. The remaining formal discussions and writing were completed by the author.

## 1.6 Scientific contributions of this work

The following summarises the specific contributions and the significance of this work.

1. The research has combined computer science and psychological protocols in the methodology to develop an effective and acceptable system for sensory regulation in children with ASD. A user-centred framework was suggested for iterative refinements of the system. The comprehensive data collection and experiments of AI algorithms ensure that the system can be robust and innovative in the current research work. Psychological methods and measurements were used in the tests for the effectiveness evaluation of the system (Refer to Chapter 3).

2. The author collected a first-hand data set from 35 children with ASD, comprised of their sensory profiles, environmental features, and physiological features with expert labels, which makes up for the current

lack of large data set for ML training. The author also developed a sensory regulation strategy knowledge base through consultations with ASD specialists. The knowledge base can be used in a rule-based model to generate suitable sensory regulation strategies for users (Refer to Chapter 3).

3. The research has identified user needs in China and proposed a comprehensive system design based on the needs, including the hardware, system architecture, user interface, and the interaction flow. The research shows evidence that in China, mobile phones and portable wearables are the best devices to implement a TBI. Real-time monitoring and sensory regulation strategy recommendations are what caregivers expected the most in a TBI for atypical sensory responses (Refer to Chapter 4).

4. The research has developed ML algorithms for attention and stress detection and a rule-based method for sensory regulation strategy-making. The accuracy of the algorithms and the inclusion of key parameters were verified. A further deep learning method was also discussed. The analysis suggests that the deep learning algorithm also has accurate results in feedback generation but requires a connection to a cloud data processing centre for strategy-making. The rule-based method is more responsive and can be deployed easily in a smartphone-based App without a connection to a cloud server (Refer to Chapter 5 and Chapter 7).

5. Following iterative design-development cycles, a final *Roomie* beta version has been released and systematically evaluated in real-life settings. Results from the comprehensive evaluation study suggest that users generally agree that the system is effective, user-friendly and various functions, such as real-time monitoring, detection, alert

and strategy-making, are well integrated (Refer to Chapter 6).

6. To the author's best knowledge, this research presents the first sensor and AI-enabled monitoring system, which fully considers the contexts of children with ASD (including their surrounding environments and their personal sensory processing patterns) for detecting atypical sensory responses and generating sensory regulation strategies, to effectively support children with ASD in dealing with atypical sensory responses.

Research outputs in this thesis have been published in below peer-reviewed publication outlets.

1. Deng, L., & Rattadilok, P. (2020). The need for and barriers to using assistive technologies among individuals with Autism Spectrum Disorders in China. *Assistive Technology, 34*(2), 242–253.

2. Deng, L., Rattadilok, P., Hadian, G. S., & Liu, H. (2021). Effect of sensory-based technologies on atypical sensory responses of children with Autism Spectrum Disorder: A systematic review [Conference Paper]. In *Proceedings of the 2021 International Conference on E-Society, E-Education and E-Technology* (pp. 208–218). Association for Computing Machinery.

3. Deng, L., Rattadilok, P., & Xiong, R. (2021). A machine learning-based monitoring system for attention and stress detection for children with Autism Spectrum Disorders [Conference Paper]. In *Proceedings of the 2021 International Conference on Intelligent Medicine and Health* (pp. 23–29). Association for Computing Machinery.

4. Deng, L., & Rattadilok, P. (2022). A sensor and machine learning-based sensory management recommendation system for children with

Autism Spectrum Disorders. *Sensors, 22*(15), 5803.

5. Deng, L., Ratavjia, S., & Rattadilok, P. (2024). Implementing a participatory design approach to create a sensory-friendly public space for children with special needs [Book Chapter]. In *Innovative Public Participation Practices for Sustainable Urban Regeneration.* Springer Nature.

## 1.7 Outline of the thesis

This thesis consists of eight chapters, following a chronological path encompassing how the research progresses from the formulation of RQs, providing incremental improvements in system capability until the final system is complete and evaluated.

Chapter 1 has provided an introduction of the disorder and sensory regulation issues in ASD. This chapter also provides an overview of TBIs, an emerging intervention for people with ASD. Moreover, the chapter clarifies the RQs that will be addressed in this thesis. An outline of the scientific contributions and publications relating to this research is presented as well.

Chapter 2 presents a review of literature. This chapter begins by exploring daily environmental influences on children with ASD and investigating common assessment tools that quantify their sensory processing patterns in daily lives. The chapter also looks at TBIs, including sensors and AI, and existing applications in the ASD field. The chapter further reports the findings from a scoping review which explores the effect of existing TBIs designed for addressing atypical sensory responses of children with ASD.

Chapter 3 describes the methodology of the research, demonstrating a combination of user-centred and iterative development framework which is implemented throughout the research. To address the RQs, an interdisciplinary approach is established. This chapter offers a description of computer science methodologies used for technological portion and psychological methodologies used for ASD-related evaluation in this study. As the research involving children with ASD and stakeholders, this chapter also describes how the author addresses potential ethical issues in this research.

Chapter 4 discusses the user needs, design specifications, and feasibility of the proposed system. It begins with an identification of user needs to facilitate the sketch of system design. The chapter presents the overall system architecture and working flow, and explores the suitable sensors and devices that can be used to achieve the proposed functions. A first *Roomie* prototype is developed and then used in a feasibility study. Detailed descriptions and discussions of these procedures are presented in this chapter.

Chapter 5 focuses on the performance of AI algorithms for supporting detection of atypical sensory responses and generating sensory regulation strategies in the proposed system. With data collected from a number of children with ASD, different ML algorithms are evaluated in this chapter for their performance on attention and stress detection. The chapter also presents the validation of fuzzy logic algorithms developed for providing real-time sensory regulation strategies. The chapter discusses the implementation of the algorithms in *Roomie*.

Chapter 6 presents the formal evaluation of the system to investigate whether and how well it can effectively deliver strategies to support sensory regulation in children with ASD. The system usability has been explored. The evaluation results are discussed to justify its potential real-life use in the future.

Chapter 7 firstly revisits the RQs formulated in Chapter 1 to ensure that they have been fully addressed throughout the research. The chapter then reports optimised ML algorithms by feeding an updated dataset obtained from the evaluation study described in Chapter 6. This chapter also reports the acceptability of the *Roomie* sensors based on specialists and caregivers' reflection. A comparison with other existing related work is made in this chapter to present the novelty of this research.

Chapter 8 synthesises the core findings from individual chapters and provides an overview of contributions, challenges and limitations of the research. The chapter also proposes future works for refining the system and discusses its wider application.

# Chapter 2

# Literature Review

This chapter reviews literature relevant to this research. It starts by considering the effects of sensory stimuli in the environment around children with Autism Spectrum Disorder (ASD). It then explores sensory processing patterns and sensory developmental trajectories of children with ASD. It also reviews sensory assessment methods and sensory regulation strategies in the current practice. Existing technology-based interventions (TBIs) designed for addressing atypical sensory responses in ASD are reviewed. This includes a scoping review which systematically browses through academic databases and screens related literature. The scoping review focuses on the use of technology and the reported efficacy. An additional section reviews the application of artificial intelligence (AI) in related studies. This chapter closes with conclusions and implications drawn from the literature review.

## 2.1 Effects of environmental factors on children with ASD

Children with ASD are among the community with special sensory needs largely due to the 'overwhelmingly disabling effects of a sensory handicapping built environment' where they dwelt (Shabha, 2006). It has been suggested that the social trigger of atypical sensory responses in children with ASD can be found in 'unfriendly environment' (Khullar et al., 2019). Particularly, hypo-or hyper-sensitivity to environmental factors such as noise, light, or room temperature is perceived as a major challenge for children with ASD (Caniato et al., 2022b; Martin, 2016; Nagib & Williams, 2017; Noble et al., 2018; Schaaf et al., 2011). Existing research has investigated the effects of environmental factors across multiple sensory modalities, such as audition, vision, touch and smell.

Understanding the effects can have important implications for developing an effective TBI for children with ASD who experience atypical sensory processing. Therefore, the following subsections review the literature which reports impacts of certain environmental factors on human-being or children with ASD over the past two decades. The comfort zone reported in the literature is reviewed as well, which will serve as the reference for determining sensory thresholds[1] while developing the *Roomie* system.

### 2.1.1 Noise

Noise refers to unpleasant sounds in one's environment which affects the person both physiologically and psychologically (Atmaca et al., 2005). Mea-

[1]Sensory thresholds in this thesis refer to the limit of sensory input required for a comfortable setting for children with ASD.

sured in decibels (dB), a normal level of everyday sounds and noises for most individuals is expected to be under 70 dB (Berglund et al., 1999; National Institutes on Deafness and Other Communication Disorders, 2019). As defined by American Academy of Audiology (2008), moderate noise level is normally between 50 dB and 70 dB. Excessive noise can result in physiological disturbances such as increased blood pressure, faster heartbeat, muscle tension and sleep disruptions (Goines & Hagler, 2007). Psychological effects can be exhibited in a variety of ways including irritation, agitation, restlessness and difficulty perceiving and concentrating (Atmaca et al., 2005). It is suggested that there is a strong link between stress and noisy environments (Kanakri et al., 2017). Not only for individuals with ASD but also for each person, continuous exposure to noise levels in excess of 80 dB can increase annoyance and anxiety, which can induce aggressive behaviour in worse scenarios (Berglund et al., 1999).

As suggested by the World Health Organisation (2011), noise exposures may be more adverse for vulnerable subgroups such as children, elder people, and people with particular diseases or medical problems. Atypical auditory processing is one of the main problems underlying sensory regulation issues in ASD (Shabha, 2006). Individuals with ASD commonly report difficulties interpreting auditory information in situations where there is environmental noise, and troubles creating an appropriate behavioural response (Wood et al., 2019). MacLennan et al. (2022) investigated sensory experiences of ASD adults and found that a majority of participants self-reported annoyance with loud noises. Kanakri et al. (2017) conducted a survey with teachers of children with ASD and suggested that children with ASD generally presented sensory regulation issues related to noise. Similarly, in some other studies, caregivers of children with ASD agreed that when their children entered a public space such as a classroom or a clinic, noise could be a key issue which resulted in children's poor performance or meltdown[2] in the public space (Ben-Sasson et al., 2009; Caniato et al., 2022a; Wood et al., 2019). There was evidence that as decibel levels increased in an environment, frequency of maladaptive behaviours in children with ASD increased (Kanakri et al., 2016). Besides, listening to and perceiving meaningful information in an environment with background noise was found to be a particular challenge for children with ASD (Alcántara et al., 2004; Rance et al., 2017).

Although literature suggests a comfortable noise level between under 70 dB, individuals with ASD may have narrowed thresholds for auditory input. For those with ASD who have hyper-sensitive auditory processing, ambient sounds are often perceived as loud, and they may take intrusive strategies such as covering ears, crying, fleeing the area, and even self-injury to decrease sensory stimulation (Kargas et al., 2014; Stiegler & Davis, 2010). For those with ASD who have hypo-sensitive hearing, they may be indifferent to noise even though the noise level around them is harmful (Kanakri et al., 2017). Although World Health Organisation has promoted that future research needs to concentrate more on vulnerable subgroups in which exposure to noise may have distinct effects (World Health Organisation, 2011), there still remains a significant gap in the literature about how to support auditory experiences and facilitate an acoustically-friendly environments for children with ASD (Kanakri et al., 2017).

### 2.1.2 Light

Much of the literature has emphasised that the light environment directly affects an individual's academic or work performance through visual ef-

[2] ASD-related meltdown refers to an explosive behavioural release resulting from stressors and overload of the nervous system (Bedrossian, 2015).

fects and indirectly affects the attention and stress levels (Lu et al., 2020; Sleegers et al., 2013). An early survey conducted by Shabha (2006) assessed the impact of the sensory environment on children with ASD in classrooms, and concluded that the source of light (e.g., fluorescent light flickering) and brightness were the main visual triggers which might have caused atypical sensory responses. Studies exploring the light comfort of individuals with ASD have been emerging in recent years, most of which were conducted with the purpose of designing an ASD-friendly building (Caniato et al., 2022b; Mostafa, 2015; Zaniboni et al., 2021). Mostafa (2015) compared the spaces of a range of special and mainstream schools. The survey with school designers and individuals with ASD highlighted that the use of natural lighting was one of the major concerns which were preferred to improve environmental comfort. Zaniboni et al. (2021) conducted a survey with caregivers of children with ASD, identifying that light flicker and prevalence of artificial or dark light might cause discomfort in people with ASD. However, a more recent study conducted by Caniato et al. (2022a) suggested that in an indoor environment such as home environment, particular visual stimuli such as light flicker, did not have strong impacts on people with ASD. Caniato et al. (2022b) admitted that atypical sensory responses to visual stimuli were associated with age. A difference between individuals with ASD aged under and over 18 years old was found in the impacts of light stimuli on stress. Their findings suggested that, when there was a high level of illumination, the perceived stress of children with ASD was significantly different from typically developing (TD) people and this significance level was even higher than the adults with ASD. Unfortunately, many studies failed to provide a confirmed answer what level of light intensity was considered to be comfortable to children with ASD. This may be because that they did not conduct controlled experiment and use physiological indicators to evaluate the light environment.

Various studies used a combination of measurements and questionnaires to evaluate visual comfort in different lighting conditions (Lu et al., 2020; Noda et al., 2020; Ricciardi & Buratti, 2018). One of the commonly used measurement indexes is the value of illuminance in unit lux (lx), which can be easily detected by luxmeters such as photoresistors. However, there is no globally uniform quantitative standard for value of illuminance in indoor environments (Lu et al., 2020). No recommended or required illuminance for children with ASD has been identified in the existing international guidelines, while China's 'Architectural Lighting Design Standards' (Ministry of Housing and Urban-Rural Development, 2014) generally requires that the average illuminance of the classroom in an educational building should not be less than 300 lx. According to the United States' 'Annual Sunlight Exposure' (Illuminating Engineering Society, 2021) index, values over 1000 lx at the student desk level in the classroom may cause visual discomfort. Ricciardi & Buratti (2018) evaluated the visual comfort in seven university classrooms, with the mean values of illuminance ranging from 49 lx to 564 lx. Discomfort to lighting conditions was identified in a classroom with excessive illuminance, of which the value of illuminance went higher than 600 lx. Noda et al. (2020) assessed the visual comfort of children aged between 9 and 11 years old in classrooms. They found that most children preferred a slightly darker classroom where the value of illuminance was around 350 lx to 600 lx. A study conducted by Lu et al. (2020) applied Electroencephalogram[3] (EEG) measurements and questionnaire to quantify the light comfort zone. The light comfort zone was determined by physiological and subjective evaluation of the effects of different light environments on people. The result showed that the comprehensive light comfort zone was between 335.9 lx and 409.4 lx. By synthesising the vi-

[3]An Electroencephalogram (EEG) is a tool to measure brain's electrical activity for evaluating brain activities or states such as resting state (Michel & Koenig, 2018).

sual comfort intervals in literature, controlling the light intensity level in an indoor environment at 300 lx to 600 lx is sufficient to make children feel comfortable. However, the comfort zone of children with ASD may be different from TD people. Literature data will then be combined with ASD specialists' suggestions when considering a comfort zone of children with ASD in this thesis.

### 2.1.3 Temperature and humidity

Temperature and relative humidity are another major environmental factor that can cause discomfort, distress and distraction in individuals with ASD (Caniato et al., 2022a; Nagib & Williams, 2017; Tavassoli et al., 2014; Zaniboni et al., 2021). Thermo-hygrometric discomfort caused by elevated indoor temperatures and low ventilation rates is considered to have negative effects on the children's performance, especially the learning activities (Wargocki & Wyon, 2007; Yun et al., 2014). Much of the literature has implied that the thermal environment has a significant influence on attention, distress and learning behaviours (Abbasi et al., 2019; Barrett et al., 2013; Riquelme et al., 2016; Wargocki et al., 2019). Findings from a multi-site study conducted by Barrett et al. (2013) suggested that temperature was one of the key parameters that accounted for children's academic performance variation over the course. Abbasi et al. (2019) suggested that very high and very low temperatures not only affected the learning performance, but also caused significant changes in heart rate. Another important finding was that individuals with ASD who were hyper-sensitive to temperature stimuli may perceive heat and cold to be painful (Riquelme et al., 2016). Studies on relative humidity found that extremely low or high relative humidity can lead to an increase in stress and fatigue. Caniato et al. (2022b) identified that children with ASD presented a higher stress level than their TD peers in low humidity conditions. Some studies found that a dry environment or a humid environment greatly increased the degree of fatigue and distraction compared to an environment at neutral humidity level (C. Liu et al., 2021; Tsutsumi et al., 2007). Typically, temperature and relative humidity at extreme levels could raise body arousal (Abbasi et al., 2019), which can lead to adapting behaviours in TD people such as adjusting layers of clothing or room ventilation. However, individuals with ASD may fall behind their TD peers in conducting thermally adapting behaviours due to cognitive and motor impairments (Chatham et al., 2018). Therefore, it is necessary to provide more support and create a comfortable thermo-hygrometric environment for individuals with ASD.

The comfortable temperature and humidity refers to the temperature and relative humidity level 'at which either the average person will be thermally neutral or at which the largest proportion of a group of people will be comfortable' (Nicol & Humphreys, 2010). According to the most commonly-used standard, the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55, the centre point temperature which corresponds to neutral thermal sensation is 25 °C (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2020). The most up-to-date ASHRAE Standard does not specify a minimum humidity level, while an earlier version of the Standard recommended an indoor relative humidity between 30% and 60% for the thermal comfort purpose (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2017). Table 2.1 displays the thermal comfort zone and potential response of human body to different temperature ranges as per the ASHRAE Standards.

**Table 2.1:** *Thermal response of human body to temperature*

| Temperature (°C) | Feeling | | Physiological Response |
|---|---|---|---|
| | Hot Cold Feeling | Comfortable Sensation | |
| 40-45 | Limit | Limit | The body temperature rises, and people will have difficulties in self-regulation |
| 35-40 | Very hot | Very uncomfortable | Sweating, blood pressure increases |
| 30-35 | Warm | Uncomfortable | Sweating, heart rate instability |
| 20-30 | Neutral | Comfortable | Normal |
| 15-20 | Slightly cool | Little uncomfortable | Heat loss is accelerated, and more clothes are needed |
| 10-15 | Cool | Uncomfortable | Vasoconstriction of the hands and feet |
| 5-10 | Cold | Very uncomfortable | Poor blood circulation and muscle soreness |

However, some thermal comfort studies have suggested that for preschool and primary school children, comfortable temperatures can be 0.5 °C to 4 °C lower than those of adults as suggested by the ASHRAE Standards (Nam et al., 2015; Teli et al., 2012, 2014; Yun et al., 2014). For example, Nam et al. (2015) reported that in Korea, a country with clear four seasons, the centre point temperatures which correspond to neutral thermal sensation for preschool children were about 22 °C on average. Teli et al. (2012) reported that a comfortable temperature range for children in the UK was 20.5 °C to 23 °C outside the heating season. These studies were conducted in kindergartens or primary schools where health conditions of participants were not articulated, which prevented the author to synthesise the thermal comfort zone for children with ASD. Nevertheless, a range of studies have found no differences in thermal detection thresholds between individuals with ASD and TD people (Cascio et al., 2008; Fründt et al., 2017; Williams et al., 2019), indicating that in general, comfortable temperatures perceived by TD children are friendly to children with ASD. However, there is strong intra-individual variability in ASD based on the different sensory processing patterns, which should be considered when customising an effective intervention for children with ASD (Williams et al., 2019).

### 2.1.4 Other factors

Some other environmental factors that also trigger atypical sensory responses in children with ASD include unpleasant smell, polluted air, and barometric pressure. However, atypical responses to these stimuli in children with ASD are still poorly studied compared to abnormalities in audition, vision and touch. There are very few studies focusing on olfactory abnormalities in children with ASD due to methodological difficulties (Kumazaki et al., 2016). Indoor odours or pollutions are scattered in the air, usually coming from different chemical particles produced by food, kitchen appliances, human emissions, furniture and many more. Therefore, measuring and controlling smell, which can be a significant challenge, are not currently included in this research when developing the proposed TBI for sensory regulation.

On the other hand, barometric pressure can be easily detected and research has found that people with psychiatric conditions can be susceptible to changes in barometric pressure (Schory et al., 2003). Impulsive and aggressive behaviours may increase, especially when barometric pressure is low. However, the reason of the phenomenon is not readily apparent. The speculation suggested that the decrease in pressure resulted in changes in cerebral blood flow and hormone levels, which can interfere with brain activity (Schory et al., 2003).

## 2.2 Sensory regulation

In ASD practice, knowing environmental stressors is not enough to generate professional sensory regulation strategies. Children with ASD have idiosyncratic sensory processing patterns that influence the way they perceive the environment (Robertson & Baron-Cohen, 2017). Therefore, data about environmental influences should be combined with knowledge of sensory regulation ability and patterns, used in a system that is capable of generating sensory regulation strategies like an ASD specialist does.

### 2.2.1 Sensory regulation ability and early childhood pattern

Since early in development, infants find themselves immersed in a rich sensory environment and acquire knowledge about the world through senses (Piccardi & Gliga, 2022). To properly interact with the multisensory world around them, individuals must be able to choose and process sensory information to plan and perform appropriate behaviours. This ability is known as sensory regulation (Dunn, 2014). However, salient sensory regulation issues in ASD are manifest early in infancy and childhood. For example, infants at elevated likelihood of ASD frequently manifest reduced responsiveness to or seeking of novel sensory inputs. Although the mechanisms underlie the atypicality in sensory responses in ASD are unclear, impairments in this fundamental ability of sensory regulation are believed to have far-reaching implications for the development of children's independent living skills.

Extensive evidence has showed that over 90% of children with ASD have experienced atypical sensory responses (Leekam et al., 2007; Marco et al., 2011; Robertson & Baron-Cohen, 2017). Sensory regulation ability may develop with age, but atypical sensory responses continue to affect children with ASD over time. A study conducted by Perez Repetto et al. (2017) observed changes in 34 children with ASD aged 3 to 4 years over a two-year interval, indicating few changes over time for sensory-related challenges. Similarily, in another study conducted by McCormick et al. (2016), children with ASD and TD children were assessed across three time points from 2 to 8 years of age. TD children decreased in reported sensory symptoms while children with ASD demonstrated no significant change across assessment time points, suggesting that atypical sensory responses in ASD remained stable over time during childhood. While some cross-sectional evidence suggested that some atypical sensory responses, such as sensitivity to bright lights and touch, diminished with age in children with ASD (Baranek, David, et al., 2007; Baranek et al., 2019; Cheung & Siu, 2009; Kern et al., 2007; Leekam et al., 2007). Studies found that this reduction was strongly linked to mental age, perhaps due to maturation of cognitive functions and sensory regulation abilities, and engagement in early interventions (Baranek, David, et al., 2007; Baranek, Boyd, et al., 2007; Baranek et al., 2019).

These findings indicate that over the several-year period in childhood, children with ASD are likely to constantly have sensory regulation issues. However, improvements in sensory outcomes are possible at this important stage with effective interventions. Therefore, interventions for sensory regulation should be introduced to ASD families during the childhood. This is also the reason why the author decides to target children with ASD when developing a certain TBI for sensory regulation.

### 2.2.2 Sensory regulation strategies

As reviewed in section 2.1, the impacts of experiencing environmental challenges have been profound for individuals with ASD. Moreover, these impacts stably and continuously affect individuals with ASD during their childhood. Strategies could be applied to address children's sensory regulation issues. Understanding sensory regulation ability and relevant strategies is always a starting point for a practitioner to tailor interventions for impairments in sensory regulation (Baranek et al., 2019).

In general, sensory regulation strategies are the recommendations that are made by therapists and followed by caregivers or practitioners to address the child's hyper-or hypo-sensitivity and support their self-regulation. Evidence shows that children with ASD can benefit from daily sensory regulation strategies being applied at home (Bagby et al., 2012). For example, a single sensory strategy can be a recommended modification to the child's home environment which helps the child to fully participate in preferred sensory experiences. A caregiver who receives recommendations may intuitively adapt their home environment to accommodate a child's sensory regulation difficulties. For example, caregivers can avoid highly stimulating environments, and apply certain strategies such as playing calming music at home for potential aversive sensory experiences. There were suggestions and evidence that introducing reduced levels of lighting and sound, and playing harmonic, rhythmic music such as classical music with repetition had the calming effects for children with ASD (G. S. Kim et al., 2024).

Sensory regulation strategies can also be applied in a public setting, including schools. There are many strategies that children with ASD and their families have used already, such as use of headphones when going to crowded places if the child is sensitive to sound (Pfeiffer et al., 2019). Some special education schools have built 'sensory rooms', which were spaces with soft cushions for sitting or lying down, pleasant displays of lights, soothing sounds such as rhythmic music. Children with ASD have found that programmes in sensory rooms had a calming effect and supported their sensory regulation (Leekam et al., 2007). Communities have attempted to promote the ASD-friendly public festivals by proactively adopting sensory strategies such as turning off fluorescent lights, electric hand-dryers in toilets, and providing items such as sensory toys and noise-cancelling headphones (Fletcher-Watson & May, 2018; Richards & Parkes, 2023).

### 2.2.3 Sensory-related assessment methods

There are various methods that have been widely used to assess a child's sensory regulation issues or sensory processing patterns, reflecting how a person process sensory information in daily lives (e.g., how sensitive a person is to auditory input). Archiving this information into an individual's profiles is beneficial in clinical settings for providing individualised intervention services to help children better deal with the challenge. These assessment methods can be questionnaire-based and caregiver-reported, mostly assessing frequencies of a child's responses to a variety of sensory stimuli across modalities and contexts (Ausderau et al., 2014; Little et al., 2011). Some assessment methods are implemented by ASD specialists, such as interviews and observations. Table 2.2 summarises a range of commonly seen assessment methods that have been used for children with ASD in the clinical practice.

**Table 2.2:** *Major clinical sensory-related assessment methods for children with ASD, adapted from Schaaf & Lane (2015) and Jorquera-Cabrera et al. (2017)*

| Assessment Method | Number of Questions | Age Range (years old) | Scale | Chinese Version Available? |
|---|---|---|---|---|
| Sensory Profile of Children Three to Ten Years Caregiver Questionnaire (Dunn, 1999) | 125 | 3-10 | A caregiver rates the observed frequency of described behaviours on a 5-point Likert scale. The tool consists of 14 subsections that refer to sensory processing, modulation, behavioural and emotional responses. | Hong Kong and Taiwan Chinese versions are available |
| Short Sensory Profile (McIntosh et al., 1999) | 38 | 3-10 | A caregiver rates the observed frequency of described behaviours on a 5-point Likert scale. The tool consists of 7 subsections that refer to sensory processing. | Hong Kong and Taiwan Chinese versions are available |
| Sensory Processing Measure-Home Form (Parham et al., 2007) | 75 | 5-12 | A caregiver rates the observed frequency of described behaviours on a 4-point Likert scale. The tool consists of 7 subsections that refer to sensory processing, social participation, and behavioural responses. | Hong Kong Chinese version is available |

| Assessment Method | Number of Questions | Age Range (years old) | Scale | Chinese Version Available? |
|---|---|---|---|---|
| Sensory Experiences Questionnaire 3.0 (Baranek, David, et al., 2007) | 105 | 2-12 | A caregiver rates the observed frequency of first 97 behaviours on a 5-point Likert scale. The tool also requires descriptive answers.<br>The tool consists of 11 subsections that refer to sensory processing and behaviours in social and non-social contexts. | No |
| Sensory Integration and Praxis Tests (Ayres, 1989) | A series of 17 tests | 4-8 | A qualified professional reports standardised scores based on the child's performance.<br>The tool mainly covers four areas of visual perception, somatosensory, praxis, and sensorimotor. | No |

It can be found that Winnie Dunn's Sensory Profile (SP) is a more comprehensive and globally adopted assessment tool compared to other assessment tools. The full SP caregiver questionnaire contains 125 questions evaluating sensory processing in 14 areas, including auditory processing, visual processing, vestibular processing, and tactile processing. The result of SP caregiver questionnaire can be converted into the classification of four sensory processing patterns using the scoring sheet. The sensory processing patterns are developed based on the Dunn's framework of sensory processing which emphasised a crucial link between neurological thresholds and behavioural responses (Dunn, 2001, 2002; Hyman et al., 2020; Williams et al., 2019).

Neurological thresholds in Dunn's framework are defined by the minimum amount of stimulation necessary to register the perception (Williams et al., 2019). For individuals with ASD who have atypical sensory processing, hyper-sensitivity to stimuli is the result of low neurological thresholds for stimulus perception, while hypo-sensitivity to stimuli is the result of high neurological thresholds for stimulus perception. Winnie Dunn's framework further suggests that the way individuals tend to respond to stimuli could be passive or positive (Dunn, 2001). Based on the intersection of neurological threshold and behavioural response, Dunn describes four sensory processing patterns as Low Registration, Sensory Seeking, Sensory Sensitivity and Sensory Avoiding (see Figure 2.1).

| | Behavioural Response | |
|---|---|---|
| Neurological Threshold | Passive | Positive |
| High | Low Registration | Sensory Seeking |
| Low | Sensory Sensitivity | Sensory Avoiding |

**Figure 2.1:** *Winnie Dunn's framework of sensory processing, adapted from Dunn (2007)*

For each pattern, every child can be classified as 'Typical Performance', 'Probable Difference', and 'Definite Difference' (Dunn, 2002). A child obtains 'Typical Performance' in these patterns indicates that the child is similar to most peers in responding to the sensory input successfully. 'Probable Difference' indicates that the child is probably different from most children while further testing is needed. 'Definite Difference' means that the child will have problems in their behaviours attributing to sensory processing patterns.

In general, a child who obtains 'Definite Difference' classification in the Low Registration pattern will probably fail to notice sensory events which others can easily detect. Obtaining 'Definite Difference' in the Sensory Seeking pattern means that the child often acts in an excessively seeking manner to extend his or her sensory stimulations. Obtaining 'Definite Difference' in the Sensory Sensitivity pattern means that the child is hyper-responsive to sensory stimuli, whilst those who obtained 'Definite Difference' in the Sensory Avoiding pattern will go to the other extreme to limit sensory events (Dunn et al., 2002; Deng, Rattadilok, & Xiong, 2021). Table 2.3 presents some examples of behaviours for each pattern being classified as

‘Definite Difference’, adapted from Geyser (2009).

**Table 2.3:** *Examples of behaviours attributing to ‘Definite Difference’ in each pattern, adapted from Geyser (2009)*

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Behavioural Response Continuum</td></tr>
<tr><td>Passive</td><td>Active</td></tr>
<tr><td rowspan="2">Neurological Threshold Continuum</td><td>High</td><td>Low Registration<br>Have trouble reacting to rapidly presented or low-intensity stimuli;<br>Dull affect;<br>Not aware when being spoken to;<br>Delayed reaction.</td><td>Sensory Seeking<br>Touch others too often;<br>Overactive and continually seeks movements;<br>Bang or tap head, arms and legs repeatedly.</td></tr>
<tr><td>Low</td><td>Sensory Sensitivity<br>Over-respond to loud noises or brightness;<br>Have difficulty paying attention;<br>Jump from one activity to another so that it interferes with play.</td><td>Sensory Avoiding<br>Withdraw from unexpected touch;<br>Fear movement;<br>Resistant to change;<br>Reliant on rigid rituals.</td></tr>
</table>

Examples of behaviours in Table 2.3 implies that the behavioural outputs of individuals with different patterns can be heterogeneous. The use of SP questionnaire can generally profile an individual’s sensory regulation ability. However, it cannot predict an individual’s atypical response in any circumstances. It can be found that these behaviours commonly occurred along with internally generated discomfort symptoms such as stress, as well as attentional symptoms such as distraction (Roley et al., 2007). Although there are studies that do not support the neurological threshold theory, such as behavioural theory (S. H. S. Kim & Lord, 2013; Lovaas & Smith, 1989) the neurological threshold model is still a leading framework and Dunn’s SP has been found to be a reliable assessment method in various studies (Bundy et al., 2007; White et al., 2007; Williams et al., 2019).

## 2.3 Scoping review of existing technology-based interventions

As introduced in the Chapter 1, a range of technologies have been used in ASD interventions which are equipped with many features that suit the needs of individuals with ASD. Although increasingly emerging over the past decades, TBIs for sensory regulation are less studied compared to those targeting social-communication deficits in ASD (Benssassi et al., 2018; Deng, Rattadilok, Hadian, & Liu, 2021). Most studies in the field have been exploratory, with inclined focuses on the design and feasibility. TBIs addressing atypical sensory processing in ASD have been perceived as an 'emerging treatment' rather than an 'established treatment' (National Autism Centre, 2015), before their effectiveness can be assessed and validated in related research (Grynszpan et al., 2013). In this section, the author reviews existing studies on TBIs targeting atypical sensory processing in ASD using a scoping review method. This scoping review maps evidence on the effects of TBIs on children with ASD in helping with particular sensory regulation issues. In addition, it enables the author to learn from previous practice what technologies and methods may be useful for developing an effective TBI for children with ASD who experience atypical sensory responses in this PhD research.

### 2.3.1 Methods used for the review

Scoping review method was used because it is suitable for examining emerging evidence when it is still unclear (Aromataris & Munn, 2020). The author conducted the review following a standard guideline, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for scoping reviews (Tricco et al., 2018), to ensure the quality of review. Two undergraduate students also contributed to the scoping review to minimise the risk of bias. The author and undergraduate students contributed to the literature screening and quality assessment phases, while the formal analysis and writing were completed by the author.

Searches were conducted in four online academic databases covering the areas of the research: (1) 'PubMed' which covers publications in medical and healthcare areas; (2) 'IEEE Xplore' which covers publications in electrical engineering, computer science and electronics; (3) 'ACM Digital Library' which covers publications in computer science; (4) 'Web of Science' which contains publications across multiple disciplines, including numerous proceeding papers submitted to international conferences. A combination of relevant keywords was entered into the search bar of databases to identify potential literature. The search string was: (Autism OR Autistic OR 'Asperger's syndrome') AND (technology OR phone OR wearable OR sensor OR device OR robot OR computer) AND (intervention OR treatment OR therapy OR training) AND (sensory OR sensitive* OR responsive*). In order to identify more recent literature, filters were applied in the initial search to include studies published after January 2000 only. The latest search was executed during the time when this chapter was developed to ensure that the review included the most up-to-date studies.

The screening for potential eligible studies followed a two-stage process, carried out by the author and undergraduate students (hereafter referred as 'us') independently. At the first stage, the screening of the articles' titles and abstracts for primary inclusion based on the selection criteria was conducted. Thereafter, full text of included articles was read to determine eligibility and documented the reason for exclusion. After each stage, decisions as to which of these resources were to be remained were settled by discussion and consensus among us and validated by one supervisor of the author. Reference sections of eligible studies were also manually reviewed to find more relevant resources. The following inclusion and exclusion criteria were applied for selecting the eligible studies.

Firstly, the study population was set to children with ASD. Studies were included if they focused on children under the age of 18 who had been formally diagnosed with ASD. Studies with focus on other disabilities were excluded. Besides, the technology used in the included studies must be for intervention purposes, conforming to the definition of TBI, and target atypical sensory responses in ASD. Studies that used technology as a diagnosis tool or merely for assessment were excluded. Studies that were written in English and were published in peer-reviewed journal or conference proceedings in or after 2000 were included. Considering that the TBI for atypical sensory responses in ASD has been a relatively new trend and many related studies were still exploratory, the scoping review did not exclude studies at earlier stage of design and test. Only empirical studies which contained data about the impact of a TBI were included for analysing the efficacy.

In order to enhance the validity of results of the scoping review, the methodological quality of each eligible study was assessed by us using the Single-Case Experimental Design (SCED) Scale (Tate et al., 2008). SCED scale is an 11-item rating scale which is designed specifically for evaluating the reliability of single-subject experiments.

### 2.3.2 Results of the scoping review

#### 2.3.2.1 Results of searching and screening process

The initial searches identified a total of 3126 articles. After removing duplicates and papers that did not meet the selection criteria, 95 studies were remained to be assessed by reading the full texts. After identifying additional studies from reference sections of eligible studies, 17 studies were finally included. Of the studies, only 52.9% ($n = 9$) measured the efficacy of a TBI in helping with a certain sensory regulation issue based on empirical evidence. The nine studies were further extracted for analysing the reported efficacy. The other studies ($n = 8$) only proposed a design or a framework, and mainly discussed the feasibility and provided recommendations. Detailed information about the screening process following PRISMA guideline is provided in Appendix A.

#### 2.3.2.2 Characteristics and methodological quality of included studies

Appendix B details summarised characteristics of eligible studies, including publication years, detailed information on technology, sample, targeted sensory regulation issues, and if any, reported efficacy in addressing targeted issues. Table 2.4 below extracts key information about technology elements and methodological quality from Appendix B and SCED quality assessment of empirical studies (SCED rating is attached in Appendix C). Overall, most studies ($n = 8$) assessed by SCED scale present a moderate to high methodological quality, indicating that most empirical studies provide trustworthy evidence to suggest the feasibility of TBIs. For studies which did not evaluate and report effects of the TBI on targeted issues, the author marked their SCED rating as 'non-empirical' to indicate a lack of evidence-based results. Although the emphasis of these studies was merely on design and guidelines, some innovative framework and architecture they proposed are also worth reviewing and discussing in this thesis.

**Table 2.4:** *Summary of characteristics of included studies (in order of publication year)*

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Schafer et al. (2013) | Phonak sound amplification system consisting of a sound sensor, a transmitter, and a receiver. | Auditory hyposensitiveness | 7 (7 males, age: 9-11 yo) | 10 | Pre-post | Improved speech recognition in noise and improved attention. |

| **Reference** | **Description of Technology Elements** | **Target Issue** | **ASD Sample** | **Evaluating the Effects of TBI in Helping with Target Issues** | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Sula et al. (2013) | An IoT-based system using a body sensor, a chair vibrator, a bed vibrator, a light controller, a smell controller, and a sound controller. | Multi-sensory processing issue | 1 (1 male, age: n.d.) | Non-empirical | / | / |

| **Reference** | **Description of Technology Elements** | **Target Issue** | **ASD Sample** | **Evaluating the Effects of TBI in Helping with Target Issues** | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Rance et al. (2014) | Phonak sound amplification system consisting of a sound sensor, a transmitter, and a receiver. | Auditory hypo-sensitiveness | 20 (17 males, age: 8-15 yo) | 8 | Pre-post | Improved speech recognition in noise and improved attention. |
| Ringland et al. (2014) | A large display device for multi-sensory environment. | Multi-sensory processing issue | 19 (19 males, age: 4-14 yo) | 7 | Pre-post | Improved engagement, attention, and sensory skills. |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | SCED Scores (Full Score = 11) | Study Design | Reported Efficacy |
| Schafer et al. (2016) | Phonak sound amplification system consisting of a sound sensor, a transmitter, and a receiver. | Auditory hyposensitiveness | 12 (gender ratio: n.d., age: 5-17 yo) | 10 | Pre-post | Improved speech recognition in noise, memory, and attention. |
| Rance et al. (2017) | Phonak sound amplification system consisting of a sound sensor, a transmitter, and a receiver (or a speaker). | Listening-related stress | 26 (20 males, age: 6-16 yo) | 9 | Pre-post | Reduced physiological stress levels. |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Mir & Khosla (2018) | A counting game-based software application using Microsoft Kinect sensor. | Sensory and motor issues | 3 (gender ratio: n.d., age: n.d.) | 3 | Time series | Increased game scores over time, improved motor, sensory and academic skills. |

| **Reference** | **Description of Technology Elements** | **Target Issue** | **ASD Sample** | **Evaluating the Effects of TBI in Helping with Target Issues** | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Schafer et al. (2019) | Phonak sound amplification system consisting of a sound sensor, a transmitter, and a receiver. | Auditory hyposensitiveness | 15 (10 males, age: 7-21 yo) | 8 | Pre-post | Improved processing of general auditory input, and attentional behaviours (e.g., eye contact and paying attention). |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | SCED Scores (Full Score = 11) | Study Design | Reported Efficacy |
| Khullar et al. (2019) | An IoT-based system consisting of a gas sensor, a VGA camera, a 3-axis accelerometer, a microphone, a display screen, and a speaker. | Multi-sensory hyper-sensitiveness | 10 (8 males, age: 8-19 yo) | Non-empirical | / | / |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | SCED Scores (Full Score = 11) | Study Design | Reported Efficacy |
| Hu et al. (2020) | A matching task-based software application using Leap Motion sensor. | Visual processing difficulty | 2 (1 male, age: 9-10 yo) | 10 | Pre-post, time series | Improved task performance over time, more engagement than traditional intervention. |
| Johnston et al. (2020) | A VR game-based software application using Oculus Rift HMD device. | Auditory hypersensitiveness | 6 (4 males, age: 16-19 yo) | 8 | Pre-post | Reduced self-reported stress levels associated with unpleasant noise. |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | SCED Scores (Full Score = 11) | Study Design | Reported Efficacy |
| S. Ali et al. (2020) | A NAO robot. | Multi-sensory hypo-sensitiveness | 12 (11 males, age: 4-10 yo) | Non-empirical | / | / |

| Reference | Description of Technology Elements | Target Issue | ASD Sample | Evaluating the Effects of TBI in Helping with Target Issues | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Polo Rodríguez et al. (2021) | An IoT-based smart home system using sensors for monitoring user presence, door opening, ambient sound, light, water leak, humidity, temperature, and mattress pressure. | Multi-sensory processing issue | n.r. | Non-empirical | / | / |

| **Reference** | **Description of Technology Elements** | **Target Issue** | **ASD Sample** | **Evaluating the Effects of TBI in Helping with Target Issues** | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Ghafghazi et al. (2021) | An AI-driven ABA system using sensors fusion, AI techniques, and front-end technologies such as VR HMD or tablets. | Stereotypical motor movement | n.r. | Non-empirical | / | / |
| Reis et al. (2021) | An Android software application. | Multi-sensory processing issue | n.r. | Non-empirical | / | / |
| Farroni et al. (2022) | Multi-sensory virtual environment using HMD display devices. | Multi-sensory processing issue | 2 (1 male, age: n.d.) | Non-empirical | / | / |

| **Reference** | **Description of Technology Elements** | **Target Issue** | **ASD Sample** | **Evaluating the Effects of TBI in Helping with Target Issues** | | |
|---|---|---|---|---|---|---|
| | | | | **SCED Scores (Full Score = 11)** | **Study Design** | **Reported Efficacy** |
| Chevalier et al. (2022) | A Cozmo robot. | Joint attention | 36 (31 males, age: 4-6 yo) | Non-empirical | / | / |

IoT – Internet of things, VGA – video graphics array, VR – virtual reality, HMD – head-mounted display, ABA – applied behavioural analysis, yo – years old, n.d. – not defined, n.r. – not reported, / – none.

As shown in Table 2.4, all the included studies were published in or after 2013, which reaffirms an emerging trait of studies investigating the TBIs for atypical sensory responses in ASD over the past decade. The trend in Figure 2.2 illustrates that the studies began to increase after 2019. Because the latest literature search was conducted in the middle of 2022, the actual number of publications after 2022 could be more.

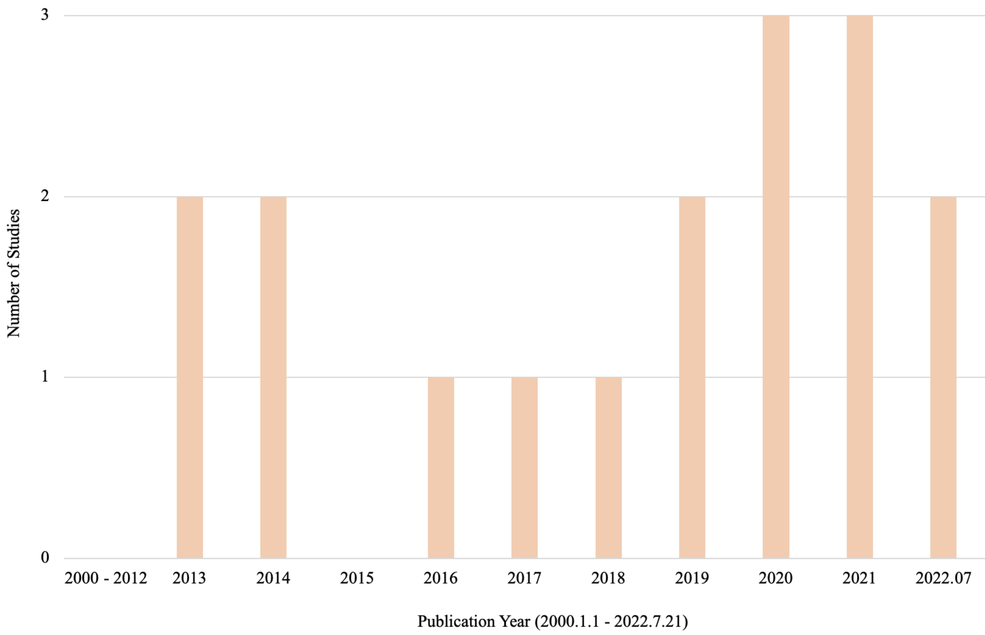



**Figure 2.2:** *Number of studies published over years*

Children of different ages were involved in many of these studies ($n$ = 14) with the youngest participant described as 4 years old. They were all with a diagnosis of ASD. Although designing TBIs for atypical sensory responses in ASD, three studies did not perform evaluation with any individuals with ASD. Over half of the studies ($n$ = 9) involved a small ASD sample which had no more than 15 children with ASD. Four studies only had less than five participants. Only two studies had more than 25 children with ASD.

#### 2.3.2.3 Use of technology

The use of technology in TBI studies was diverse, containing a range of hardware devices, such as sensors, robots, and display devices, as well as software applications, and systems combining hardware devices and AI.

**Sensors**

Sensors have been most frequently used in these studies. Recent advancement in sensing technologies has made the sensors working similarly as human senses (Khullar et al., 2019). Firstly, maturation of sound sensors has facilitated an early and prevalent adoption of this kind of device in studies for addressing atypical auditory responses. Mentioned previously, children with ASD who have atypical auditory processing often face difficulties in focusing on and perceiving meaningful information in a noisy environment. Similar sound amplification systems have been developed in many identified studies to target auditory recognition using Phonak, a well-known technology provider of hearing solutions (Thibodeau, 2020). The sound amplification system included a sound sensor, a transmitter, and earphones to improve children's auditory attention in a classroom with background noise. This device simply used the sensor to collect the teacher's speech and earphones to amplify the sound signal for children with ASD. A similar classroom amplification system was developed which amplified the sound signal via loudspeakers instead of earphones (Rance et al., 2017). A range of studies have evaluated these TBIs with moderate ambient noise, hypothesising that they were effective for children with ASD in helping with auditory-related issues (e.g., speech-in-noise recognition, stress), especially for those who were hypo-sensitiveness in audition (Rance et al., 2014, 2017; Schafer et al., 2013, 2016, 2019).

The development of non-invasive body and motion sensors have enabled recent research to capture behaviours related to atypical sensory responses. For instance, Mir and Khosla (2018) developed a Kinect-based counting game for children with ASD. Kinect is a well-rounded non-invasive sensor developed by Microsoft which can track body motion, infrared, and depth data (Azure, 2022). The TBI proposed by Mir and Khosla (2018) was in the form of the game with the help of Kinect sensor which tracked the user's motion and responses in the game. Similarly, a more recent study conducted by Hu et al. (2020) used a Leap Motion sensor in a visual matching task for children with ASD. Leap Motion is another touch-free gesture-tracking device (Ultraleap, 2022). Among the identified studies, Hu et al. (2020) firstly integrated a TBI into Chinese special education classrooms for atypical sensory responses. The Leap Motion-based sensor was used detecting children's correct responses in hand gestures to the visual matching task.

Sensor fusions and Internet of things (IoTs), benefiting from the Internet and wireless connectivity, allow a range of sensors to work with smart devices without cables, which significantly reduce the reliance on dimensions for a TBI. For example, Sula et al. (2013) described an IoT-based system which integrated body and hand movement sensors, a chair vibrator, a light controller, a smell controller, and a sound controller in a 'sensor box' to relax and calm the children with ASD who experienced atypical sensory responses. Khullar et al. (2019) designed another IoT-based system using a gas sensor, a 3-axis accelerometer, a microphone and a camera to detect the environmental information. More recently, Polo Rodríguez et al. (2021) proposed an IoT-based smart home. They discussed a range of suitable hardware devices for detecting atypical sensory responses and adjusting environmental features. After comparing different devices, their framework finally included a smartwatch, a sound speaker, a smart light bulb, a door controller, a smart mattress, and a range of ambient sensors for presence detection, humidity and temperature measuring. Ghafghazi et al. (2021) proposed a sensor fusion-based framework which suggested that a combination of invasive and non-invasive motion sensors, EEG sensors, smartwatches, and game environments could facilitate the applied behavioural analysis intervention effectively.

### Display devices

Some studies have used display devices, such as a projection technology that superimposed the image in front of the people. Ringland et al. (2014) designed a multimodal sensory system which used a large display to provide sensory integration interventions to children with ASD. The system had a tangible display surface which combined sounds with visual stimuli. Children can paint on the display and see their moving shadows projected onto the display. Ringland et al. (2014) believed that this TBI was likely to balance children's attention between their own bodies and sensory stimuli, had a calming effect, and decreased children's inappropriate behaviours in tactile interactions. However, there was a lack of statistical evidence to strengthen their arguments. The IoT-based system developed by Khullar et al. (2019) also involved a display device to provide video feedback to calm down children with ASD.

Nowadays, virtual reality (VR) experience delivered through a head-mounted display (HMD) makes it possible to implement sensory regulation interventions in a simulated sensory environment (Lubetzky et al., 2022). Johnston et al. (2020) used Oculus Rift, a commercial HMD, to design a VR game for auditory hypersensitivity in children with ASD. It realistically simulated an exposure-based training, which was a specific sensory regulation training to address auditory hypersensitivity in game contexts (Koegel et al., 2004). Farroni et al. (2022) developed a multimedia TBI including an HMD, which allowed children with ASD to undergo different virtual experiences according to their sensory processing patterns. Although display devices can easily project any objects that people want and provide a safe platform for interventions, it was suggested that some display devices had negative sensory effects, such as anxiety and visually induced motion sickness when individuals with ASD faced an HMD display (Bradley & Newbutt, 2018).

### Robots

Robots, usually package with characteristics such as humanoid appearance, tactile sensors and programmable prompts, are widely used as an interactive assistant to facilitate the ASD interventions (Deng, Rattadilok, Hadian, & Liu, 2021). Their strengths and limitations were debated in the literature. One limitation correlated with the nature of robots that the robot is mostly controlled by an extra specialist. Therefore, they cannot operate autonomously according to children's response (Cai et al., 2019). The author did not identify any robot-directed TBIs that targeted atypical sensory responses in ASD until very recent years (Alabdulkareem et al., 2022).

In the identified studies, the purpose of robots was mainly to generate sensory cues in certain conditions. These sensory stimuli generated, however, were reported to affect the interventions differently. The study conducted by S. Ali et al. (2020) programmed NAO, a widely used robot in ASD interventions (SoftBank Robotics, 2020), to give three different kinds of sensory stimuli (i.e., visual, auditory and motion) to address distraction in children with ASD. However, the study only compared the effectiveness of three stimuli. It was concluded that visual stimuli were more effective compared to auditory and motion stimuli in improving children's atypical visual responses, while effectiveness of the robotic intervention was not discussed. Chevalier et al. (2022) used the Cozmo, a low-price toy robot, to deal with attentional issues in 34 children with ASD who experienced atypical sensory responses. They assessed the children's sensory preference and aversion before the intervention. The results showed that hyper-sensitive children were more likely to be annoyed by the noise from the robot's motors.

**Software Apps**

To improve the autonomy of a TBI, many recent studies not only used hardware devices but also developed software Apps to focus on data acquiring, fusing, interpreting, and sharing (Cai et al., 2019). The IoT studies (Khullar et al., 2019; Polo Rodríguez et al., 2021; Sula et al., 2013) all involved computer programs for data fusing. Caregivers or therapists could monitor children's states via these Apps in real time. For two HMD studies (Farroni et al., 2022; Johnston et al., 2020), there were compatible software Apps developed for delivering the content to users. For two sensor-based games (Hu et al., 2020; Mir & Khosla, 2018), the hardware devices were used to identify users' actions. The core of the intervention part was the content to be displayed to users, which was programmed as software Apps.

There were also few TBIs implemented only by software Apps. Reis et al. (2021) developed an Android-based App, named 'Regul-A', for sensory regulation of children with ASD in the home environment. The App allowed the caregivers to manage the Sensory Profiles of the child with ASD and provided sensory strategies that aimed to regulate the child in their daily lives. Reis et al. (2021) conducted a focus group consultation with ASD specialists to obtain sensory regulation strategies in home routines, such as sleep, play, eating and bathing. This study described the design and consultation phases of the App in details and briefly indicated that the App was going through a testing phase. However, this App did not provide real-time monitoring and detection, while their testing results and effectiveness of the App have not been released yet.

**Systems combining hardware devices and AI**

Recent advancements in AI have enabled real-time human state and health monitoring from sensory-related data (Ghafghazi et al., 2021). The identification of atypical sensory responses has become so important that the use of AI increased from none to several after the year 2019. The system developed by Khullar et al. (2019) used fuzzy logic (FL) algorithms in combination with emerging hardware technologies such as display, sound sensor, and speaker. The FL algorithms processed the sensory-related data obtained by sensors and made decisions for the given conditions. Based on the decision made by the FL, the system generated alerts to caregivers regarding environmental risks, and controlled the display device to play video to calm down children with ASD. In the sensor fusion-based system developed by Ghafghazi et al. (2021), they proposed to use a deep learning (DL) algorithm to process EEG and motion sensor data for anomaly detection in children with ASD. The DL algorithm was able to generate personalised behavioural intervention plan for the child. Unfortunately, their study did not provide any more details about the DL algorithm (e.g., training process, accuracy) and its real-life testing.

#### 2.3.2.4 Reported efficacy

The following sections summarise the efficacy of the TBIs in helping with specific sensory regulation issues (i.e., poor attention, stress, sensory integration) of children with ASD that have been reported in the literature.

**Effect on attention**

Poor attention is one of the most common sensory regulation issues in children with ASD. Extensive studies have observed and assessed children's attention throughout the use of TBIs. A series of studies applying sound amplification devices proved that the device was efficient in enhancing the auditory attention of children with ASD (Schafer et al., 2013, 2016, 2019). Data from a total of 21 pre- and post-intervention events in studies by Schafer and colleagues showed a positive outcome ($z = 6.98$, $p < 0.01$), which reinforced the evidence for the effectiveness of the TBI on attention. Strengthened attention was also identified in the study conducted by Ringland et al. (2014) using a large display device. Ringland et al. (2014) conducted a qualitative discourse analysis and contended that caregivers and psychologists who observed the intervention expressed that this large display device improved the attention level of children with ASD. Mir and Khosla (2018) used the Kinect-based game to provide sensory training for three children with ASD for 10 days. No direct evidence showed that the TBI could improve the basic attention, but authors suggested that the participants' obtained higher scores in the game after 10 days. However, the improvement of performance might be attributable to increased familiarity with the game. Hu et al. (2020) conducted a more comprehensive comparison between the TBI and a teacher-delivered intervention. They found that both interventions were effective in performance improvement while TBI was more efficient than traditional teacher-delivered intervention.

**Effect on stress**

Children with ASD who experience atypical sensory responses are susceptible to high levels of stress, particularly in an unfriendly environment. Various included studies evidenced that the TBI they proposed had positive impacts on stress self-regulation in children with ASD. In the study conducted by Rance et al. (2017), comparisons between pre- and post-intervention results demonstrated that sound amplification devices could reduce listening stress in children with ASD. Based on the caregiver-reported questionnaire results, caregivers perceived that their child's anxiety levels were considerably lower after using the TBI. Physiological data (cortisol concentrations) were also used for measuring stress level in this study. Children with ASD showed significantly reduced cortisol concentrations in the TBI condition, illustrating an effective reduction in stress levels with the provision of TBI. The HMD-based application developed by Johnston et al. (2020) was evaluated with six individuals with ASD who were hyper-sensitive to auditory stimuli. Following a period of intervention, comparisons between pre- and post-intervention results also showed a significant decrease in stress level.

**Effect on sensory integration**

Sensory integration theory believes that the sensory integration interventions could improve a person's ability to integrate their senses in the brain to promote adaptive responses, which lead to facilitative effects on improving self-regulation, including heightened attention and reduced stress (Greenfield, 2017). Some studies focused on sensory integration and found that compared to classical sensory integration interventions, TBIs can have same efficacy and be easier accessed for classroom or home use. Over the course of using sound amplification devices, the auditory integration ability (i.e., binaural listening, speech recognition) of children with ASD was generally improved (Rance et al., 2014). Johnston et al. (2020) employed HMD to simulate a sensory integration training, which was used to improve sensory integration ability in children with ASD. Although there was evidence that participants' stress levels decreased significantly, no detailed data were provided to prove the improved sensory integration. Ringland et al. (2014) also used its TBI to facilitate a classical sensory integration intervention where children with ASD were engaged. They suggested that the use of TBI balanced children's attention between their own bodies and sensory stimuli, and improved their performance in the classical sensory integration intervention.

### 2.3.3 Lessons learnt from the scoping review

Atypical sensory responses in ASD have obtained more and more TBI studies' attention in recent five years. This scoping review synthesises the technological features and reported efficacy from related studies. Many studies have successfully adopted a range of technological methods, including sensors, IoTs or AI techniques, for addressing atypical sensory responses in children with ASD. Some TBIs are found to be effective on a range of outcomes associated with atypical sensory responses, especially attention and stress self-regulation.

However, several limitations are commonly found in the included studies. Firstly, over one third of included studies ($n = 6$) do not actually evaluate the effects of their proposed TBIs. This leads to unknown practicability and acceptance among ASD population in real-life use. Small sample and short-term evaluation in many studies make it challenging to obtain a generalisable result. Sometimes it is the dimension and complexity of TBIs which limit their long-term use among ASD population. For example, some IoT studies have attractive designs but must be deployed in a lab setting at an early stage (Ghafghazi et al., 2021; Polo Rodríguez et al., 2021; Sula et al., 2013), which are less likely to reach out to participants with ASD. Studies using small, portable sensors, or software Apps are more likely to involve more ASD sample.

Notably, there is also a heterogeneity in evaluation designs and outcome measures. This may be a result of lacking a uniform and standard measures for atypical sensory responses. Besides, since atypical sensory responses include a variety of symptoms, different studies usually have different focuses which make the outcome measures vary from study to study. Studies with high SCED scores generally apply a pre- and post-intervention design for evaluation. Atypical sensory response outcomes are usually described as episodes of distraction, discomfort, and anxiety. The outcome measure methods used in the previous studies include task performance, self-defined survey, as well as validated measurement tools for assessing the intensity and frequency of these states, such as Child Behaviour Checklist and Caregiver-Teacher Report Form (Achenbach & Rescorla, 2020).

Among the included studies, only four studies have used validated assessment methods to assess the participants' sensory processing patterns (Chevalier et al., 2022; Reis et al., 2021; Schafer et al., 2016, 2019). This indicates that most studies designed and discussed the TBI for atypical sensory responses in ASD without considering their sensory processing patterns. In a study with limited sample size, subcategorising undoubtedly further reduces the samples in a group. Therefore, many previous studies prefer not to differentiate participants with varied sensory processing patterns in the design and evaluation. However, there is evidence that knowing an individual's sensory processing pattern is important for improving the effectiveness of the TBI (Chevalier et al., 2022; Deng, Rattadilok, & Xiong, 2021), suggesting that sensory processing patterns of children with ASD should be assessed prior to engaging the children in a TBI.

## 2.4 Artificial intelligence (AI) for addressing atypical sensory responses

During the screening phase of the scoping review, the author found that the appearance of AI techniques was increasing in relevant studies. AI techniques have been successfully applied in some ASD research to use a wide variety of sensory inputs to detect human behaviours, make diagnosis, or analyse brain states (Ghafghazi et al., 2021). At the present day, the convergence of sensing technology and AI provides a new direction for developing innovative TBIs to address atypical sensory responses in ASD. Considering AI can play an important role in a TBI by identifying atypical sensory responses accurately, studies which have used AI for such kind of detection are reviewed and discussed more deeply in this section.

### 2.4.1 Features for AI modelling

Atypical sensory responses are difficult to measure using standard methods due to its complexity and unclear mechanisms. However, physiological features can be used to provide sensitive measure of assessing changes in sympathetic arousal associated with anxiety and attention (Khullar et al., 2021). For example, some physiological features, such as body sweating, increased body temperature, abnormal heart rate or facial expressions could be noticed during stress or distraction-related states (Di Nuovo et al., 2018; Sigman et al., 2003). Body or hand movements can provide a convenient measure of detecting stereotypical behaviours (Coronato et al., 2014; Mohammadian Rad et al., 2018). Besides, it can be seen from the scoping review that there are some sensors which can extract physiological features. These sensors are attached to the skin and are accepted by children with ASD (Ghafghazi et al., 2021). Therefore, physiological features, such as heart rate, Galvanic Skin Response (GSR), Electroencephalograms (EEG) and skin temperature can be used as key data sources to assist the AI modelling in related studies (Ghafghazi et al., 2021; Khullar et al., 2021; Sundaresan et al., 2021; Tomczak et al., 2020).

**Table 2.5:** *Features considered in prior studies for AI modelling*

| Reference | Features |
|---|---|
| Coronato et al. (2014) | HM |
| Mohammadian Rad et al. (2018) | HM |
| Di Nuovo et al. (2018) | Facial features |
| Khullar et al. (2019) | Auditory stimuli, visual stimuli, tactile stimuli, smell stimuli |
| Tomczak et al. (2020) | HR, ST, GSR |
| Sundaresan et al. (2021) | EEG |
| Ghafghazi et al. (2021) | EEG, HR |
| Khullar et al. (2021) | HR, ST, GSR |
| Mauro et al. (2020, 2022) | Noise, brightness, crowding, smell, openness of places, sensory preference and aversion |

HM – Hand Movement, HR – Heart Rate, ST – Skin Temperature, GSR – Galvanic Skin Response, EEG – Electroencephalograms.

As reviewed in section 2.1, environmental features are also determinants that affect sensory-related behaviours in children with ASD. Some TBIs aim at supporting children with ASD in detecting uncomfortable environments. Noise, temperature, light intensity, smell and crowding are some of the environmental features concerned in AI studies (Khullar et al., 2019; Mauro et al., 2020, 2022). For example, non-invasive ambient sensors were used in the study conducted by Khullar et al. (2019) to collect environmental information. There were some studies using environmental data from public websites which reported people's feelings about a certain place for AI modelling, while sensory preferences of individuals with ASD were collected by means of a self-defined questionnaire (Mauro et al., 2020, 2022). Table 2.5 presents a range of physiological and environmental features that are considered in the related studies.

### 2.4.2 Applied AI algorithms and study designs

AI in smart systems for individuals with ASD can be achieved by a range of algorithms such as rule-based, machine learning (ML) and DL algorithms.

Data are more important in ML and DL compared to rule-based algorithms in which rules are more important (Campesato, 2020). There are two key challenges that limit the application of ML and DL in ASD studies: limited amount of labelled data to train ML algorithms and black-box nature of DL algorithms (Ghafghazi et al., 2021). Therefore, some studies which do not have a first training dataset, opt to use rule-based algorithms, instead of ML or DL, for developing a detection system (Khullar et al., 2019; Tomczak et al., 2020). For example, Khullar et al. (2019) used a rule-based fuzzy logic algorithm in their TBI for identifying triggering events of atypical sensory responses. The algorithm predefined a set of fuzzy rules in the MATLAB's Fuzzy Inference System. The inputs to the algorithm were auditory, visual, tactile and smell stimuli in the surroundings of a child with ASD, which were acquired by ambient sensors. The output of the algorithm was the overall meltdown risk caused by atypical sensory responses.

Khullar et al. (2019) evaluated the caregivers' level of satisfaction which suggested that most caregivers were satisfied with the technological functions such as real-time monitoring, analysis, and feedback. Tomczak et al. (2020) developed a stress monitoring system for people with ASD using a heuristic rule-based algorithm. The algorithm initialisation was triggered by an accelerometric motion sensor at the time when the device applied to the skin was on. The sensor can obtain heart rate, GSR and body temperature data, which were then calculated as the mean values over time. All the data were continually updated for a long period of time. The values of the parameters for detection of the child' stress episode were evaluated basing on the observations of the sensor readings on participants under various stress and no stress conditions.

Due to the lack of data from ASD population, some studies adopt datasets from TD individuals for AI modelling. Studies conducted by Mauro et al. (2020, 2022) developed a recommender system for users to avoid uncomfortable places based on compatibility-aware recommendation models. They extracted information about environmental features from public tourism websites, while they took a user's sensory preferences and aversions to noise, brightness, and other features into account. The model based the personalised suggestion of places on the acquisition of environmental features and user profiles that were matched to each other. Their testing results demonstrated the feasibility of using user preferences and public datasets to predict a safe and comfortable location for individuals with ASD. Moreover, Coronato et al. (2014) and Mohammadian Rad et al. (2018) used wearable accelerometers to record hand movements from TD subjects. They used the TD data (data obtained from TD individuals) to training DL models, including Artificial Neural Network, Naïve Bayes and other models, attempting to enable the models to detect stereotypical motor movement in

ASD. Both studies verified the DL models with real data from individuals with ASD. The results showed that the Artificial Neural Network model yielded an accuracy of over 99% on data from TD subjects, but an accuracy of 92% taking the data from one individual with ASD in the hospital setting. The worse performance of the model on real ASD data implied the limitation of models using data merely from TD people, as motions, sensory processing patterns and physiological responses to stimuli between ASD and TD people can be very different.

In recent few years, some efforts have been put on building a training dataset containing data from real individuals with ASD. Although still very challenging, few studies have successfully collected physiological features of children with ASD and used the data to train an ML or DL model for detecting atypical sensory responses (Di Nuovo et al., 2018; Khullar et al., 2021; Sundaresan et al., 2021). Di Nuovo et al. (2018) conducted data collection with six children diagnosed with ASD for over one month, attempting to estimate attention level from the child's face. Each data collection session was videotaped by a camera on a NAO robot for approximately 6–8 minutes per child. To build the ground truth for attention detection training, Di Nuovo et al. (2018) labelled the situation when the child was staring at the robot as 'Attention', and other situations as 'Distraction'. They applied Viola-Jones and Conventional Neural Network (CNN) for face detection in camera images, and applied CNN and Histograms of Oriented Gradients (HOGs) for features extraction. With facial features and attention labels, Di Nuovo et al. (2018) used several classification ML algorithms, including K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Decision Trees, and Naïve Bayes classifiers for attention classification. A combination of CNN-HOGs-KNN algorithms achieved the best overall result with an accuracy of 88.2%. The study also considered the computational execution time for the purpose of future application. The combination of CNN-HOGs-KNN was the fastest approach which could process two frames from the video per second. This study verified the feasibility of estimating attention level of the child with ASD directly from the robot sensors using ML and DL approaches, suggesting its potential for further application in robot-assisted therapies.

Sundaresan et al. (2021) collected EEG data from eight adolescents with ASD during a stress induction session and proposed ML and DL algorithms to identify anxious states from ongoing EEG signals. They created a 25-minute session of stress induction and breath modulation tasks. Specifically, they selected a widely used arithmetic task as the 'stressor' and simplified it to minimise the possibility of overstimulating participants with ASD (Sundaresan et al., 2021). Following each arithmetic task and breathing task, participants were required to rate their current stress level on a 5-point Likert scale. The analysis of self-reported stress level indicated that the selected arithmetic task can reliably induce mental stress in the participants. Therefore, the EEG recorded during the arithmetic task was labelled as 'Stressor', with other classifications defined as 'Guided Breathing', 'Unguided Breathing' and 'Baseline'. Sundaresan et al. (2021) performed classification analysis on the selected EEG training samples using SVM, CNN, Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) and a hybrid Long Short-Term Memory Fully Convolutional Network. The accuracies of the SVM models were computed across four classification pairs ('Guided Breathing' vs 'Stressor', 'Unguided Breathing' vs 'Stressor', 'Unguided Breathing' vs 'Guided Breathing', and 'Baseline' vs 'Stressor') as the SVM classifiers were binary. The overall classification accuracy of SVM, around 82%, was satisfactory, while the multi-class LSTM-RNN obtained the best classification accuracy at around 93%.

**Table 2.6:** *AI algorithms for users with ASD*

| Reference | Algorithm | Detection Targets | Evaluation | Subjects Involved for Evaluation |
|---|---|---|---|---|
| Coronato et al. (2014) | ANN | Stereotypical motor movement | Model accuracy | 1 subject with ASD |
| Mohammadian Rad et al. (2018) | CNN, CNN-LSTM | Stereotypical motor movement | Model accuracy | 6 subjects with ASD and 5 TD subjects |
| Di Nuovo et al. (2018) | VJ, CNN, HOG, KNN, SVM, DT, NB | Attention level | Model accuracy | 6 subjects with ASD |
| Khullar et al. (2019) | FL | Meltdown or tantrum | Model accuracy<br>System usability | Not reported in model validation<br>10 subjects with ASD in system usability evaluation |
| Tomczak et al. (2020) | Heuristic rule-based model | Stress level | System usability | 20 subjects with ASD |
| Sundaresan et al. (2021) | SVM, CNN, LSTM-RNN, LSTM-FCN | Stress level | Model accuracy | 8 subjects with ASD |
| Ghafghazi et al. (2021) | DL (not specified) | Vocal stereotypy | Not reported | Not reported |
| Khullar et al. (2021) | CNN, LSTM, CNN-LSTM | Meltdown or tantrum | Model accuracy<br>System usability | Not reported in model validation<br>10 subjects with ASD and 5 TD subjects in system usability evaluation |
| Mauro et al. (2020, 2022) | Compatibility-aware recommendation model | Safe and comfortable places | Model accuracy | 20 subjects with ASD |

ANN – Artificial Neural Network, CNN – Conventional Neural Network, LSTM – Long Short-Term Memory, VJ – Viola-Jones, HOG – Histograms of Oriented Gradients, KNN – K-Nearest Neighbour, SVM – Support Vector Machines, DT – Decision Trees, NB – Naïve Bayes, FL – Fuzzy Logic, RNN – Recurrent Neural Network, FCN – Fully Convolutional Network, DL – Deep Learning.

The studies conducted by Di Nuovo et al. (2018) and Sundaresan et al. (2021) both provided a comprehensive design of data collection, data processing, AI model training and comparison, addressing the limitations of prior studies in ASD data. Unfortunately, Di Nuovo et al. (2018) considered an estimation of the attention from only one of its components which was the visual focus of an object. Other components of the attention, such as child's behaviour, task performance as well as the environment influences were not evaluated nor considered. It was mentioned by Sundaresan et al. (2021), two participants presented unusually high impedances at the time of EEG recording probably due to forehead tactile sensitiveness, indicating that the acceptance of hardware sensors is one of the important factors that affect the success of a study in this field. Alternatively, Khullar et al. (2021) only applied a wristband to collect heart rate, GSR and skin temperature from individuals with ASD. A hybrid CNN-LSTM model for meltdown and tantrum detection was trained and yielded an accuracy of 96%, suggesting the feasibility of combining non-invasive sensors and AI techniques for the development of a detection system for atypical sensory responses in children with ASD. Table 2.6 summarises the AI algorithms applied in related studies and their detection targets associated with atypical sensory responses.

## 2.5 Summary: Research gaps and implications

This chapter has shown the impact of environmental factors on individuals with ASD. In particular, children with ASD have great difficulties in adapting to and behaving appropriately in an environment of extreme conditions, such as escalated noise, temperature and light intensity. The associated outcomes can often be seen to be stressful, disengaged attention, which will result in significant problems in sensory regulation in a public space. Although previous studies emphasise that noise, temperature, humidity, light and some other factors should be considered as triggers of atypical sensory responses, none has ecologically validated the comfort zone for children with ASD. In general, studies believe that noise level under 70 dB, indoor light intensity at 300 lx to 600 lx, temperature around 25 °C and humidity between 30% and 60% are moderate for most people, while children may perceive lower temperature around 22 °C as comfortable. These data will be combined with knowledge from ASD specialists to determine the comfort zone for children with ASD in this research.

Traditional clinical practice to address atypical sensory responses in ASD includes an assessment of sensory processing patterns, followed by effective sensory-based interventions. Sensory developmental trajectories in ASD demonstrate that early intervention in the childhood can be helpful for improving their sensory regulation abilities, decreasing behaviours associated with atypical sensory responses. It shows why many studies, including this study, focus on developing a TBI system that can be used by young children with ASD.

The scoping review of literature has highlighted the feasibility and potential of TBIs for mediating the effects of sensory stimuli on issues related to atypical sensory responses in ASD. There is research evidence suggesting positive outcomes associated with the TBI used to support children with ASD who experience atypical sensory responses, especially in attention, stress, and sensory integration aspects. The author also identifies several research gaps and shortcomings in current research that need to be addressed by further efforts. Although prior studies demonstrate the potential of a wide range of technologies, existing TBIs that show effectiveness in addressing the target issue are still very limited. Especially when a study attempts to design a TBI for individuals with ASD, limitations such as small ASD sample or absolute lack of ASD sample are noticeable. Therefore, to engage more children with ASD, many studies designed their experiments based on games or educational activities to offer learning opportunities to participants, which required high collaboration among ASD specialists, ASD families, technology developers and academic researchers.

Regarding the use of technology, Table 2.7 summarises the advantages and disadvantages of technological elements in current TBI studies. As shown in Table 2.7, sensor devices have been more widely applied in previous studies compared to robots, display devices and other techniques. A range of off-the-shelf sensors have shown usability in capturing real-time environmental features as well as physiological features. However, some wearable sensors such as EEG headsets and Phonak devices have been found to have negative effects on children with ASD, such as causing anxiety (Schafer et al., 2016; Sundaresan et al., 2021). Besides, the purpose of most sensors has been purely for monitoring which makes the sensor-based TBI less interactive and educational. Display devices and robots have provided more fun to children. However, display devices have been found to cause dizziness among users and the settings where they can be used are more limited. Robots are often more expensive. For example, a NAO Robot Autism Pack costs around 20,000 dollars (RobotLab, 2022), which is hard for many families to afford. Software Apps, which can gather useful information with low cost, have compatibility with other sensors, and fast access mobility, are envisioned as a modern format of TBI. Without wireless-connected external sensors, a software App itself is also able to provide general sensory regulation strategies which are obtained from a panel of ASD specialists (Reis et al., 2021). In addition, efficient AI algorithms could extract useful information from varying signals and be used for atypical sensory responses detection, while accurate AI algorithms rely heavily on a meaningful training dataset and powerful computation capacity.

**Table 2.7:** *Advantages and disadvantages of different technological elements in existing TBIs*

| **Technological elements** | **Advantage** | **Disadvantage** |
|---|---|---|
| Sensors | Widely applied and validated; Some are wearable and portable; Highly commercialised and easy to buy. | Wearable sensors may cause tactile defensiveness and anxiety in children with ASD; Mainly for monitoring instead of interacting. |
| Display devices | Can create any virtual environment with controllable stimuli; Can be interactive and educational. | Some devices such as VR glasses may cause tactile defensiveness and dizziness in children with ASD; Some devices can be expensive, limited by space for usage. |
| Robots | Equipped with human appearance and personality to improve engagement; Can be interactive and educational; Touch-free. | Some robots can be very expensive; Some robots produced motor noise; Low portability. |
| Software Apps | Wireless connectivity with sensors; Integrate and present information; Low cost; High mobility and accessibility. | May cause excessive use of or addiction to digital devices in children. |
| Systems combining hardware devices and AI | Provide accurate detection about several targets related to atypical sensory responses, such as stereotypical motor movement, stress, poor attention, and many more. | AI algorithms rely on large amount of data to obtain better accuracy; High computational capacity may be needed for data processing. |

As mentioned, atypical sensory responses are complex and hard to measure. Prior research that monitors the sensory environments and responses of individuals with ASD tends to focus on identifying situations of poor attention and stress, as having difficulty paying attention and being stressful yield the highest frequencies of atypical sensory responses (Tomchek & Dunn, 2007). Physiological features, such as heart rate and GSR, and environmental features, such as noise, light, and temperature, are key parameters that have been used in AI models for anomaly detection. Many AI algorithms have shown validity in detection, including conventional rule-based models, ML models such as KNN, and further improved DL models such as ANN. Although prior research suggests that sensory processing patterns of children with ASD should also be considered, few studies have taken their sensory processing patterns, such as hyper- or hypo-sensitiveness, into consideration in TBI designs or AI models.

In this research, the author hopes to design and develop an innovative system, to effectively support children with ASD in dealing with atypical sensory responses. It should be structured to take into account the current research evidence and gaps, using existing knowledge and validated practice to guide the development of the system. The research strengths reviewed in this chapter are further explored in this research, while the research weaknesses identified in the literature review will be addressed as many as possible with the following recommendations:

- It is important to explore commercially available sensors that are affordable, accurate and acceptable for real-time monitoring of environment and physiology;
- An effective and ASD acceptable TBI can be designed in a form of a smartphone-based App for convenient and discreet use;

- It is feasible to employ ML and DL models for stress and attention detection, and to use environmental features, physiological features and Sensory Profiles as key predictive parameters;

- Implementing data collection sessions with meaningful attention tasks and stressors to obtain a dataset not only is crucial for AI algorithm training but also become particularly educational for children participants;

- Focus group consultations with ASD specialists can help to obtain sensory regulation strategies and strengthen the effectiveness of the system with sharing of knowledge by the professionals involved;

- It is necessary and important to evaluate and establish the effectiveness of the system by conducting a well-designed system evaluation study with real end-users (i.e., children with ASD and caregivers) in a real-life setting.

# Chapter 3

# Methodology

This chapter describes the entire methodologies used throughout the research. It firstly looks at the theoretical framework for system design and development and how this shapes the lifecycle of developing *Roomie*, a system proposed for addressing atypical sensory responses in children with Autism Spectrum Disorder (ASD). Computer science methods and psychology methods are both used in different sections of this research to achieve the interdisciplinary research aims. A description of these different methods is given and why they both are essential for this research is discussed.

## 3.1 Theoretical framework for system design and development

The findings from literature review show that technology-based interventions (TBIs) continue to proliferate with limited evidence for the effectiveness and little support for practicing how best to design an ASD individual acceptable system. Many interventions have been designed on the basis of existing technological system constructs and may not be as effective as those traditional interventions that involve children with ASD in the practice and evaluation. Premature adoption of untested TBIs may limit positive outcomes (Schnall et al., 2016). Therefore, there is a need for a development framework that results in systems that are acceptable, usable, and can effectively support behaviours of children with ASD in daily lives.

The end-users of the proposed system, *Roomie*, include children with ASD and their caregivers (i.e., parents, or grandparents). Caregivers are included because, in general, children with ASD may lack prior experience of using technological systems and their cognitive abilities may also have an impact on the usage of the system functions. Besides, as mentioned in section 2.2.2, caregivers play an important role in delivering sensory regulation strategies in home contexts. Specifically, with aims to develop an ASD acceptable system for sensory regulation, the system development requires considerations of all potential users' needs, preferences, and their capabilities. This research intended to 'centre' around the end-users. The user-centred and iterative development frameworks were thus, in this case, applied throughout the process.

### 3.1.1 User-centred framework

The development of *Roomie* has employed a user-centred framework as people with special needs usually benefit the most from the approach which involves them in the development process and ensures that their needs are met (Frauenberger et al., 2011). World Health Organisation (2011) suggested that a user-centred model should be integrated within the lifecycle of healthcare technologies in order to ensure effective outcomes. User-centred framework may be presented as methodologies but more frequently referred as a set of principles or guidelines that engage with, and prioritise the needs of end-users during the development of a service or artefact (Farao et al., 2020; Schneiderman, 1998). In a user-centred project, a main principle is that users are centred and involved appropriately so they may influence the system development.

Although previous research has suggested that more people with special needs had been involved in the decision-making process about things that affected their lives (Mathers, 2004), the scoping review in section 2.3 which assesses methodological quality of related studies highlights that many designs involved no or only a few individuals with ASD. There is limited preliminary research fully considering the needs of individuals with ASD in the design process. Although user-centred principles are believed to be crucial for TBI developments, developers usually find it unexpectedly difficult to work with individuals with ASD. It is not only because individuals with ASD may face extra difficulties to express their needs or desires, but also, they may be reluctant to be involved during such complex and usually long processes (Hervás et al., 2019). Capabilities and individual preferences can be very different among children even if they all have atypical sensory responses. In the case of children with ASD, the challenge of this involvement can be bigger (Frauenberger et al., 2011). Therefore, many previous studies only presented novel ideas generated from discussions within the research team, relying a lot on their own experiences and understandings. However, creating ideas by 'imagining' the position of the individuals with ASD makes it easy to lose sight of maintaining the system in a user-centred manner.

The make-up of insufficient involvement of individuals with ASD for a system development includes some other key stakeholders, such as ASD specialists, engineering researchers, and service providers (Craven et al., 2014). The importance of key stakeholder engagement is evident, including increasing the potential for interaction between system developers and end-users, and addressing other ethical and research governance requirements. For example, a collaboration with engineering researchers and service providers could facilitate the effective testing of a system prototype for its functionality, usability, and reliability in a real-world setting, and capture end-user data for the study. The ASD specialists, including healthcare professionals and teachers, can typically supply the user needs based on their expertise and observations. A stakeholder may also be a 'user' especially at the early prototype stage or in a pilot study. While the author, who acted as the engineering researcher and principal investigator, should be responsible for all the stakeholder engagement, system development and implementation of the user requirements throughout the process. A number of implementation choices had to be made by the author in parallel with understanding the user needs, such as the choice of devices, operating platforms, system functions, and many more (Wasserman, 2010).

### 3.1.2 Iterative development framework

The iterative development framework is usually employed in combination with the user-centred framework, in which a system undergoes a series of iterations before release to ensure the user requirements are met. The user-centred framework requires the project to begin with the focus on the user needs, which allows the system specifications to be informed by user needs and requirements whilst taking into account characteristics and potential limitations of the technologies. An iterative process is established which allows further modifications to be informed by professional review and evaluations of the system prototypes. The basic principles of the iterative development framework include (Centre for Medicare and Medicaid Services, 2008):

- The key objective is for fast development and delivery of a high-quality system at a relatively low investment cost.
- Iterative development attempts to providing more ease-of-change during the development process.
- Iterative development aims to produce the system through iterative prototyping, active user involvement and computerised development tools.
- Key emphasis is on fulfilling the user needs, while technological excellence is of lesser importance.
- Active user involvement is imperative.

Figure 3.1 shows the overall iterative development process and the emphasis of each iteration in this research, adapted from Eeles et al. (2014). As shown in Figure 3.1, each element, namely User Needs, Architecture, Development and Test, was repeatedly addressed in every iteration. The size of box within each of the elements illustrates the relative emphasis spent on the element. The first iteration (Iteration 1) was focused more on understanding user needs, while some architecting, development and testing were performed. Iteration 2 put the emphasis on stabilising the architecture, together with more development and testing. Iteration 3 was focused on completing the final *Roomie* system based on a relatively stable set of user needs and architecture, and there was an emphasis on development and testing.

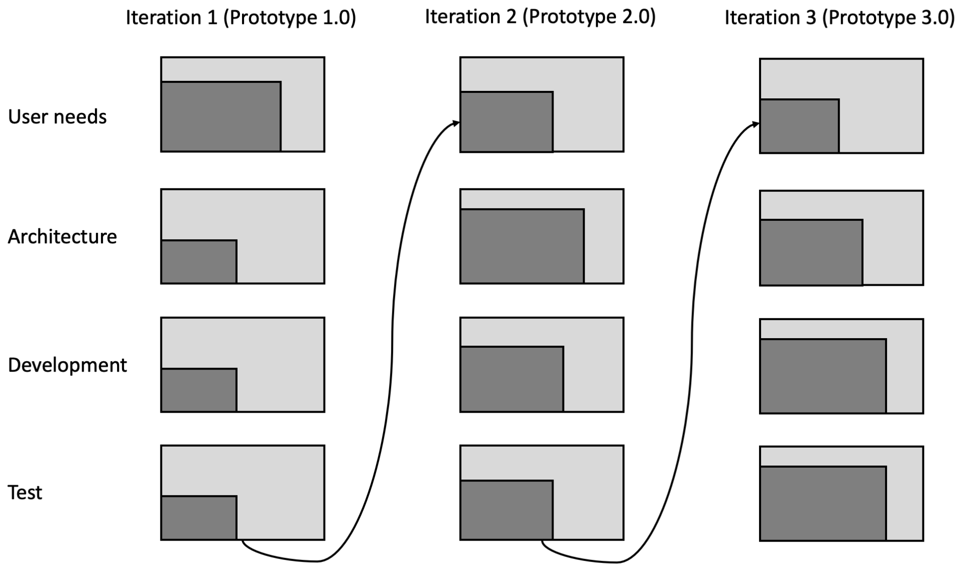



**Figure 3.1:** *Iterative development process and emphasis of each iteration, adapted from Eeles et al. (2014)*

It can be seen from Figure 3.1 that each iteration Test resulted in further understanding of the User Needs. ASD specialists, caregivers and engineering researchers provided understanding of the needs of end-users followed by real testing of *Roomie* prototypes. An advisory panel of 10 ASD specialists (hereafter referred as advisory panel) was formed in the beginning of this research. The average years of ASD-related practice experience of the advisory panel was about 10. They worked together, undergoing review of the prototype in each iteration to ensure the *Roomie* is finally robust, useful and usable. Appendix D provides more detailed information about the advisory panel members.

A main advantage of the iterative development framework is that each iteration can be produced quickly, making it appropriate to a project where stakeholders' long-term participation commitment is usually unrealistic. The iterative process potentially reduces the drop-out rates of key stakeholders (Craven et al., 2014). However, care must be taken to ensure that the system development is truly accepted by children with ASD, not merely by other stakeholders, iterative involvement of children with ASD is also critical to the project. Therefore, the methods and technologies applied to facilitate user involvement in the project have to be the most appropriate for young children with ASD.

## 3.2 Understanding user needs

Understanding user needs is an indispensable phase in order to develop a system adapted to the special needs of ASD populations. An online survey and face to face interviews have been conducted with key informants. Although the main end-user of *Roomie* is the child with ASD, they may not be able to collaborate in this phase due to communication difficulties. In this case, key informants including caregivers, ASD specialists, and engineering researchers become a valuable resource for presenting a wider context taking into account barriers and needs that children with ASD may not be aware of.

### 3.2.1 Online survey

The online questionnaire was conducted anonymously, including questions about age and gender, the awareness of TBIs and scenario-based questions investigating the needs for the proposed system. A snowball sampling strategy was used in the recruitment of the participants. The snowball sampling strategy is usually beneficial for studies on hidden populations who tend to be difficult for researchers to access (Hewitt-Taylor, 2011). Some members of the local ASD community were initially contacted, then they recruited more participants by encouraging other members to participate and reassured them of confidentiality. In China, the questionnaires were distributed firstly through ASD parental support groups and childcare facilities in Ningbo. Ningbo is a sub-provincial city in southeast China. As defined by Sun et al. (2019), Ningbo can be regarded as a 'Median Economic Level (neither extremely affluent nor extremely poor)' city. An English version of the questionnaire (Appendix E) was used and sent to counterparts in the United Kingdom (UK) which enabled a cross-regional comparison between China and a country that has better developed healthcare services. The questionnaires were distributed through the author's network of schools, universities and charities to their ASD clients in the UK. The organisations helping to distribute the questionnaires included a national training centre for children with sensory processing difficulties and relevant departments within the universities in London, Nottingham, Leicester and Northampton. All the questions of the online survey were given in Chinese or English to participants according to the country where they lived.

### 3.2.2 In-depth interview

Interviews were another method used to explore Chinese individuals' personal perceptions of using a TBI for children with ASD. The study population was intended to consist of caregivers and ASD professionals who had close relationships with children with ASD. The process of conducting the online survey has helped the author to establish a relationship with the ASD community and further recruit participants for the interview. The specific sampling strategy was purposive and targeted. The ASD parental support groups and childcare facilities in Ningbo were contacted to send out the interview invitation while distributing the online questionnaire. Participants who agreed to take part in the interviews should have completed the online questionnaire and provided their answers to the last question. The last question in the survey provided participants with a scenario of using *Roomie* to address sensory regulation issues in ASD. Participants who were willing and unwilling to use such a TBI were both intentionally invited to the interviews. The occupation and years of experience related to ASD were also considered when choosing participants.

Interviews were conducted face-to face and individually, semi-structured with a number of close-ended and open-ended questions. The questions were differentiated for caregivers and ASD professionals. Each interview session lasted for around 45 minutes. Some commonly asked questions were: 1) What are the barriers that may prevent individuals with ASD from using a certain TBI? 2) What functions are desired in a system for sensory regulation for the benefits of individuals with ASD? Appendix F listed the pre-determined interview questions for caregivers and ASD specialists separately. Questions for caregivers paid additional attention to their feelings and concerns about the effect of TBIs on their child, while questions for professionals laid special emphasis on the prospective application of techniques in the interventions.

### 3.2.3 Synthesis

A thematic method was applied to synthesise the user needs. The thematic analysis allowed the flexibility to organise data obtained via different above-mentioned methods. Data from the online survey in China and the UK were managed in SPSS Statistics Version 26.0 (IBM SPSS, 2019) together, and interpreted quantitatively to offer descriptive information for the analysis. The interview data were recorded by the audio recorder and transcribed into text documents. The author then sent transcripts to the participants to check for accuracy and missing points. An inductive analysis approach was used as the codes and themes were drawn from the raw data (Braun & Clarke, 2006). The coded data were then categorised into themes and sub-themes in the analysis. Codes, themes and text segments were developed and analysed in Chinese first to avoid misinterpreting. The author who originally comes from China translated important quotes into English. Finally, their needs were interpreted into the system design requirements.

## 3.3 System development

### 3.3.1 Development platform

Based on the preliminary investigation on the user needs, the author decided to deploy the proposed system on mobile devices, creating an App for mobile phones and smartwatches which are generally easier for ASD population to access. The iOS platform was chosen as the main deployment target for *Roomie* in this thesis considering the availability of diverse iOS devices within the research team. It was a suitable choice to use existing iPhones, macOS, and watchOS devices to save the cost in the beginning of the project. Although Android is more popular in China and more customisable than iOS (Global Stats, 2023), the testing and implementation are relatively faster with iOS. iOS's development generally requires less development time and budgets for maintenance (IBM, 2023). Android's dominance in the Chinese market should not be neglected but attempting to create an App for both iOS and Android within the limited time leads to technical issues, high costs and many more challenges. Therefore, it was decided to use iOS platform initially to build *Roomie*, while the author also expected to use other platforms for the possibility of transferring it later if required for commercial distribution.

Xcode is the Integrated Development Environment (IDE) for iOS development (Atanasov, 2018). Xcode version 14 was used in this project, working together with Swift version 4. Swift is the native programming language specifically for iOS development, which is more convenient and requires less coding work compared to the programming languages for Android development such as Java and Kotlin. The Xcode's project window (see Figure 3.2) provides a primary interface for viewing, editing and managing all parts of the development.

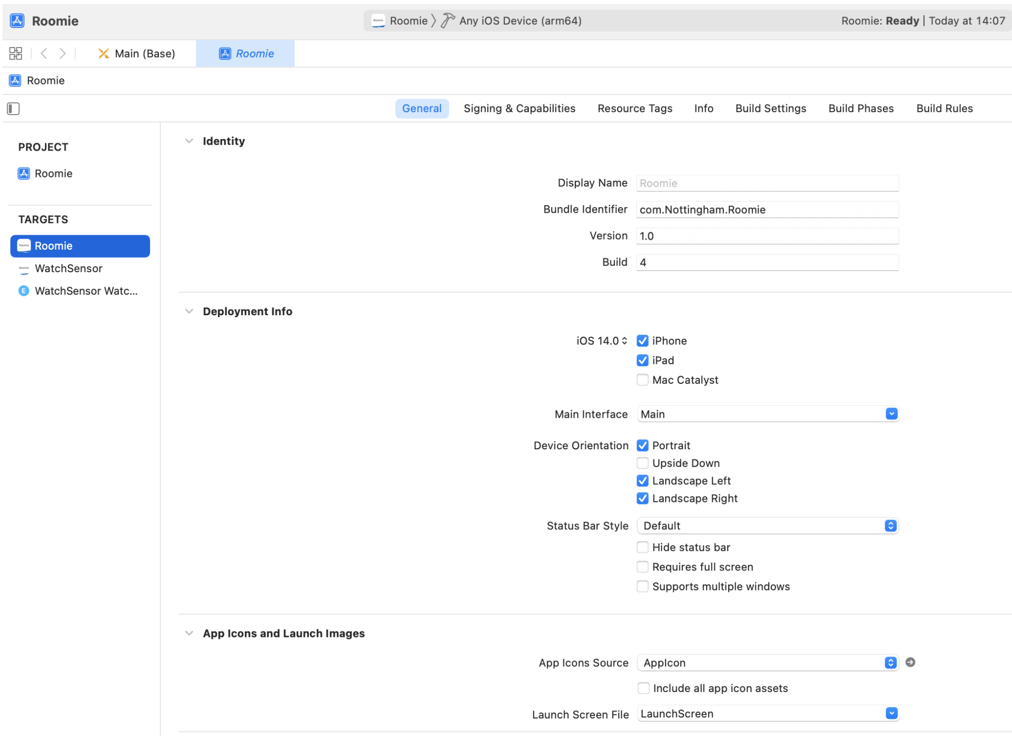



**Figure 3.2:** *Xcode IDE developer interface*

Xcode IDE allows the developers to manage the entire development workflow, from creating the application, to testing and finally releasing the application to the public. It offers the versatility and the features which could facilitate the completion of development in the given time. Necessary development frameworks integrated in Xcode which were used for system development included user interface (UI) frameworks (SwiftUK and UIKit), HealthKit, Core ML and many others (see Figure 3.3). Reasons for using below main development frameworks were down to user friendliness and practicality of *Roomie*.

```
import SwiftUI
import AVFoundation
import ImageIO
import CoreData
import UIKit
import CoreMotion
import WatchConnectivity
import HealthKit
import CoreBluetooth
import DSFSparkline
import SwiftUICharts
import CoreML
```

**Figure 3.3:** *Code of selected development frameworks*

#### 3.3.1.1 UI frameworks

Storyboard and SwiftUI were the Xcode UI builders used in this project, which served as a visual design editor that graphically connected the objects and navigation components (Shahrasbi et al., 2021). The Storyboard is a traditional UI framework with which a developer can easily and quickly describe and depict complex UI dependencies (Atanasov, 2018). SwiftUI framework has been introduced in 2019 by Apple, which is a revolutionary development framework that makes building powerful UI easier than ever before (Apple, 2019). It is decided to use Storyboard at the early development stage because it can rapidly prototype UI flows by 'dragging and dropping' and have an overview of the workflows in Xcode's Storyboard editor (Figure 3.4). It can visualise the connections between different screens as shown in Figure 3.4. SwiftUI cannot provide such an overview of the whole project and only supports iOS devices with iOS 14.0 or later. While SwiftUI is easier to maintain and provides a better-looking interface when the App design grows more complicated. SwiftUI builds interfaces programmatically and can work alongside Storyboard so that developers can adopt it iteratively in an existing prototype. Since the development for final prototype when it was time to construct a more user-friendly interface, the author started using SwiftUI for completing the system UI.


**Figure 3.4:** *Storyboard UI builder in Xcode IDE*

### 3.3.1.2 HealthKit

HealthKit is a framework that provides a wide variety of health data, covering body measurements, reproductive health, hearing, vital signs, nutrition, mobility and many others (Apple Developer, 2023c). HealthKit is especially helpful for a health App that allows a clinical care team to send and receive health data. HealthKit capabilities need to be enabled in Xcode to access the user's health data. Through HealthKit, data can be automatically synced between the phone and watch devices. However, accessing an individual's health data presents potential confidential risks. Therefore, HealthKit originally requires user's authorisation. When HealthKit is enabled, user's permission must be requested to both read and share health data. Only when the permission is obtained from the user can the App start recording the health data.

#### 3.3.1.3 Core ML

Core ML framework is developed by Apple to integrate machine learning (ML) algorithms into an App and deploy them on the user's device (Coremltools, 2022). Core ML Tools Python package can be used to convert ML algorithms from third-party training libraries such as Scikit-learn into the Core ML model package format. Once an ML algorithm is deployed on a user's device, developers can use Core ML to re-train or fine-tune it on-device, with that user's data. Although other cloud services could be used to perform ML tasks, they do not supply the level of customisation as Core ML's on-device training, and the requirement of continuous Internet connection could limit the usability of the App. Besides, running an ML algorithm strictly on the user's device without network connection helps keep the user's data private and the App responsive (Apple Developer, 2023b).

### 3.3.2 Prototyping

Once the user needs have been elicited and the development platform has been decided, the information can be transformed into detailed development specifications and development can begin. The development of *Roomie* must ensure the feasibility, acceptability and appropriateness for the particular users. One of the methods used to aid the achievement of these objectives was to construct prototypes. Prototyping can involve two variations, paper-based and functional version. Paper-based prototyping is usually used in early ideation where developers draw sketches of interfaces. Although creating a paper-based prototype is easy and rapid, it does not involve real user interaction (Kentaro & Hirayama, 2006). Alternatively, functional prototypes can fully interact with users and hence are recommended by previous research (McCabe & Innes, 2013), especially for an iterative development process that is user-centred. A series of prototypes may be created with each version accommodating more design ideas from target users and identifying suitable technologies (Keay-Bright, 2007). Therefore, following the user needs investigation, the author initially drew a paper-based prototype for *Roomie* and confirmed initial design decisions with caregivers and advisory panel. The author then developed functional prototypes which allowed users to try the system and provide more robust feedback.

The system development consisted of three functional prototypes within the proposed iterative process. Objectives for each prototype version were different and built on each other. The prototype 1.0 was built based on the use of technology and theoretical mechanisms behind the proposed system. The testing of the prototype 1.0 with a large sample of children with ASD allowed the author to obtain data for ML training and to expand on the further objectives (i.e., attention and stress detection, strategy-making). The prototype 2.0 implemented the AI algorithms successfully and improved the UI of the system. The prototype 3.0 improved its usability, making it fully meet the functional and non-functional requirements and reach the readiness level for real-life evaluation. The prototype 3.0 was the beta version of *Roomie*.

The development of *Roomie* also required the selection of sensors to detect potentially useable features. Nowadays, smartphones and smartwatches have the capability of capturing data sources from sensors that are either internal to the device (built-in sensors) or external where they are present in the near location and connected to the device (Craven et al., 2014). In this research, the prototype 1.0 used sensors available on the iPhone and Apple Watch for environmental and physiological measurements. However, some key parameters identified in the literature review were not yet readable by iPhone or Apple Watch sensors by the time of thesis writing, such as ambient temperature and humidity, Galvanic Skin Response (GSR) and Electroencephalograms (EEG). Therefore, external sensors were also included as additional measuring tools to obtain more data from the sensory events. The accuracy, ease of use, stability, acceptability and affordability were main factors considered when selecting external sensors for prototyping. Section 4.3 investigates and details the characteristics of different sensor devices. Since sensing technologies have become so mature that there were a lot of off-the-shelf products, the author did not investigate all the products on the market but looked at the most used ones or those available within the university lab. For environmental measurements, external sensors like light sensors and temperature sensors, which are highly commercial, open source, low cost, accurate and durable (Pateraki et al., 2019), were investigated. For physiological measurements, external sensors investigated included GSR and EEG sensors that can be borrowed from the university lab or purchased through research grant scheme.

## 3.4 Dataset creation

Two datasets were needed for developing AI algorithms to be used by *Roomie*. They were named as Sensory Dataset (hereafter referred as SD) and Strategy Knowledge Base (hereafter referred as SKB) in this research.

A description of both datasets and corresponding data acquisition methods are given below.

### 3.4.1 Sensory Dataset (SD)

#### 3.4.1.1 Data acquisition

SD was supposed to contain full information about children's Sensory Profiles (SP), physiological activities, ambient environments, and a user's attention and stress level. This dataset was needed because it can be used to 'teach' an ML algorithm to provide information about attention and stress with minimal human involvement. This dataset was collected completely by the *Roomie* prototype in controlled environments because, by the time of development, there were no prior public resources that provided the desired feature data. The data acquisition for SD were performed simultaneously when testing the prototype 1.0.

A total of 35 children (aged from 3 to 7 years, mean age: 5.3; 29 males, 6 females, gender ratio: 4.83 : 1) who had been formally diagnosed with ASD were involved. Caregivers' informed consent and children's SPs were obtained in the registration phase. As suggested by the findings from literature review, Sensory Profile of Children Three to Ten Years Caregiver Questionnaire (Dunn, 2002) was adopted by *Roomie* to profile user's sensory processing patterns. A Chinese standard version (attached in Appendix G) of the questionnaire was used. Caregivers completed the 125-question SP questionnaire, reporting the frequency with which their child or grandchild responded to various sensory stimuli. The frequency of behaviours was determined from a Likert scale where an Always (100% of the time) answer was scored with 1 point, Frequently (at least 75% of the time)

2 points, Occasionally (50%) 3 points, Seldom (25%) 4 points, and Never (0%) 5 points. Item scores were then transferred to the quadrant grid and totalled. A raw score was obtained and converted into a classification of the sensory processing pattern as mentioned in section 2.2.3. The calculation method is detailed in Appendix H.

Since many caregivers were unwilling to have their children involved in a long testing period, the author adopted a method by discussing with caregivers and the advisory panel which can both cater to children with ASD and for the needs of adequate data. The data acquisition was finally conducted within a rehabilitation centre in Ninghai County, Elim Autism. Participants were recruited within the rehabilitation centre, and the data acquisition sessions were arranged at their break time to ensure participation commitment. A reading room in the rehabilitation centre, which was quiet and private, equipped with air conditioner, study lamps, speakers, video recorder, table and chairs, was used as the data acquisition room. Each participant agreed to undergo 15 sessions in total following a predefined procedure. During each session, a child with ASD was required to enter the room accompanied by their caregiver. Environmental influences (i.e., temperature, noise and light intensity) were controlled in the room. Each of these variables had five different settings, namely Low level, Low-Moderate level, Moderate level, Moderate-High level and High level in order to stimulate as many real-life conditions as possible. Before each session started, one of the variables was adjusted to a required level and the other two variables were controlled to be 'Moderate'. Details about controlled variables are provided in Table 3.1.

**Table 3.1:** *The value of the controlled variables*

| Variable | Values | | | | | Unit |
|---|---|---|---|---|---|---|
| | **Low** | **Low-Moderate** | **Moderate** | **Moderate-High** | **High** | |
| Temperature | 20 | 22 | 25 | 28 | 30 | °C |
| Noise | 40 | 50 | 60 | 70 | 80 | dB |
| Light intensity | 225 | 300 | 375 | 450 | 525 | lx |

Each session lasted about 15 minutes. The preparation phase (first five minutes) was used for coaching three attention tasks, equipping the device and getting the participant to adjust to the condition. During this time, the author placed an iPhone on the desk and the wearable devices on the participant. The prototype App was installed on the iPhone and kept turned on to collect the data until the session ended. Following the first five minutes were three attention tasks with on-site ASD specialists monitoring the performance and managing potential risks. Each task 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.

Attention tasks that have been widely used to induce stress and indicate attention levels were chosen. Referring to the advisory panel's suggestions and previous practice in the literature review, the author simplified the tasks to minimise the possibility of over-stressing young children with ASD. The design of these attention tasks specifically considered the capabilities of children with ASD aged under 7 years and was for the benefits of participants, hoping to improve their numerical, cognitive and motor skills. The tasks were counting, picture matching, and drawing tasks, delivered by an iPad App (Figure 3.5) with below specifications.

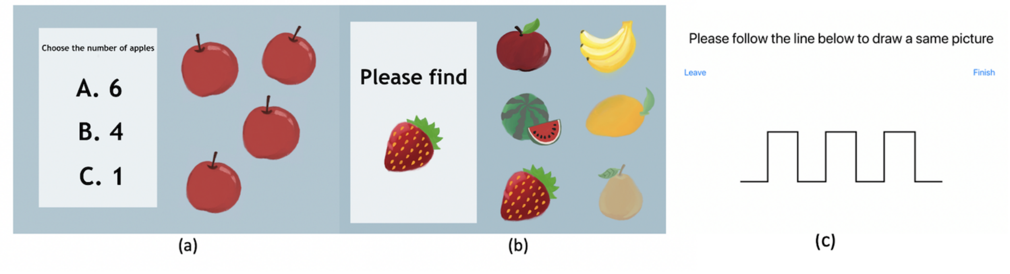



**Figure 3.5:** *Counting task (a), picture matching task (b), and drawing task (c)*

(a) Counting task. The counting task assessed the figure cognition and attention aspects, at which children with ASD may not be as good as TD children of the same age. The task displayed a random number of apple(s), which the participant would count and select the correct quantity from a list (see Figure 3.5a). The participant's choices were recorded, and data were extracted to identify the percentage of correct answers as an indicator of attention performance. The task performance was calculated using Equation (3.1).

$$Counting\ task\ performance = \frac{Correct\ answers\ the\ child\ made}{Total\ number\ of\ questions} \tag{3.1}$$

(b) Picture matching task. The picture matching task assessed the recognition and matching ability of the participant. This task displayed an image on the left-hand side of the screen which the participant needed to match to a matching image from a collection of images on the right-hand side of the screen (see Figure 3.5b). Similar to the first task, participant's choices were recorded, and the data were extracted to identify the percentage of correct answers as an indicator of attention performance. The task performance was calculated using Equation (3.2).

$$Picture\ matching\ task\ performance = \frac{Correct\ answers\ the\ child\ made}{Total\ number\ of\ questions} \tag{3.2}$$

(c) Drawing task. In the drawing task, the participant was presented with five images on the iPad and were required to trace the line in each image by using an iPad Pencil (see Figure 3.5c). This task aimed to help improve the eye gaze and motor skill of the participant. The participant's attention was assessed since they need to pay attention on the original line when tracing to get better result. This task recorded the overlaps between the lines and touch position of the iPad Pencil. The matching rate between the original image and the image drawn by the participant was calculated by examining each pixel of the original line in a specific mask and checked if the corresponding pixel value in the participant's image matched. A successful match occurred when the pixel values at the same position were identical. Conversely, if the pixel values differed, it was considered a failed pixel. The task performance of a single drawing was calculated using Equation (3.3).

$$Drawing\ task\ performance = \frac{Number\ of\ matched\ pixels}{Total\ number\ of\ pixels} \tag{3.3}$$

A flowchart for a single data acquisition session is presented in Figure 3.6.

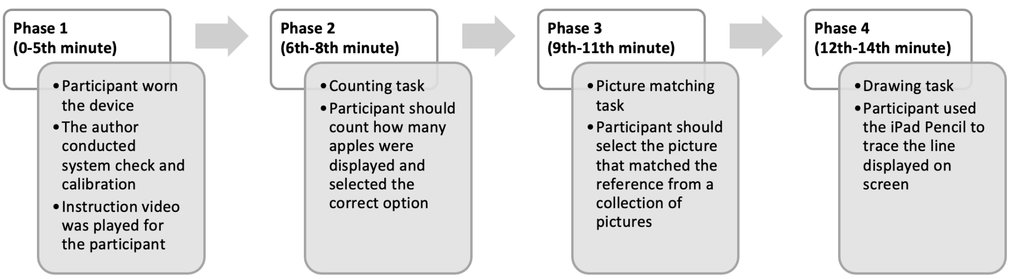



**Figure 3.6:** *Sensory Dataset acquisition flowchart*

Overall, the majority of participants showed acceptance of the experimental conditions and the devices worn on their wrists and fingers. Out of the 35 children, 31 successfully completed all the required sessions. However, three children experienced anxiety and were unable to complete the tasks in the High temperature condition. Additionally, one child did not complete the tasks in the Low noise level setting as he appeared to be distracted by the animation on the Apple Watch and did not hear the task instructions.

#### 3.4.1.2 Data pre-processing

A total of 521 successful data acquisition sessions were conducted, and data were stored in a raw dataset. SP classifications were encoded in a format suitable for ML algorithm training. Each sensory processing pattern in the SP can be classified into three classes: 'Typical Performance' (coded as 1 in SD), 'Probable Difference' (coded as 2 in SD), and 'Definite Difference' (coded as 3 in SD). The author incorporated pattern classifications, together with age and gender information, to create the final SD for ML training. In the raw SD, there were originally 29 features as presented in Table 3.2.

**Table 3.2:** *Features in the Sensory Dataset*

| **Feature** | **Description** |
|---|---|
| Time | Local time in China |
| Temperature | Environmental temperature |
| Humidity | Environmental humidity |
| Noise | Environmental noise level |
| Brightness | Environmental light intensity |
| Pressure | Atmospheric pressure |
| Magnetometer:x | Magnetic field strength on the x axis |
| Magnetometer:y | Magnetic field strength on the y axis |
| Magnetometer:z | Magnetic field strength on the z axis |
| Gyroscope:x | Phone rotation around the x axis |

| Feature | Description |
|---|---|
| Gyroscope:y | Phone rotation around the y axis |
| Gyroscope:z | Phone rotation around the z axis |
| Accelerometer:x | Phone acceleration on the x axis |
| Accelerometer:y | Phone acceleration on the y axis |
| Accelerometer:z | Phone acceleration on the z axis |
| 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 |
| Heart_rate | Heart beats per minute |
| GSR | Galvanic Skin Response |
| Task | Task the child was playing |
| Question | Question or subtask the child encountered in that task |
| Correct_or_error | Response accuracy to that question or subtask |
| SP_registration | The child's pattern of Low Registration in SP. Three classifications are 'Typical Performance', 'Probable Difference' or 'Definite Difference' |
| SP_seeking | The child's pattern of Sensory Seeking in SP. Three classifications are 'Typical Performance', 'Probable Difference' and 'Definite Difference' |
| SP_sensitivity | The child's pattern of Sensory Sensitivity in SP. Three classifications are 'Typical Performance', 'Probable Difference' and 'Definite Difference' |
| SP_avoiding | The child's pattern of Sensory Avoiding in SP. Three classifications are 'Typical Performance', 'Probable Difference' and 'Definite Difference' |
| Age | Age of the child at the time of testing |
| Gender | Gender of the child (boy or girl) |

The author performed pre-processing on the raw SD before entering the phase of training ML algorithms. Features irrelevant to the analysis, such as magnetometer, gyroscope, phone accelerometer data were discarded by common-sense knowledge.

Although there was at least one teacher being on-site to observe and ensure the safety, they worked in rotation among teachers from Elim Autism as they had different available time slots. Asking multiple observers to label children's attention and stress level may lead to low labelling reliability. To address this issue, all the sessions were recorded by the video recorder. Two ASD specialists from the advisory panel, different from on-site teachers to avoid observer bias, were involved afterwards reviewing video records and labelling each child's attention and stress in each session. They labelled each child's attention level in each of four phases as either Low or Normal. They labelled each child's stress level in each of four phases as Low, Moderate, or High. Due to the limited budget of the project to pay their extra work, they reviewed 222 from 521 records and provided suggestions that their task performance can be a reliable indicator for classification.

Since there was an incomplete set of specialist labels for all sessions, task performance was considered for inferring attention levels especially. To determine suitable cutting-off points for classifying attention, the author combined the task performance scores with the labels provided by the ASD specialists. The author employed an approach based on entropy and information gain theory (Shannon, 1948), which is a classical computation method for determining the best split. As two independent assessors have done the split on 'Attention' for each session, the entropy (level of uncertainty) of the given dataset ($S$) can be calculated by Equation (3.4).

$$Entropy = -\sum_{i=1}^{2} p_i \log_2 p_i \tag{3.4}$$

Where $p_1$ represented the probability of randomly selecting a result of 'Low' attention from the sample, and $p_2$ represented the probability of obtaining a result of 'Normal' attention. The calculation yielded an entropy value of $Entropy(S) = 0.99789$. An entropy value close to 1 indicated higher uncertainty of the outcome (Reddy & Chittineni, 2021). To improve predictability, it was necessary to calculate the information gain for a split. The information gain equation was used to evaluate the impact on uncertainty when the dataset $S$ was split by a range of task performance scores. When a value of task performance scores ($v$) split $S$ into subsets $S^v$, the information gain was determined by Equation (3.5).

$$Information\ gain = Entropy(S) - \sum_{i=1}^{v} \frac{|S^v|}{|S|} Entropy\,(S^v) \tag{3.5}$$

As the split value changes, the information gain fluctuates. The greater the information gain, the greater the decrease in entropy or uncertainty. Figure 3.7 shows the information gain fluctuation as the split value changes. When the split value is 0.6, the dataset has the highest information gain value.

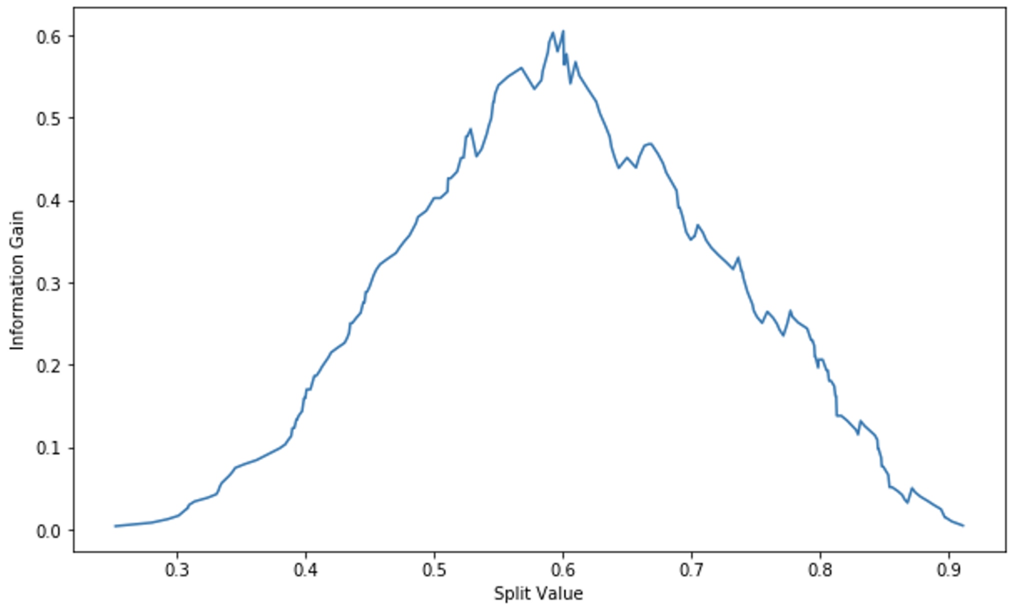



**Figure 3.7:** *Information gain results on different split points*

Therefore, the author defines task scores above 0.6 as indicative of a 'Normal' level of attention, suggesting that the children generally exhibit the ability to focus and attend to tasks. Task scores equal to or below 0.6 are considered indicative of 'Low' (below-normal) attention levels, reflecting decreased focus and attention.

The attention task performance cannot directly indicate stress levels. Therefore, classification of stress level was determined by applying ASD specialists' suggestions. They suggested that children experienced low stress when relaxing, not doing any tasks under moderate (i.e., Low-Moderate, Moderate and Moderate-High) environmental conditions. Engaging in tasks in these conditions increased their stress level, but still manageable. However, engaging in tasks in some extreme environmental conditions (i.e., Low and High temperature, High noise, Low and High light intensity) always made them highly anxious. Therefore, engaging in tasks under moderate (i.e., Low-Moderate, Moderate and Moderate-High) and extreme environmental conditions (i.e., Low and High temperature, High noise, Low and High light intensity) are classified as 'Moderate' stress and 'High' stress, respectively. Relaxing under moderate (i.e., Low-Moderate, Moderate and Moderate-High) environmental conditions and extreme environmental conditions (i.e., Low and High temperature, High noise, Low and High light intensity) are classified as 'Low' and 'Moderate' stress, respectively.

Subsequently, real-time data were extracted from the corresponding segments that have been properly labelled. Environmental and physiological data were derived by calculating the average values of the respective segments. For example, the heart rate value for the counting task was obtained by averaging the heart rate values recorded throughout the entire duration of the task. Watch accelerometer data on three 3 axes were converted to mean absolute value (MAV) data, which were obtained from the average of the absolute value of each signal from 3 axes. This pre-processing approach was adopted because it has been found effective for extracting statistical features useful for atypical sensory response detection (Coronato et al., 2014).

After data pre-processing, the feature vectors consist of 14 features. The 14 features are categorised and listed in Table 3.3. Categorical features in the input data were pre-processed using one-hot encoding, while numerical features were normalised using Min-Max Normalisation.

**Table 3.3:** *Selected data features*

| **Category** | **Included Features** | **Data Type** |
|---|---|---|
| Environmental features | Temperature, Noise, Humidity, Brightness | Numerical |
| SP features | SP_registration, SP_seeking, SP_sensitivity, SP_avoiding | Categorical |
| Physiological features | Watch_accelerometer_MAV, Heart_rate, GSR | Numerical |
| Personal characteristics | Gender | Categorical |
| | Age | Numerical |

### 3.4.2 Strategy Knowledge Base (SKB)

One of the key functional requirements of *Roomie* is to provide real-time sensory regulation strategies to help children with ASD. Therefore, an SKB was needed to enable the final *Roomie* prototype to provide strategies automatically based on real-time information collected. The acquisition of SKB adopted a similar method applied in the study conducted by Reis et al. (2021). The author firstly gathered information about sensory regulation strategies through focus group consultations with the advisory panel.

Focus group consultations or focus group interviews mentioned in this thesis refer to the method of gaining information from face-to-face meetings with stakeholders who have related knowledge. The focus group consultations here were semi-structured based on the conditions that had been found to trigger atypical sensory responses in children with ASD. Five consultation meetings were conducted separately, each of which involved two ASD specialists of the advisory panel due to unavailability of all the panel members at the same time. Specialists were informed that the strategies they recommended must be suitable for children aged between three and ten. Although a list of common questions was prepared (see Table 3.4), additional questions were asked throughout the process according to the suggestions and different perspectives of the specialists involved. Besides, existing sensory toolkits that provide sensory regulation strategy guidelines were also searched to complement the provided knowledge (Bundy et al., 2002; Autism Services, Education, Resources and Training, 2021).

**Table 3.4:** *Common questions asked in the focus group consultations*

| **Questions** |
|---|
| 1. When children with ASD feel anxious in a noisy environment, what strategies do you usually adopt? |
| 2. If at the same time, they find it hard to complete tasks in timely manner, what strategies do you usually adopt? |
| 3. When they suddenly become anxious in a quiet environment, or has been unable to concentrate, what strategies do you usually adopt? |
| 4. When they show anxiety and avoidance of bright lights (e.g., sunlight coming in from a window), what strategies would you recommend? |
| 5. When they are particularly excited in brightly lit areas and unable to concentrate on other tasks, what strategies would you recommend? |
| 6. When they experience extreme anxiety or are interrupted from getting activities completed in very cold or hot environments, what strategies would you recommend? |

| Questions |
| --- |
| 7. When they are interrupted from activities by small or new sensory stimuli, what strategies would you recommend? |
| 8. Can you recommend any references/guidelines for sensory regulation strategies? |

The data collected through the method were fully transcribed from the scripts and subsequently interpreted and organised into combinations of inputs and outputs in a computer science manner so that an algorithm can be programmed to implement the strategy-making. As suggested by the advisory panel, the length of time that atypical sensory responses lasted was also a factor that should be considered before making a certain sensory regulation strategy. The strategy for long-term and short-term atypical sensory responses could be different, given that children with ASD have some degree of self-regulation ability. The advisory panel suggested that continuous 'distraction' and 'anxiety' for more than 30 seconds should have reflected the risky state of atypical sensory responses, which needs a certain sensory regulation strategy. In order to ensure the robustness of sensory regulation strategies, the author went further to conduct a survey with more ASD specialists. Scenarios describing environmental conditions and responses of a child with ASD were shortlisted in an online questionnaire. Sensory regulation strategies obtained from focus group consultations and toolkits were listed as options. The questionnaire consisted of 41 questions and were distributed through collaborative ASD institutions to their employed ASD specialists. Sample questions are presented in Table 3.5 and more questions are attached in Appendix I.

**Table 3.5:** *Sample questions of online questionnaire for acquiring sensory regulation strategies*

| Questions with Multiple Options |
|---|
| Question-1. If the environment becomes less bright (e.g., power outage), the child shows short-term anxiety and distraction, but quickly recovers, what strategy would you recommend the most? |
| ☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.) |
| ☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist. |
| ☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favorite pictures or videos on mobile phone or other electronic devices. |
| ☐ Take him or her away from the current environment and change to another comfortable environment. |
| Question-16. If the environment is getting cold, the child shows a long-term anxiety with normal attention level, what strategy would you recommend the most? |
| ☐ Take no action. |
| ☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and observe if atypical responses persist. |
| ☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately give him or her some fidget toys such as balls with texture that the child likes to help reduce tension. |
| ☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension. |
| ☐ Immediately take him or her away from the current environment and change to another comfortable environment. |

**Questions with Multiple Options**

Question-23. If the environment is noisy (e.g., under renovations), the child shows a short-term distraction with low stress level, but quickly recover, what strategy would you recommend the most?

☐ Take no action.

☐ Just remind him or her to pay attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise cancelling headphones), and observe if their atypical responses persist.

☐ Try to block out the noise (e.g., by playing other music or put on noise cancelling headphones), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to attract his or her attention.

☐ Immediately take him/her away from the current environment and change to another comfortable environment.

Question-40. If the environment is relatively comfortable and quiet, the child shows short-term anxiety and distraction, but quickly recovers, what strategy would you recommend the most?

☐ There will be no impact. No action.

☐ There will be ignorable impact. Keep observation.

☐ There will be severe impact. Consider whether there are other interfering factors and comfort them immediately.

Through the online survey, responses from 242 ASD specialists were obtained, including 233 special education teachers, 18 sensory integration specialists, 6 behavioural analysts, 1 psychiatrist and 1 ASD-related social worker (totalled to more than 242 because some specialists had various qualifications). The results were finally interpreted into input-output rules for strategy-making algorithms detailed in section 5.2.1. Figure 3.8 depicts the overall process of acquiring SKB.

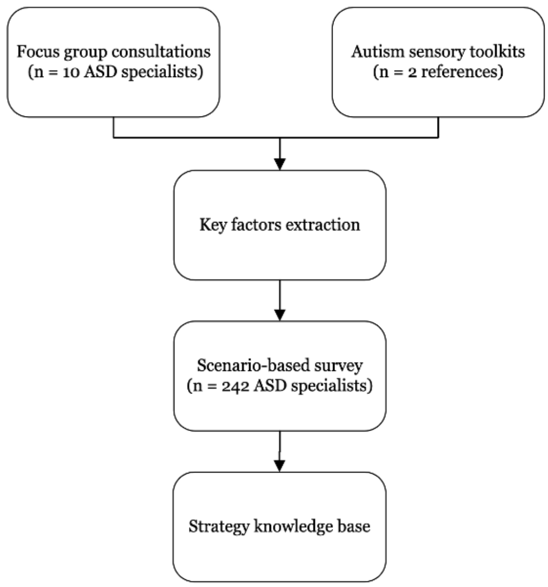



**Figure 3.8:** *Strategy Knowledge Base acquisition flowchart*

## 3.5 Model development and validation

As described above, datasets comprising of comprehensive sensory-associated data from children with ASD and sensory regulation strategies were obtained. In order to make use of SD and SKB to enable attention and stress detection as well as strategy-making, the author developed and evaluated AI algorithms which were appropriate depending upon the number of features and nature of detection tasks.

### 3.5.1 Attention and stress detection algorithms

Supervised ML algorithms can be trained with labelled datasets. The author explored multiple supervised ML algorithms for attention and stress detection. The algorithms investigated in this thesis encompass K-Nearest Neighbours (KNN), Random Forest (RF), Artificial Neural Network (ANN), and Gradient Boosting Decision Tree (GBDT).

#### 3.5.1.1 K-Nearest Neighbours

KNN is an effective supervised learning algorithm extensively used for classification (Portugal et al., 2018). It measures the Euclidian distance between the $k$ nearest objects and the target object and generated predictions based on the majority label of its neighbours. As a case-based learning method, KNN keeps all the training data for classification (Guo et al., 2003). In the development of the algorithms for attention and stress detection, KNN plays a pivotal role in the attention detection because it is more suitable for binary classification problems. The algorithm is trained using labelled data, where each data point represents a specific session, and its associated label indicates the level of attention exhibited during that session. During the testing phase, the KNN algorithm predicts the classification of an unlabelled data by taking into account the features and labels of the training dataset (Uddin et al., 2022). For instance, in attention detection, the algorithm identifies the $k$ nearest sessions that closely resembles the input session and predicts the attention level based on the majority label among those neighbours.

Firstly, a training dataset $D = \{(x_t, y_t)\}_{t=1}^{N}$ is given for KNN task, where $x_t$ and $y_t$ are the input and the corresponding labels of the $t$-th instance. For each instance, KNN tends to retrieve $N(x_t) = \left\{\left(x_t^{(i)}, y_t^{(i)}\right)\right\}_{i=1}^{k}$ that are closest to $x$ based on an Euclidian distance function $d$. Then, the predicted label $y$ is obtained as a weighted combination of the labels $y^{(1)}, \ldots, y^{(k)}$ based on a weighting function $w$ along with the Euclidian distance function $d$ as represented by Equation (3.6) and (3.7) (Kang, 2021).

$$\hat{y} = f(x; D) = \frac{\sum_{i=1}^{k} \omega\left(d\left(x, x^{(i)}\right)\right) \cdot y^{(i)}}{\sum_{i=1}^{k} \omega\left(d\left(x, x^{(i)}\right)\right)} \tag{3.6}$$

$$d = \sqrt{(x^2, x^{(i)^2})} \tag{3.7}$$

#### 3.5.1.2 Random Forest

RF is a classification algorithm introduced by Breiman (2001). It is based on the fundamental bagging principle of constructing multiple small, weak Decision Trees (DTs) which have low bias and high variance in parallel and then combining them to form a robust learner. The merging process can be done by taking the mean performance of the individual DTs or by selecting the most popular prediction among them. In an RF, the features are randomly selected in each DT split, and the prediction performance is improved by the random selection of features (J. Ali et al., 2012). To make a prediction at an input label $x_t$, RF calculates the $\hat{y}$ based on Equation (3.8) (Cutler et al., 2012).

$$\hat{y} = argmax_y \sum_{i=1}^{k} I\left(\hat{h}_j\left(x_t\right) = y_t\right) \tag{3.8}$$

Where $\hat{h_j}(x_t)$ is the prediction of the response variable at $x_t$ using the $i$-th DT.

In terms of application and practicality, RF is known to provide more accurate classifications compared to a single DT through the use of bagging on samples (J. Ali et al., 2012). The ensemble nature of RF helps to reduce overfitting and increase the generalisation ability of the model. By combining the predictions of multiple DTs, RF can effectively capture complex relationships and patterns in the data, improving the overall performance of the classifier. Therefore, RF is widely used in various domains, including healthcare, finance, and image recognition, due to its versatility and effectiveness. It is capable of handling high-dimensional data, categorical features, and missing values. Additionally, RF provides measures of feature importance, allowing for better understanding of the underlying data and aiding in feature selection.

#### 3.5.1.3 Artificial Neural Network

ANN is a type of DL technique that seek to emulate the behaviour and functioning of the human brain (Appiahene et al., 2020). It consists of interconnected nodes, or artificial neurons, organised in layers. Each neuron receives input signals and a bias along with them, applies a mathematical function to them, and generates an output signal (Peterson & Rögnvaldsson, 1992). The mathematical function that defines how the weighted sum of the input is transformed into an output from a node or nodes in a layer of the network is known as the activation function. The choice of activation function has a large impact on the capability and performance of the ANN, and different activation functions may be used in different parts of the algorithm. Weights represent the strength of connections between neurons, and determines the impact of each input on the output. By iteratively adjusting the weights through a process known as training, ANN can learn complex patterns and relationships in the data.

#### 3.5.1.4 Gradient Boosting Decision Tree

GBDT is a popular ML algorithm that belongs to the ensemble learning category. It is known for its powerful predictive capabilities and has been successfully applied in various domains, including regression and classification tasks (Chen & Guestrin, 2016). Unlike traditional DTs and RF, GBDT builds a strong predictive model by combining multiple weak learners that have high bias and low variance, typically DTs, in a sequential manner. Each weak learner is trained to correct the mistakes made by the previous learner, with a focus on the instances that are incorrectly predicted. This iterative process continues until a specified number of weak learners, known as boosting iterations, are reached.

The key idea behind GBDT is to create an ensemble model that learns from the mistakes of previous models, thus continuously improving its prediction accuracy. Each weak learner is trained on a subset of the data, with more emphasis given to the instances that are previously misclassified. By combining the predictions of all weak learners, GBDT produces a final prediction that is a weighted sum of the individual learners' predictions. GBDT can be regarded as an additive model of DTs, which can be calculated by Equation (3.9) (Friedman, 2001).

$$\hat{y} = \sum_{i=1}^{k} T_m(x) \tag{3.9}$$

Where $T_m(x)$ represents the $m$-th DT, and $k$ is the number of DTs.

#### 3.5.1.5 Feature selection

Feature selection is a crucial step in ML training because it allows the estimation and rank of most important features, then helps to remove irrelevant and redundant features out of the raw dataset. The main feature selection approaches can be categorised into three methods: filter methods, wrapper methods and embedded methods (W. Liu & Wang, 2021). The filter methods are based on statistical methods and, as a rule, consider each feature independently. They do not use any learning algorithm to guide the feature selection process and therefore are much faster than wrapper and embedded methods (Artur, 2021). Moreover, they work well even when the number of features exceed the number of examples in the training dataset. The essence of wrapper methods is that the classifier is run on different subsets of features of the original training dataset. A subset of features with the best parameters on the training sample is chosen and tested on the test dataset subsequently. All wrapper methods require much more computation than filtering methods. In case of large number of features and small training dataset size, the wrapper methods have a risk of overfitting. Embedded methods do not allow to separate feature selection and classifier training, but select within the computation process. In addition, the embedded methods require less computation than wrapper methods, but more than filtering methods. Among the three types, wrapper methods often provide better performance (Artur, 2021). This is because the usage of a consistent learning algorithm for subsequent classification can benefit more from the feature selection process.

Since the number of remaining features in SD was relatively small, a popular wrapper feature selection algorithm, Recursive Feature Elimination (RFE) was used. RFE works by recursively removing features and building an algorithm based on the remaining features. It uses detection accuracy to determine which features (and combinations of features) contribute the most to detecting the target feature. RFE requires a specified number of features to keep, however it is often not known in advance how many features are optimal. To find the optimal number of features, cross-validation scores are usually used with RFE to score different feature subsets and select the best scoring collection of features (Artur, 2021).

#### 3.5.1.6 Model validation

In all experiments the cross-validation, a procedure for empirically evaluating the generative ability of ML algorithms trained on precedents, was used for model evaluation. The algorithm fixes some set of partitions of the original sample into two subsets: a training dataset and a testing dataset.

For each partition, the ML algorithm is tuned for the training dataset, and then its average error on the testing dataset is estimated. For the purpose of algorithm validation, the author split the complete dataset into the training and testing dataset by adopting $80 : 20$ as the ratio of training : testing dataset. Stratified 5-fold cross-validation approach was applied to evaluate the quality of the ML algorithm. Stratified 5-fold cross-validation was based on a variation of 5-fold which returned stratified folds where each set contained approximately the same percentage of samples of each target class as the complete set.

The evaluation metrics used for ML algorithm validation were common metrics used in classification problems, including classification accuracy and measures derived from confusion matrix. The classification accuracy can be mathematically defined as the ratio of the number of detections done correctly by the ML algorithm to the total number of detections made (Equation (3.10)).

$$Classification\ accuracy = \frac{Number\ of\ correct\ detections}{Total\ number\ of\ detections\ made} \tag{3.10}$$

Confusion matrix is a commonly-used tool that provides a better view of classification errors (Harrington, 2012). It can be applied to two-class as well as for multi-class classification problems. An example of a confusion matrix for binary classification is shown in Figure 3.9.

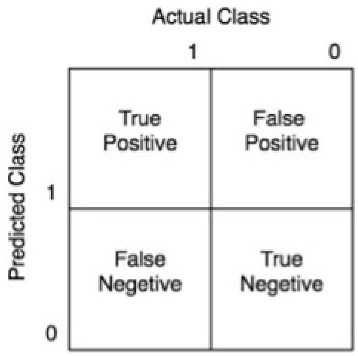



**Figure 3.9:** *Confusion matrix for binary classification, from Sharma et al. (2022)*

True positive (TP) indicates the number of positive examples classified accurately. False positive (FP) indicates the number of actual negative examples classified as positive. True negative (TN) shows the number of negative examples classified accurately. False negative (FN) is the number of actual positive examples classified as negative.

Apart from classification accuracy, other frequently used performance metrics obtained from confusion matrix include precision, sensitivity, and F1-score. F1-score is an important measure of the test's accuracy. For attention detection which was a binary classification, a regular F1-score was calculated, while macro F1-score was computed for stress detection which was a multi-class problem. Macro F1-score calculates F1-score for each class and sums them up, with each class the same weight. For each class, F1-score can be calculated by using Equation (3.11), (3.12) and (3.13) (Pedregosa et al., 2011).

$$Precision = \frac{TP}{TP + FP} \tag{3.11}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3.12}$$

$$F1 - score = 2 \times \frac{Precision \ \times \ Sensitivity}{Precision \ + \ Sensitivity} \tag{3.13}$$

Considering the ML algorithms needed to be implemented on an iPhone-based system, the response time of the algorithm was another critical factor worth examining. All the ML algorithms were processed on a laptop central processing unit and the inference time of each ML algorithm was calculated by using Equation (3.14) and compared.

$$Inference\ time = \frac{Total\ time\ taken\ to\ calculate\ the\ outputs}{Number\ of\ samples} \tag{3.14}$$

### 3.5.2 Sensory regulation strategy-making algorithm

Along with the SKB was a rule-based strategy-making algorithm using fuzzy logic (FL), which took in ML detection results and environmental information, leading to a specific output. This process was rule-based and fuzzified because, from ASD specialists' point of view, the comfort zone of environmental factors has fuzzy boundaries and strategy-making in real life is always complex, influenced by many factors (i.e., self-regulation capability, specialists' personal preference of strategy using). The advisory panel suggested that not all low attention or high stress states would finally lead to unmanageable situations such as meltdown. Given the fact that children with ASD also have self-regulation capability, recovery from low attention or high stress sometimes can be nearly instant. Continuous 'distraction' and 'anxiety' within unfriendly environment, usually for more than 30 seconds (as suggested by the advisory panel), reflects the risky state of atypical sensory responses which needs certain sensory regulation strategy. For a single situation, there can be many suitable strategies based on specialists' expertise.

An FL-based system is able to transfer expert knowledge into automated algorithms to recommend an appropriate strategy to an existing condition (Mahfouf et al., 2001), addressing the vagueness presented in the language when describing some phenomena that does not have sharply defined boundaries (Contreras-Valenzuela et al., 2022). Therefore, in this context, FL was used, which took the uncertainty from its inputs and compromised with it in a condition that the results were not affected by this variability.

#### 3.5.2.1 Defining the input and output variables

Before an FL algorithm could be used for strategy-making, all the input and output variables must be predefined. Consistent with the study conducted by Khullar et al. (2019), the author has applied a simple risk assessment as the output of FL. Three levels of risk (Low, Medium and High) have been determined and the impacts on the sensory regulation strategy-making, agreed by sensory toolkits (Bundy et al., 2002; Autism Services, Education, Resources and Training, 2021), have been defined as:

- Low Risk: there is no negative impact on the child's health or state and no sensory regulation strategy is needed.
- Medium Risk: there is an ignorable impact on the child's health or state. Distraction or anxiety generally stops by self-regulation or disappearing of the stressors. Some adjustments can be made to environmental conditions to prevent high risk.
- High Risk: there is a severe impact on the child's health or state and a certain intervention is needed. Once the child with ASD has reached this risk level, they cannot maintain control of themselves the en-

tire time. Adjustments made to environment and sensory regulation strategies are needed.

The input variables for the decisions included sensory stimuli (i.e., temperature, noise and light intensity), duration of atypical sensory responses (i.e., distraction and anxiety), attention and stress levels. It is necessary to establish general thresholds for sensory inputs (i.e., temperature, noise and light intensity). The parameters suggested by the literature review in section 2.1 and ASD specialists were used. Table 3.6 summarises the comfort zones for the three sensory input variables.

**Table 3.6:** *Comfort zones for the sensory input variables*

| **Variable** | **Comfort Zone from Literature** | **Comfort Zone Suggested by ASD Specialists** |
| --- | --- | --- |
| Temperature | 20 °C – 30 °C for adults, for TD children, comfortable zone may be 0.5 °C to 4 °C lower than those of adults. | 22 °C – 28 °C would be most comfortable for children with ASD. |
| Noise | Under 70 dB for general population. | No specific limit, but higher noise level always refers to higher risk in children with ASD. |
| Light intensity | 300 lx – 600 lx for TD children. | 300 lx – 500 lx would be most comfortable for children with ASD. |

As suggested by the focus group, the length of time that atypical sensory responses lasted was a factor that should also be considered. The decision of strategy-making for long-term and short-term atypical sensory responses could be different given that children with ASD have some degree of self-regulation ability. ASD specialists mostly agreed that continuous 'distraction' and 'anxiety' for more than 30 seconds reflecting the risky state of atypical sensory responses which needed a certain sensory regulation strategy. The other two inputs to FL were the attention and stress levels. Attention had two levels (Low and Normal) and stress had three levels (Low, Moderate, and High).

### 3.5.2.2 Fuzzy sets

Each input or output variable is associated with levels through fuzzy sets. A fuzzy set is defined as one in which its elements belongs to it with a certain degree of membership function defined as a number $x$ between 0 and 1 (interval [0, 1]), and are used to process uncertainty and characterise knowledge through rules (Contreras-Valenzuela et al., 2022). Thus, the concept of a fuzzy set associated with a certain level, defined by a word, adjective, or linguistic label $A$, is introduced. A fuzzy set $A$ is defined as a membership function that links or matches the elements of a domain or universe of discourse $X$ with elements of the interval [0, 1]; for each fuzzy set, a membership function $A(x)$ should be defined, which represents the degree to which a value for the variable $x$ is included in the concept represented by the label $A$. The closer $A(x)$ is to the value 1, the greater the membership of object $x$ to set $A$. Membership values vary between 0 (does not belong at all) and 1 (total membership). Therefore, a fuzzy set is a class of objects with continuous degrees of membership. For example, the linguistic labels for Brightness (referred to light intensity) are Low, Moderate, or High. A membership function is an application that links every element of a fuzzy set to the degree it belongs to the associated linguistic value. A fuzzy set can also be represented graphically as a function, especially when the universe of discourse $X$ (or underlying domain) is continuous (not discrete), as can be seen in Figure 3.10.

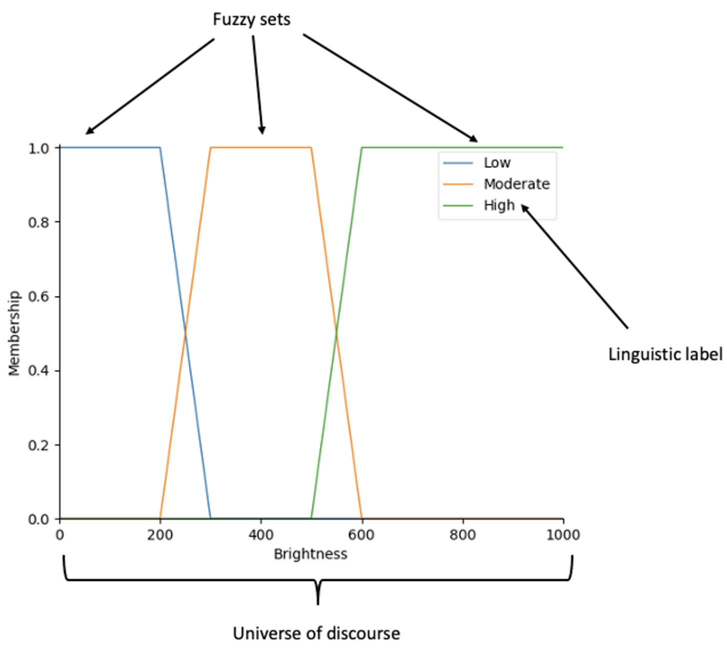



**Figure 3.10:** *The representation of the universe of discourse, linguistic label and fuzzy sets*

All the input variables were implemented to their membership function to determine the degree of truth of each premise. For example, for the Temperature input variable, the membership of three trapezoidal fuzzy sets has been built considering the suggestions from ASD specialists. As seen in Figure 3.11, the temperature below 18 °C had a membership set to 1, indicating a low temperature with certainty. With a trapezoidal membership function, it was necessary to create a decreasing ramp between 18 °C and 22 °C with the aim of creating a transition from low temperature to moderate temperature. The temperature higher than 32 °C was certainly a high temperature. Therefore, it had a membership set to 1. In the opposite case, it was necessary to build an increasing ramp between 28 °C and 32 °C, creating a transition from moderate temperature to high temperature. The temperature between 22 °C and 28 °C was moderate temperature with all certainty. The temperature between 18 °C and 22 °C, and 28 °C and 32 °C represented the vagueness of the boundary.

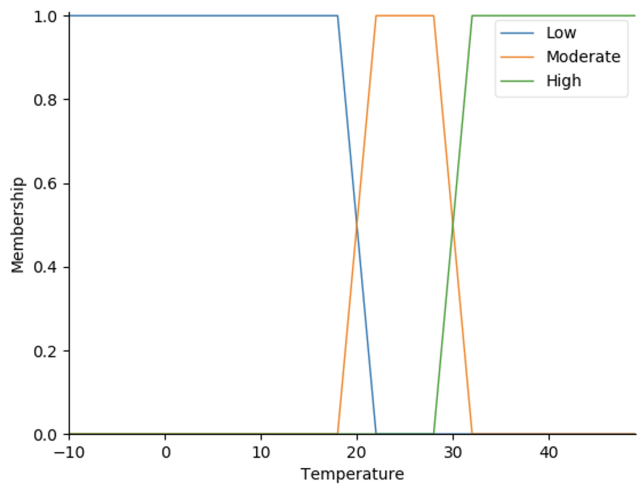



**Figure 3.11:** *Membership function plot of Temperature*

For the Brightness input variable, the membership function of three trapezoidal fuzzy sets has been built. As shown in Figure 3.12, the brightness below 200 lx had a membership set to 1 with all certainty, indicating low brightness level. In the opposite, the brightness above 600 lx had a membership set to 1, as the brightness more than 600 lx was certainly high. The brightness in the range of 300 lx to 500 lx was defined as moderate.

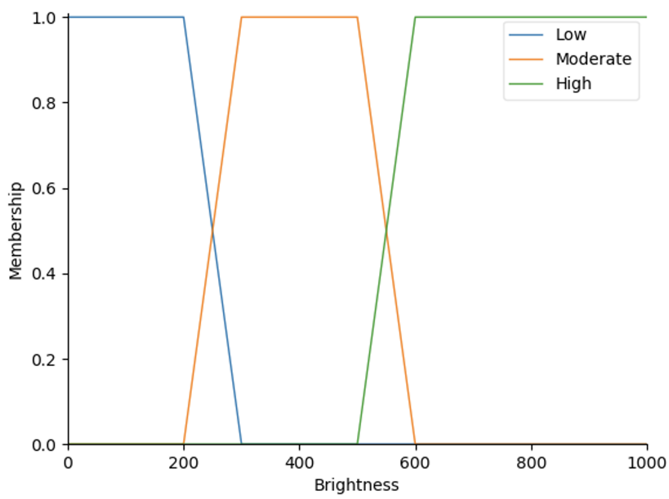



**Figure 3.12:** *Membership function plot of Brightness*

For the Noise input variable, different from the previous two input variables, only two fuzzy sets (Low and High) were built and the Gaussian membership function was applied. The Noise input variable was defined in this way because the linguistic label for noise was rather vague. There was no clear and sharp edge for labelling low and high noise levels. Therefore, based on the prior information, the author developed a membership function for the Noise as Figure 3.13.

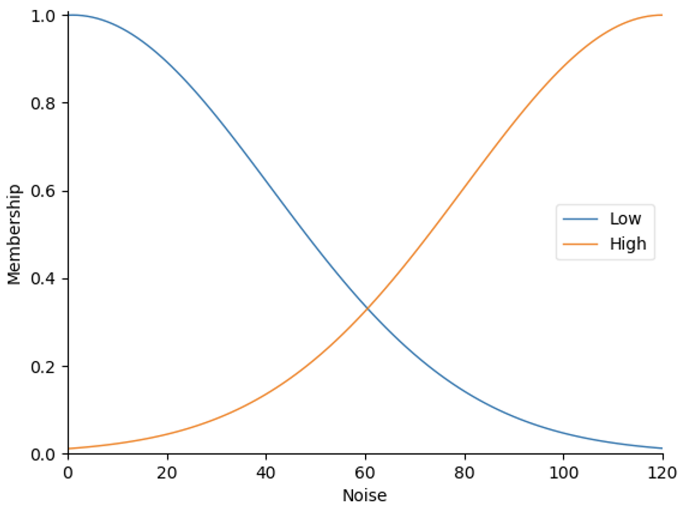



**Figure 3.13:** *Membership function plot of Noise*

For the Duration input variable, which referred to the length of a constant state of attention or stress, two trapezoidal fuzzy sets were built (Figure 3.14). The duration from 0 to 10 seconds represented short-term atypical sensory responses, and the duration more than 30 seconds represented long-term atypical sensory responses. Duration between 10 and 30 seconds represented the vagueness of the decision.

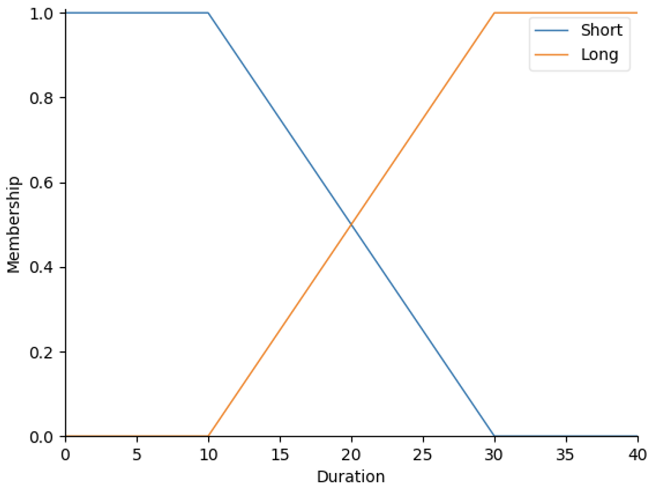



**Figure 3.14:** *Membership function plot of Duration (of atypical sensory responses)*

The other variables, including Attention Level, Stress Level, and the output variable (Outcome, which referred to Risk Level) were discrete variables. Their membership functions are plotted graphically in Figure 3.15.

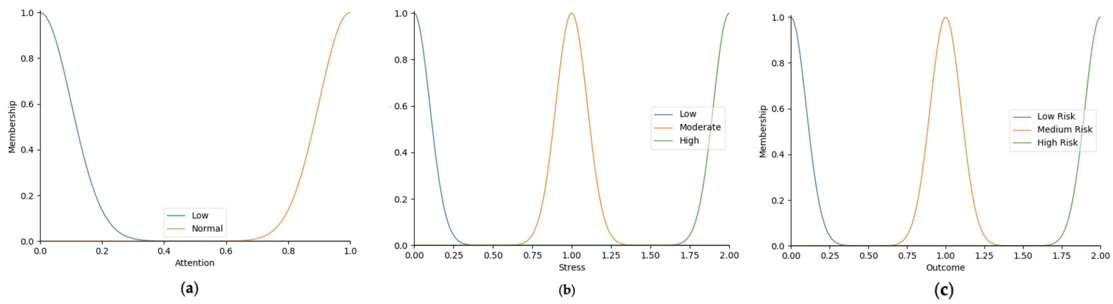



**Figure 3.15:** *Membership function plots of Attention (a), Stress (b), and Outcome (c)*

### 3.5.2.3 Fuzzy rules

FL allows the interpretation of data with predefined linguistic descriptions using conditional (IF-THEN) operators, defined as fuzzy rules, written as:

IF situation 1 AND situation 2 AND situation 3 AND ... THEN the decision

Where each situation can reflect the level of each input variable. The output is the expected decision similar to a decision made by an ASD specialist after evaluating the situations. Therefore, FL can perfectly simulate the strategy-making mechanism of ASD specialists to reach the output value related to risk levels. It is an intuitive model which represents the ASD specialists' knowledge by determining the risk levels based on the user situations.

#### 3.5.2.4 Validating the FL algorithm

In the validation, results of 21 different combinations of conditions evaluated by ASD specialists were used as validator results, called 'expected results'. The experimentation then used the FL algorithm to simulate results in 21 conditions and verified if the algorithm could correctly replicate the results made by the ASD specialists.

Defuzzification is a process that combines the fuzzy set and the aggregation and produces an output in the form of a scalar number. Its value depends on the range of values assigned to the output variable, which represents the risk level assigned (Contreras-Valenzuela et al., 2022). The selection of defuzzification method usually influences overall performance of the FL algorithm (Perumal & Nagi, 2012). In the validation, the author compared two most popular defuzzification methods, Centroid and Largest of Maximum, in order to obtain the FL algorithm with better performance.

## 3.6 System usability and effectiveness evaluation

Evaluation of system functionality included the evaluation of system usability and effectiveness using psychological methodologies. This section describes the details in this particular evaluation process.

After each prototype was developed, evaluation sessions allowed the author to focus on specific features, usability, bugs of each version. The evaluation methods used in these procedures involved both qualitative and quantitative methods to gain feedback on the user experience and potential effectiveness of *Roomie*.

Qualitative methods such as focus groups and interviews are widely applied to gain feedback after testing a technology. Observation methods are usually heavily relied upon for qualitative evaluation of TBIs with special needs user groups. Observational data is particularly important in an ASD-related study, where self-report data is often limited (Neale et al., n.d.).

The prototype 1.0 was firstly tested in a small-scale ($n_1 = 4$) feasibility study with three TD children and one child with ASD at a local childcare centre. The aim of the feasibility study was to assess the acceptance of the design concept and wearable devices. Children in the feasibility testing also went through the same data acquisition procedure as described in section 3.4.1. However, because the prototype 1.0 was an incomplete version of the system and participants had to travel a long way to the childcare centre for participation, four children only completed 9 out of required 15 sessions. Two ASD specialists provided on-site support and guidance in case of any difficulties throughout the period. Children's caregivers and

ASD specialists made observations on the use of technology and took a record on the child's performance. When the feasibility testing period was finished, a focus group meeting with two ASD specialists and caregivers who were willing to participate was conducted.

After the feasibility study, the prototype 1.0 was presented to a larger sample ($n_2 = 35$), most of whom completed 15 sessions following the data acquisition procedure as described in section 3.4.1. The data acquisition sessions were conducted in an ASD rehabilitation centre, where a total number of four ASD specialists were involved to provide on-site support and make observations. Similar to the evaluation in the feasibility study, caregivers and ASD specialists were interviewed in a follow-up focus group meeting. Feedback from the focus group interviews was used to further adjust the system and build the prototype 2.0. Appendix J lists the common questions that were asked in the focus group sessions based on the semi-structured interview.

It is anticipated that the prototype 3.0 (beta version) will lead to better outcomes for children with ASD who experience atypical sensory responses. During the later stage of the study, a more comprehensive evaluation was conducted with 30 children with ASD and 30 TD children ($n_2 = 60$). The following sections provide a more comprehensive description of the methods and measurements used to evaluate the prototype 3.0.

### 3.6.1 Single-case within-subjects experimental design

The author applied a single-case within-subjects design to field-test the effectiveness and usability of the prototype 3.0. A single-case within-subjects design is a standardised experimental design where researchers repeatedly measure a dependent variable before and after introducing an independent variable to a single participant (Barlow et al., 2009). A typical single-case study implements multiple trials within a group, but involved only one individual each time. It presents the intensive study of the individuals, including systematic observation, manipulation of variables, repeated measurement and data analysis. The advantage of the experimental design is its flexibility and capacity to individually tailor an intervention to the specific characteristics or behaviours of the individual, with adequate information for estimating intervention effects in a population (Tate et al., 2008). Although single-case within-subjects experimental design has been widely used over the past two decades, it is not a gold standard for clinical research and some problems must be addressed to ensure the methodological robustness.

The author has considered key domains relating to potential problems with this study design. In terms of subject selection, the author adopted a purposive sampling strategy with clear inclusion and exclusion criteria. Preschool-age children formally diagnosed with ASD and TD children were recruited. An additional brief ASD diagnostic tool, Autism Spectrum Quotient 10 items (AQ-10, attached in Appendix K), was used to confirm their conditions. All the participants were recruited from special education schools or public kindergartens and should have been enrolled in the school for at least two weeks and have adapted to the school settings. Children whose caregivers were unable to use smartphone devices should be excluded. Children who were reluctant to participate or agreed to participate but their caregivers did not give consent, should be excluded as well. Figure 3.16 provides a flow chart of this recruiting process.

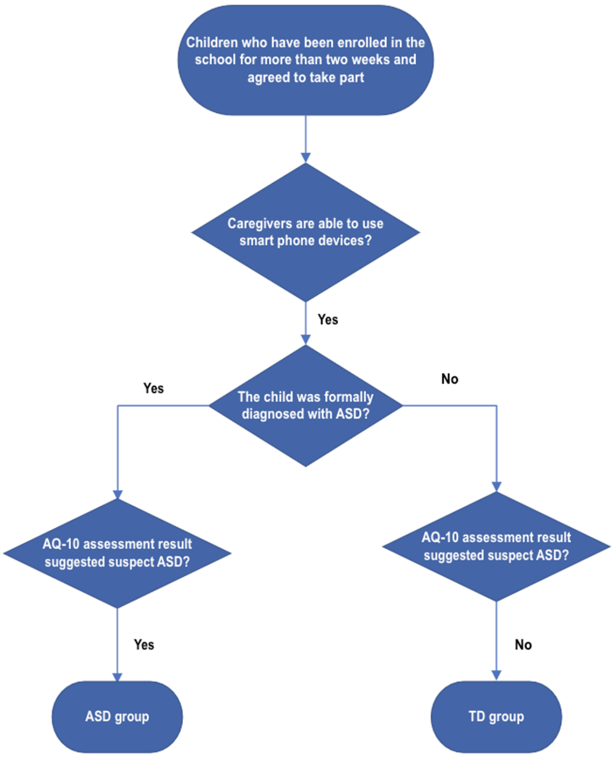



**Figure 3.16:** *Participant recruitment process in the final evaluation study*

A suggested experimental design for single-case study is an AB design where baseline/non-intervention phase (A) always precedes an intervention phase (B) (Lourenco et al., 2021). The AB design has also been widely applied by studies which obtained high methodological quality scores in the scoping review in section 2.3. Therefore, the author decided to adopt the AB design in the final evaluation of prototype 3.0. Each child should go through a baseline phase and an intervention phase with continuous sensory response measures. Another key concern of single-case design is the observer bias. Teachers who provided assistance to children in the testing sessions should be independent from the assessor to reduce the possibility of observer bias. Therefore, all the sessions should be videotaped and later independently assessed by a different ASD specialist, who was blinded[1] to which phase of the design was in effect in each test session.

[1]Blinded here means that the ASD specialist was unaware of A or B phase during their assessment.

To demonstrate the effectiveness of *Roomie* in addressing atypical sensory responses, the author adapted a well-validated measuring instrument, Caregiver-Teacher Report Form (C-TRF) (Achenbach & Rescorla, 2020), which evaluates behavioural problems that occur in the classroom across multiple domains including anxiety, stress, attention, and social interaction. Each item on the problem section of the C-TRF contains a statement about a child's behaviour. Response choices include: 'Not True' (scored as 0), 'Somewhat or Sometimes True' (scored as 1), and 'Very True or Often True' (scored as 2). The adapted version of C-TRF used in this study included items listed in 'Attention Problem' and 'Anxious or Depressed' domains for measuring children's performance on attention and stress respectively. Appendix L presents the adapted version of C-TRF. The score of each domain was calculated by adding up the points that an ASD specialist or caregiver selected on the individual items that comprised the domain. A paired-samples $t$-test was performed to statistically compare the measurements over the study phases. When there was a significant difference in anxiety and attention performance between A and B phase, effect size was calculated which indicated the actual magnitude of the difference between A and B phase. There are several ways to measure effect size. One of the most commonly used methods in within-subjects studies, Cohen's $d$, was used in the analysis. Cohen's $d$ explores effect size by examining differences relative to within-subject samples and standard deviation (Mayers, 2013).

To demonstrate the functional utility of *Roomie*, the author also conducted a post-session evaluation upon completion of all testing sessions. The overall usability performance of *Roomie* was evaluated by the standardised System Usability Scale (SUS), which is a Likert scale-based questionnaire designed by Brooke (1996) to measure users' perceived usability and satisfaction of a system. The SUS has 10 items designed to measure users' perceived usability and satisfaction of a system (Brooke, 1996). As shown in Appendix M, questionnaire statements arranged as odd numbers are positively expressed and statements with even numbers are negatively expressed. Responses of each statement range from ‘Strongly Disagree’ to ‘Strongly Agree’ on a 5-point Likert scale.

### 3.6.2 Procedure and measurements

The evaluation sessions were conducted in normal classrooms within testing sites equipped with desk, chairs, and necessary facilities (such as Figure 3.17(a)). The external sensor box was placed near the participant. An Apple Watch and Grove-Galvanic Skin Response (GSR) sensor were worn by the participant (Figure 3.17(b)). As shown in Figure 3.17(c), in each testing room, there were one teacher and one participant at a time, with the caregiver using *Roomie* App and observing around the corner.

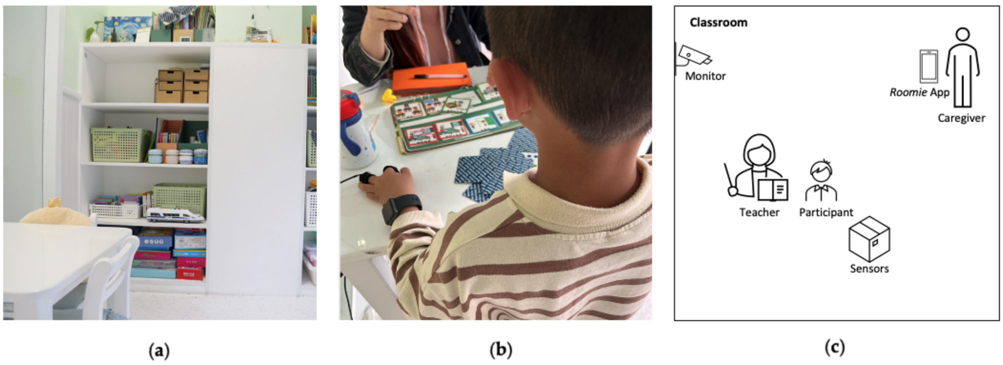



**Figure 3.17:** *A real classroom setting (a), a child worn sensors in the evaluation (b), and a classroom setup for an example session (c)*

Before the formal evaluation sessions, caregivers were invited to install *Roomie* beta version and sign up an account for their children. If the caregivers did not own an iPhone or Apple Watch, test iOS devices belonged to the author’s university were lent to them. All the participants and corresponding stakeholders (i.e., caregivers and teachers) were given coaching sessions about App use and testing settings in advance. Caregivers were asked to complete the questionnaire for identifying children's SP in the App before the formal evaluation sessions. Each participant should undergo three sessions: no-*Roomie* session, *Roomie* session 1, and *Roomie* session 2. The duration of each individual session was 30 minutes. Any two sessions for each participant were not scheduled in one day to avoid the possible short-term effect such as fatigue and stress.

#### 3.6.2.1 No-*Roomie* session

Prior to the first testing session using *Roomie* App, the ASD specialist and caregiver provided a baseline rating regarding the child's attention and stress in a no-*Roomie* condition. The child took a class as he or she did in normal life, and caregivers did not use *Roomie* App in the session. After the session, the ASD specialist and caregiver rated the child's performance by using the adapted C-TRF.

#### 3.6.2.2 *Roomie* session 1

In the first *Roomie* session, children and caregivers used *Roomie* system, in the same class as the no-*Roomie* session. The author helped the child put the watch and Grove-GSR sensor on before the class started. The caregiver held the phone and used *Roomie* App on the phone in the classroom. Caregivers were asked to observe their child's attention and stress levels, and check if *Roomie* made correct detection. If the detection results regarding attention or stress were false, the caregiver should make a real-time correction on the anomaly detection to provide true labels on the phone. In this session, the caregiver or teacher would not follow immediate sensory regulation strategies recommended by *Roomie* for attracting the child's attention or calming down the child. After the session, the caregiver and

ASD specialist completed the adapted C-TRF. Results from this session were used to evaluate how accurately *Roomie* identified the abnormal attention and stress levels of the children with ASD. Besides, by comparing the reported scores between the no-*Roomie* session and the *Roomie* session 1, the author could discuss whether the implementation of wearable devices would influence children's attention and stress in the classroom or not.

#### 3.6.2.3 *Roomie* session 2

The procedures described for the testing preparation in the *Roomie* session 1 were identical for the *Roomie* session 2. However, during this session, when *Roomie* identified an abnormal situation and generated a recommended sensory regulation strategy, the teacher in the classroom would receive a Short Message Service text message of the recommended strategy. The teacher should take actions immediately as instructed by the strategy, such as using deep pressure (Figure 3.18(a)), fidget toys (Figure 3.18(b)), or playing a calming video (Figure 3.18(c)), to help the child pay attention or calm down during the class. Similarly, after the session, the ASD specialist and teacher completed the adapted C-TRF. By comparing the reported scores between the *Roomie* session 1 and the *Roomie* session 2, the author could investigate whether the sensory regulation strategies recommended by *Roomie* were helpful on children performance improvement. If no alerts happened when conducting sessions with a child from the ASD group, the child would be asked to go through the *Roomie* sessions again with caregiver's consent.

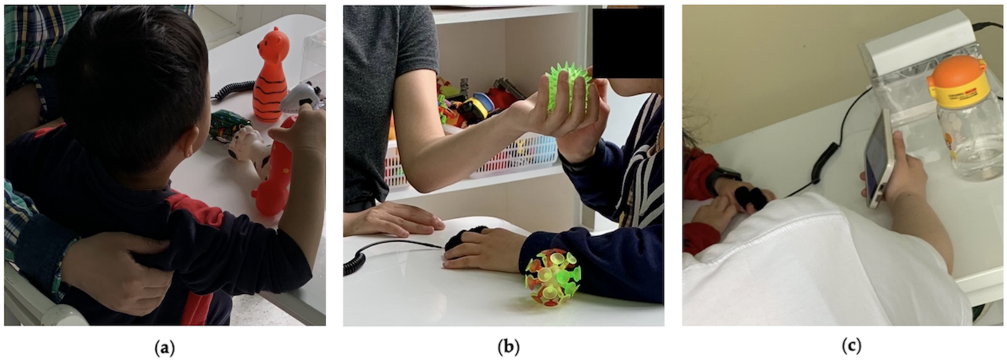


**Figure 3.18:** *The teacher applied strategies recommended by Roomie: Deep pressure strategy (a), fidget toy strategy (b), and calming video strategy (c)*

#### 3.6.2.4 Post-session evaluation

Caregivers were involved in the post-session evaluation as well to evaluate the utility of the system, as caregivers and children were the main users who were supposed to finally use *Roomie* in daily life. Following the completion of previous sessions, caregivers of the participants were invited to evaluate the overall functionality of *Roomie* by completing the SUS questionnaire.

## 3.7 Ethical approvals

Crucial to this research is the adherence to the professional and ethical standards. Ethical considerations have included the practical aspects of ensuring personal data security and confidentiality. Other ethical considerations have been related to potential burden on the children with ASD due to frequent monitoring and data collection, and impacts on clinical care. Assessment of such ethical issues at an early stage of system development was advisable. The author submitted three ethics applications for each plan of involving human participants from 2019 to 2022, and obtained approval from the University's Research Ethics Committee (attached in Appendix N). During the whole period of study, the author complied with the University's Code of Research Conduct and Research Ethics. A summary of the specific ethical considerations which relate to this study are presented below.

### 3.7.1 Informed consent

Informed consent has been gained from all adult participants. This research also involved a number of ASD and TD children. Some children may be unable to fully understand the purpose of the study. To ensure that children's participation in this study was totally voluntary, all the caregivers sought consent from their children, and they were informed of their right to withdraw from the study at any time. The caregivers provided informed consent for the child before participation. See Appendix O for the information sheets and consent forms.

### 3.7.2 Data security and confidentiality

All the information has been treated confidentially and that neither adult participants, nor children's real name has been mentioned in the research or any publications of the results. All the paper documents signed by the participants have been stored securely in locked file cabinets when not in use. The study also involved using video recorders or surveillance system to record the participants' performance. These video records will be only kept on the author's personal computer with secured access or within the collaborative schools in accordance with the schools' security law. The signed documents and video records will be retained for at least five years following the close of the study, or until participants' request their disposal in writing. Two data sets associated with existing publications, SD and SKB, will be archived at Nottingham Research Data Management Repository. All identifying information will be removed before archiving.

### 3.7.3 Acting for the benefits of participants, minimising harm to participants

Working with the vulnerable group, in addition to its research purposes, the author always hopes to make the study safe and full of educational purposes for children with or without ASD conditions. Therefore, the author selected classrooms in local rehabilitation or childcare centres with which the children felt secure and comfortable, rather than an office room or a lab at the university, as the testing room. The selected rooms must be quiet and private, equipped with air-conditioning, curtains, light system, surveillance and furnished with chairs and tables (such as Figure 3.19).

**Figure 3.19:** *A testing room where a single testing session was conducted*

As mentioned, the testing was conducted in controlled settings for the purpose of data acquisition, with some stressors induced when necessarily. The method author adopted to minimise the risk was to keep the settings within the safety limits on healthy levels. The safety limits were determined after reviewing previous research practice and consulting the advisory panel. The author controlled the environmental factors within the suggested limits, trying to avoid inducing harm or negative consequences beyond the risks encountered in normal life. However, some children with ASD might be hyper-sensitive to external stimuli. Some children were also hyper-sensitive to wearable devices. It was unlikely to exclude every possibility of inducing stress or anxiety in children with ASD. Therefore, there were always at least one ASD specialist and one caregiver being on-site to ensure the safe and ethical practices during the whole sessions. The on-site ASD specialist or caregiver could say stop if they spotted continuous distress from the child. Besides, the caregivers were informed that they could withdraw themselves and their children from the testing at any time, and this would not affect their children's rehabilitation or education in the future. When any problems in the child were identified during the testing, the on-site ASD specialist would provide timely and effective interventions.

Besides, the tasks assigned to the participants in the data acquisition sessions were commonly-used attention tasks appropriate for children with ASD. The author simplified those widely-used tasks to minimise the possibility of over-stressing children with ASD. The adjustment of these attention tasks specifically considered the capabilities of children with ASD aged under seven years and was for the benefits of children with ASD. They can obtain some training in their numerical, cognitive and motor skills while playing those tasks.

# Chapter 4

# Prototype design: What are the components and functionality of the system that match the needs of children with ASD?

This chapter provides a description of the initial stages of the research, focusing on the system design and development of the prototype. Building upon the literature review and methodology, it is evident that there is a lack of comprehensive research in the field of Autism Spectrum Disorder (ASD) regarding technology-based interventions (TBIs) for sensory regulation. There is a need for a systematic framework that is grounded in a deep understanding of the contexts, users, and technologies involved.

To address this gap, the chapter commences by examining the user needs and exploring the potential features of technologies that can be applied to this specific project. The gathered information serves as a foundation for the design of *Roomie*, which is a sensor and artificial intelligence (AI)-based monitoring system aimed at supporting sensory regulation in children with ASD. Various sensors and devices will be discussed, and a system infrastructure will be proposed, followed by a prototyping process. The feasibility of the *Roomie* prototype is then evaluated, and stakeholders provide early feedback through a review process. This chapter establishes a solid groundwork for the subsequent phases of development and refinement.

## 4.1 Identification of user needs

In section 2.3, the scoping review of existing TBIs shows that there have been very few TBIs with special focus on sensory regulation for children with ASD. Their needs for this kind of TBI have not been fully explored. Therefore, identification of user needs will be a necessary place to start. The methods used in this phase have been described in section 3.2.

### 4.1.1 Sample characteristics

The online user needs survey received a total of 93 responses, including 69 from caregivers of children with ASD, 21 from ASD specialists, and 3 from technology developers. Among them, 38 responses were from participants in China and 55 were from participants in the United Kingdom (UK). Appendix P summarises the demographic information about the participants involved in the online survey.

Seven of 93 survey participants also attended the in-depth interview. The seven participants in the interview had different lengths of ASD-related experience, ranging from 2 years to 20 years. As the study sample consisted of participants who had close relationships with children with ASD, individual interviews instead of a group interview were conducted to protect the confidentiality. Table 4.1 provides a snapshot of the relationship and experience that participants had with ASD.

**Table 4.1:** *Interview participants' ($n = 7$) relationship to the child with ASD, work settings, and ASD-related experience by the time of participation*

| # | Relationship to the Child with ASD | Work Setting | Years of ASD-Related Experience |
|---|---|---|---|
| P1 | Father | Private-owned company | 4 years since the child was suspected of ASD |
| P2 | Father | Special Training Institute | 14 years since the child was suspected of ASD |
| P3 | Mother | University | 4 years since the child was suspected of ASD |
| P4 | Mother | Unemployed | 2 years since the child was suspected of ASD |
| P5 | Occupational therapist | Childcare Centre | 6 years of occupational therapy experience with children with ASD |
| P6 | Psychiatrist | Hospital | 20 years of ASD diagnosis and intervention experience |
| P7 | Teacher | Special Education School | 10 years of ASD special school experience |

### 4.1.2 Online survey findings

The online survey firstly provides valuable insights into the author's understanding of the overall demand and awareness of a TBI like *Roomie* for children with ASD in China and the UK. Table 4.2 provides an overview of TBI awareness, utilisation and willingness of use of *Roomie* among participants. The survey results indicate that in China, there is a significant lack of knowledge about any TBIs for individuals with ASD. Only three mothers reported that they have heard of TBIs specifically designed for children with ASD, which was considerably lower compared to UK parents ($n$ = 24). China had an even lower use (7.9%) of TBIs for children with ASD compared to the UK (30.9%). Mothers were generally more aware of TBIs than fathers. Furthermore, it was noteworthy that participants in both China and the UK expressed similar demands for a TBI. More than three-quarters of the participants in both countries indicated their willingness to use a sensor and AI-based monitoring system like *Roomie* to support the sensory regulation of children with ASD.

The online survey also asked a question about what TBIs that participants have ever used. Figure 4.1 shows the most frequent keywords in the answers to the question. The most frequently reported TBIs were iPad-based Apps, such as Proloque2Go App, which is an augmentative and alternative communication tool designed specifically for children with communication difficulties (AssistiveWare, 2023). Other TBIs mentioned included Apps which provide sensory regulation strategies on eating and toileting, and listening programs such as sound amplification systems.


**Figure 4.1:** *Most frequently mentioned TBIs that participants have used*

**Table 4.2:** *TBI awareness, utilisation and willingness of using Roomie among participants* ($n = 93$)

| **Nationality and Relationship to the Child with ASD** | | **Have Heard of TBIs for Children with ASD** | | | | **Have Used TBIs for Children with ASD** | | | | **Willing to Use the Proposed *Roomie* System** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Yes** | | **No** | | **Yes** | | **No** | | **Yes** | | **No** | |
| China | Mother | 3 | 11.1% | 24 | 88.9% | 2 | 7.4% | 25 | 92.6% | 20 | 74.1% | 7 | 25.9% |
| | Father | 0 | 0.0% | 4 | 100.0% | 0 | 0.0% | 4 | 100.0% | 4 | 100.0% | 0 | 0.0% |
| | Healthcare professionals | 4 | 100.0% | 0 | 0.0% | 1 | 25.0% | 3 | 75.0% | 3 | 75.0% | 1 | 25.0% |
| | Educators | 0 | 0.0% | 1 | 100.0% | 0 | 0.0% | 1 | 100.0% | 1 | 100.0% | 0 | 0.0% |
| | Technology developers | 2 | 100.0% | 0 | 0.0% | 0 | 0.0% | 2 | 100.0% | 2 | 100.0% | 0 | 0.0% |
| | Total | 9 | 23.7% | 29 | 76.3% | 3 | 7.9% | 35 | 92.1% | 30 | 79.0% | 8 | 21.1% |
| UK | Mother | 12 | 36.4% | 21 | 63.6% | 12 | 36.4% | 21 | 63.6% | 24 | 72.7% | 9 | 27.3% |
| | Father | 0 | 0.0% | 4 | 100.0% | 0 | 0.0% | 4 | 100.0% | 4 | 100.0% | 0 | 0.0% |
| | Not mentioned | 0 | 0.0% | 1 | 100.0% | 0 | 0.0% | 1 | 100.0% | 1 | 100.0% | 0 | 0.0% |
| | Healthcare professionals | 7 | 53.9% | 6 | 46.2% | 4 | 30.8% | 9 | 69.2% | 12 | 92.3% | 1 | 7.7% |
| | Educators | 1 | 33.3% | 2 | 66.7% | 0 | 0.0% | 3 | 100.0% | 2 | 66.7% | 1 | 33.3% |
| | Technology developers | 1 | 100.0% | 0 | 0.0% | 1 | 100.0% | 0 | 100.0% | 1 | 100.0% | 0 | 100.0% |
| | Total | 21 | 38.2% | 34 | 61.8% | 17 | 30.9% | 38 | 69.1% | 44 | 80.0% | 11 | 20.0% |

| Nationality and Relationship to the Child with ASD | Have Heard of TBIs for Children with ASD | | | | Have Used TBIs for Children with ASD | | | | Willing to Use the Proposed *Roomie* System | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Yes** | | **No** | | **Yes** | | **No** | | **Yes** | | **No** | |
| China and UK Total | 30 | 32.3% | 63 | 67.7% | 20 | 21.5% | 73 | 78.5% | 74 | 79.6% | 19 | 20.4% |

### 4.1.3 Interview findings

In the interviews, all participants ($n = 7$) have discussed desirable functions that can be delivered by *Roomie* and raised concerns of potential effects that *Roomie* may have on an individual with ASD. The most mentioned functions and concerns raised by the participants can be categorised under the following themes.

#### 4.1.3.1 Monitoring and informing

Four participants (P1, P3, P6 and P7) expressed their desire for *Roomie* to provide real-time physiological and psychological information about children with ASD. During the interviews, it became evident that many caregivers had full-time jobs and limited time to dedicate to their children's care. As a result, grandparents often assumed the role of caregivers. These participants had a strong desire to stay informed about their children's physical and psychological well-being, including being alerted to any potential meltdowns when they were not present. The teacher (P7) from a public-owned special education school mentioned the challenges they faced due to a shortage of teachers and an increasing number of students, making it difficult to identify every instance of behavioural problem in the classroom. Thus, a system that monitored children's behaviours and identified potential risks would be invaluable. P6 working in a psychiatric hospital emphasised that it was normal for caregivers to occasionally lose sight of their children, and having a monitoring and informing system in place would greatly assist caregivers in their daily lives by facilitating case reporting.

'*. . . My husband and I are both working full-time, and it is grandparents who take care of my son during working days. Even so, I still want to be* *kept informed of how he is doing to assure his performance.'* (P3)

*'Roomie can assist with staff shortage issues by providing effective monitoring and informing support for us.'* (P7)

*'We do notice parents' difficulties arise relating to providing 24/7 (twenty-four hours a day, seven days a week) care for their children. Monitoring and informing support provided by Roomie can improve the safety and efficiency of care to children with ASD... Informing system can also help establish referral networks between families and external services in the future.'* (P6)

These insights highlighted the importance of *Roomie*'s monitoring and informing capabilities, providing caregivers with real-time information about their children's well-being and assisting caregivers in detecting and addressing potential risks in sensory regulation.

#### 4.1.3.2 Professional and friendly strategy making

One of the urgent challenges that participants identified was providing most current, professional sensory regulation strategies for individuals with ASD, especially for those living in remote areas in order to improve the quality as well as the utilisation of professional support in China. This can be attributed to a chronic issue that there has been an extreme shortage of licensed, well-trained ASD specialists, or specialised educational programs for students to be trained to become specialists. As few specialised services were available in most rural areas, people in these areas had more limited awareness of and access to intervention services. Therefore, P5 and P6 suggested that the development of *Roomie* should focus on the provision of the professional sensory regulation strategies to caregivers of individuals with ASD based on their symptoms so that caregivers can obtain professional advice and strategy recommendations at home.

*‘. . . A professional sensory regulation strategy recommending function could address some of the barriers faced by the parents of children with ASD. They can be assisted to access useful and effective sensory regulation strategies like others who enter mainstream services.’*(P5)

*‘This may help a number of families suffering ASD issues in remote areas where access to external help and the development of intervention services have been limited.’* (P6)

Additionally, new caregivers of children with ASD seemed to struggle with mixed emotions, feeling scared, overwhelmed, and confused. They were less confident to talk about their children’s diagnoses and conditions with others. At the same time, they were at a stage of requiring guidance and help to be empowered to support themselves later. Searching online became one tool to acquire professional information on how to assist their children, and what services were available for them. However, the information available online can be overwhelming and unreliable, written by someone with little knowledge about ASD or only representing a single case which may be misleading. A professional healthcare system which included accurate and most current information was desired to offer precise interventions to children’s symptoms.

Two parent participants (P2 and P3) further suggested that they preferred their children to behave with their natural interests rather than to be much trained or changed. Children with ASD had their own patterns of sensory and interactive behaviours, such as, being hyper-responsive to sensory stimuli or being independent in play. They mentioned that an intelligent system which identifies children’s emotional, sensory and behavioural patterns and interacted friendly in responding to the identified patterns will be useful in their daily life.

*'We certainly do not want to change our son's behaviours or interests. We prefer a technology that can understand what he likes or dislikes and communicate with him following the way he likes.'* (P3)

*'I used to recruit domestic assistants to stay with my daughter when she was small. Most of the time they just learnt what she liked and created a friendly environment for her. If Roomie can do this, making the environment to be most comfortable, it will help many families of children with ASD like us to save a lot of expenses...Parents can also spend more time on their own job.'* (P2)

#### 4.1.3.3 Cost efficiency

A common barrier identified in the interviews that may prevent participants from using the technology was the high price of TBIs. The economic burden for individuals with ASD and caregivers can be severe since a vast majority of individuals with ASD cannot get a job when they grew up. Evidence also suggested that many caregivers had to give up full-time jobs for taking care of their children with ASD. A study investigating on caregivers' employment condition by Xiong et al. (2011) revealed that 32.6% of the mothers of children with ASD in China were unemployed, compared to 18.4% in the case of TD children. Even from a median economic level city such as Ningbo, caregivers had raised some concerns about the cost of TBIs in the interviews. ASD specialists (P5, P6 and P7) all agreed that cost-effective TBIs would be more acceptable by Chinese caregivers of children with ASD.

*'I am currently out of work in order to take care of my daughter... She has been regularly attending a one-hour training session each afternoon which already costs a lot...I am not unwilling to spend money, but I don't think I will spend too much on a product when I am unsure of the effectiveness.'*

(P4)

#### 4.1.3.4 Privacy

Another barrier preventing participants from using TBIs was fear of privacy and confidentiality breaches. Caregivers were concerned if they would be asked to give children's medical records or other information, or videotape children's face while using technologies. An application that helped track individuals' physical activities or locations can also disclose this information and raise risks. Although all participants invited were finally interested in trying *Roomie*, two participants (P4 and P6) insisted that they were unwilling to use any technological products unless they would not be asked to provide any identifying information.

Participants concerned not only about information security but also potential public exposure of the child. It was because TBIs relying on wearable devices, such as headband and smart glasses, can be noticeable, which raised many participants' concerns about exposing children's disability to the public. P5 contended that if a product made an individual with ASD conspicuous, people might consider the person to be abnormal and judge the parenting styles or family traits which would hurt both individual and caregivers. Therefore, participants concerned if the *Roomie* system could be made small in size and turned into a mute mode in public spaces. P1 and P2 both mentioned that mobile phone Apps would be suited well to most families of children with ASD in China, as viewing an App on the mobile phone could not be more normal.

#### 4.1.3.5 User interface (UI) and interaction design

Participants also emphasised the importance of UI and interaction design in the *Roomie* system. They believed that the system should have an easy-to-use interface to enable children with ASD and their caregivers to understand and interact with it. Additionally, caregivers were likely to be bombarded with numerous behavioural problems of their children with ASD and chaotic information every day. Therefore, the interface should adhere to simple and intuitive design principles, providing clear visual cues and explicit instructions to assist them in accurately understanding the system's functionality and usage.

P5 suggested that children with ASD were often more sensitive to visual information, thus the system should present information and feedback through graphics, icons, or animations. For example, the system could use colour changes or animation effects to indicate different states or alert messages, aiding children with ASD or their caregivers in better understanding and responding to the information presented.

UI and interaction design played a crucial role in the *Roomie* system. By incorporating principles of simplicity and visual feedback, the system can better meet the needs of children with ASD and their caregivers, providing a user-friendly experience. This can enhance the interaction between users and the system, and improve user's willingness for long-term use.

### 4.1.4 User needs overview

Figure 4.2 summarises the main design requirements extracted from the user needs investigation. These ideas determine the appropriate sensors and devices to be selected for *Roomie* to optimise user experience. The user needs investigation highlights that the mobile phone App with some small sensors is seen as the most appropriate form of the system. It is also suggested that *Roomie* should be designed at reasonable low cost.

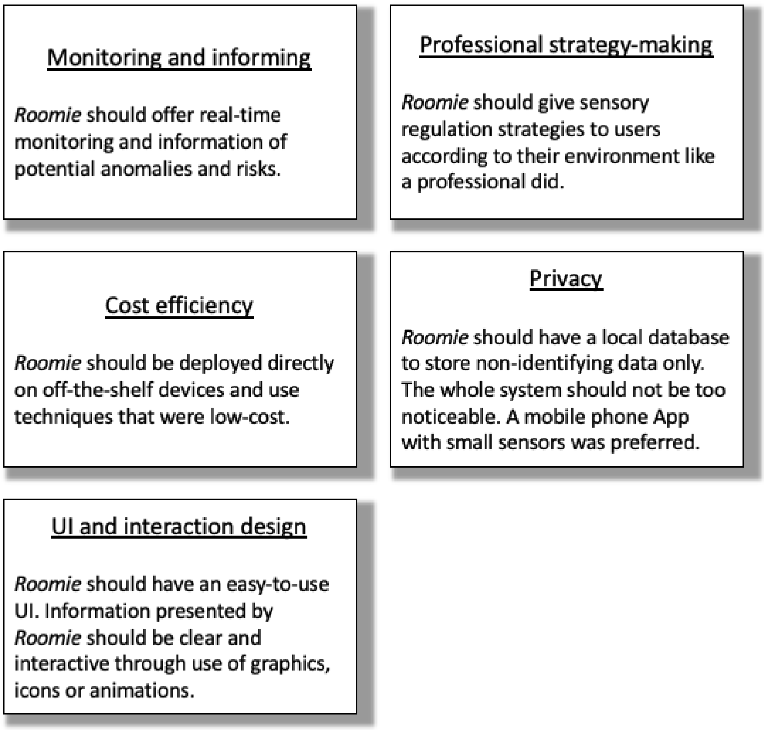



**Figure 4.2:** *Identification of design requirements*

## 4.2 System requirement specification

The user need investigation presents user requirements in a natural language of what functions the system is expected to provide to users. The system requirements specification presents more detailed descriptions and constraints of a system based on the agreement of users. Functional requirements reflect the needs of users for a system that serves as the guideline of software engineering and implementation (Sommerville, 2020).

### 4.2.1 Functional requirements

- *Roomie* shall be compatible with iPhones with iOS 13.0 or higher version.

- *Roomie* shall provide clear navigation to help users get started with the software.
- *Roomie* shall support both English and Chinese languages, allowing users to choose either. Language selection should appear after the splash screen, and users should be able to switch language settings within the software.
- *Roomie* shall be used under the consent of the user.
- New users shall be able to register without providing identifying information.
- Registered users can log in and log out of *Roomie* using their account and password.
- After successful login, the software should display the user's account name and profile. Users can create, view, and edit their personal profile.
- Users can click on the sensory profile questionnaire to enter the questionnaire page. Users need to answer each question sequentially. Upon completion, they can view the analysis of their entered answers. Users can click the exit test button at any time to terminate the questionnaire.
- By accessing the system's real-time monitoring function, *Roomie* shall collect sensory information and display real-time monitoring results.
- *Roomie* shall be able to detect user's attention and stress levels based on sensory profile, environmental and physiological data through machine learning analysis.

- *Roomie* shall provide real-time sensory regulation strategy recommendation based on detection results and sensory data. A caregiver or teacher of the user can choose to enable the text alert function by providing their mobile phone number, and the system will send a text alert to their phone via Short Message Service (SMS). They can disable the function at any time, and the system should provide a confirmation prompt.

### 4.2.2 Software planning and implementation

In software development, performance and interface requirements are crucial. The author needs to ensure that the system can efficiently and accurately process data and notify users promptly. Overall, the author adopted a modular design and continuous integration approach to improve the maintainability and performance of the system (Pressman, 2010).

The author has planned the basic operational flow for users. Users can register, log in and log out of *Roomie* with non-identifying personal information within the software. Additionally, users can choose the language of the software interface based on their preferences and switch language settings within the software. The sensory profile questionnaire function allows users to receive the individualised analysis report quickly, without the aid of an ASD specialist. Furthermore, the real-time monitoring function provides users with physiological and environmental data of their current status, along with corresponding sensory regulation strategies to improve comfort and health conditions.

In the implementation phase, the author adopted a modular design to ensure that the system is easy to maintain and expand. The attention and stress detection function was implemented with the machine learning models discussed in Chapter 5 using Core ML. Sensory regulation strategy generation was embedded with the fuzzy logic algorithms discussed in Chapter 5 using Python. Swift version 4 was used for both frontend and backend development. Frontend interface development used the iOS UI frameworks. Following implementation, the author conducted unit testing, integration testing, and system testing to ensure the stability and reliability of the software. Unit testing validated the functionality of individual components, while integration testing validated the interactions between different modules. System testing was conducted to evaluate of overall functionality, consistency, and performance of the system.

*Roomie* was expected to be deployed in phases, gradually expanding its user base. Initially, it was deployed to a small group of potential users for pilot testing and feedback. In the follow-up testing, the author decided to expand the deployment scope and increase the software's accessibility by releasing the software on a beta testing platform.

The hardware implementation, interface implementation and overall system design are discussed in the following sections.

## 4.3 Selection of sensors and devices

As mentioned in the section 3.3.1, given the availability of iOS devices within the research team, the author decided to prototype parts of *Roomie* on iOS devices with additional off-the-shelf sensors, which are easy-to-deploy, low-cost, accurate and highly customisable for prototyping embedded sensing and interactive systems. The reasons for choosing candidate sensors and materials are discussed in below sections.

### 4.3.1 iOS sensors

iOS sensors are feasible for this project because they come with Application Programming Interfaces to allow third-party developers to stream and analyse raw data from the sensors in real time. In this research, the author used several built-in sensors in an iPhone XR and an Apple Watch version 4. iPhone built-in sensors used included the sound sensor and the barometer sensor. These two iPhone sensors were found to be useful for monitoring and analysing the atypical sensory processing of children with ASD. Other iPhone built-in sensors such as accelerometer sensor, gyroscope sensor and magnetometer sensors were also accessed in prototyping. However, these sensors were not used in later stages considering iPhone acceleration, rotation and magnetic field strength were not valuable features for atypical sensory responses detection. Apple Watch sensors used included the heart rate sensor and the watch accelerometer sensor.

#### 4.2.1.1 iPhone sound sensor

The sound sensor (microphone) of the iPhone XR was utilised as a sound level meter (SLM) in *Roomie*. The received sound signals from the sensor were converted into decibel (dB) unit to quantify the intensity of the noise. To assess the accuracy of the *Roomie* SLM, the author employed a highly precise mobile SLM App developed by the National Institute for Occupational Safety and Health (NIOSH) Noise and Occupational Hearing Loss research team for testing. The NIOSH SLM App is renowned for its ability to accurately measure sound levels and is widely used in various sound measurement tasks (Celestina et al., 2018). The author tested the accuracy of *Roomie* SLM by comparing the five sets of average noise data measured by *Roomie* in one minute with the results obtained from NIOSH App. According to the results shown in Table 4.3, *Roomie* SLM can accurately measure ambient noise by using iPhone sound sensor, with an acceptable mean difference (+1.98 dB) according to NIOSH guideline (National Institute for Occupational Safety and Health, 2023).

**Table 4.3:** *Comparison on noise measurements*

| **Noise Condition** | ***Roomie* SLM (dB)** | **NIOSH App (dB)** | **Difference (NIOSH-*Roomie*)** |
|---|---|---|---|
| 1 | 81.98 | 84.2 | +2.22 |
| 2 | 88.30 | 91.4 | +3.10 |
| 3 | 73.01 | 74.7 | +1.69 |
| 4 | 62.00 | 63.5 | +1.50 |
| 5 | 55.09 | 56.5 | +1.41 |
| | | **Mean Difference** | +1.98 |

#### 4.2.1.2 iPhone barometer sensor

The iOS barometer sensor is a type of sensor embedded in Apple devices which is used to measure changes in atmospheric pressure. This sensor utilises the device's built-in pressure sensor to detect the atmospheric pressure in the surrounding environment. It provides a convenient way to obtain real-time atmospheric pressure data without the need for additional external devices or sensors. However, the supplier and technical specifications of the iPhone barometer sensor have not been reported by Apple. Previous research has assessed the iPhone XR barometer accuracy by comparing it with Bosch barometer sensor (BMP280) which was known as one of the most accurate pressure sensors by the time of study (Manivannan et al., 2020). The research reported that the barometer sensor embedded in iPhone devices generally had a relative accuracy of 10 pascal (Pa), indicating that the iPhone barometer is an accurate and reliable sensor for measurements of atmospheric pressure.

#### 4.2.1.3 Apple Watch heart rate sensor

The heart rate sensor is a wearable sensor embedded in an Apple Watch that automatically tracks the user's heart rate. The Apple Watch utilises two optical sensors, one for visible light and one for infrared to measure heart rate. The back of the Apple Watch flashes green light, and the amount of blood flow is estimated by the amount of green light absorbed (Apple Support, 2022). Heart rate can be calculated using algorithms as blood flow increases when the heart beats and blood flow decreases between heart beats. It was found that Apple Watch heart rate sensor produced the least amount of error and provided more validity than similar devices including Fitbit, Microsoft Band and Samsung Gear in heart rate monitoring (Shcherbina et al., 2017). The Polar H7 heart rate sensor was identified as the most accurate among common commercially available heart rate sensors compared with professional high-solution sensors. Previous research comparing Apple Watch with Polar H7 suggested Apple Watch heart rate sensor generated results that were reliable and in agreement with Polar H7 (Pasadyn et al., 2019).

#### 4.2.1.4 Apple Watch accelerometer

The watch accelerometer is a built-in sensor in Apple Watch that measures the device's acceleration changes across three axes. It captures the user's wrist movements and body activities, providing real-time acceleration data to monitor the user's movement patterns and physical activity levels. Similar watch accelerometer sensors have been used in previous studies to detect hyperactive behaviours in children with ASD (Coronato et al., 2014; Mohammadian Rad et al., 2018). For children with ASD, they may display excessive excitement or restlessness. By monitoring the watch acceleration data, these abnormal hyperactive behaviours can be promptly identified and recorded, contributing to a better understanding and management of the anomalies.

### 4.3.2 External sensors

Some necessary environmental and physiological parameters were not yet readable by iPhone or Apple Watch built-in sensors by the time of prototyping, such as temperature, humidity and Galvanic Skin Response (GSR). Therefore, off-the-shelf external sensors were also used in this project.

#### 4.2.2.1 DHT11 temperature and humidity sensor

DHT11 (Figure 4.3) is a commonly-seen temperature and humidity composite sensor, whose transmission is based on calibrated digital signal output via one wire bus. The sensor consists of a capacitive moisture sensing element and a temperature measuring element and can be connected to high-performance microcontrollers. Each DHT11 sensor is calibrated in an extremely accurate humidity laboratory. Calibration coefficients are stored in the one-time programmable memory in the form of a program, and these calibration coefficients are called by the inner part of the sensor during the detection signal processing (Mouser Electronics, n.d.). Therefore, comparing with other temperature and humidity sensors, it is more accurate and has wider range from -40 to 80 °C, which is suitable to be used in detecting environmental temperature. Also, single wire serial interface makes sensor deployment easy and fast. Therefore, this sensor has the advantages of fast response, strong anti-interference ability and is cheap. Ultra-small size, extremely low power consumption, signal transmission distance of up to 20 meters, making it most appropriate for *Roomie*.

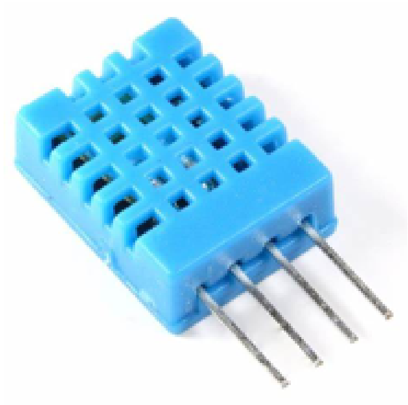


**Figure 4.3:** *DHT11 temperature and humidity sensor, sourced from Microsoft Bing*

#### 4.2.2.2 Light sensor (photoresistor)

The light sensor (Figure 4.4), also known as a photoresistor or Light Dependent Resistor, is a passive electronic component that exhibits a change in resistance based on the amount of incident light. The data acquired by the sensor is illuminance (referred as light intensity or brightness level hereafter) in lux (lx) unit. It operates on the principle of the photoconductivity of certain materials, where the conductivity increases as light intensity increases. The photoresistor consists of a semiconductor material, which has a high resistance in the dark and low resistance in the presence of light (Haraoubia, 2018). When exposed to light, photons are absorbed by the material, exciting the electrons and allowing them to flow more freely, thus reducing the resistance. Photoresistors can quickly and accurately detect changes in light intensity, thus are widely applied in various fields including automatic lighting systems, security systems, and photography. Besides, photoresistors are inexpensive compared to other light-sensing technologies (Regtien & Dertien, 2018), making them suitable for cost-sensitive applications.

**Figure 4.4:** *Light sensitive photoresistor, sourced from Microsoft Bing*

#### 4.2.2.3 Galvanic Skin Response (GSR) sensor

The level of stress of an individual can be inferred through the electrical conductance of the skin using sensors such as a GSR sensor. When a person experiences stress or was aroused, moisture collects under the skin, increasing the skin's electrical conductivity. Candidate GSR sensors investigated in this research included some wrist-worn GSR sensors and one glove-shape GSR sensor developed by Seeed Studio in its Grove sensor kit (hereafter referred as Grove-GSR sensor).

The initial GSR sensor the author used was the GSR wristband developed by Xinhua Net, as shown in Figure 4.5. However, it has significant drawbacks. It is outdated and requires the use of a Secure Digital card to retrieve raw data. Moreover, in real life use, the electrodes need to be attached steadily to the skin with sellotape, making it unsuitable for application among children with ASD.

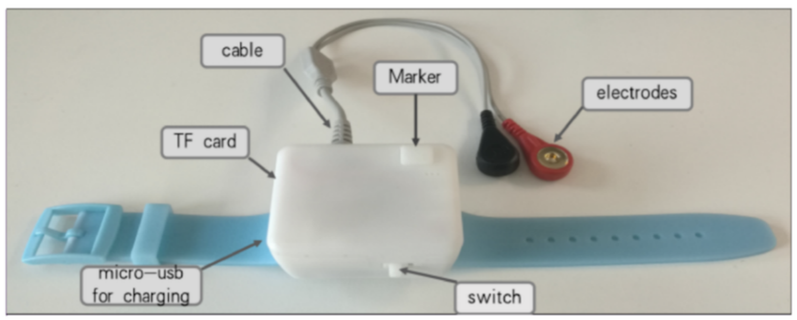



**Figure 4.5:** *GSR sensor developed by Xinhua Net, sourced from S. Li (2019)*

Grove-GSR sensor, as shown in Figure 4.6 is more suitable for children to wear, as it can be easily fixed on their fingers, providing a more comfortable experience. Such style avoids direct contact with the sensitive area of children with ASD and is less conspicuous as a wide range of wristband products in real life also adopt similar style of finger tapes for measuring GSR, such as Shimmer3 wristband (Shimmer, 2023). However, off-the-shelf commercial GSR wristbands can be expensive, and often require additional costs to retrieve raw data. Compared to Xinhua and Shimmer3 GSR wristbands, the Grove-GSR sensor is more cost-effective. Grove-GSR sensor can also provide reliable and accurate measurements without the need for a Secure Digital card and an extra wrist-worn processor (Seeed Studio, 2014). It works perfectly with popular microcontroller platforms such as Arduino and Raspberry Pi, ensuring seamless integration and development, thereby improving development efficiency while reducing costs. Therefore, the Grove-GSR sensor was used in the end for an efficient and responsive system to support sensory regulation in ASD.

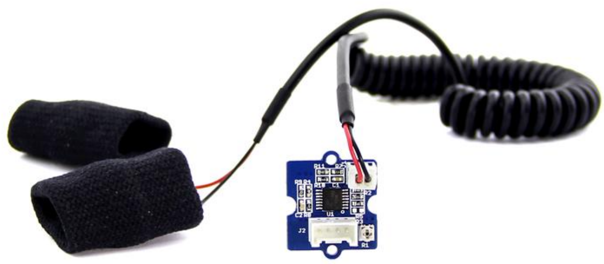


**Figure 4.6:** *Grove-GSR sensor, sourced from Seeed Studio*

#### 4.2.2.4 Electroencephalograms (EEG) sensor

The author has attempted to use one EEG sensor available at the University, the Muse EEG headband as shown in Figure 4.7. It is a portable four-channel EEG recording tool that includes two electrodes behind the ears, two on the forehead and three reference sensors for detecting and measuring the activity of a user's brain. A calm score can be calculated at the end of each recording session, which reflects the percentage of attention that is detected during the session (Kerr et al., 2013). However, it also has significant drawbacks. It is too conspicuous, and the size is too large for children. The electrodes must be in close contact with the scalp to obtain accurate data, while some children with ASD are sensitive to forehead touch, making it extremely difficult to collect usable EEG data from individuals with ASD for analysis.

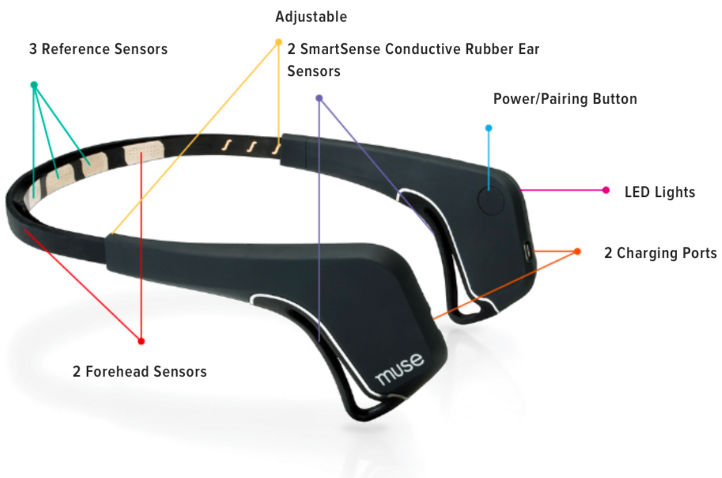



**Figure 4.7:** *Muse EEG headband device, sourced from Microsoft Bing*

### 4.3.3 Microcontroller and necessary materials

To implement external sensors, microcontroller platforms should be used to read data from sensors and transmit data to *Roomie* data processing unit on the phone. Table 4.4 presents some common microcontroller platforms on the market.

**Table 4.4:** *Comparison of common microcontrollers: Arduino vs Raspberry Pi vs ATMEL AT89*

| **Microcontroller platform** | **Advantage** | **Disadvantage** |
|---|---|---|
| Arduino | Simple and easy to use;<br>Rich libraries and example codes;<br>Low power consumption;<br>High Speed computing. | Limited storage capabilities;<br>Limited expandability and hardware interfaces. |
| Raspberry Pi | Abundant interfaces and expansion boards;<br>High Speed computing. | Higher power consumption;<br>Higher development complexity;<br>Relatively higher price. |
| ATMEL AT89 | Low power consumption;<br>High programmability;<br>Hardware timers and interrupt capabilities. | Limited processing power and storage space;<br>Lack of advanced features and expansion interfaces;<br>Do not support modern operating systems and graphical interfaces. |

Both Arduino and Raspberry Pi have wide adaptability and high-speed processing capabilities (up to 32bit). The 8-bit ATMEL AT89 is short in computation power and speed, which has become too out-of-date. Arduino and Raspberry Pi have more active user community than AT89. Arduino has more open-source resources than Raspberry Pi, making it more friendly to non-mechanical engineering students (Jamieson & Herdtner, 2015). One module taught within the author's university provided abundant learning materials for Arduino and off-the-shelf Arduino kit. Considering Arduino and Raspberry Pi have similar features and performance, the author decided to use the existing Arduino microcontroller. The Arduino Integrated

Development Environment (IDE), a software available on Windows, Mac and Linux to program the microcontroller in simplified C++ was used for microcontroller programming. Figure 4.8 shows the Arduino materials used for this project. An Arduino Uno R3 microcontroller was used along with a breadboard and jumper wires to connect the external sensors. The Arduino Uno R3 is known for its simplicity and ease of use, and is compatible with the DHT11 sensor, photoresistor, and Grove-GSR sensor mentioned in section 4.3.2.

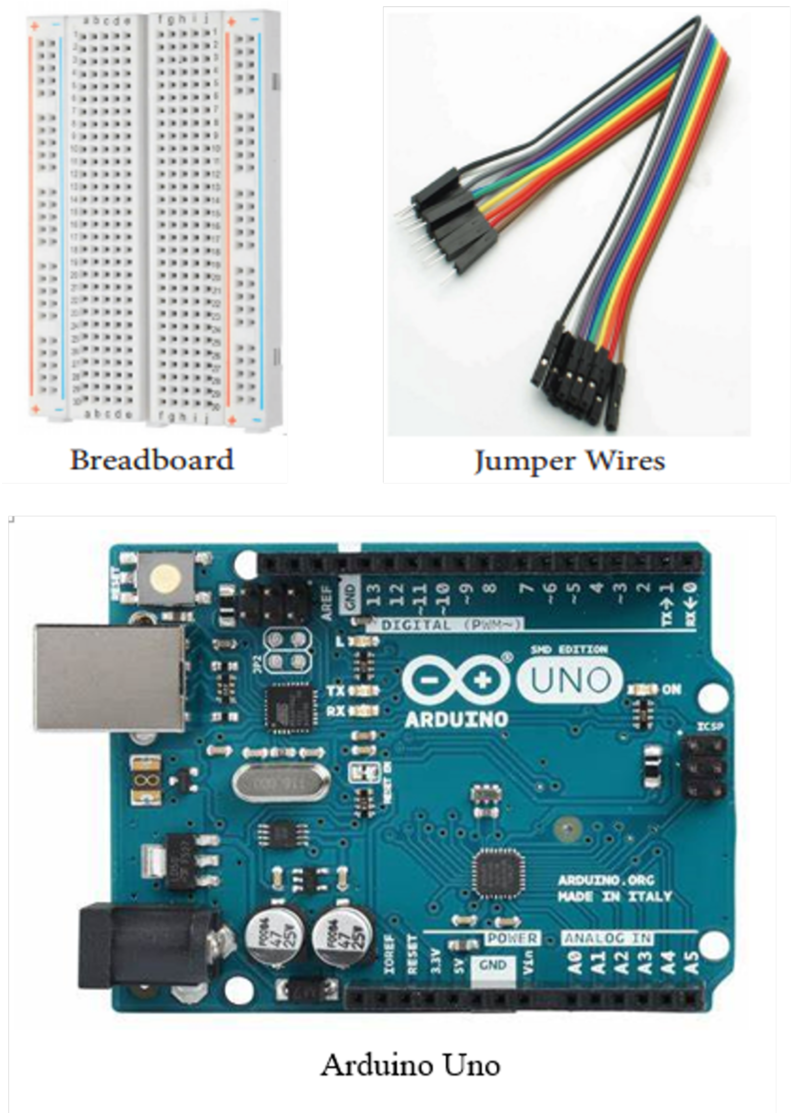



**Figure 4.8:** *Basic Arduino kits used for building Roomie*

A summary of sensors and microcontrollers that were finally used in the

*Roomie* system are listed in Table 4.5, along with the purpose of each component.

**Table 4.5:** *Sensors and microcontrollers used in Roomie system*

| **Sensor/ Microcontroller** | **Unit** | **Purpose** |
|---|---|---|
| Arduino Uno R3 | N/A | To fetch and transmit signal from sensors. |
| Apple Watch three-axis accelerometer | Sensor value | To identify the hand movements. |
| Apple Watch heart rate sensor | Beats per minute (bpm) | To measure heart rate. |
| DHT11 temperature and humidity sensor | Celsius (°C) for temperature, percentage (%) for humidity | To measure temperature and humidity level. |
| iPhone sound sensor | Decibel (dB) | To measure noise level. |
| iPhone barometer | Kilopascal (kPa) | To measure atmospheric pressure. |
| Light sensor (photoresistor) | Lux (lx) | To measure brightness level. |
| Grove-GSR sensor | Sensor value | To detect skin conductivity. |

N/A – Not applicable.

## 4.4 System design

The overall design of the system was based on the use of selected iOS built-in sensors and external sensors embedded in Arduino to capture and monitor sensory responses of children with ASD and their environmental information in real-time. Through these sensors, *Roomie* should be able to gather children's physiological data, such as heart rate, hand movements, and GSR, as well as environmental data like noise, temperature, humidity, brightness and atmospheric pressure.

These data can be transmitted to an iPhone, where an App should be developed to receive and process the data. The data processing unit of the App was expected to utilise AI algorithms to analyse data and detect children's atypical sensory responses, associated with their attention and stress levels. AI algorithms embedded in the system should also allow the real-time generation of sensory regulation strategies. Users can access these real-time detection and recommended strategies remotely via *Roomie*'s user-friendly UI. The overall system architecture of *Roomie* is visualised in Figure 4.9.

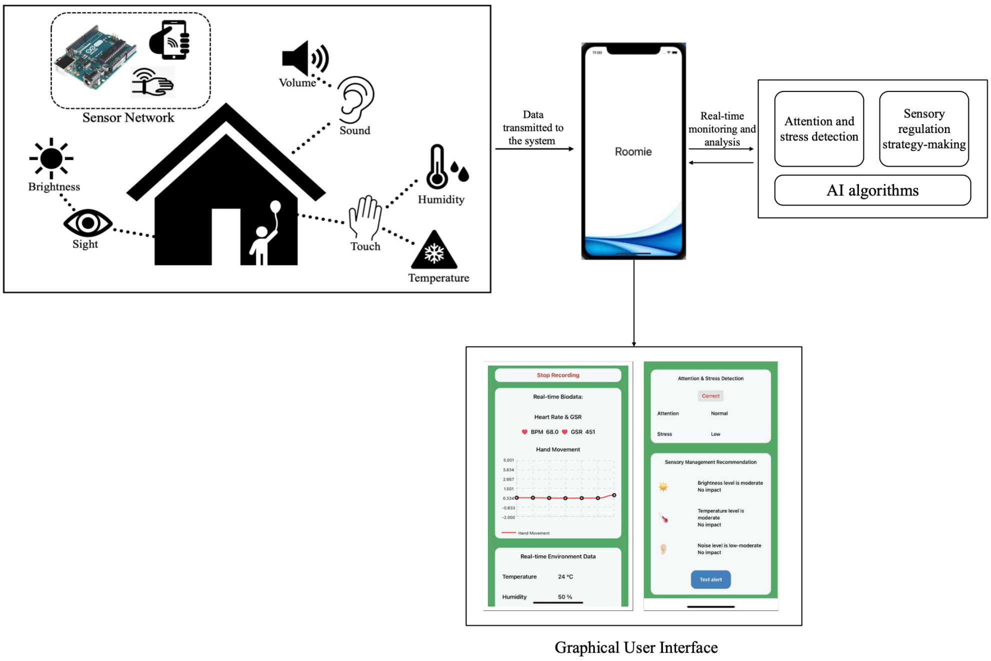



**Figure 4.9:** *The system architecture of Roomie*

More specifically, *Roomie* was expected to collect a child user's Sensory Profiles (SP). Therefore, *Roomie* should integrate a standard SP questionnaire within the App allowing the system to classify the child user's sensory processing patterns under four quadrants (i.e., Low Registration, Sensory Seeking, Sensory Sensitivity and Sensory Avoiding) based on Winnie Dunn's framework of sensory processing. Another unique design was a remote text alert. When needed, *Roomie* can issue appropriate warnings or sensory regulation strategies to caregivers or teachers via SMS regarding the occurrence of atypical sensory responses so that they can apply the sensory regulation strategies as suggested by *Roomie* timely. The working flow of *Roomie* is detailed in Figure 4.10.

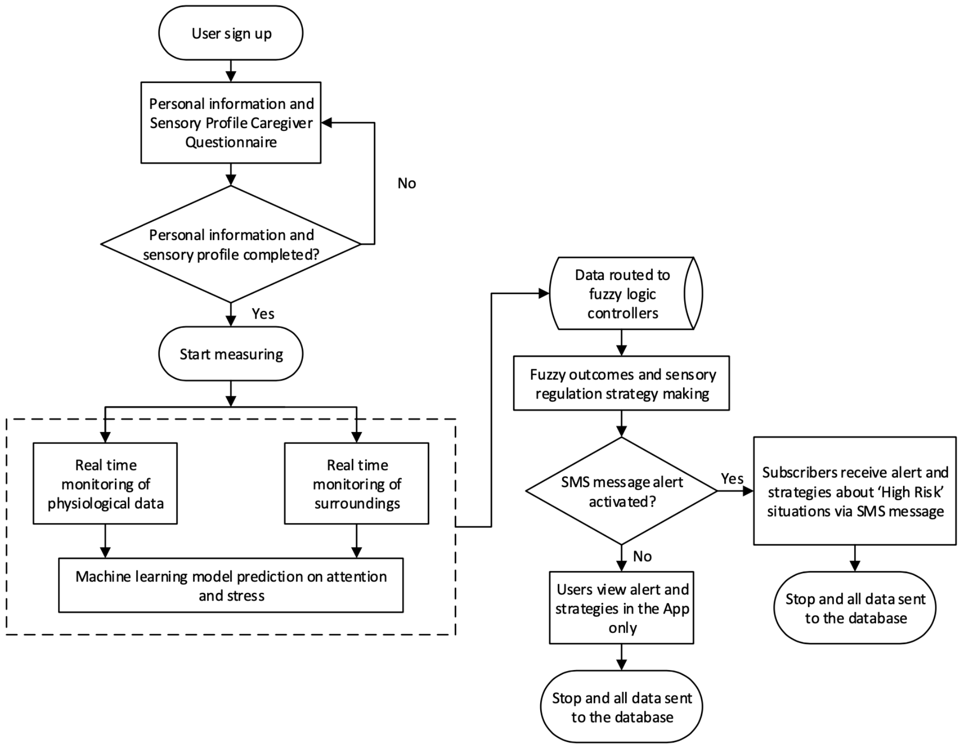



**Figure 4.10:** *Roomie working flow*

The UI design has been brainstormed and discussed with stakeholders at the early stage. Since caregivers were expecting an easy-to-understand data page, a hand-drawn interface for data visualisation has been derived from the brainstorming, as shown in Figure 4.11(a). A paper-based prototype has also been derived, examples of which can be seen in Figure 4.11(b) and (c). The comprehensive paper-based design is attached in Appendix Q.


**Figure 4.11:** *Hand-drawn data visualisation interface (a), and paper-based data visualisation interface (b) and (c)*

The design and development of *Roomie* have followed an iterative framework, which meant that the prototypes the author developed have been reviewed by stakeholders and redesigned accordingly. Time constraints on the project meant that there was insufficient time to fulfil every need identified in the user needs investigation, such as making environment adjustment automation possible. Core functions that were commonly wanted by users or beneficial for future development, including sensory profiling, monitoring, detecting, strategy-making and informing, were prioritised in the current project.

## 4.5 Prototype 1.0

Following the system design, the author has developed a first prototype of *Roomie* system. The aim of this first iteration was to achieve the key sensory profiling and monitoring functions. This allowed the key elements of *Roomie* to be assessed and be applied in the data acquisition as soon as possible. Basically, prototype 1.0 has achieved 1) effective sensor fusion and data transmission, 2) data visualisation, and 3) SP questionnaire completion within an App.

### 4.5.1 Sensor fusion and data transmission

iOS built-in sensors were accessed directly by an iPhone App developed for prototype 1.0 using CoreMotion, HealthKit and WatchConnectivity frameworks. Prototype 1.0 also integrated external sensors to complete comprehensive data collection and transmission. External sensors were connected with the Arduino Uno adhering to the circuit diagram as shown in Figure 4.12.

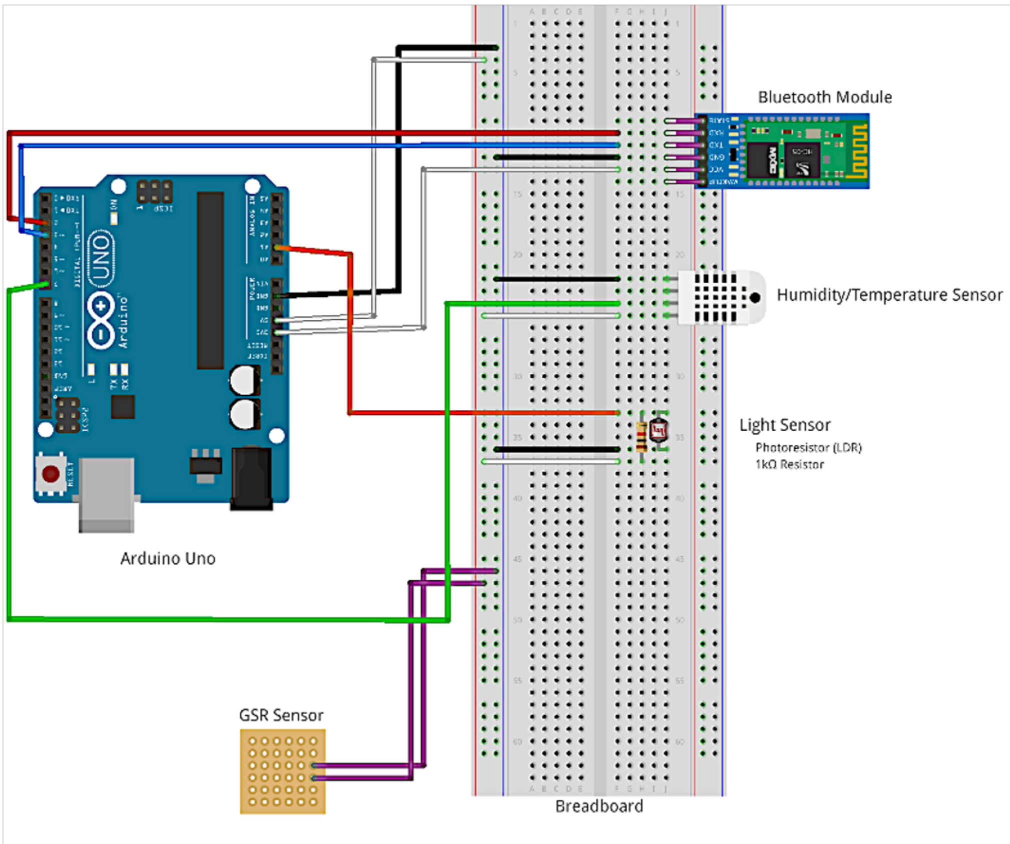



**Figure 4.12:** *Arduino Uno circuit diagram*

Communication between the Arduino Uno and DHT11 temperature and humidity sensor utilised a single-bus data format to ensure synchronisation. The photoresistor (light sensor) was connected to Arduino Uno with a fixed resistor (1000 $\Omega$) to form a voltage divider circuit. The Grove-GSR sensor provided standardised connectors which enabled simple deployment on the Arduino board. The wiring details for the three sensors are given below:

- DHT11: Connect one end to the GND (ground) of the Arduino Uno and the other end to the PIN7 of the Arduino Uno.
- Photoresistor: Connect one end to the GND of the Arduino Uno and the other end to the A0 pin of the Arduino Uno.
- GSR: Connect one end to the GND of the Arduino Uno and the other end to the A5 pin of the Arduino Uno.

Data transmission between external sensors and the App was achieved through a Bluetooth module. An AT-09 Bluetooth Low Energy (BLE) module was used in this project. The module supports serial communication through Universal Asynchronous Receiver and Transmitter protocol, which allows for simple and straightforward data exchange between the module and a microcontroller or other BLE-enabled devices such as iPhones. The serial communication is completed through the Receiver (RX) and the Transmitter (TX) ports. Both interfaces are available on both the Arduino microcontroller and the Bluetooth module. The RX and TX ports of the Arduino microcontroller directly communicate with the TX and RX ports of the Bluetooth module. The data is then serially sent on the TX port, bit by bit. On the RX port, the receiving device reads the data stream bit by bit (Peña & Legaspi, 2020). The AT-09 BLE module communicated with an Arduino board adhering to the wiring diagram as shown in Figure 4.13.

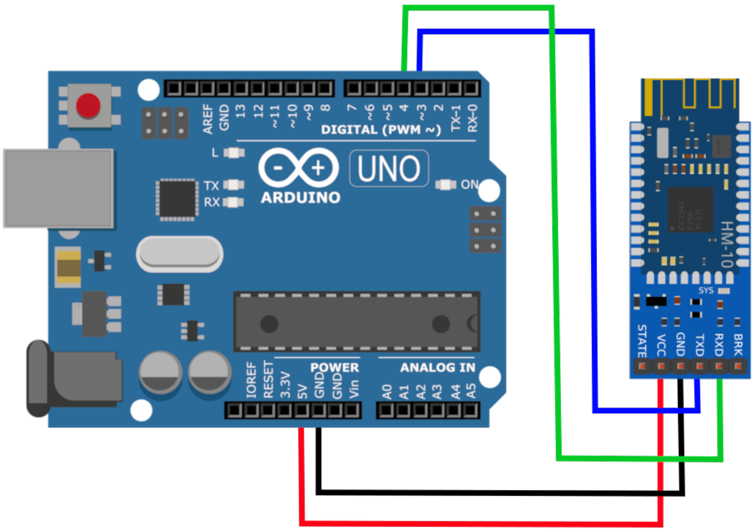



**Figure 4.13:** *AT-09 BLE module wiring diagram, sourced from Hrisko (2019)*

The AT-09 module contains a CC254x BLE chip, which is a power-optimised true single-chip solution specifically designed for low-power and proprietary 2.4GHz applications. It enables the establishment of robust network nodes with low overall bill of materials cost. The CC254x chip combines outstanding performance of leading RF transceivers with an industry-standard enhanced 8051 microcontroller, on-chip programmable flash memory, 8 kilobytes RAM, and many other powerful features and peripherals (Hrisko, 2019). Therefore, the use of AT-09 BLE module ensures ultra-short data transmission time with low power consumption.

Using the Arduino programming language, the author has successfully implemented the capture and transmission of sensor signals. The code in Figure 4.14 demonstrates the process.

```
// Start by initializing and selecting the appropriate library function
#include <SoftwareSerial.h>
#include "dht.h"

// Define the pins for each sensor
#define DHT11_PIN 7 // DHT11 sensor
#define LIGHT_PIN A0 // Light sensor
#define GSR_PIN A5 // Grove-GSR sensor

// Define the Bluetooth module
SoftwareSerial bleSerial(3, 2); // AT-09.

dht DHT;

// Set the baud rate, keeping it the same throughout the process
void setup() {
  Serial.begin(9600);
  bleSerial.begin(9600);
}

// Loop section, analyse each task separately
void loop() {
  // Read values from the pin connected to DHT11 sensor and save the results
  DHT.read11(DHT11_PIN);
  int temperature = DHT.temperature;
  int humidity = DHT.humidity;
  // Read values from the pin connected to the photoresistor and GSR sensor and save the results as string data
  int light = analogRead(LIGHT_PIN);
  int GSR = analogRead(GSR_PIN);
  Serial.println(GSR);
  String data = String();

  // Temperature in 4 hexadecimal characters
  String temperatureHEXString = String(temperature, HEX);
  for (int i = 0; i < 4 - temperatureHEXString.length(); i++) {
    data.concat("0");
  }
  data.concat(temperatureHEXString);
  // Humidity in 4 hexadecimal characters
  String humidityHEXString = String(humidity, HEX);
  for (int i = 0; i < 4 - humidityHEXString.length(); i++) {
    data.concat("0");
  }
  data.concat(humidityHEXString);
  // Light in 4 hexadecimal characters.
  String lightHEXString = String(light, HEX);
  for (int i = 0; i < 4 - lightHEXString.length(); i++) {
    data.concat("0");
  }
  data.concat(lightHEXString);
  // GSR in 4 hexadecimal characters
  String GSRHEXString = String(GSR, HEX);
  for (int i = 0; i < 4 - GSRHEXString.length(); i++) {
    data.concat("0");
  }
  data.concat(GSRHEXString);

  // Read data from AT-09. using serial communication.
  char dataBuffer[20];
  data.toCharArray(dataBuffer, 20);
  bleSerial.write(dataBuffer);
  delay(10);
}
```

**Figure 4.14:** *Arduino code for sensor fusion and data transmission*

### 4.5.2 Data visualisation

After receiving various data captured by the sensors, data visualisation was needed. The raw data consisted of a series of numbers, which may be difficult to comprehend. Therefore, the author decided to present them in an easily readable format, according to the user needs, which allowed children with ASD or their caregivers to understand the current environmental and physiological data.

Data visualisation functions were programmed in Xcode IDE to present the data in the form of line charts. The collected sensor data was transformed into a suitable format for line chart visualisation. Necessary data preprocessing and transformations were performed to ensure that the sensor data can be viewed normally within the display area.

Taking temperature data visualisation as an example, it was implemented using the following code snippet (Figure 4.15), where the **displayTemperature()** function was responsible for updating the temperature data display. Firstly, the temperature label's text was modified based on the temperature property in the **AppData** class. Then, the decision to draw new lines and points or to shift the display area was made based on the value of **temperatureShiftGraph**.

```
    func displayTemperature() {
        // Modify label text.
        temperatureLabel!.text = "Temperature: " + String(AppData.temperature) + "."
        if temperatureShiftGraph {
            // Draw new line and new point.
            let pointX = Double(temperatureDivideRatio) / 100 * Double(temperatureGraph!.frame.width)
            let pointY = Double((50 - Double(AppData.temperature)) / 100) *
                Double(temperatureGraph!.frame.height)
            CATransaction.begin()
            AppData.drawLine(graph: temperatureGraph!, startX: temperatureLastPointX!, startY:
                temperatureLastPointY!, endX: pointX + Double(temperatureGraph!.frame.width) /
                Double(100 / temperaturePointSpacingRatio), endY: pointY, color:
                UIColor.blue.cgColor, width: 3, speed: 1.0 + 4.0 / Float(temperatureSampleInterval))
            AppData.drawPoint(graph: temperatureGraph!, positionX: pointX +
                Double(temperatureGraph!.frame.width) / Double(100 / temperaturePointSpacingRatio),
                positionY: pointY, color: UIColor.red.cgColor, size: 5, speed: 1.0 + 4.0 /
                Float(temperatureSampleInterval))
            CATransaction.commit()
            temperatureLastPointX = pointX
            temperatureLastPointY = pointY
            // Shift the display area to the left.
            CATransaction.begin()
            temperatureGraph!.layer.sublayers?.forEach {
                $0.transform = CATransform3DTranslate($0.transform, -temperatureGraph!.frame.width /
                    CGFloat(100 / temperaturePointSpacingRatio), 0.0, 0.0)
            }
            CATransaction.commit()
```

**Figure 4.15:** *Visualisation code for temperature data (part 1)*

If **temperatureShiftGraph** was true, the position of the new point was determined using a specific calculation, and the **drawLine()** and **draw-**

**Point()** methods from the **AppData** class were used to draw the connecting line and the new point.

Meanwhile, the author used **CATransaction** to shift the display area of the temperature chart to the left by a fixed distance. If **temperatureShiftGraph** was false, new points and connecting lines were drawn based on the current ratio and checked if the segmentation boundary has been reached (see Figure 4.16).

```
        } else {
            if temperatureIsFirstPoint {
                temperatureCurrentRatio -= temperaturePointSpacingRatio
            }
            temperatureCurrentRatio += temperaturePointSpacingRatio
            // Draw new point and new connection.
            let pointX = Double(temperatureCurrentRatio) / 100 * Double(temperatureGraph!.frame.width)
            let pointY = Double((50 - Double(AppData.temperature)) / 100) *
                Double(temperatureGraph!.frame.height)
            if temperatureIsFirstPoint {
                temperatureIsFirstPoint = false
            } else {
                AppData.drawLine(graph: temperatureGraph!, startX: temperatureLastPointX!, startY:
                    temperatureLastPointY!, endX: pointX, endY: pointY, color: UIColor.blue.cgColor,
                    width: 3, speed: 1.0 + 4.0 / Float(temperatureSampleInterval))
            }
            AppData.drawPoint(graph: temperatureGraph!, positionX: pointX, positionY: pointY, color:
                UIColor.red.cgColor, size: 5, speed: 1.0 + 4.0 / Float(temperatureSampleInterval))
            temperatureLastPointX = pointX
            temperatureLastPointY = pointY
            // Check for division boundary.
            if temperatureCurrentRatio == temperatureDivideRatio {
                temperatureShiftGraph = true
            }
        }
```

**Figure 4.16:** *Visualisation code for temperature data (part 2)*

Finally, the author removed the layers that were beyond the boundaries to maintain the display range of the chart (see Figure 4.17).

```
        // Remove layers that go out of boundaries.
        temperatureGraph!.layer.sublayers?.forEach {
            if $0.frame.origin.x < -temperatureGraph!.frame.width {
                $0.removeFromSuperlayer()
            }
        }
```

**Figure 4.17:** *Visualisation code for temperature data (part 3)*

After the above visualisation operations, whenever a new detection data was encountered, it can be displayed in the chart according to the visualisation rules. The visualisation methods for other sensor data were very similar. Based on the processing and visualisation of sensor data described above, the App can obtain a rich variety of sensor data visualisation charts, as shown in Figure 4.18.


**Figure 4.18:** *Data visualisation interface of the prototype 1.0*

### 4.5.3 Sensory Profile (SP) questionnaire

Sensory Profile of Children Three to Ten Years Caregiver questionnaire was implemented in this prototype 1.0 with an information page to display relevant instructions (Figure 4.19(a)). The SP questionnaire page included a 'Withdraw' button if users wished to withdraw their consents, in corresponding to the ethical requirements (Figure 4.19(b)). No information would be recorded if a user withdrew from the questionnaire. In this version, the questionnaire results were stored locally in a Comma Separated Values (CSV) file format and can be distributed only by sending an email. As reviewed in the section 2.2.3, every child's SP can be interpreted into classifications of four sensory processing patterns. The four patterns are Low Registration, Sensory Seeking, Sensory Sensitivity and Sensory Avoiding, each of which has a score and is classified based on the questionnaire answers. However, due to time constraints on the first iteration phase, prototype 1.0 was unable to calculate the classification automatically and displayed the results for users. The detailed interpretation of SP can be issued by an occupational therapist manually upon caregivers' request.

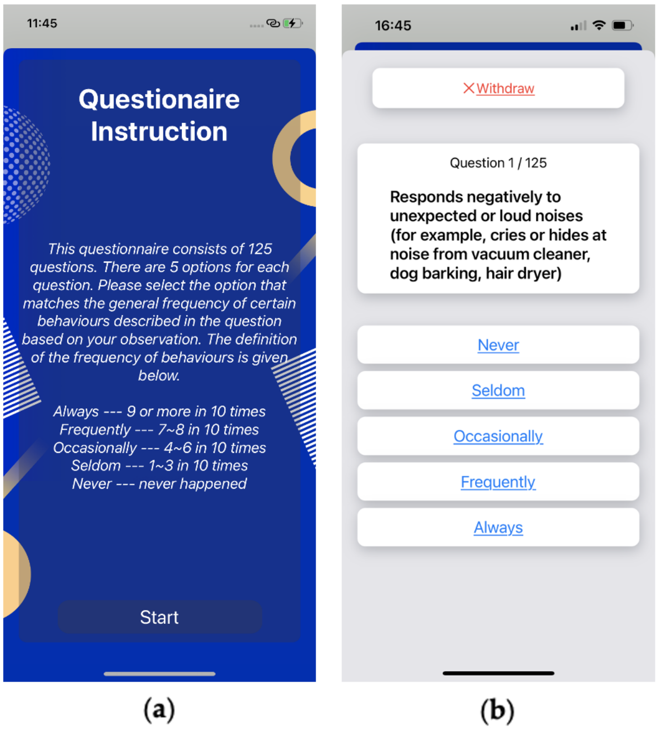



**Figure 4.19:** *Sensory Profile questionnaire instruction (a), and a sample question in the Sensory Profile questionnaire (b)*

Figure 4.20 presents part of the questionnaire text read by the prototype 1.0, which were converted from the paper-based SP questionnaire. The numerical label $i$ following each question refers to the $i$-th quadrant under which the question answer is included for calculation, consistent with the scoring sheet in Appendix H. For example, the first question is labelled as 4, which means the question answer will be considered when calculating classification of the 4th quadrant, Sensory Avoiding.

```
Responds negatively to unexpected or loud noises (for example, cries or hides at noise from vacuum cleaner, dog barking, hair dryer).4
Holds hands over ears to protect ears from sound.4
Has trouble completing tasks when the radio is on.3
Is distracted or has trouble functioning if there is a lot of noise around.3
Can' t work with background noise (for example, fan, refrigerator).4
Appears to not hear what you say (for example, does not "tune-in" to what you say).1
Doesn't respond when name is called but you know the child's hearing is OK.1
Enjoys strange noises/seeks to make noise for noise's sake.2
Prefers to be in the dark.4
Expresses discomfort with or avoids bright lights (for example, hides from sunlight through window in car).4
Happy to be in the dark.4
```

**Figure 4.20:** *Sample Sensory Profile questionnaire questions*

## 4.6 Feasibility study

A preliminary study investigating the feasibility of the system prototype was conducted with a small-scale sample in a classroom setting at a local childcare centre which provided sensory integration training for both TD children and children with ASD. The aims of this feasibility study were to 1) make sure that the expected functions have been achieved in the first iteration, 2) examine the feasibility of Sensory Dataset acquisition method, and 3) obtain initial user feedback for further development. Three TD children and one child with ASD participated in this feasibility study. Due to long travel distance to the childcare centre, each participant completed nine experiment sessions following the procedure mentioned in section 3.4.1. Environmental, physiological data, and task performance were recorded during the experiment sessions, which involved the manipulation of temperature, brightness, and noise levels to create controlled settings. Table 4.6 lists the condition of each session that each participant underwent.

**Table 4.6:** *Experiment conditions in the feasibility study*

| # | Age | Gender | ASD/TD | Experiment Conditions |
|---|---|---|---|---|
| P1 | 6 | Male | ASD | Temperature: 20 °C, 25 °C, 30 °C |
| P2 | 3 | Male | TD | Noise: 60 dB, 70 dB, 80 dB |
| P3 | 3 | Male | TD | Brightness: 225 lx, 375 lx, 525 lx |
| P4 | 6 | Male | TD | |

### 4.6.1 Implementing prototype 1.0

Before the experiment sessions started, SPs of participants were collected through the App developed for prototype 1.0. Each participant entered the testing room individually, accompanied by one caregiver and one ASD specialist. The participant was helped to wear Grove-GSR sensor and Apple Watch on their left wrists. The author also tried to put Muse EEG headband on each participant's forehead (Figure 4.21) and used Muse App to record the EEG data. This step played a crucial role in ensuring the participant's comfort with the wearable devices. An iPhone XR which has installed the App of prototype 1.0 should be placed on the table, with sensors and the App connected successfully. The author then started the experiment session, keeping the prototype recording the data until the session ended. The recording frequency was 1 hertz. After checking that all the devices were running normally, the participant was asked to undertake the attention tasks as mentioned in section 3.4.1 on an iPad.

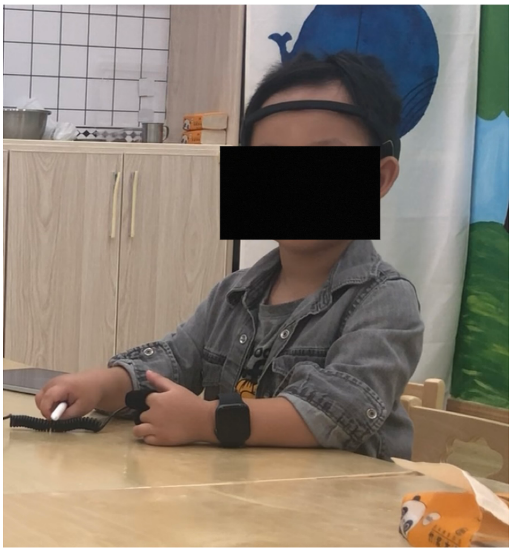


**Figure 4.21:** *Participant wearing sensors in the feasibility study*

### 4.6.2 ASD specialists rating

Two on-site ASD specialists observed the experiment session and provided rating on the participants' level of attention and stress using a 5-point Likert Scale, with 1 indicating 'being very low' and 5 indicating 'being very high'. They independently scored the attention and stress levels of the participant during four phases of the session, as shown in Figure 4.22. Higher rating on the attention level meant that the participant had higher level of attention, focusing more on the task, while higher rating on the stress meant that the participant was more anxious. The performance of each attention task was compared with ASD specialists' rating for a preliminary examination that if the tasks given can be feasible indicators for attention and stress levels.

| | **Phase 1 – Preparation** | **Phase 2 – Counting task** | **Phase 3 – Picture matching task** | **Phase 4 – Drawing task** |
|---|---|---|---|---|
| Attention level | 3 | 3 | 2 | 2 |
| Stress level | 3 | 4 | 4 | 5 |

*Please observe the participant's performance in each phase and rate the child's attention and stress level (from 1-5, where 1 being very low to 5 being very high)

**Figure 4.22:** *An example of ASD specialist scoring sheet, interpreted from an original Chinese version*

### 4.6.3 Sensory Profile

Each participant's SP was successfully recorded using the App of prototype 1.0. Figure 4.23 demonstrates the sensory processing patterns of four participants. P2 and P4 had similar SPs as they were not identified as 'Definite Difference' in any of Low Registration, Sensory Seeking, Sensory Sensitivity and Sensory Avoiding patterns. P3 obtained 'Definite Difference' in Sensory Seeking, indicating that he enjoyed sensory stimuli and sought stimulation frequently. However, his interest in sensory stimuli might lead to difficulties with task completion because he may get distracted with sensory stimuli and lose track of tasks. The child with ASD (P1) obtained 'Definite Difference' in Sensory Sensitivity and Sensory Avoiding. This meant that P1 noticed and was bothered by sensory stimuli more than others. When environments were too uncomfortable, he may be easily interrupted from getting tasks completed in a timely manner.

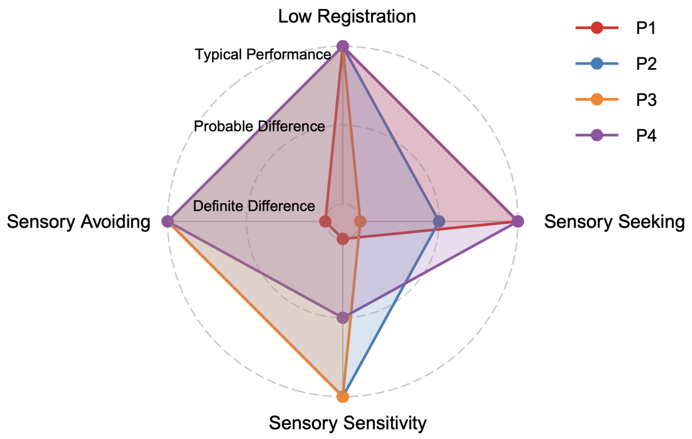



**Figure 4.23:** *Participants' Sensory Profiles*

### 4.6.4 Overall performance

Each participant's average task performance in different experiment conditions is displayed in Figure 4.24, 4.25 and 4.26. Accuracy on the y-axis refers to overall performance calculated by averaging all three task performance results.

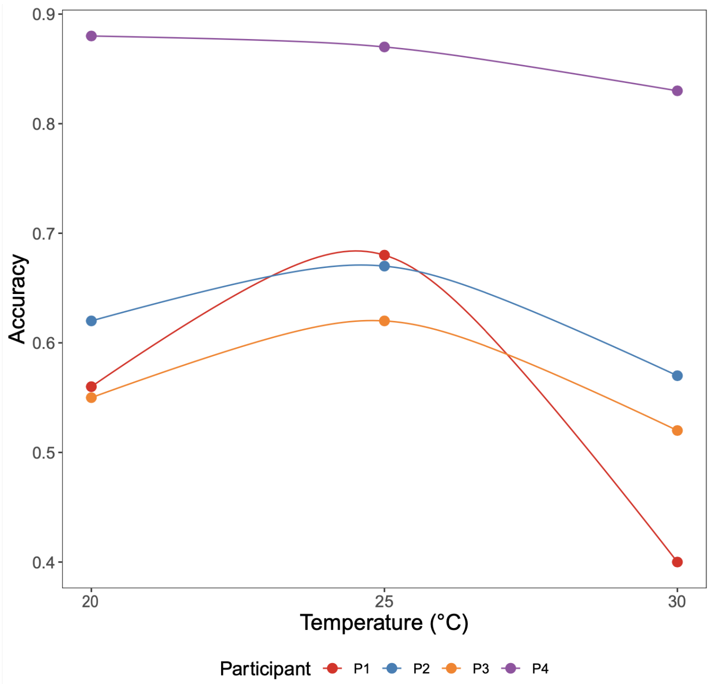



**Figure 4.24:** *Average accuracy at different temperature levels*

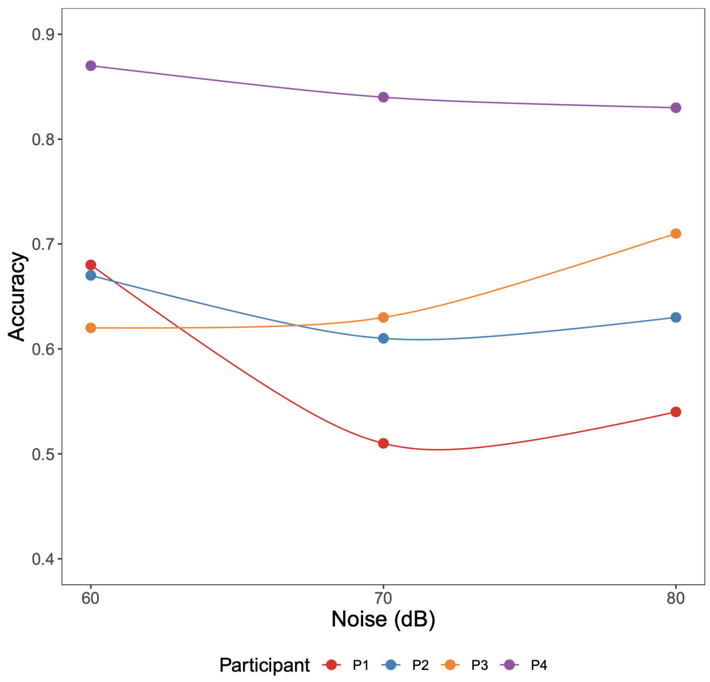



**Figure 4.25:** *Average accuracy at different noise levels*

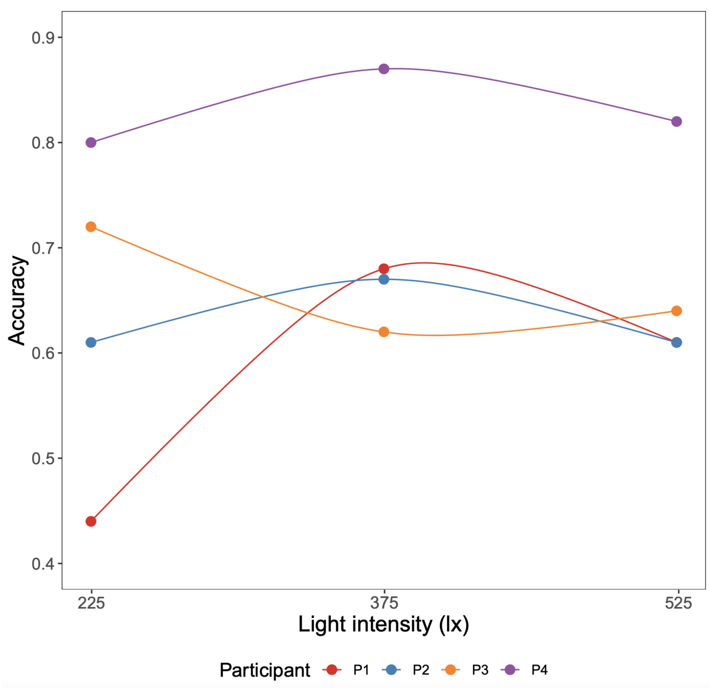



**Figure 4.26:** *Average accuracy at different light intensity levels*

It can be found that sensory responses among participants were idiosyncratic. The performance of P1 was more responsive to the environmental changes than TD participants, given the higher variances of his task performance in different settings. This can be explained by his sensory processing pattern which suggested that he was more sensitive to challenging environments. P1, P2 and P4 had the best performance when the noise level was at 60 dB. However, P3 had better performance when the noise level was at 80 dB. P3's better performance in a noisy environment related to his Sensory Seeking pattern. P3 has obtained 'Definite Difference' in the pattern, which meant that he enjoyed the environment with more auditory stimuli, thus was more active and continuously engaged in the environment.

A correlational analysis was performed to identify whether there was a significant relationship between task performance and ASD specialists' rating on the attention. The results showed that there was a significantly positive correlation between the two measures (Pearson's $r = 0.64$, $p < 0.01$), indicating the task performance scores of participants generally matched the ASD specialists' rating on the attention. The higher the task performance, the higher the attention score. This suggests that the children's performance on the attention tasks that the author designed can be used to infer the variation of their attention levels.

### 4.6.5 Feedback from caregivers and specialists

Following the experiment sessions, two on-site ASD specialists, mother of P1, and mother of P2 and P4 (P2 and P4 are siblings) participated in a focus group interview, giving feedback of using prototype 1.0 and experiment design. The mother of P1 suggested that P1 showed lower tolerance to wearable devices, especially EEG headband. It was found that P1 tried several times in the experiment session taking off the headband, making EEG data collection unlikely. Grove-GSR sensor and Apple Watch were accepted in most sessions. When the indoor temperature went higher, P1 tended to take off the Grove-GSR sensor as well. This may be because P1 was uncomfortable with the thick cotton material in a hot environment.

Mother of P2 and P4 indicated that although the data visualisation was available, they did not get real-time feedback of children's states, like attention and stress levels. Then the author explained that this was an incomplete pilot version of the system. This feedback indicated that caregivers showed needs for receiving information about attention and stress.

In addition, all caregivers and ASD specialists suggested that the use of CSV output to deliver SP results and raw data was inconvenient. It also increased the author's workload for data analysis, as it required manual transmission of datasets each time. To streamline data transmission and analysis, an automated data transfer function should be developed. This function would eliminate the need for manual transmission of CSV files, reducing the workload and potential data loss. By integrating data directly from the hardware devices to the analysis tools or database, the efficiency and accuracy of data management can be significantly improved.

In addition, expanding the sample size was vital for obtaining more robust and representative results. A large data set was crucial to the development of AI algorithms. Caregivers' feedback has revealed challenges regarding the participation commitment for data acquisition. Ensuring strong commitment to participation over a period has been considered difficult. Initially, the author has recruited two more children with ASD, but they both decided to withdraw from the study. One reason for their withdrawal was the long travel distance to the childcare centre for testing an incomplete prototype. One suggestion given by the mother of P1 to enhance participation commitment was taking ASD rehabilitation centres or special education schools as sites for data acquisition. Therefore, the author established collaboration with local ASD rehabilitation centres, such as Elim Autism in Ninghai, China, which can provide a more convenient and accessible location for participants. Collaborating with multiple ASD institutions allowed for a larger pool of participants. Conducting experiment sessions within these sites, specifically after the completion of their regular classes, ensured the availability of children with ASD and increased their willingness to participate.

By collecting caregiver and specialists' feedback and suggestions, the author can overcome the limitations identified in the first iteration, and propose strategies to address the limitations. These discussions helped the author collect sufficient data for the subsequent work, contributing to the overall effectiveness and reliability of the research.

# Chapter 5

# AI algorithms for supporting detection of atypical sensory responses and generating sensory regulation strategies

This chapter focuses on evaluating artificial intelligence (AI) algorithms for their use in *Roomie* to support the detection of atypical sensory responses and generating sensory regulation strategies.

This chapter explores multiple machine learning (ML) algorithms for detecting attention and stress levels. In addition to ML algorithms, a strategy-making algorithm using fuzzy logic (FL) has been developed to make decisions on whether to recommend a certain sensory regulation strategy and which strategy to recommend. A refined prototype (prototype 2.0) implements the validated ML and FL algorithms to provide real-time assessments of attention and stress, and to automatically generate sensory regulation strategies.

## 5.1 Machine learning for attention and stress detection

The proposed system would need better performing and more responsive algorithms for attention and stress detection. This section focuses on this purpose particularly, reporting the development and validation results of some common types of supervised ML algorithms. The ML algorithms discussed in this section include K-Nearest Neighbours (KNN), Random Forest (RF), Artificial Neural Network (ANN), and Gradient Boosting Decision Tree (GBDT), of which the performance on attention and stress detection are compared. The characteristics of each algorithm, the training dataset (Sensory Dataset), and the training procedure have been detailed in the Methodology chapter (section 3.4.1 and section 3.5.1).

### 5.1.1 Feature selection

As mentioned in section 3.4.1, after data pre-processing, there remained 14 features in the Sensory Dataset (SD) (see Table 3.3). However, testing each possible feature individually in ML training could lead to lengthy training times and complex computations. On the other hand, selecting the most relevant features allows the ML algorithm to train faster and improve accuracy when the correct subset of features is utilised. Hence, Recursive Feature Elimination (RFE) was employed to effectively select features in the dataset that were more or most relevant in classifying the target variable. One important hyperparameter for RFE was to find the number of features to be selected. RFE estimator **RandomForestClassifier** was used to illustrate how each configured number of features from 1 to 14 contribute to the accuracy. Figure 5.1 and Figure 5.2 illustrate the stratified 5-fold cross-validation scores for each configured number of input features.

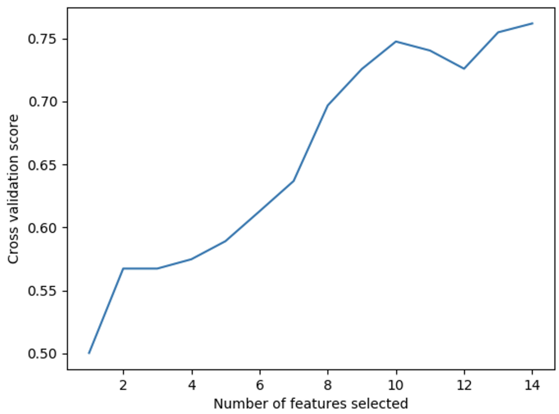



**Figure 5.1:** *RFE feature selection results for attention detection*

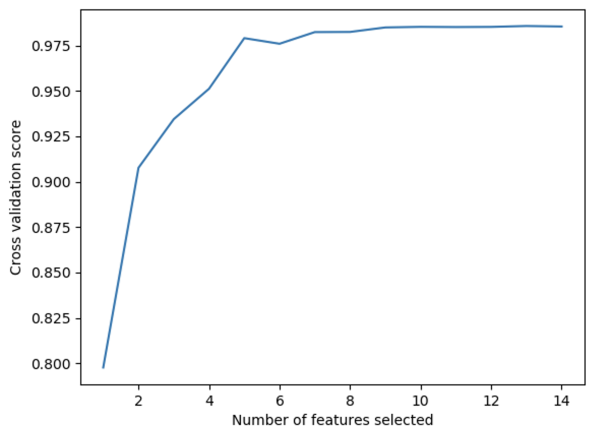



**Figure 5.2:** *RFE feature selection results for stress detection*

RFE **RandomForestClassifier** suggested that for attention detection, the optimal number of features was 14. For stress detection, the optimal number of features was 13. This indicates that all the 14 features are crucial features for attention detection. **RFE.support** results show that 'SP_registration' feature is not selected. Therefore, 13 features excluding 'SP_registration' are the most relevant features for stress detection. Different sets of features were fed into the ML algorithms for different detection targets.

### 5.1.2 Algorithm performance

For attention detection, which was a binary classification task, KNN, RF, ANN, and GBDT algorithms were evaluated.

Choosing an appropriate $k$ value is of great importance to a KNN algorithm for a good and responsive performance. Therefore, for KNN, the fine-tuned parameter was the **n_neighbors**, which referred to the value of $k$ to use for $k$-neighbours queries. In general, smaller $k$ values can reduce computational cost. In this experiment, the author run the algorithm many times with different set of $k$ values and decided to choose an appropriate $k$ value from the range of 1 to 14. The stratified 5-fold cross-validation was used to find the optimal **n_neighbors**. The **weights** function was set to 'distance'. In this case, closer neighbours of a query point would have a greater influence than neighbours further away. The **algorithm** function was set to 'auto', which meant the algorithm would attempt to decide the most appropriate algorithm based on the values passed to fit method. Figure 5.3 presents the cross-validation scores of $k$ values in the range of 1 to 14. As a smaller $k$ value required less computation, the optimal $k$ value in this experiment was 3.

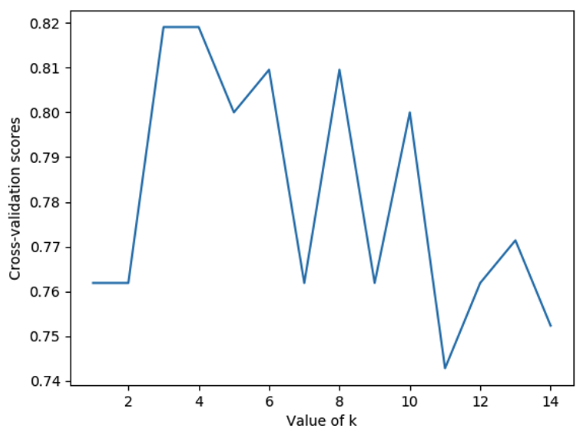



**Figure 5.3:** *KNN tuning results*

By leveraging the ensemble of Decision Trees, RF can effectively capture the intricate relationships between the input variables and the target variable. This enables an accurate detection of attention or stress states in real-time scenarios. For RF, the fine-tuned parameter was the **n_estimators**, which referred to the number of trees in the forest. Similarly, the author also applied the stratified 5-fold cross-validation to find the most suitable **n_estimators**. The **criterion** function, which is the function to measure the quality of a split, was set to 'entropy'. The **max_depth**, which is the maximum depth of the tree, was set to a common value 30. Figure 5.4 presents the cross-validation scores of **n_estimators** values in the range of 1 to 100 and the optimal **n_estimators** in the experimentation on attention detection was 56.

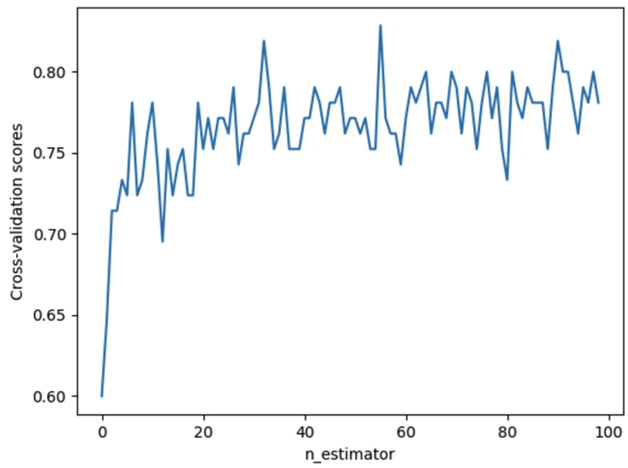



**Figure 5.4:** *RF tuning results*

For ANN, considering the number of features was small and the depth of layers can influence the computation efficiency of such algorithm significantly, the author developed three ANN algorithms with number of layers ranging from two to four. For each algorithm, the loss function was the Cross-Entropy Loss and the Adam optimiser was used to optimise the algorithms. The activation function used for the output layer was the

Softmax. The linear net and used functions can be represented by Equation (5.1), (5.2), (5.3) and (5.4) (Lederer, 2021).

$$net^l = \sum_{j=1}^{m_l} W_j^l \cdot \hat{y}_j^{l-1} + b^l \tag{5.1}$$

$$\hat{y}^l = active(net^l) \tag{5.2}$$

$$Softmax = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_i}} \tag{5.3}$$

$$Cross - Entropy\ Loss = -\frac{1}{m} \sum_{j=1}^{m} \sum_{i=1}^{n} (y \cdot log(\hat{y}) + (1 - y)log(1 - \hat{y})) \tag{5.4}$$

Where $l$ is the $l$-th layer, $m_l$ is the number of nodes in the $l$-th layer, $W_j^l$ is the weight, $\hat{y}_j^{l-1}$ is the output from the $(l-1)$-th layer, $b^l$ is the bias, $x$ is the value of inputs, $N$ is the number of output nodes, $m$ is the number of samples in current batch, and $n$ is the number of classes.

As for backpropagation, it is an algorithm to calculate the gradient descent of errors with respect to the neural network's weights and biases. The gradient descent of errors can be calculated by Equation (5.5) and (5.6) where $E$ is the error function, $w$ is the number of outputs, and $\frac{\partial E}{\partial W}$ is the gradient descent of $E$. Figure 5.5 shows the architecture of an ANN algorithm.

$$E = \min_{w} \sum_{i=1}^{w} \|\hat{y} - y\|^2 \tag{5.5}$$

$$W_j^{l+} = W_j^l - \eta \cdot \frac{\partial E}{\partial W_j^l} \tag{5.6}$$

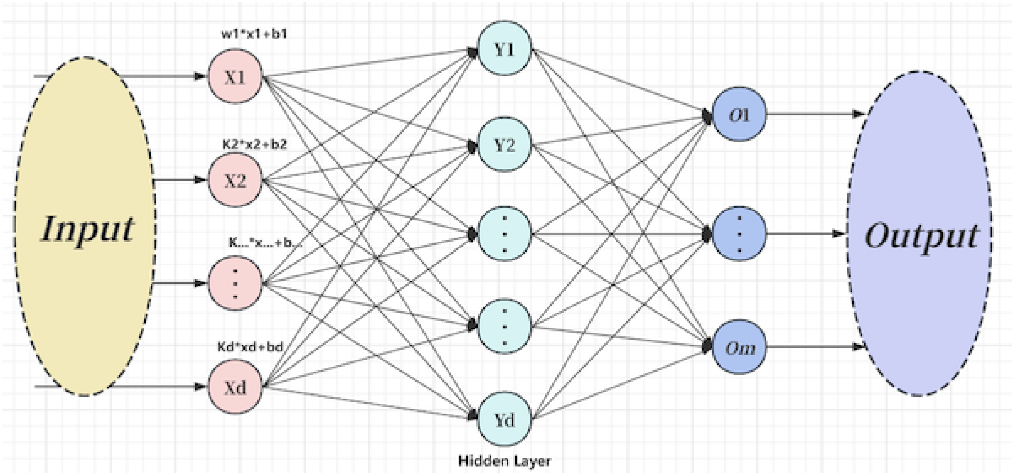



**Figure 5.5:** *The architecture of ANN, where X is the inputs, Y is the outputs of the hidden layers, and O is the final outputs*

Figure 5.6 compares the accuracy of attention detection by ANN with different layers on the testing dataset. The three-layer ANN algorithm had slightly better performance than the others.

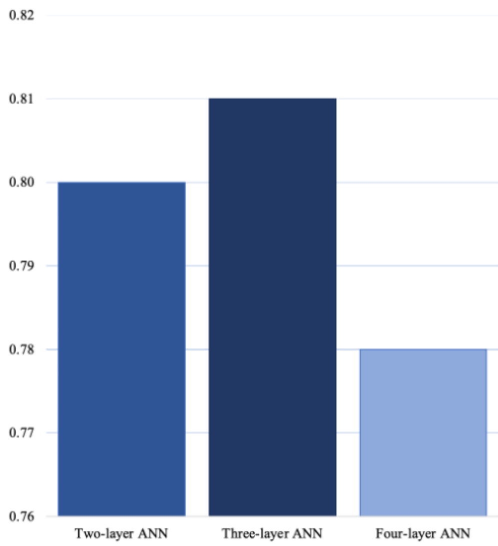



**Figure 5.6:** *Accuracy of ANN algorithm with different neural network layers*

Figure 5.7 shows the net of neurons of the three-layer ANN. It had three linear layers, of which the first layer had 14 input variables and 16 outputs passing to the neurons of the subsequent layer. The output (third) layer had 8 inputs and 2 outputs for binary classification.

```python
# Three-layer
class Net(nn.Module):
    def __init__(self):
        super(Net,self).__init__()
        self.fc1 = nn.Linear(14, 16)
        self.fc2 = nn.Linear(16, 8)
        self.fc3 = nn.Linear(8, 2)

    def forward(self,x):
        x = self.fc1(x)
        x = F.elu(x)
        x = self.fc2(x)
        x = F.elu(x)
        x = self.fc3(x)
        return x

    def predict(self,x):
        pred = F.softmax(self.forward(x))

        pred = torch.argmax(pred, axis=1)

        return pred
```

**Figure 5.7:** *Three-layer ANN net structure*

Figure 5.8 shows the accuracy of this three-layer ANN on the training dataset and testing dataset with epochs adjusted from 0 to 8000. The trend clearly shows that over-fitting occurred after 1000 epochs. To prevent over-fitting, when selecting the best parameters for the three-layer ANN, the interval for epochs selection was set to [0, 1000]. The fine-tuned ANN was saved and further compared with other algorithms.

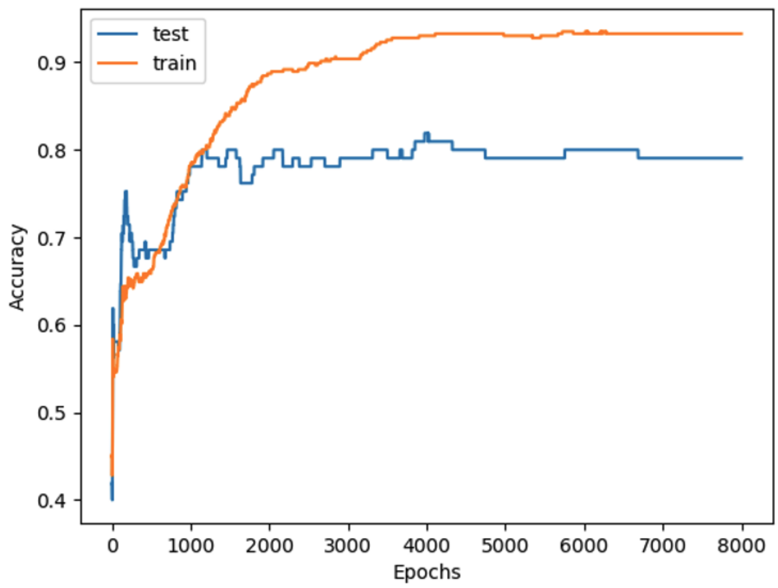



**Figure 5.8:** *Three-layer ANN training results*

The use of ANN in the attention and stress detection can have several advantages. Firstly, ANN is capable of capturing non-linear relationships and complex patterns in the data, which is beneficial for understanding the intricate nature of attention and stress. By employing ANN in the algorithm, attention and stress levels can be effectively predicted based on the input features. Additionally, ANN can handle large amounts of data and generalise well to unseen instances, making it suitable for real-world applications. However, one challenge with ANN is its potential as a black box model, meaning the inner working mechanism and decision-making processes may not be easily interpretable.

When optimised, GBDT can also have excellent performance to deal with complex nonlinear relationships in a high-dimensional dataset. For GBDT, the fine-tuned parameters were the **n_estimators** and the **learning_rate**, which are the two most critical hyperparameters for GBDT. The **n_estimators** is the number of boosting stages to perform, while the **learning_rate** means how fast the algorithm learns. The **n_estimators** was selected from [0, 100] and the learning_rate was selected from [0, 1]. Figure 5.9 is an extraction of the GBDT tuning results. In this experimentation on attention detection, when the **n_estimators** was 56 and the **learning_rate** was 0.865, the GBDT obtained best stratified 5-fold cross-validation scores.

```
Best n_estimators: 40.00000, best learning_rate: 0.511, cv_scores: 0.7619047619047619
Best n_estimators: 40.00000, best learning_rate: 0.513, cv_scores: 0.7714285714285715
Best n_estimators: 40.00000, best learning_rate: 0.525, cv_scores: 0.8
Best n_estimators: 40.00000, best learning_rate: 0.5730000000000001, cv_scores: 0.8095238095238095
Best n_estimators: 40.00000, best learning_rate: 0.8400000000000003, cv_scores: 0.8380952380952381
Best n_estimators: 40.00000, best learning_rate: 0.8660000000000003, cv_scores: 0.8476190476190476
Best n_estimators: 56.00000, best learning_rate: 0.8650000000000003, cv_scores: 0.8666666666666667

Process finished with exit code 0
```

**Figure 5.9:** *GBDT tuning results*

The author then compared the four ML algorithms. The detection accuracy, F1-score and inference time on the testing dataset of KNN, RF, ANN and GBDT algorithms with optimal hyperparameters for attention detection are presented in Table 5.1.

**Table 5.1:** *ML algorithm performance on attention detection*

| | Attention Detection | | |
|---|---|---|---|
| **Model** | **Accuracy (%)** | **F1-Score** | **Inference Time (ms)** |
| KNN | 81.90 | 0.8319 | 0.0291 |
| RF | 79.05 | 0.8000 | 0.0958 |
| ANN | 80.95 | 0.8246 | 0.0040 |
| GBDT | 86.67 | 0.8772 | 0.0046 |

The results show that GBDT significantly outperforms the other three algorithms on attention detection with the highest accuracy (86.67%) and F1-score (0.8772). GBDT and ANN are two of the fastest algorithms among all the algorithms.

ANN, RF and GBDT algorithms were used for stress detection because these three algorithms are capable of handling multiple classes directly (Géron, 2017). A similar tuning process was conducted for stress detection. Algorithm performance on the testing dataset is shown in Table 5.2. The results illustrate that ML algorithms have overall better performance on stress detection than attention detection. The detection accuracies of all three algorithms are over 95%. One reason for this may be that the detection performance of ML algorithms is greatly affected by the supportive features. The current combination of features has critical impact on the stress, while for attention detection there might be a lack of stronger indicators such as Electroencephalograms (EEG) features.

**Table 5.2:** *ML algorithm performance on stress detection.*

| | Stress Detection | | |
|---|---|---|---|
| **Model** | **Accuracy (%)** | **Macro F1** | **Inference Time (ms)** |
| RF | 98.82 | 0.9851 | 0.0182 |
| ANN | 96.89 | 0.9592 | 0.0021 |
| GBDT | 98.50 | 0.9812 | 0.0366 |

Compared with ML algorithms, ANN does not show better performance for detecting stress level in this experiment. Although the inference speed of ANN is higher than RF and GBDT, it can be found that all the algorithms can process an input within 0.1 millisecond (ms). The results suggest that two ensemble learning algorithms: GBDT and RF, could be chosen to be implemented into the *Roomie* for effective attention and stress detection respectively.

## 5.2 Fuzzy logic for sensory regulation strategy-making

Following attention and stress detection was a rule-based strategy-making algorithm using FL, which maps ML detection results and environmental information (inputs) to a specific outcome (output).

### 5.2.1 Fuzzy logic controllers

ASD specialists' responses to the focus group consultations and survey were finally interpreted into a rule base, which consisted of 63 fuzzy rules.

The rule base was coded according to particular values for inputs. The membership functions of inputs were defined in section 3.5.2. The outcome of FL was an assessment of the risk level. Three risk levels (Low, Medium, and High) have been defined in section 3.5.2 as well. ‘Low Risk’ means there is no negative impact on children’s health or state, hence will not trigger any sensory regulation strategy. ‘Medium Risk’ means that there is an ignorable impact on children’s health or state. Without sensory regulation strategies, distraction or anxiety generally stops by self-regulation or disappearing of the stressors. While ‘High Risk’ indicates that there is a severe impact on children’s health or state and a certain intervention is needed. Three independent FL controllers were developed using Python language to deal with brightness, temperature, and noise variation in parallel. They had the objective of simulating the assessment of ASD specialists. For example, a rule to determine a noise-related assessment is:

IF Noise is High AND Duration is Short AND Attention is Normal AND Stress is Moderate THEN Outcome is Low Risk

A rule to determine a temperature-related strategy:

IF Temperature is Low AND Duration is Short AND Attention is Normal AND Stress is High THEN Outcome is Medium Risk

A rule to determine a brightness-related strategy:

IF Brightness is Low AND Duration is Long AND Attention is Normal AND Stress is High THEN Outcome is High Risk

Rules for making noise-related decisions are shown in Figure 5.10. Appendix R shows all rules in the rule base, which represent all possible combinations of inputs and output.

```
Noise_rule1 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] &
Attention['Normal'] & Stress['Moderate']) | (Noise['High'] & Duration['Short'] &
Attention['Low'] & Stress['Low']) | (Noise['High'] & Duration['Short'] & Attention['Low']
& Stress['Moderate']) | (Attention['Normal'] & Stress['Low'])), consequent =
Outcome['Low Risk'], label = 'Low Risk')

Noise_rule2 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] &
Attention['Normal'] & Stress['High']) | (Noise['Low'] & Duration['Short'] &
Attention['Normal'] & Stress['Moderate']) | (Noise['Low'] & Duration['Short'] &
Attention['Normal'] & Stress['High']) | (Noise['Low'] & Duration['Short'] &
Attention['Low'] & Stress['Low']) | (Noise['Low'] & Duration['Short'] & Attention['Low']
& Stress['Moderate']) | (Noise['Low'] & Duration['Short'] & Attention['Low'] &
Stress['High']) | (Noise['Low'] & Duration['Long'] & Attention['Normal'] &
Stress['Moderate'])), consequent = Outcome['Medium Risk'], label = 'Medium')

Noise_rule3 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] &
Attention['Low'] & Stress['High']) | (Noise['High'] & Duration['Long'] &
Attention['Normal'] & Stress['Moderate']) | (Noise['High'] & Duration['Long'] &
Attention['Normal'] & Stress['High']) | (Noise['High'] & Duration['Long'] &
Attention['Low'] & Stress['Low']) | (Noise['High'] & Duration['Long'] & Attention['Low']
& Stress['Moderate']) | (Noise['High'] & Duration['Long'] & Attention['Low'] &
Stress['Moderate']) | (Noise['High'] & Duration['Long'] & Attention['Low'] &
Stress['High'])), consequent = Outcome['High Risk'], label = 'High Risk')
```

**Figure 5.10:** *Fuzzy rules for making noise-related decisions*

### 5.2.2 Algorithm performance

For validating the FL algorithm, 21 different combinations of inputs were evaluated through the fuzzy rules defined previously. The experimentation was conducted using a random dataset containing all the 21 combinations. The validation stage included feeding these data to the FL algorithm and verifying if the results returned by the algorithm were consistent with the 'expected results' obtained from ASD specialists.

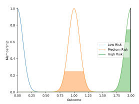
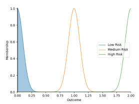
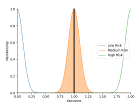
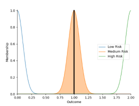
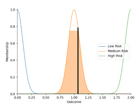
Two of the most popular defuzzification methods, Largest of Maximum (LOM) and Centroid were compared. Two methods were tested on 21 different combinations of inputs. Some of the testing results are shown in Table 5.3. All results are presented in Appendix S.

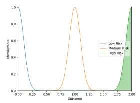
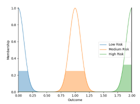
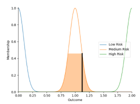
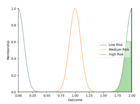
**Table 5.3:** *Example outputs returned by Centroid and LOM defuzzification methods*

| Condition | Duration | Attention | Stress | Expected Results | Returned Outcome by Centroid | Returned Outcome by LOM |
|---|---|---|---|---|---|---|
| High temperature | Short | Low | High | High risk | Medium risk | Hign risk |
| Low temperature | Long | Normal | Moderate | High risk | Medium risk | High risk |
| High temperature | Long | Normal | High | High risk | Medium risk | High risk |
| High noise | Short | Normal | Moderate | Low risk | Medium risk | Low risk |
| High noise | Short | Low | High | High risk | Medium risk | High risk |
| High brightness | Long | Normal | High | High risk | Medium risk | High risk |

The complete results presented in Appendix S show that the Centroid method only returned 79.4% of outcomes as expected in the testing because it usually leads to a reasonable control action. To simplify, if there are two rules: 'IF Temperature is High AND Duration is Short, THEN Outcome is Low Risk', 'IF Temperature is High AND Duration is Long, THEN Outcome is High Risk', when the temperature level is high, and the duration of atypical sensory responses is approaching long, the Centroid method averages the two possible outcomes, which then produces the unwanted result 'Medium Risk'. In this context, it is more important to detect 'High Risk' accurately. Therefore, the LOM method, which selects the largest output value whose membership value reaches the maximum, can be more precise. In the testing, the LOM method yielded superior results by returning all outcomes accurately. Table 5.4 provides some examples of the tested inputs and outputs based on the LOM method, and potential subsequent strategies.

**Table 5.4:** *Output of FL algorithm and recommended strategies on different combinations of inputs*

| Inputs | | | | Outcome Responses | |
|---|---|---|---|---|---|
| **Sensory Stimuli** | **Attention** | **Stress** | **Duration (Second)** | **Fuzzy Outcome** | **Recommended Strategy** |
| Brightness = 100 lx | Low | High | 25 |  | Brightness level is low. Enhance indoor brightness (e.g., draw the curtains open), use a phone to show pictures or videos that child likes for comfort and attention. |
| Brightness = 400 lx | Normal | Low | 40 |  | Brightness level is moderate. No impact. |
| Brightness = 750 lx | Normal | High | 10 |  | Brightness level is high. Reduce indoor brightness (e.g., draw the curtains). Keep observing. |
| Temperature = 15 °C | Normal | High | 10 |  | Temperature level is low. Enhance temperature level (e.g., turn up the air-conditioner). Keep observing. |
| Temperature = 26 °C | Normal | Moderate | 25 |  | Temperature level is moderate. Keep observing. |

| Inputs | | | | Outcome Responses | |
|---|---|---|---|---|---|
| **Sensory Stimuli** | **Attention** | **Stress** | **Duration (Second)** | **Fuzzy Outcome** | **Recommended Strategy** |
| Temperature = 32 °C | Low | High | 40 |  | Temperature level is high. Reduce temperature level (e.g., turn on the fan). Provide some deep pressure (e.g., hugs or massage) input to child for comfort and attention. |
| Noise = 60 dB | Low | Low | 25 |  | Noise level is moderate. Check other factors that may distract your child. |
| Noise = 70 dB | Normal | High | 10 |  | Noise level is moderate-high. Keep observing. |
| Noise = 80 dB | Low | Moderate | 40 |  | Noise level is high. Try to reduce loud (e.g., use noise-cancelling headphones or play calming music). Provide a fidget toy with texture that child likes for comfort and attention. |

## 5.3 Implementing AI algorithms

Previously in Chapter 4, the prototype 1.0 has been presented, which was a semi-finished system. Sensors and questionnaire modules were used to capture data, and with the help of data visualisation tools, users can view simple data charts. Prototype 1.0 was of no use for providing real-time feedback for children with ASD as AI algorithms have not been developed and implemented at that stage.

This chapter presents the major work undertaken in the second iteration phase, including verifying ML algorithms for effective attention and stress detection and FL algorithms for strategy-making. GBDT and RF algorithms with the highest accuracy and generally short inference time, were chosen to be embedded into the prototype 2.0 for attention and stress detection respectively. Real-time environmental data and detected outcomes were further processed by FL algorithms. FL algorithms evaluating the risk levels with good precision and deciding the recommendations of sensory regulation strategies were implemented at this stage as well.

One advantage of implementing classical ML and FL is that they can be easily deployed on the local device and process quickly without any need for a network connection, keeping the system responsive and data private (Apple Developer, 2023b). Deployment of complex deep learning algorithms requires a backend data analysis module on a cloud server which has a higher computation power than the phone device. Data should also be uploaded to server with reliance on a network connection. In some general systems, little network communication delay or feedback delay may be acceptable, but for children with ASD who experience atypical sensory responses, feedback delay is undoubtedly very serious. Therefore, the author chose ML and FL algorithms which can be embedded directly into the local device to reduce the delay caused by network uploading, and directly used the data processor of the mobile device for computation. Another reason to adopt ML for detection and then FL for strategy-making is that end-users can choose to receive either information about attention and stress, or sensory regulation strategy, whichever they like, making the system more customisable.

### 5.3.1 Implementing ML for attention and stress detection

To implement the ML algorithms in an iOS App, the author used Core ML framework to deploy the trained ML algorithm. The trained ML algorithms, namely GBDT and RF, were converted and exported as Core ML files. When they were added to the prototype 2.0, the classes of the Core ML framework were used to create and initiate requests to be performed using the ML algorithms.

Core ML framework also allowed on-device training and updating the ML algorithm to achieve better accuracy. Prototype 2.0 has tried to prompt the user through a feedback interface to provide true labels for detection in order to construct and improve the algorithm performance. The author decided that for every 300 true labels, on-device training utilised the new input data and its true label to continue training the algorithm based on the specified parameters. When the training was completed and there was an improvement on the detection accuracy, the new algorithm would be saved to a temporary file. The temporary file of the new algorithm then replaced the file of the original ML algorithm. This process is visualised in Figure 5.11.

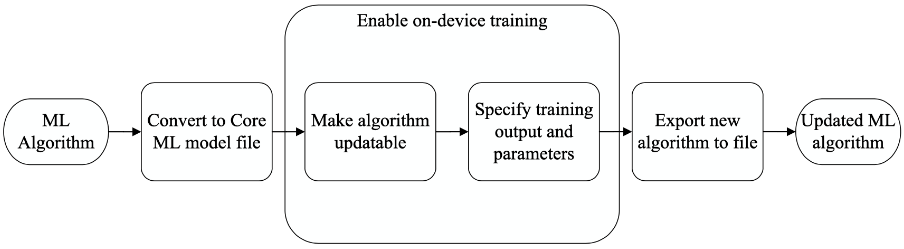



**Figure 5.11:** *ML algorithm deployment and update*

However, time constraints on the second iteration phase made this function incomplete and imperfect. The feedback interface in this prototype only provided a simple detected result of attention level (Figure 5.12). It required the user to leave the data visualisation page and enter a different interface. This meant that the users needed to take additional steps of clicking several buttons to upload the feedback, which was considered to be redundant by the end-users.

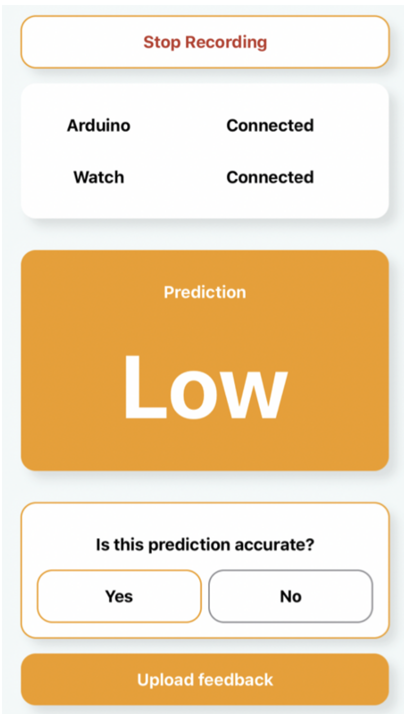



**Figure 5.12:** *Detection feedback interface of prototype 2.0*

### 5.3.2 Implementing FL for strategy-making

The FL controllers were deployed in Xcode Integrated Development Environment (IDE) using Python Application Programming Interface.

The output of a FL controller was an assessment of Risk Level, namely Low Risk, Medium Risk and High Risk. When the FL output was Low Risk, no sensory regulation strategies would be generated. When the FL output was Medium Risk, if an uncomfortable environmental factor was identified, a recommendation on adjusting the environment would be made. However, no further sensory regulation strategy was generated as Medium Risk was considered to have ignorable impact on the child with ASD. However, when the FL output approached High Risk, the *Roomie* system should generate both recommendation on adjusting the environment and a corresponding sensory regulation strategy so that the caregivers can make adjustments and calm-down the child within the uncomfortable situation.

A range of sensory regulation strategies have been collected through the focus group consultations and literature review. These strategies were validated through a survey with 242 ASD specialists. The strategies that obtained most recommendations during the survey served as a basis for establishing the Strategy Knowledge Base contained in the App of *Roomie*. Some strategies that ASD specialists recommended the most according to the scenarios of atypical sensory responses are presented in Table 5.5.

**Table 5.5:** *Example sensory regulation strategies*

| **Scenario** | **(Assessment of Risk) Recommended Strategies** |
|---|---|
| The environment become less bright (e.g., power outage), the child shows long-term anxiety and distraction. | (High Risk) Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices. |
| The environment is too bright, the child shows long-term distraction with low stress level. | (Medium Risk) Adjust the brightness to a comfortable level (e.g., by drawing the curtains, turning off the lights), and observe if their atypical responses persist. |
| The environment is cold, the child shows a long-term distraction with medium stress level. | (High Risk) Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately give him or her some fidget toys such as balls with texture that the child likes to attract his or her attention. |
| The environment is hot, the child shows a long-term anxiety with normal attention level. | (High Risk) Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension. |
| The environment is noisy (e.g., noise from interior renovations), the child shows a short-term distraction with low stress level, but quickly recover. | (Low Risk) Take no action. |
| The environment is noisy (e.g., noise from interior renovations), the child shows a short-term distraction with moderate stress level, but quickly recover. | (Medium Risk) Try to block out the noise (e.g., by playing calming music or put on noise-cancelling headphones), and observe if their atypical responses persist. |

Bilingual (Chinese and English) sensory regulation strategies were coded in Xcode IDE (Figure 5.13). An **FLResultConverter** function with conditional commands was programmed to support *Roomie* to generate sensory regulation strategies based on the FL outcomes.

```
case .keepObserving:
    realString("保持观察", "Keep observing")
case .checkFactor:
    realString("查看是否有其他干扰因素，帮助安抚和吸引注意力", "Check other factors,
        help child relax and pay attention immediately")
case .enhanceBrightness:
    realString("建议调高环境亮度（如拉开窗帘或开灯）", "Enhance brightness level
        (e.g., draw the curtains open/put the light on)")
case .reduceBrightness:
    realString("建议调低环境亮度（如拉上窗帘或关灯）", "Reduce brightness level (e.g.,
        draw the curtains/put the light off)")
case .enhanceTemperature:
    realString("建议调高环境温度（如调高空调温度）", "Enhance temperature level (e.g.,
        turn up the air-conditioner)")
case .reduceTemperature:
    realString("建议调低环境温度（如调低空调温度）", "Reduce temperature level (e.g.,
        turn down the air-conditioner)")
case .reduceNoise:
    realString("建议阻断噪音（如播放安抚音乐或给孩子戴上降噪耳机）", "Try to reduce loud
        (e.g., use noise-cancelling headphones or play calming music)")
case .showPicture:
    realString("用手机给孩子看他/她喜欢的图片或视频去安抚和吸引", "Use a phone to show
        pictures or videos that child likes for comfort and attention")
case .deepPressure:
    realString("给孩子一些深压觉输入（如大力拥抱、按摩）", "Provide deep pressure(e.g.,
        hugs or massage) input to child for comfort and attention")
case .fidgetToy:
    realString("给孩子一个他/她喜欢的触觉玩具", "Provide a fidget toy with texture
        that child likes for comfort and attention")
```

**Figure 5.13:** *Code snippet for managing sensory regulation strategies in Xcode*

*Roomie* was expected to generate two or three separate statements (Figure 5.14). The first statement was a summary of environmental conditions, such as 'the temperature level is moderate'. The second statement was a decision on whether to make any adjustment to the environment. If the FL algorithm returned 'Low Risk', then the second statement would be 'there is no impact on the child's health or state' and the third statement would not show up. If the FL algorithm returned 'Medium Risk', then the second statement would be a recommendation on adjusting the environment, such as 'turn up the air-conditioner'. The third statement was a decision on whether to provide a further sensory regulation strategy. If the FL algorithm returned ‘Medium Risk’, then the third statement would remind the caregiver or teacher to keep observing. If the FL algorithm returned ‘High Risk’, then a specific sensory regulation strategy would be given, such as ‘give a fidget toy with texture that the child likes to him or her’.

```
//1st statement: environment condition
resultModel.temperatureModel.firstStr = showString(.temperatureIs) +
    StimuliLevel(value: 2, enviromentValue: temperature)
resultModel.noiseModel.firstStr = showString(.noiseIs) + StimuliLevel(value: 3,
    enviromentValue: noise)
resultModel.brightnessModel.firstStr = showString(.brightnessIs) +
    StimuliLevel(value: 1, enviromentValue: brightness)

//2nd statement: environmental adjustment recommendation
resultModel.brightnessModel.secondStr =
    BrightnessSecondOutput(FLModel.out_Decision_Brightness, brightness:
    brightness)
resultModel.temperatureModel.secondStr =
    TemperatureSecondOutput(FLModel.out_Decision_Temperature, temperature:
    temperature)
resultModel.noiseModel.secondStr = NoiseSecondOutput(FLModel.out_Decision_Noise,
    sound: noise)

//3rd statement: sensory regulation strategy recommendation
resultModel.brightnessModel.thirdStr =
    BrightnessThirdOutput(FLModel.out_Decision_Brightness, brightness:
    brightness)
resultModel.temperatureModel.thirdStr =
    TemperatureThirdOutput(FLModel.out_Decision_Temperature, temperature:
    temperature, duration: duration, stress: stress)
resultModel.noiseModel.thirdStr = NoiseThirdOutput(FLModel.out_Decision_Noise,
    noise: noise, duration: duration, stress: stress)
```

**Figure 5.14:** *Code snippet for interpreting FL output into statements about sensory regulation strategies*

A more succinct user interface (UI) has been developed to showcase the system outputs, with clear feedback of sensory regulation strategies at a glance. The improvement of UI can be seen in Figure 5.15. The original design (Figure 5.15(a)) only displayed raw data without any interpretations. An update of the design was implemented in this iteration to make the measured data, detected attention, detected stress, and recommended strategies overviewed simply by swiping the page (Figure 5.15(b)).

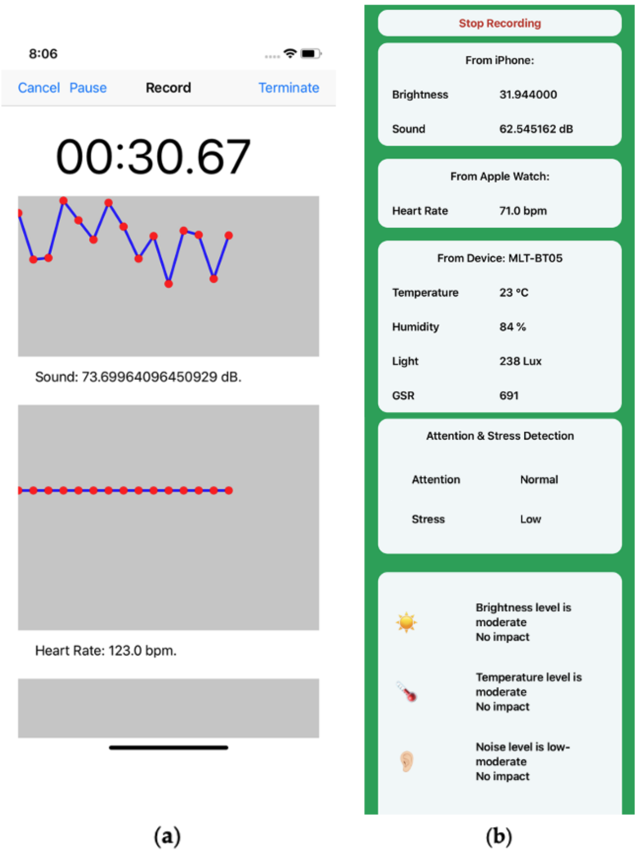



**Figure 5.15:** *Data visualisation interface of prototype 1.0 (a), and prototype 2.0 (b)*

# Chapter 6

# System Evaluation

The previous two chapters have discussed overall system design and validation of artificial intelligence (AI) algorithms. In addition to that, system effectiveness and usability should be another important area of focus at the final stage. This chapter adopts a more psychological methodology to probe into the efficacy and end-users' perceived satisfaction of *Roomie*. A beta version of *Roomie* (prototype 3.0) has been developed at this stage with some refinements made to the prototype 2.0 based on technical feedback obtained from the second iteration phase. Following the release of the beta version, a comprehensive evaluation study has been conducted, and the results are reported in this chapter.

## 6.1 Beta version development and release

Integrating the algorithms and functions mentioned in Chapter 5, the beta version of *Roomie* has been developed and ready for final testing and evaluation. The system user interface (UI) has been further refined and better structured, combining animations, icons and clear data display. Figure 6.1

presents the new data visualisation interface compared to the interface of prototype 2.0. Physiological data, environmental data, detection results, and strategy feedback were displayed in separate boxes so that the users could take a glimpse at the summary box to view their interested information. The overall UI of the beta version was improved as closely as possible to the paper-based design derived from the brainstorming session with Autism Spectrum Disorder (ASD) stakeholders.


(a) (b)

**Figure 6.1:** *Data visualisation interface of prototype 2.0 (a), and beta version (b)*

The function of providing true labels for machine learning (ML) algorithms has been finalised. As suggested by the caregivers during the second iteration phase, they did not want to leave the data visualisation page to upload true labels. Therefore, a button 'correct' that led to a true label provision popped-out was placed on the top of attention and stress detection storyboard (see Figure 6.2). Users can upload true labels by simply selecting the true labels and clicking 'confirm', without leaving the page.

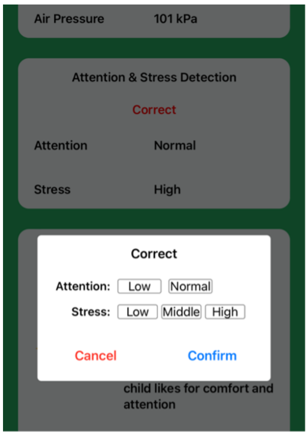



**Figure 6.2:** *Detection feedback interface of beta version*

The registration and Sensory Profile (SP) modules have also been refined. The improved registration module enabled the caregiver to create a username and password to enter the App (Figure 6.3(a)), ensuring the data security of children. The caregiver can manage children's SPs in the App, such as completing a new SP questionnaire as the child grows or deleting old SPs from the database. However, the most recent SP of a registered child must be kept in the database to enable the ML detection. Caregivers can also view the results of SPs in the App (Figure 6.3(b)).

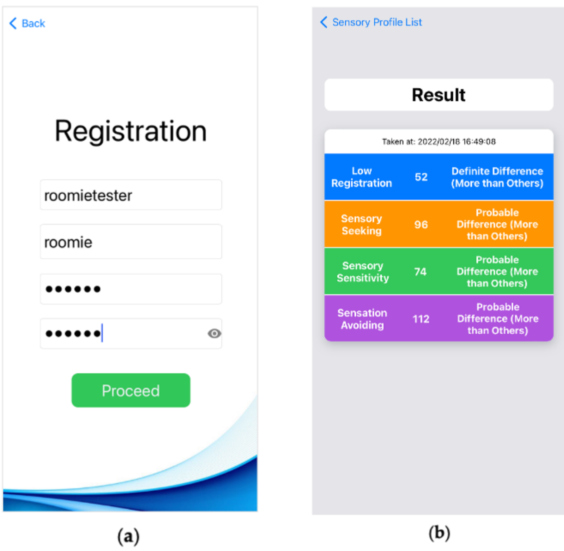



**Figure 6.3:** *Registration interface (a), and Sensory Profile results displayed in the beta version (b)*

To make it convenient for participants in the final evaluation study to install *Roomie* App on their own iPhones, the author decided to submit the beta version to TestFlight, which is an Apple's beta testing service with which developers can invite testers simply by sharing a public link.

To sign the App for submission to the TestFlight for distribution, an iOS distribution certificate must be generated in the Apple Developer Program so that testing can be distributed to testers' physical iOS devices. Figure 6.4 shows the distribution certificates that the author has created for App submission. Profiles of which the name contains '_dis' are the certificates that have been used to sign the App for distribution.

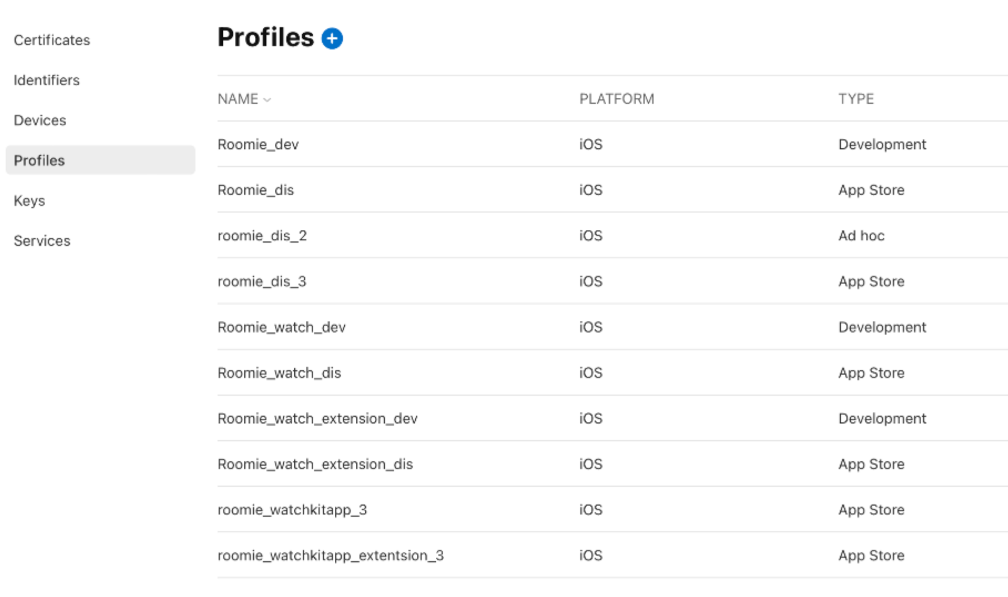



**Figure 6.4:** *Lists of iOS certificates generated for Roomie development and distribution*

Before the submission of the beta version, the entire App must be archived in Xcode. Once the distribution profile was created in the Apple Developer Program as shown in Figure 6.4, the author used the Xcode Archive menu option to pack up the beta version ready for testing. Figure 6.5 displays the Archive screen in Xcode. When this process was complete, the entire App can be exported and saved locally as a *Roomie*.ipa file, as shown in

Figure 6.6.

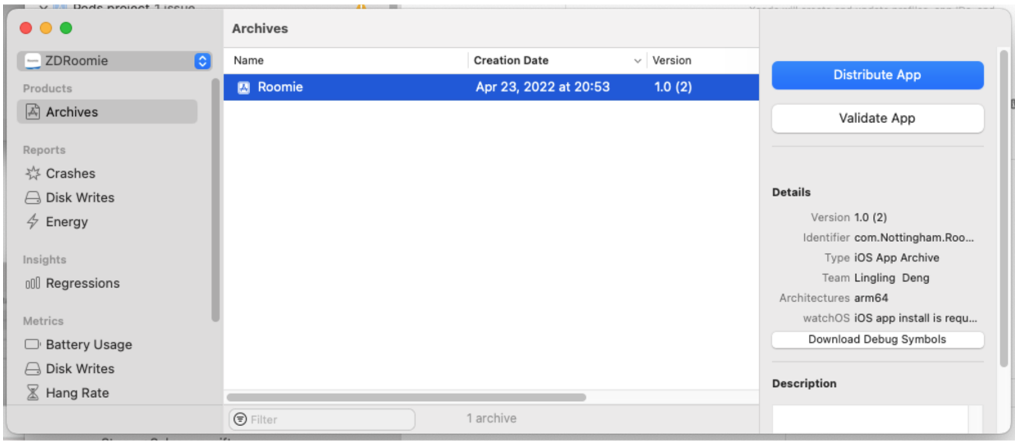



**Figure 6.5:** *Archive screen of the beta version ready for submission and distribution*

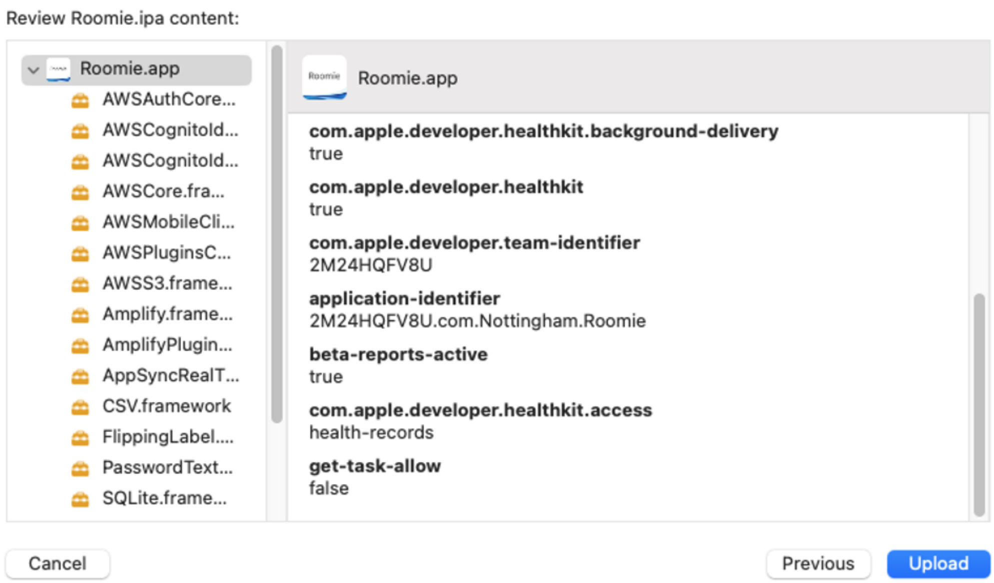



**Figure 6.6:** *Archived Roomie.ipa file*

This file was then uploaded to TestFlight and needed to be reviewed by Apple before release. In the review process, Apple's experts and editorial team evaluated if the App fulfilled the technical, content and design criteria to ensure a safe and trusted experience for users. Especially, the review process also confirmed if the submitted App was suitable for children (Apple Developer, 2023a). If the App was rejected, reasons for rejection were stated and the App may be resubmitted after addressing the issues. *Roomie* beta version obtained Apple's approval for TestFlight beta testing in April 2022, indicating the App has met the iOS standards in terms of safety, performance, design, ethics and children friendliness. A full list of approval emails is attached in Appendix T.

After the release of *Roomie* beta version, an evaluation study was conducted in order to measure how accurately *Roomie* identified the abnormal attention and stress levels of children with ASD in real-life cases of different environmental conditions. Besides, the evaluation investigated the effectiveness of sensory regulation strategies recommended by *Roomie* on children performance improvement. Furthermore, the caregivers' level of satisfaction in terms of system utilisation, such as UI, intention of long-term use, were assessed as well.

## 6.2 Participants

The evaluation study was performed on preschool-age children formally diagnosed with ASD and typically developing (TD) children. They were recruited from several childcare centres in Wenzhou and Ningbo, two major coastal cities in East China. Participants were recruited in different cities to ensure that the evaluation can be conducted across sites to demonstrate the results of evaluation were not limited to a specific place or setting.

The recruitment information was circulated within the collaborating institutions by the school leading administrators or teachers. Caregivers were fully informed of study design and procedures through reading the recruitment information. Caregivers then voluntarily reported their willingness of participation to the leading administrators or teachers. The author confirmed each child's condition (ASD or TD), assessed and determined their eligibility. The author firstly completed the recruitment of 30 children with ASD. Their ages ranged from three to five years old. Subsequently, the author screened another 30 gender and age-matched TD children for forming a comparison group. For each participant, evaluation sessions were arranged within the site where they received education to ensure participation commitment. Table 6.1 highlights the sample characteristics of ASD group and TD group, including the information about the testing sites, number of participants, average age, and gender ratio.

**Table 6.1:** *Sample characteristics of ASD group and TD group*

| **Condition** | **Testing Site** | **Number of Participants** | **Average Age** | **Gender Ratio (Male : Female)** |
|---|---|---|---|---|
| ASD | An ASD Rehabilitation Center in Wenzhou | 15 | 4.3 | 12 : 3 |
| | An ASD Rehabilitation Center in Ningbo | 15 | 4.0 | 12 : 3 |
| TD | A Public Kindergarten in Wenzhou | 15 | 4.4 | 12 : 3 |
| | A Private Childcare Center in Ningbo | 15 | 4.3 | 12 : 3 |

## 6.3 Results

In this evaluation study, all the ASD and TD participants completed required three sessions, no-*Roomie* session, *Roomie* session 1, and *Roomie* session 2, as described in section 3.6.2. Each caregiver observed their child's performance in each of the three sessions. During each *Roomie* session, a caregiver's real-time reports on false detection through the interface in Figure 6.2 were interpreted into the number of false detection cases made by *Roomie*. The false detection cases were averaged for both groups of participants to give an indication of, overall, how many false detections were made by ML algorithms in 30 minutes. Average false detection cases, average ratings from the adapted Caregiver-Teacher Report Form (C-TRF) of

ASD and TD groups and standard deviations were presented in Table 6.2.

**Table 6.2:** *ASD and TD group data of different measures.*

| Group | Sample | Session | Rating Parameters: Mean (Standard Deviation) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | **False Detection Cases - Attention** | **False Detection Cases - Stress** | **C-TRF Attention Score - Caregiver** | **C-TRF Attention Score - ASD Specialist** | **C-TRF Stress Score - Caregiver** | **C-TRF Stress Score - ASD Specialist** |
| ASD | 30 | No-*Roomie* | / | / | 8.1 (3.5) | 8.6 (2.8) | 4.3 (3.5) | 4.9 (4.0) |
| | | *Roomie* #1 | 21.9 (15.7) | 6.7 (5.0) | 8.3 (3.2) | 8.7 (3.3) | 4.4 (3.6) | 4.9 (3.9) |
| | | *Roomie* #2 | 11.0 (7.7) | 4.2 (2.5) | 6.5 (2.8) | 7.0 (2.9) | 3.4 (3.3) | 3.7 (3.4) |
| TD | 30 | No- *Roomie* | / | / | 1.6 (1.6) | 2.0 (2.0) | 1.6 (1.9) | 1.5 (1.9) |
| | | *Roomie* #1 | 5.2 (4.2) | 18.6 (8.4) | 1.8 (1.8) | 2.2 (2.2) | 1.7 (2.1) | 1.7 (1.9) |
| | | *Roomie* #2 | 4.8 (3.4) | 13.3 (7.2) | 1.5 (1.5) | 1.8 (2.0) | 1.2 (1.8) | 1.3 (1.6) |

### 6.3.1 Detection accuracy

When examining false detection cases, the author identified that ASD group reported more false detection cases on attention than stress in the real-life situation. This meant that the accuracy of attention detection algorithm was not as satisfactory as stress detection algorithm in the real-life practice, consistent with the results of ML training in the section 5.1.2. TD group obtained lower average ratings of C-TRF on both attention and stress domains, indicating that TD children might have better ability of attention and stress self-regulation than ASD group. TD children were more likely to make their attention or stress stable at a normal level, with higher tolerance to unfriendly environment. The attention detection algorithm could detect most state of TD children correctly as well. However, caregivers of TD children reported more false detection cases of stress than those of children with ASD. One reason for this could be that the data used for ML training were all from children with ASD. Inputs corresponding to ‘uncomfortable level' for a child with ASD might be still within a TD child's 'comfort zone', making the ML algorithm generate false detections for TD children.

By comparing detection accuracy between the *Roomie* session 1 and session 2, number of false detection cases dropped in the session 2 where the classroom teacher implemented sensory regulation strategies to adjust environment and help children. It was suggested that the ML algorithms embedded in *Roomie* were more usable for children with ASD and had better performance in a comfortable environment. Admittedly, the accuracy of the attention detection algorithm needed further improvement.

### 6.3.2 Effectiveness of the *Roomie* intervention

To investigate the effectiveness of the *Roomie* intervention on children performance improvement, a paired-samples $t$-test was employed to identify if differences in the attention and stress scores existed between the no-*Roomie* session and the *Roomie* session 2 for two groups. Each participant's attention score consisted of the sum of points that the caregiver or ASD specialist provided for the individual items comprised the C-TRF 'Attention Problem' category, recorded as the C-TRF Attention Score (Caregiver or ASD Specialist). Similarly, each participant's stress score consisted of the sum of points that the caregiver or ASD specialist provided for the items listed in the C-TRF 'Anxious or Depressed' category, recorded as the C-TRF Stress Score (Caregiver or ASD Specialist). Besides, the magnitude of the differences between the no-*Roomie* session and the *Roomie* session 2 was examined by calculating the effect size (Cohen's $d$). Cohen's $d$ of a paired-samples $t$-test was computed by dividing the mean difference by the standard deviation of the difference scores between two sessions. The formula for calculating Cohen's $d$ is represented by Equation (6.1).

$$d = \frac{M_1 - M_2}{S_D} \tag{6.1}$$

Where $M_1$ and $M_2$ denoted the mean C-TRF scores for the no-*Roomie* session and the *Roomie* session 2 in each pairwise comparison, and the $S_D$ denoted the standard deviation of the difference scores between the two sessions. According to Cohen (1988) guidelines, an effect size is considered to be 'small' if $d \geq 0.2$ and $< 0.5$, 'moderate' if $d \geq 0.5$ and $< 0.8$, or 'large' if $d \geq 0.8$.

Summary of the *t*-test results are presented in Table 6.3. The analyses for each rating score given by the caregiver and ASD specialist on the C-TRF revealed significant performance differences in ASD group between no-*Roomie* session and *Roomie* session 2 ($p < 0.01$). It indicated that the use of *Roomie* and application of strategies recommended by *Roomie* could help improve attention and reduce stress in children with ASD. Although differences in TD group were not significant on the C-TRF rating of attention, caregivers also observed reduced stress in TD children ($p < 0.05$). Overall, *t*-test results suggested the positive impact of the *Roomie* intervention on sensory regulation in children with ASD. However, another index, effect size was found only to be moderate for attention improvement and small for stress relief.

**Table 6.3:** *Summary of the t-test results for ASD and TD groups.*

| Measures | No-*Roomie* Session – *Roomie* Session 2 | | | | | |
|---|---|---|---|---|---|---|
| | ASD | | | TD | | |
| | $t$ | $p-$value | $d$ | $t$ | $p-$value | $d$ |
| C-TRF Attention Score – Caregiver | 4.732 | <0.001 | 0.505 | 0.769 | 0.448 | / |
| C-TRF Attention Score – ASD Specialist | 4.533 | <0.001 | 0.561 | 1.229 | 0.229 | / |
| C-TRF Stress Score – Caregiver | 4.160 | <0.001 | 0.265 | 3.340 | 0.002 | 0.216 |
| C-TRF Stress Score – ASD Specialist | 5.288 | <0.001 | 0.323 | 1.649 | 0.110 | / |

### 6.3.3 Level of satisfaction in terms of system utilisation

Caregivers' perceived satisfaction in terms of system utilisation was measured using the SUS. The average mean score for the 10 SUS items are presented in Table 6.4. As mentioned, SUS statements with odd numbers are positively expressed and statements with even numbers are negatively expressed. Caregivers' rating for the 6th statement was scored below 2, suggesting that they generally disagreed that there was too much inconsistency in the system. They also did not perceive the system to be cumbersome to use or unnecessarily complex, given the scores of the 2nd and 8th statement were low. Mean scores relating to the 5th statement 'I found the various functions in this system were well integrated' were particularly high with similar standard deviations for both ASD and TD groups. However, it was noticeable that the 4th statement 'I think that I would need the support of a technical person to be able to use this system' also obtained high scores, indicating that some instruction and assistance were required by the end-users before they were able to use the system themselves.

**Table 6.4:** *Caregivers' SUS rating of the system.*

| **Statement** | **Mean Score (Standard Deviation)** | |
|---|---|---|
| | **ASD Group** | **TD Group** |
| 1. I think that I would like to use this system frequently. | 3.87 (0.64) | 3.67 (0.72) |
| 2. I found the system unnecessarily complex. | 1.67 (0.72) | 2.07 (0.80) |
| 3. I thought the system was easy to use. | 3.67 (0.72) | 3.73 (0.80) |

| Statement | Mean Score (Standard Deviation) | |
|---|---|---|
| | **ASD Group** | **TD Group** |
| 4. I think that I would need the support of a technical person to be able to use this system. | 3.73 (0.80) | 3.93 (0.70) |
| 5. I found the various functions in this system were well integrated. | 4.20 (0.68) | 4.33 (0.62) |
| 6. I thought there was too much inconsistency in this system. | 1.07 (0.26) | 1.07 (0.26) |
| 7. I would imagine that most people would learn to use this system very quickly. | 3.53 (0.83) | 3.40 (0.51) |
| 8. I found the system very cumbersome to use. | 1.13 (0.35) | 1.20 (0.56) |
| 9. I felt very confident using the system. | 3.33 (0.90) | 3.40 (0.74) |
| 10. I needed to learn a lot of things before I could get going with this system. | 2.80 (0.68) | 2.93 (0.46) |
| **Overall SUS Score (calculated as per Sauro (2011))** | **70.5 (3.92)** | **68.3 (3.62)** |

The overall SUS scores in Table 6.4 were calculated with reference to the practical guidance developed by Sauro (2011). The raw score for each statement was firstly converted to a new number on a normalised scale of 0 – 4. For odd-numbered, positively-worded statements, the normalised score is the raw score minus 1. For example, for the 1st statement, if the respondent answers 4, the corresponding normalised score is 3. For even-numbered, negatively-worded statements, the normalised score is obtained by subtracting 5 from the raw score given by the respondent. For example, if the respondent answers 3 for the 2nd statement, then the corresponding normalised score is 2. Once the normalised scores have been calculated, they were summed and multiplied by 2.5 to obtain the SUS score between 0 and 100.

Generally, SUS score above 68 were considered to have above-average usability. The mean SUS score of ASD group and TD group was 70.5 and 68.3 respectively, over the average SUS rating of 68. According to the practical guideline on the interpretation of SUS score (Sauro, 2011), a score above 70 suggests that the user-friendliness is good.

## 6.4 Implications

The system evaluation results suggest the benefits of *Roomie* for preschool children with ASD in real-life classroom settings. *Roomie* could provide overall correct detection on attention and stress levels of children with ASD, identifying distraction and anxiety situations. Statistical analysis reveals that the application of sensory regulation strategies recommended by *Roomie* has positive impact on children's sensory regulation in class, improving their attention level and reducing stress. The results of SUS survey suggest that caregivers of children with ASD generally contend that *Roomie* beta version is user-friendly and various functions, such as real-time monitoring, detection, alert and strategy making, are well integrated.

The feedback obtained from users in the evaluation reveals that such a sensor and AI-based system could work as an efficient 'specialist' companion in real-life classroom settings for children with ASD. *Roomie* effectively senses children's environment, detects their attention and stress, and provides sensory regulation strategies to help mediate negative affect of unfriendly environment.

Besides, successful release of *Roomie* beta version on TestFlight allows continuous test of the system and data collection in children with ASD. In this evaluation study, the age of participated children only ranges from three to five, while the targeting users of *Roomie* are children with ASD aged from three to ten. Theoretically, every iPhone user can install *Roomie* on their phone, which means that replication of the evaluation in a sample with wider age range is feasible. *Roomie* could also be tested for other sensory-related disorders in the future. With increased data size and accumulation of true labels, ML algorithms can be further trained to improve detection accuracy. Considering the moderate effect size of the *Roomie* intervention in an ASD group which sample size is still limited, further efforts could be made to expand the Strategy Knowledge Base by adding more effective intervention strategies, and to involve more participants in the evaluation.

Moreover, the author has noticed a slight increase of C-TRF scores in the *Roomie* session 1 compared to the no-*Roomie* session. The increased C-TRF scores suggest that sensors that touched the body of the child have made the child stressful or more easily distracted to some extent. Therefore, the acceptance of the wearable devices by children with ASD needs to be fully discussed in Chapter 7. Moreover, the implications for future development and research will be discussed in Chapter 8.

Overall, in this chapter, a complete *Roomie* beta version has been released and evaluated, integrating all the desirable functions that the author has discussed in Chapter 4. It meets the iOS distribution standards, helpfully collecting data, preprocessing data and delivering it to the embedded AI algorithms for detection and strategy-making, and providing timely feedback to users in an easy-to-understand visual way. Unlike many previous studies in which the proposed systems were only tested in a lab setting, *Roomie* is open to real end-users, enabling real-life application and large-scale evaluation.

# Chapter 7

# Discussion

This chapter first reviews the research questions (RQs) formulated in the beginning and summarises the answers in response to the RQs. It is then followed by broader discussions on the improvement of artificial intelligence (AI) algorithms, and reflection on the acceptance of wearable devices among children with Autism Spectrum Disorder (ASD). The author has a detailed discussion of other existing technologies for sensory regulation in ASD. By comparing *Roomie* with existing technologies, the novelty and significance of this research is established.

## 7.1 Revisiting the research questions

The overall aim of this research is to create an innovative sensor and AI-enabled system to assist children with ASD, providing appropriate real-time sensory regulation strategies as needed. In Chapter 1, the author has proposed the following three RQs:

RQ1. What are the components and functionality of the system that match the needs of children with ASD?

RQ2. What AI algorithms can be embedded in such a system to better support monitoring of atypical sensory responses and to generate suitable sensory strategies?

RQ3. To what extent can the sensor and AI-enabled monitoring system developed for the purpose of this research effectively deliver those intervention strategies to support sensory regulation in children with ASD?

Children with ASD are the target users and above RQs all have emphasised the necessity to take their needs into account. Therefore, user centred framework and iterative design process have been used throughout this research to ensure the proposed system evolves based upon the user needs, technical capabilities, and feedback input by users. Each RQ has been addressed in detail in the associated chapter(s). The following sections discussed and summarised findings related to the RQs.

### 7.1.1 Answers to RQ1 – What are the components and functionality of the system that match the needs of children with ASD?

Children with ASD and their caregivers have been centred in this project. The author has worked closely with them and designed the functionality of *Roomie* considering their needs. Besides, an advisory panel of ASD specialists has also been approached to provide professional feedback regarding the design. Involvement of professionals and end-users in the design process is essential to ensure that the final *Roomie* is acceptable by the ASD community, and can be easily used by the children with ASD, providing effective interventions for them. The user needs investigation leads to initial design specifications, while the whole design and development process is iterative with the feedback from users and ASD panel feeding back into the loop for the next iteration. Each version of prototype has been used by users in experiment or data acquisition sessions with ASD specialists observing the sessions. This process continuously provides information on bugs in the system that require fixing, until *Roomie* has complete functionality, usability and robustness for it to be fully tested in the final evaluation study.

Because many of the ASD specialists and users are not computer science professionals, the author has to decide the use of technologies, and design the interface through research and experience. Nevertheless, the selection of technologies generally matches the user needs and project budget. By investigating most common environmental features that affect children with ASD, commercially available sensors that can accurately monitor these features have been explored, including temperature and humidity sensor, light sensor and sound sensor. Similar to previous studies, physiological features, such as heart rate, Galvanic Skin Response (GSR) and hand movements have been used as some key parameters to assist the AI modelling. Data transmission has been achieved based on a Bluetooth Low Energy which eliminates the need for Internet in the first place.

ML algorithms have been used to analyse sensor data and children's Sensory Profiles (SP) to determine the child's attention and stress levels. Fuzzy logic (FL) algorithms have been used to provide appropriate feedback and strategies as needed. The ML-FL algorithm has been deployed locally to implement intelligent strategy-making, reducing network communication delays and data computation delays, and improving the system's responsiveness, privacy, and stability.

Other design specifications considered by the author include text alerts, data visualisation, and data security. *Roomie* allows for automatic Short Message Service (SMS) alerts to notify caregivers to act on timely. The system is expected to have a visual interface that displays real-time environmental data, physiological data, and feedback information in a user-friendly way, facilitating observation and analysis by caregivers or other potential guardians. The author has adopted security measures to protect the privacy and data security of children, complying with relevant Chinese laws, Apple Developer criteria, and university's ethical standards. *Roomie* can be used without a requirement of providing identifying information nor sending data to cloud server to make sure that no personal information will be disclosed.

### 7.1.2 Answers to RQ2 – What AI algorithms can be embedded in such a system to better support monitoring of atypical sensory responses and to generate suitable sensory strategies?

Once the *Roomie*'s monitoring function was complete, the data acquisition using the monitoring function of the prototype was performed on 35 children with ASD at a local rehabilitation centre for several months. Data have been labelled by ASD specialists and task performance scores. Environmental, physiological and SP features were found to be effective predictor variables that can determine the levels of attention and stress in ASD. Several supervised ML algorithms, which have been widely-applied in attention and stress detection studies, were applied to train the acquired data.

Evaluation of ML algorithms indicates that ML algorithms have overall good detection performance. Most models could process an input within 0.1 ms on a laptop central processing unit (CPU), suggesting that they are suitable for local deployment on a mobile phone device of which the CPU is now as fast as that of a laptop. Gradient Boosting Decision Tree (GBDT) algorithm significantly outperforms K-Nearest Neighbours (KNN), Artificial Neural Network (ANN) and Random Forest (RF) algorithms on attention detection with the highest accuracy and F1-score. RF algorithm has higher accuracy and F1-score than ANN and GBDT on stress detection. Therefore, GBDT and RF with the highest accuracy and generally short inference time, are chosen to be embedded into the *Roomie* for attention and stress detection respectively.

Real-time data collected by sensors and detection outcomes are further processed through another local processing module where a FL algorithm is implemented. FL is employed because it is a very classic and easily implemented method which can imitate an expert's strategy-making mechanism. It takes the best decision for the given conditions based on some set of rules.Three independent FL controllers have been designed to process environmental information and atypical sensory responses detected by sensor fusion. Inputs to the FL controllers include sensory stimuli (i.e., temperature, brightness, and noise), duration of atypical sensory responses, attention and stress level. Suitable membership functions have been used to fuzzify the inputs. The Largest of Maximum defuzzification method which yields accurate results as expected has been adopted. The output of FL is an evaluation of risk levels. When the FL returns a 'High Risk' output, then *Roomie* identifies the triggering sensory input and recommends a proper sensory regulation strategy. The implementation of FL in *Roomie* enables the automation in strategy-making and lays the foundations for continuous refinement when a greater number of FL rules are validated and added in the future.

### 7.1.3 Answers to RQ3 – To what extent can the sensor and AI-enabled monitoring system developed for the purpose of this research effectively deliver those intervention strategies to support sensory regulation in children with ASD?

A beta version of *Roomie* has been released since February 2022, and an evaluation study has been conducted in real life settings. In the evaluation study, caregivers were involved to observe the ML detection results and reported in the App if the detection results did not match the reality. Besides, a standardised performance measurement tool, Caregiver-Teacher Report Form, was used to allow caregivers and teachers to report children's overall attention and anxiety. The author adopted this method, using both ASD teachers and caregivers' rating for assessing system effectiveness, because caregiver-only measurements may not be enough for accurate evaluation. Caregivers, who have not received any ASD training, or were biased by parental relationship, were likely to provide inaccurate ratings. Therefore, the approach the author adopted was more robust. Both caregivers and teachers revealed significant performance improvements in the ASD group between the no-*Roomie* session and the *Roomie* session 2. Effect sizes (Cohen's $d$) evaluated by teachers were slightly larger than those evaluated by caregivers in the ASD group. This result indicates that the proposed sensor and AI-enabled system shows effectiveness in detecting atypical sensory responses and generating useful sensory regulation strategies. By providing professional and timely sensory regulation strategies, it is an effective tool that can help with the regulation of attention and stress levels of children with ASD.

Involving various families who suffered from ASD and testing *Roomie* in real-life settings are necessary as caregivers and children with ASD are the main users who will finally use *Roomie* in daily life. Observation by caregivers allows the author to evaluate the utility of the system. System utility survey has been completed by caregivers after sessions of use of the system. System Usability Scale, a standardised questionnaire has been used to measure user's perceived usability and satisfaction of a system. The results of system usability evaluation suggest that end-users generally agree that the system is acceptable, user-friendly and various functions, such as real-time monitoring, detection, strategy-making and alert, are well integrated.

## 7.2 Re-training machine learning algorithms using the updated dataset

The final evaluation study has brought new data from another 30 children with ASD, contributing to the update of the Sensory Dataset (SD). After true labels were given by the caregivers, the SD were expanded, containing data from 65 children with ASD in total. However, as noted in section 7.1.3, caregivers who have not received any ASD training, or were biased by parental relationship were likely to provide inaccurate labels. Therefore, the author did not use labels provided by the caregivers for further ML training. Instead, an ASD specialist from the advisory panel was recruited to go through video clips of all the *Roomie* sessions to provide expert labels.

Further ML training experiments using the updated training dataset were performed. ML algorithms discussed in Chapter 5 were re-trained. The experiment using the updated training dataset observed a noticeable accuracy improvement on attention detection when the sample size was larger, as shown in Table 7.1.

**Table 7.1:** *Performance of attention detection algorithms using original training set and updated training set*

| | **Performance using original training set** | | **Performance using updated training set** | |
|---|---|---|---|---|
| **Model** | **Accuracy (%)** | **F1-Score** | **Accuracy (%)** | **F1-Score** |
| KNN | 81.90 | 0.8319 | 93.30 | 0.9304 |
| RF | 79.05 | 0.8000 | 91.55 | 0.9104 |
| ANN | 80.95 | 0.8246 | 90.85 | 0.9058 |
| GBDT | 86.67 | 0.8772 | 92.61 | 0.9236 |

Using the updated dataset, all the ML algorithms obtained an accuracy over 90%. The increase in accuracy (13.9%) was more drastic in KNN algorithm, which yielded the highest accuracy (93.3%) among all the algorithms. This implies that KNN can outperform other algorithms when more samples are available. The optimal value of $k$ used in the updated KNN algorithm was still 3, which meant its accuracy improvement did not compromise on the computational cost.

Meanwhile, the accuracy of stress detection was also slightly increased. The increase was not as noticeable as that of the attention detection because the overall performance of previous ML algorithms on stress detection has already been good. Table 7.2 provides a comparison of performance on stress detection before and after using the updated training dataset. RF algorithm still slightly outperformed other algorithms, with an outstanding accuracy of 99.05%.

**Table 7.2:** *Performance of stress detection algorithms using original training set and updated training set*

| | **Performance using original training set** | | **Performance using updated training set** | |
|---|---|---|---|---|
| **Model** | **Accuracy (%)** | **Macro-F1** | **Accuracy (%)** | **Macro-F1** |
| RF | 98.82 | 0.9851 | 99.05 | 0.9904 |
| ANN | 96.89 | 0.9592 | 98.72 | 0.9839 |
| GBDT | 98.50 | 0.9812 | 98.94 | 0.9836 |

In addition to re-training the previous ML algorithms, the author also investigated the feasibility of using a deep learning (DL) method for prospective use which can achieve the same strategy-making alert without pre-defined rules.

Based on the available data collected from the final evaluation study, the author extracted data files of the sessions in which at least one sensory regulation strategy alert has been generated by *Roomie*. The 20-second record preceding an SMS alert was labelled as 'High Risk' in agreement with FL generated outcomes. 375 records of the 20-second interval labelled as 'High Risk' were extracted. Another 408 records of the 20-second interval that did not generate any recommendations on environment adjustment nor SMS alert, were labelled as 'Low Risk' in agreement with FL generated outcomes. All the extracted data were merged into a single data file, then transformed into a PyTorch tensor of type float32 and shaped to dimensions of **batch_size**, **sequence_length**, and **input_size**. The **sequence_length** was set to 20 because the interval of each record was 20 seconds. The **input_size** was 14 as all the 14 features mentioned in Table 5.1 were used.

A Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) was employed, which is a DL technique containing an input gate, a memory block, and an output gate with recurrent network connections (Staudemeyer & Morris, 2019). The memory blocks in LSTM are associated with input and output gates. Memory blocks are intriguing structures with input and output gates that regulate access, ensuring only relevant information enter or exit. Additionally, these blocks feature forgets gates that assess the importance of information stored in the cells. When certain information becomes irrelevant for specific cells, the forget gate resets its states within the block. This ability to forget previous states enables continuous time-series detection and helped prevent biases in detection.

The author used some commonly-seen parameters for DL training. The **learning_rate** was 0.001, and **hidden_layer_size** was 100. A Sigmoid activation function was used in the output layer. Epochs were increased from 0 to 100. Loss functions with Adam optimizer, which returned loss results together with accuracy, were used to prevent over-fitting. Figure 7.1 shows the training loss and accuracy trends of the algorithm. The LSTM-RNN algorithm finally yielded an accuracy of 98.81% on the testing dataset with training loss at 0.06 for 100 epochs. Compared with the ML-FL solution selected for *Roomie*, although DL algorithm presented high accuracy, the proposed ML-FL remained a prioritised method with rapid computation and low complexity. A combination of ML and FL algorithms enables the user to know both states of the children and the sensory regulation strategies. In the real application, ML algorithms provides overall correct detections on 'Distraction' and 'Anxiety' situations to remind caregivers. The rule-based FL algorithm is also suitable for interpreting the risk of anomalies which serves a role mimicking expert strategy-making. Since the DL algorithm discussed here yields excellent results in the absent of rules, it is also promising for future use. For example, it can be embedded in a simple meltdown detection system for children with ASD.

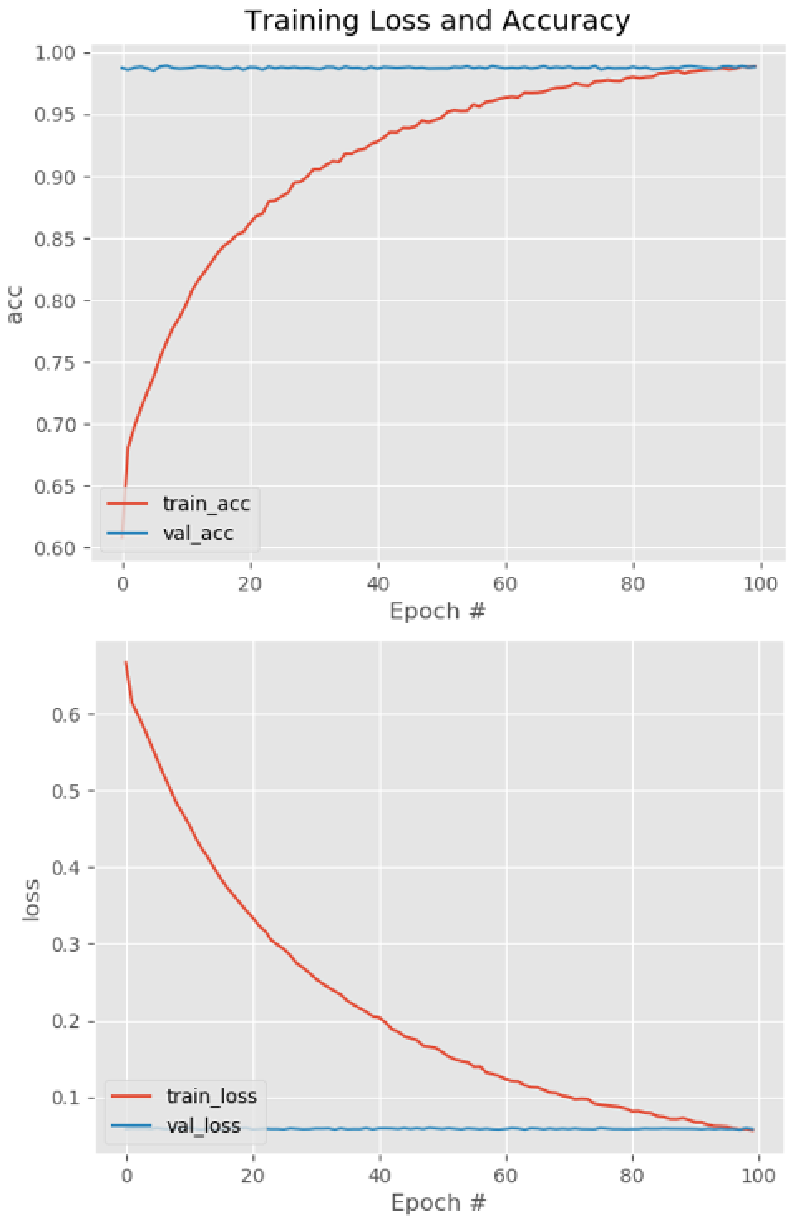



**Figure 7.1:** *Training loss and accuracy of LSTM-RNN algorithm*

## 7.3 Reflection on the acceptance of the wearable devices by children with ASD

In this research, the author has used multiple wearable devices, including an Apple Watch and a GSR sensor. The Apple Watch can be worn on the child's wrist, while the GSR sensor can be worn on the fingers. Initially, a Muse headband was also tried to capture Electroencephalograms (EEG) data, which should be placed on the forehead. However, in the testing where children were required to wear the devices, some children presented reluctance to put on the devices in the beginning and caregivers expressed some concerns regarding the use of wearable devices. The author and ASD specialists had to inform caregivers that theoretically the system can provide more accurate feedback based on data collected by these devices. With the help of caregivers and ASD specialists, children with ASD finally used the Apple Watch and the GSR sensor. However, children with ASD and their caregivers still showed low acceptance to EEG headband. Children with ASD always resisted it when the author tried to put it on. Caregivers insisted not to use EEG headband. Not only because children showed negative reaction to it, but also because it was too noticeable on the body, making children look atypical among their peers.

In addition, in the feasibility study, the GSR sensor that the author first tried was the wristband developed by Xinhua Net. During the testing, the child with ASD expressed discomfort with the heavy GSR wristband on their body. He also exhibited unintentional aggressive behaviours towards the device. It is true that many devices may contain easily damaged core components, such as CPUs and sensors. When the children become uncomfortable or even aggressive, they may damage the device, leading to increased maintenance costs that most families cannot afford.

Therefore, it was necessary to choose ASD-friendly devices as sensor solutions. The author assumed that the closer the device was to the clothing materials or the more imperceptible it was, the less impact it would have on children with ASD, and there would not be a strong resistance by caregivers. Comparing with existing head-mounted and heavy devices, light wristbands or clothing-like materials were selected for use in this research.

This is not a project undertaken by an expert in industrial design, therefore, the materials of wearable devices used in this project are less likely to be altered from the original design. However, the author conducted a short follow-up survey with caregivers investigating the materials that were preferred by their children. The survey results showed that cotton and silicone, were two of the most comfortable materials for children with ASD. Most caregivers contended that children with ASD would not feel depressed or unhappy due to wearing the cotton or silicone-made wristband. Some caregivers suggested that their children may be more engaged or more relaxed than before wearing the devices.

These follow-up investigations suggest that the author's current selection of wearable devices is generally acceptable. Both Apple Watch and Grove-GSR sensor use skin-friendly materials. The Apple Watch band used in this project is made by silicone. The wearable part of Grove-GSR sensor is made by cotton, like the glove worn by ordinary people.

Besides, to prevent potential damage to the sensors in the real practice, the author has tried several methods, including longer retractable wires and buffer protection shells to protect the core wiring and processing unit. However, the author admits that if there are aggressive activities, sensors' stability and reliability cannot be fully guaranteed. Therefore, although the author receives much positive feedback from the participants regarding the selected wearable devices, they are not perfect technological solutions. Their greatest value lies in being an auxiliary tool in the daily life for more accurate detection. For example, using Apple Watch and GSR sensors can collect heart rate and skin conductivity signals, which are strong predictive variables for detecting their children's anxiety in a timely manner.

## 7.4 Comparing with other existing technologies

In this section, the author compares *Roomie* with some other existing technology-based interventions (TBIs) that have been designed for sensory regulation in ASD. Table 7.3 lists *Roomie* and other studies reporting related technologies. As there are no previous studies that have utilised exact same materials and methods, comparisons mainly focuses on the system features and methodological quality.

**Table 7.3:** *Comparison with other existing TBIs*

| Reference | Technology Features | | | | | Methodology Quality | |
|---|---|---|---|---|---|---|---|
| | Sensory Profiling | Physiological Monitoring | Environmental Monitoring | Data Analysis | Strategy Making | Evaluation | ASD Sample in the Evaluation |
| This research | Yes | Yes | Yes | Yes | Yes | Yes | 30 |
| Khullar et al. (2021) | No | Yes | No | Yes | No | Yes | 10 |
| Reis et al. (2021) | Yes | No | No | Yes | Yes | Not reported | Not reported |
| Mauro et al. (2020) | Yes | No | Yes | Yes | Yes | Yes | 20 |
| Tomczak et al. (2020) | No | Yes | No | Yes | No | Yes | 20 |
| Coronato et al. (2014) | No | Yes | No | Yes | No | Not reported | Not reported |
| S. Ali et al. (2020) | No | Yes | No | No | No | Yes | 12 |
| Khullar et al. (2019) | No | No | Yes | Yes | Yes | Yes | 10 |
| Costa et al. (2015) | No | Yes | No | No | No | Yes | 8 |
| Sula et al. (2013) | No | Yes | Yes | No | No | Yes | 1 |

As shown in Table 7.3, it can be found that most technologies for addressing atypical sensory responses have similar monitoring modules. However, many of them do not profile users' sensory processing patterns and make recommendations on sensory regulation strategies to help users. There is evidence suggesting that sensory processing patterns are idiosyncratic in children with ASD (Tomchek et al., 2015). Moreover, the feature selection results in section 5.1.1 indicate that the inclusion of SP features could help ensure the performance of AI detection. Although many sensory profiling tools have been widely used in healthcare services, very few TBIs have involved these tools in the design.

The study conducted by Mauro et al. (2020) has considered the unique sensory processing patterns of children with ASD, which can impact their experiences in different environments. They proposed a personalised top-N recommendation model that combined users' sensory aversions and preferences to suggest the most preferable Points of Interest. The model aimed to strike a balance between user-specific compatibility and interest while integrating heterogeneous evaluation criteria. The article emphasised the importance of considering individuals' sensory preferences in Points of Interest recommendations and proposed a novel approach for personalised recommendations in the context of ASD. However, it remained at the theoretical level without delving into implementation details or discussing how it can be applied to ASD interventions.

Regarding data analysis, three studies (S. Ali et al., 2020; Costa et al., 2015; Sula et al., 2013) still depend on an ASD specialist's manual analysis, which will require the continuous involvement of human assistance. It complicates the use of technologies in daily life and increases the cost for ASD families. Seven out of ten studies in Table 7.3, including the author's, have used ML or cloud computing to enable data analysis. Most of them were published in or after 2019, suggesting an emerging trend of studies executing computation directly in the system. However, many systems fail to provide potential interventions or suggestions, with a focus still on the behaviour detection of children with ASD. They do not have a complete strategy-making modules, and ultimately still rely on educators or specialists for interventions.

Three studies (Khullar et al., 2019, 2021; Sula et al., 2013) similarly applied IoT technologies aiming at addressing atypical sensory responses of children with ASD. Sula et al. (2013) implemented and evaluated an IoT-based system which can encouraged children with ASD to tell their caregivers what they were interested in, what they needed, and possibly even their feelings. The system utilised the JXTA-Overlay platform and a sensor box to monitor children, and established peer-to-peer communication between the children, caregivers, and ASD specialists. However, this system was mainly used to teach vocabulary skills, mathematical skills, and other life skills, without a particular focus on sensory regulation.

Khullar et al. (2019) designed an IoT-based system for children with ASD who exhibited sensory hypersensitivity patterns. The primary method was the design of a multi-sensor hardware prototype named 'Assistive Companion for Highly Sensitive Individuals'. It gathered children's sensory-related information through sensors, made decisions based on the sensory information obtained via FL, and then transmitted the generated information to the Internet, and sent alerts to caregivers. Their system can also provide sensory regulation strategy to help with calming the children with ASD. Their study was the first study that embedded preliminary sensory regulation interventions, but they were not yet comprehensive, focusing only on hyper-sensitive children, thus lacking in broad applicability.

Khullar et al. (2021) recently proposed another meltdown detection system. It no longer relied on rule-based algorithms and expert knowledge for meltdown detection but adopted DL algorithms to process physiological data and classify the state of meltdown as 'active' or 'inactive'. Similar to the author's training results in section 7.2, the DL algorithm developed in their study achieved a high accuracy of 98%. However, this approach can only be used for meltdown detection and did not provide any sensory regulation strategies to address the meltdown.

Another recent study conducted by Reis et al. (2021) developed a mobile App for sensory regulation named 'Regul-A'. The App also used the SP questionnaire to classify the user's sensory processing patterns. It then recommended sensory regulation strategies to caregivers, helping caregivers regulate children with ASD regarding their activities in home routines. However, this App was analogous to a sensory regulation strategy toolkit for caregivers to obtain constant suggestions. It did not provide real-time monitoring nor strategies with the environment changes, and their testing results and effectiveness of the App have not been released yet.

To date, to the author's best knowledge, *Roomie* is the first work which combines standardised sensory profiling tool, sensor monitoring, data analysis and sensory regulation strategies in one low-cost system for supporting ASD families to deal with atypical sensory responses. The majority of the technologies discussed above only develop partial detection or strategy-making modules for sensory regulation, and do not provide a fully systematic solution. This research, on the other hand, offers an integrated technological approach from sensory profiling, detection to intervention. The research considers unique sensory processing patterns of users and collects their SPs using the system, which outfits wearable devices with a multitude of sensors to collect multidimensional data for stress and attention detection. Then, the strategy-making module determines the risk levels and relevant sensory regulation strategies with precise processing through the

FL algorithm. When certain anomalies are detected in a child's state, there will be recommendations of strategies to intervene and regulate their behaviours, such as deep pressure, or playing music, videos, and many more. These features highlight the novelty of the research. Moreover, one challenge for many previous studies is to evaluate the intervention with a large sample of individuals with ASD. Some studies only involve a few individuals with ASD in the evaluation or do not report evaluation. This research includes evaluation with a larger sample than previous studies following a well-defined protocol aiming to make the results more generalisable.

## 7.5 A framework for designing systems for special needs and its extensibility to other platforms

In this thesis, the author presents a user-centred participatory framework for designing and developing a TBI for children with special needs. The advocacy for using the proposed framework can be dated back to previous valid computer science and engineering research that focused on user experience to make a TBI useful in naturalistic situations (Benssassi et al., 2018). The methodology of this research reflected the author's decision to not only design algorithms to infer atypical sensory responses in children with ASD, but also to consider what sensory regulation strategies should be delivered, when, through what medium, and how effective. The framework requires several efforts ranging from user need investigation, large scale data collection, to implementation and evaluation to address the aims (Figure 7.2).

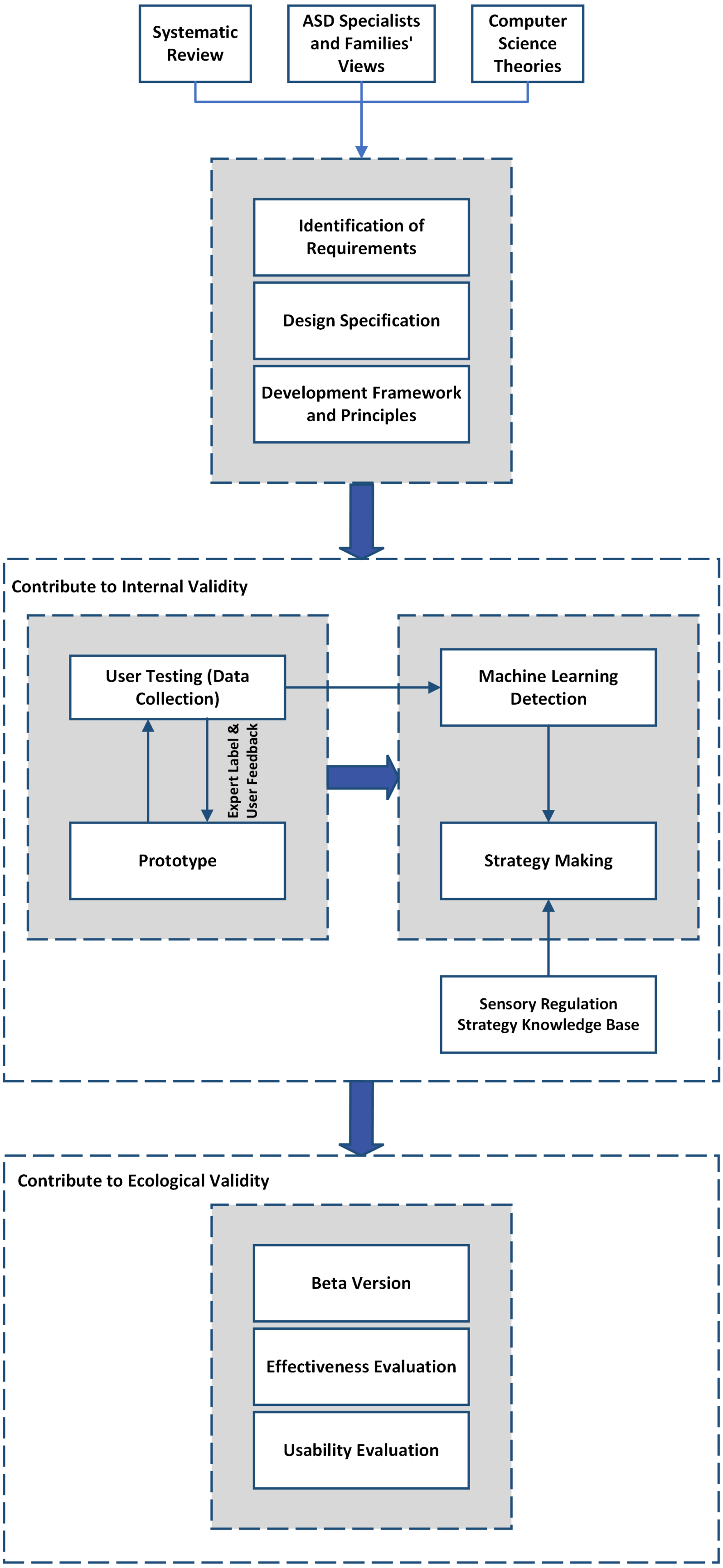



**Figure 7.2:** *Proposed framework for developing an effective system for children with ASD*

One gap that the author identified by reviewing previous research is the lack of long-term technology deployment in the ASD field, which prevents innovative technologies from going downstream to evaluation and implementation in the wild (Benssassi et al., 2018; Y. Huang, 2020). One reason is the long-term deployment often requires social acceptability and trust from the stakeholders. Therefore, the author felt an urge to apply the iterative development process within the framework, which allowed the author to quickly establish the feasibility and acceptability of the system with continuous fine-tuning and feedback loop.

Developing a cross-platform system can make the implementation particularly time-consuming and challenging because it will require more testing and validation of the hardware supported by different operating systems. Not always the reliability of one version for a specific platform could be maintained in other versions. For example, the iOS heart rate sensor is incompatible with an Android phone. For *Roomie* to be deployed on a non-iOS device, some sensors should be replaced and re-tested. Therefore, with the iterative aim, it is acceptable to carry out the development on one available platform first and summarise the process of development into a systematic framework to inform future cross-platform deployment. Various existing tools can be used to run Swift iOS applications on Android devices without much rewriting of the code for user interface or functionality, such as Mutata (Kodika.io, 2021). The extensibility of *Roomie* lies in its replicable framework which can provide detailed guidance for cross-platform deployment and evaluation.

# Chapter 8

# Conclusion

This chapter details the main contributions of the author's work to the Autism Spectrum Disorder (ASD) and computer science fields as well as contributions to a wider application of such a sensor and artificial intelligence (AI)-enabled system in broader areas. Although *Roomie* has been developed, showing the effectiveness and usability of the proposed innovative system, there are still some limitations existed in the current research. Therefore, the challenges and limitations of the research are presented in this chapter. This chapter ends up with implications for future research and a summary of works conducted in this PhD research.

## 8.1 Contributions to the field

### 8.1.1 Identification of gaps in current knowledge

The systematic scoping review of related work finds that most technologies nowadays take advantage of sensors for environment monitoring in ASD. However, many of them fail to profile users' sensory processing pattern and make recommendations on sensory regulation strategies to help users. Regarding data process and analysis, many recent studies published in or after 2019 have used machine learning (ML) and rule-based algorithms to enable on-device data analysis. However, by the time of thesis writing, no prior study has combined standardised sensory profiling tool, real-time monitoring, data analysis and sensory regulation strategy-making in one low-cost system for supporting ASD families to deal with sensory regulation issues. There is little knowledge of the feasibility and effectiveness of such a system.

The author concludes that overall, the way current technology-based interventions (TBIs) addresses atypical sensory responses have three preferred forms. One form is using stimuli amplification techniques, such as sound amplification system, virtual reality and head-mounted display. In these cases, TBIs usually act as a medium between stimuli sender and receiver to augment sensory input and to facilitate children with ASD to sense. However, these TBIs may cause sensory overload in ASD if there are no clear instructions on how long they can be used by children with ASD and how many additional stimuli they should provide. Therefore, these TBIs are only suitable for children with ASD who are hypo-sensitive to stimuli.

Another form is more interactive and inclusive through assistance of robots or Internet of things. These TBIs generally take advantage of multimodal system and intelligent human-computer interaction to make the interventions adaptive and interactive, capturing the information from the user and providing timely responses. Some are even humanoid that act as a real-world friend for children with ASD. However, most of these TBIs can be very expensive and are only available in educational and clinical settings. Many ASD families from remote areas do not have awareness of and access to these high-end TBIs, which prevents them from seeking the help of technology, even though some products have been proven to be effective.

On the other hand, it is found that software Apps that can be easily deployed on the mobile devices have great potential in the development of TBIs for children with ASD. They can enable individuals with ASD as well as their family members to access professional services and information at anytime and anywhere to address a variety of problems (Koumpouros & Kafazis, 2019). In China, software Apps designed specifically for individuals with ASD have also emerged, although many applications are used merely as platforms on which users share experience and information with others while receiving knowledge about symptoms, diagnosis, potential interventions and relevant services.

The author has evidenced that there is a lack of low-cost and easy-to-use TBIs targeting atypical sensory responses of children with ASD in their daily lives. Sensing technologies are essential towards addressing the research and development gaps within computer science and ASD areas. Mobile devices and Apps that can use sensors are vital with great potential in the TBI development nowadays. The detection of atypical sensory responses requires not only the application of sensing technologies, but also AI techniques to convert data to meaningful information. These technologies can be integrated in one system, made affordable and valuable for monitoring, detecting, providing professional sensory regulation strategies for daily use.

### 8.1.2 A comprehensive system suitable for sensory regulation in children with ASD

In the current technological field, most of the research tends to focus on using sensors and AI algorithms for the ASD diagnosis or emotional assessment. For example, deep learning (DL) methods have been employed to analyse the neuroimaging data of children with ASD for diagnosis. Neuroimaging data are the brain signals that obtained by neuroimaging techniques such as Electroencephalograms (EEG) (Erol & Hunyadi, 2022). EEG data can also be used for analysing emotional states of a child with ASD and determine whether they are in an abnormal emotional state. However, there has been relatively little research focusing on providing a sensor and AI-based system for intervention purposes. Systems developed to provide interventions targeting atypical sensory responses in children with ASD are even rarer. There has been a lack of computer science research on systematically capturing, analysing and providing reasonable intervention strategies for sensory regulation. There is also a lack of grounded work that fully considered the needs of Chinese ASD families in the development process. This research fills the previous research and development gaps by introducing an effective TBI for sensory regulation in ASD. The *Roomie* system not only serves as an innovative and distinct TBI, but also a scientific tool to explore the research questions put forward by the author in this research.

The entire *Roomie* system can be divided into three main modules: a monitoring module based on sensors such as watch accelerometer, heart rate sensor, temperature sensor and light sensor, an AI-enabled data processing module with on-device ML detection algorithms and fuzzy logic (FL) strategy-making algorithms, and a feedback generating module within a well-programmed App on visual devices such as iPhones and Apple Watches.

For the monitoring module, the author proposes an infrastructure that combines multiple sensors for fusion analysis. For example, the watch accelerometer can be used to capture hand movement data and analyse whether the child is in an atypical state. The light sensor module can monitor the light intensity in the room and provide feedback adjustment when the light intensity exceeds the comfort zone. The author also uses the Grove-Galvanic Skin Response (GSR) sensor, which can be worn in an imperceptible manner to capture the child's stress level. Various sensing technologies work together to collect comprehensive sensory-related information of a child with ASD. The author has streamlined the wiring as much as possible, using a single skin-friendly wire instead of complex point-to-point connections. Additionally, the author has chosen wearable devices of which the materials are mostly comfortable to children with ASD to minimise potential negative impact on the child's normal state. Otherwise, the sensors will become a hindrance and not serve any substantial purpose.

Secondly, the author programmes AI algorithms for the development of the data processing module. The iPhone device receives and stores data captured by the sensors, which can be analysed using ML algorithms to detect the child's atypical sensory responses such as abnormal attention and stress levels. FL algorithms further process the detected atypical sensory responses and environmental stressors to make a recommendation on sensory regulation strategies.

Apart from monitoring and data processing, feedback in the form of graphs or messages is provided through an iPhone-based App with a user-friendly interface. The development of *Roomie* App considers the Chinese ASD families' needs for a low-cost, private, and informative system in dealing with a child's atypical sensory responses. The author seeks ASD specialists' advice in a number of iterative phases with consequent refinement and programming of the App to ensure that *Roomie* is an ASD-friendly and ASD-acceptable system.

Through the above-mentioned three modules, *Roomie* is proven to be effective in real-time monitoring of children with ASD and can function as a professional therapist or an intimate friend to children with ASD. Although some previous research has focused on individual modules, this research organically combines these modules using techniques explored through practical experiments. Instead of solely relying on ASD service providers for intervention delivery, the overall *Roomie* system can be used to assist in at-home or at-school interventions for children with ASD in a companion-like manner.

### 8.1.3 Real-time detection and strategy-making: Local ML-FL

In this thesis, the author analyses the performance of various ML algorithms in processing sensory-related data for detection and classification. When conducting such ML training, it is crucial to utilise ASD datasets as the capability of ML algorithms heavily rely on the richness of input data. However, current public ASD datasets are very limited. The most comprehensive free ASD-based dataset is the Autism Brain Imaging Data Exchange dataset which contains data from more than 1,000 individuals with ASD (Di Martino et al., 2014). However, this dataset only contains the geographical information and neuroimaging data, thus is more suitable for detecting diagnosis. Some other EEG datasets are also available

(Tawhid et al., 2020). However, their sample size is relatively small. Similar to the Autism Brain Imaging Data Exchange dataset, the features of these EEG datasets are more suitable for detecting diagnosis.

Therefore, in this research, the author has collected a first-hand ASD dataset. The first dataset contains data from 35 children with ASD, consisting of 29 features (15 features obtained by the iPhone sensors, 4 features obtained by the Apple Watch sensors, 4 features obtained by the external sensors, 4 features obtained by the SP questionnaire, and 2 features relating to gender and age). The raw dataset contains more than 150,000 rows of data. These data have been preprocessed in order to extract features useful for classification and detection. The feature selection finally yields 14 and 13 effective features for attention and stress detection, respectively.

The author has comprehensively analysed the performance of different ML algorithms and found that the Gradient Boosting Decision Tree (GBDT) algorithm had a short processing time and higher accuracy on attention detection, while the Random Forest (RF) algorithm had similarly better performance on stress detection. Therefore, GBDT and RF are suitable for real-time attention and stress detection respectively. After training the ML algorithms, the author did not directly deploy them on cloud servers but used Core ML framework to embed ML algorithms fully on-device. With more true labels collected through daily use, on-device training is possible, and ML algorithms can be replaced automatically by the personalised algorithms.

A FL algorithm has been developed to achieve strategy-making function. Before developing FL algorithm, focus groups consisting of ASD specialists have been consulted in order to discuss sensory regulation strategies that should be included in the App and rules to generate them. The FL algorithm has been validated by comparing simulated results with 'expect results' made by ASD specialists. When FL generates a 'High Risk' output, *Roomie* App will implement the generation of sensory regulation strategies. If users activate the automatic Short Message Service (SMS) text alert function, *Roomie* will send the sensory regulation strategies to the respective caregivers via SMS messages.

The author has used Python Application Programming Interface to embed FL algorithms locally as well. Fuzzy rules can be easily maintained and adjusted by a programmer if more rules and sensory regulation strategies are validated by ASD specialists. Replacement of the FL algorithm can be achieved simply by updating the App on the phone.

By embedding ML and FL algorithms on local devices instead of interacting with cloud servers, network latency can be reduced. The detection and strategy-making components are directly embedded locally, avoiding the process of uploading data to servers for computation, significantly reducing the delay caused by network uploading and improving system responsiveness. Moreover, due to the unavoidable instability of networks, remote processing centre on cloud servers may occasionally be inaccessible. For children with ASD who have difficulties in sensory regulation, system malfunction may be extremely serious and can lead to the inability to timely detect and regulate their current behaviours. The development of *Roomie* has fully considered potential barriers of children with ASD and ensured that the system can constantly perform well, thereby providing better user experience for ASD families.

### 8.1.4 Systematic evaluation

Although it is recognised that the use of technologies in ASD can be really helpful in many domains such as behavioral and sensory regulation issues (Koumpouros & Kafazis, 2019), TBIs are still generally perceived as emerging treatment for ASD rather than established treatment according to the 2009 and 2015 review of intervention for ASD (National Autism Centre, 2009, 2015). This means that many TBIs may produce favourable outcomes, while their effectiveness still remains a matter of debate. The scoping review of TBIs conducted in this research suggests that the effect of TBIs on atypical sensory responses is only reported in a handful of studies. Small sample, short-term assessment, lack of statistical analysis in many previous studies make them difficult to strengthen the results. Caregivers participating in the user needs investigation of this research have showed concerns about the effect of a particular TBI. ASD specialists in the user needs investigation agreed that they normally would not apply technology-based approaches or recommend a TBI to the clients if they were uncertain of the effect of particular technologies. It is apparent that TBIs for atypical sensory responses in ASD are a significant area in which the effectiveness of TBIs needs persistent investigation. Unlike many previous studies focusing only on the design and testing in a lab setting, the author has conducted a real-life evaluation of the *Roomie* system. Therefore, another important contribution of the author's work is produced through the systematic evaluation of effectiveness using a psychological protocol.

The evaluation study has been performed with 30 children with ASD and typically developing (TD) children to assess the functionality of the *Roomie* system, including its accuracy, efficacy, and user-friendliness. An AB study design has been employed, where baseline/non-intervention phase (A) preceded intervention phases (B). Standardised attention and anxiety performance assessments have been conducted. The beta version App has been released for easier access of *Roomie* for teachers and caregivers who participated in the evaluation study. The statistical analysis results suggest that the use of the *Roomie* system has positive impacts on children's performance in attention and stress domains. The caregivers have been excited with the important features of the *Roomie* system and contended that its design was user-friendly. Their feedback suggests that various functions, such as real-time monitoring, detection, alert and strategy making, have been well integrated in *Roomie*, making it a reliable companion for children with ASD and caregivers that helps with sensory regulation by recommending proper strategies in relation to the real time information about the children's environment.

## 8.2 Challenges and limitations

### 8.2.1 Sensor fusion

Although the author has achieved significant advances with the deployment of a substantial number of sensors on the proposed system, it is crucial to acknowledge that physical hardware remains vulnerable to potential damage. This susceptibility can stem from unexpected behaviours of a child. For example, a child may accidentally hit a sensor while engaged in play, or forget to remove the sensor before washing their hands. In the throes of various physical activities, sensors can incur damage, threatening their functional integrity. Since *Roomie*'s detection and strategy-making functions heavily rely on the data collected by these sensors, its ability to accurately monitor children with ASD could be severely compromised if the sensors are too fragile.

Therefore, if a child accidentally knocks a sensor against a table corner, thereby causing a malfunction in one of the sensors, then such malfunction would require the replacement of the broken sensor. Although the current design has modularised the sensors, which means that the specific damaged sensor can be replaced individually, the reality is that most households may still be unwilling to routinely replace the individual sensors. Therefore, more robust sensors that are less prone to damage could be permanently integrated into the design.

Despite the efforts to counteract sensor damage, the sensor components still face a significant challenge pertaining to the reliability and accuracy of the data detected by these sensors. Environmental conditions can exert varying influences on sensors. For instance, if a child accidentally splashes water onto the sensor device, it might cause the humidity or GSR sensor to register a more-than-actual level, resulting in data deviations. A child might be calm, yet *Roomie* could interpret his/her states as being overly stressed. Such incorrect interpretations could lead to confusing feedback and sensory regulation strategies for users.

To proactively tackle these challenges, further efforts can implement a strategic deployment of sensors throughout the home. This could include humidity sensors, temperature sensors, and light sensors strategically placed in areas where children with ASD engage in activities. By establishing multiple clusters of these sensors within the indoor areas, the veracity of the *Roomie* sensor data can be validated. If an above-mentioned situation happens that leads to a dramatic change in humidity due to handwashing, *Roomie* can immediately check the room's actual conditions. If a hardware anomaly is identified, such as a saturated humidity sensor or a covered light sensor, *Roomie* could alert the user to replace or verify it, while simultaneously suspending data analysis and capture from that sensor.

### 8.2.2 Limitations on the dataset

Although the author has collected a large dataset to train the ML algorithm, the dataset does not include children who are extremely sensitive to tactile stimuli. This is because most children who are sensitive to touch display aversion to wearable devices. Keeping them wearing the wearable devices presents a huge challenge. Therefore, many caregivers have to withdraw their tactile-sensitive children at the early stage. In the final evaluation study, tactile-sensitive children were less involved, which made the sample slightly biased. Limited involvement of tactile-sensitive children presents a major limitation of the research that their responses may not be accurately identified through the current ML algorithms. Besides, the effectiveness of *Roomie* on tactile-sensitive children is unknown.

This also reveals a limitation of using wearable devices for *Roomie.* Even though *Roomie* attempts to use the skin-friendly and comfortable materials, achieving complete comfort remains a formidable task. In the evaluation study, the author noticed a slightly worsened classroom performance of children in *Roomie* sessions compared to the no-*Roomie* session, suggesting that sensors that touched the body of the child might make the child stressed or more easily distracted. To mitigate potential discomfort in children with ASD, further efforts will be needed to seek sensors with minimal touch on the body.

The results of evaluation study in this research only report a moderate effect size of the *Roomie* intervention in an ASD group which sample size is still limited, further efforts could be made to expand the Strategy Knowledge Base by adding more effective intervention strategies, and to involve more participants in the evaluation.

Another limitation of this study relates to the restricted condition and age range of the users. The children with ASD in this study were all recruited from rehabilitation centres who had a formal diagnosis of ASD. However, the severity of their condition (low-functioning or high-functioning) was not confirmed, partially due to lack of detailed diagnosis of the severity. The author tried to minimise this limitation by recruiting participants from different classes catering for children with different levels of ability. There was a mix of low-functioning and high-functioning children involved in the data collection. The Sensory Profile (SP) questionnaire used by *Roomie* is for children aged between three and ten only. The age of children involved in this research ranges from three to seven. However, sensory regulation issues in ASD may last throughout an individual's life. Using adolescent SP questionnaire and replication of the research with other age groups would increase the utility of the *Roomie* system.

Each individual with ASD is unique. The ultimate solution to address the limitations on the dataset is to continuously reach out to more ASD families and involve children of any sensory processing patterns. This would not only contribute to the increasing of ML detection accuracy, but also ensure that the *Roomie* system can be widely applied in most families of children with ASD, regardless of their sensory processing patterns or severity of symptoms.

## 8.3 Future work

### 8.3.1 Handling missing data and data security

For a system involving the use of remote wearable devices, missing data can come from a child with ASD choosing to take off a certain sensor, the battery on a device running out, or signal interferences. Missing important feature data will lead to a decrease in detection sensitivity and accuracy. Therefore, future work will focus on developing and validating theoretically-informed method to handle the missing data. For example, Dempster Shafer theory is a promising theory that works well in dealing with imprecise data (R. Li et al., 2022). The fundamental proposal of the theory is that the missing data can be replaced by a range of values, the lower and upper bounds of which are assigned by a degree of belief. Available input data streams are then fused to produce the probability of an anomalous event of interest, such as stress. Missing data can be examined using a set of techniques, such as a conditional Gaussian distribution with probabilistic correlations (Sagha et al., 2021), or joint distribution estimations based on dependency (Gilula et al., 2006).

Privacy concerns, particularly for those children whose privacy-sensitive data will be captured by the technology, are one of the major barriers identified when the author interviewed potential users. In the current design, the data processing takes place locally, rather than in the cloud, to ensure the ultra low-latency data processing and high data security. The current version does not require any identifying information, and therefore, is relatively low in privacy risks. However, in the future, if the system is connected into a smart home system or a smart healthcare system giving rise to higher privacy risks, the integration protocol should focus on security mechanisms to protect the privacy of people. For example, defence strategies should be applied, such as rigorous authentication and intrusion detection system. A new computing paradigm, edge computing (Pérez et al., 2022), which limits the data processing at the edge of the network to alleviate some of the privacy risks, could be an ideal computing infrastructure for the future system. However, there are potential privacy concerns in edge computing that have not been comprehensively studied. For example, due to the involvement of large number of edge nodes and terminal devices in the edge computing environment, these edge nodes may leak users' personal information during data collection and may not support complex security mechanisms (Yao et al., 2023). Future work will discuss the feasibility of an edge computing-based system, from a privacy point of view.

### 8.3.2 New ideas and wider application: It's not an end

Time constraints on the project mean that the current *Roomie* system cannot fulfill all the user needs identified in the user needs investigation. In the future, the author hopes to integrate the *Roomie* system with smart home control. A smart home is a popular technology nowadays that automates the operation of connected smart devices to the monitored environment using predefined responses or by using an intelligent strategy-making system (X. Zhang et al., 2022). For example, recently, in many households, smart curtains, smart speakers, and smart TVs are ubiquitous. For smart devices that are embedded with intelligent chips and interconnected, one of their functions is to receive commands from users and then give certain feedback actions. A very normal scenario can be: a person says 'turn on the TV' to a smart speaker, and the speaker recognises the voice, transmitting the signal to the processing module of the smart TV to perform the operation. It is also possible to let a strategy-making system like *Roomie* provide commands for the smart home control centre. Therefore, the nature of smart home technology makes it a suitable platform to support the wider application of *Roomie*. For example, when the room lighting is dim and the child with ASD is affected, *Roomie* can analyse the condition and determine that there is a need to increase the room brightness. It can then send feedback instructions to the smart home control unit inside the room to increase the brightness or open the curtains. Similarly, if the room is too cold and causes discomfort of the child, the smart home control unit can open a heater based on *Roomie*'s detection results to maintain the room's environment in a most suitable condition for that particular child with ASD. This kind of regulation also needed to be customised based on the specific user, learning and analysing the optimal feedback state for them (e.g., whether it's turning on the lights or opening the curtains that the child likes the most), and automatically selecting the best strategy that is preferred by the child, beyond relying on human manipulation.

Despite the fact that *Roomie* is originally designed for supporting the sensory regulation in children with ASD, it can also be applied to a wider user group. For example, ML algorithms can be modified for different applicable groups. The wearable devices do not need to be replaced. The only changes that the future development needs are in the internal detection and strategy-making logic.

For example, *Roomie* can also be adapted to provide significant support in the care of people suffering from Alzheimer's disease. By having individuals with Alzheimer's disease wearing sensor devices and modifying the core ML algorithms to recognise abnormal behaviours, reasonable feedback and regulation strategies can be provided. For example, if it is detected that an old person suffering from Alzheimer's disease frequently wakes up at night or wanders around the house, the *Roomie* system can tell their caregivers to help them calm down and go back to sleep by dimming the lights or playing soft music. In addition, a diary module can be added to *Roomie* to assist people suffering from Alzheimer's disease in maintaining daily life routines by reminding them to perform daily activities (such as taking medicine or drinking water).

For children with Attention Deficit Hyperactivity Disorder (ADHD), *Roomie* can be extended to facilitate a better learning and entertainment environment based on their sensory processing patterns. *Roomie* can help the caregivers monitor the attention and stress levels of a child with ADHD. If a child appears to be anxious or impatient when completing homework, *Roomie* can alert their caregivers to take some regulation strategies. *Roomie* can also help them refocus by changing the environment, such as adjusting the light intensity or playing relaxing music, with the help of smart home technology.

Moreover, future development of *Roomie* should consider that there may be more than one child with ASD in a household who have sensory regulation issues. Therefore, *Roomie* in the future should be capable of allocating space in the system for each child and process the data independently for different children. However, if multiple children with ASD are in a same environment, according to their sensory processing patterns, *Roomie* may generate different strategies. *Roomie* should be made more intelligent, providing personalised sensory regulation strategy for one child while not compromising the comfort of the other child. Data from different children in a same environment can be collected to estimate the loss and gain in comfort associated with the strategy or mix of strategies. An additional optimisation algorithm can be applied to select a most suitable strategy, such as the strategy that will lead to the fewest discomfort among multiple children. From a hardware perspective, such improvement only requires a larger-capability storage space to allocate each child to an independent memory space. This means that the improvement of *Roomie* can provide a suitable and smart solution for families of two or more children with ASD without a great increase of the cost, relieving the financial burden of families of multiple children with ASD.

## 8.4 Conclusions

Atypical sensory responses are one of the most common issues observed in children with ASD. Technologies that can address the issue undoubtedly serve a more and more important role in interventions for children with ASD nowadays. In this research, the author presents a sensor and AI-enabled system, *Roomie*, which is designed to help children with ASD deal with atypical sensory responses by providing effective monitoring and sensory regulation strategies. The system employs sensing technologies and ML techniques to identify abnormal attention and stress levels, and the potential causes in the surroundings. Another novelty of the proposed system includes a sensory regulation strategy-making algorithm based on FL, which generates alerts to inform caregivers about children's states and risky environmental factors. Sensory regulation strategies are recommended to help improve children's attention or calm children down. The real-life evaluation results suggest that the use of the *Roomie* system has positive impacts on children's attention and stress problem and its design is user-friendly. Therefore, it is concluded that a sensor and AI-enabled system can be an intelligent companion for children with ASD and be widely applied in the future. The smart home technology nowadays creates opportunities for machine-to-machine communications, in which way *Roomie* can react autonomously without human intervention. Future development could make use of advanced hardware to create a better user experience, such as implementing more touch-free sensors, and automatic environmental control so that the system can be more robust, and fully automated.

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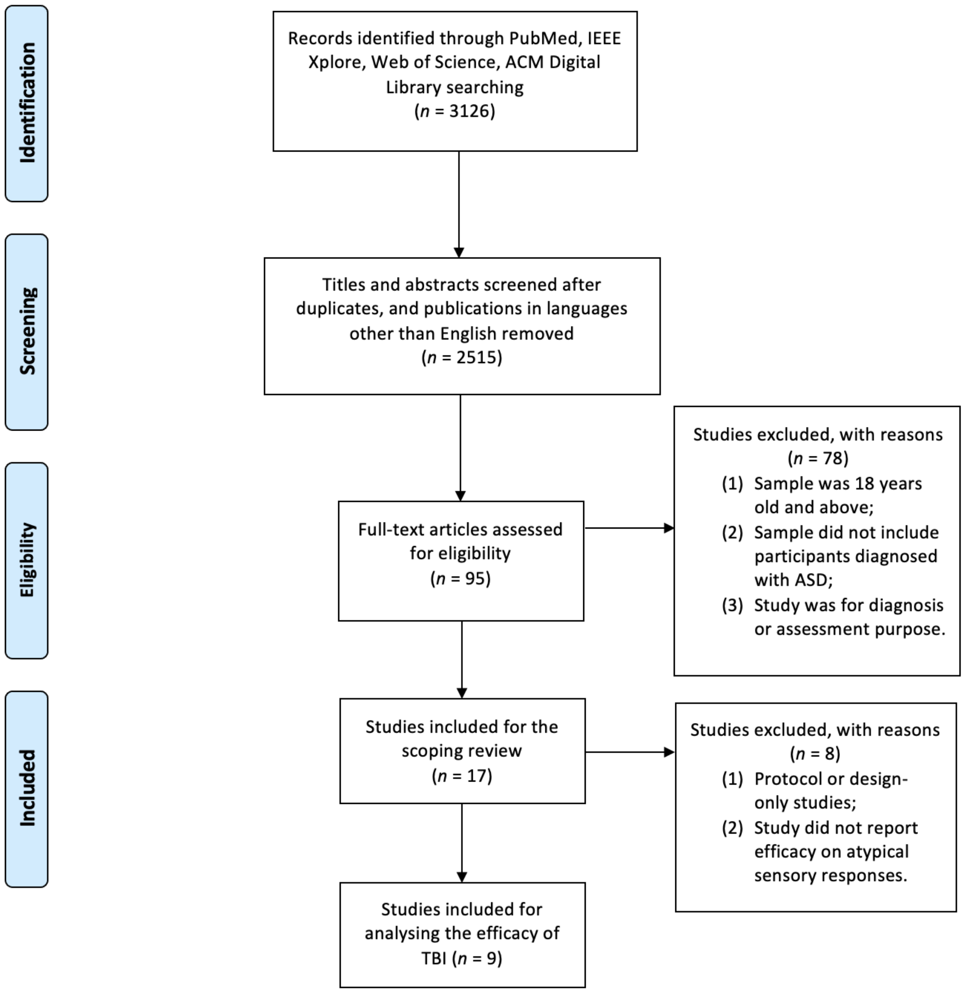
# A Search results and screening process of the scoping review (Latest search date: 21 July 2022)



# B Characteristics of studies included in the scoping review (in order of publication year)

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| Schafer et al., 2013 | Phonak sound amplification system consisting of a sound sensor, a transmitter and a receiver | Auditory hypo-sensitiveness | 7 (7 males, age: 9-11 yo) | Yes | Pre-post | SIFTER, CHAPS (quantitative) | Improved speech recognition in noise and improved attention. |
| Sula et al., 2013 | An IoT-based system using a body sensor, a chair vibrator, a bed vibrator, a light controller, a smell controller, and a sound controller | Multi-sensory processing issue | 1 (1 male, age: n.d.) | No | n.r. | n.r. | n.r. |
| Rance et al., 2014 | Phonak sound amplification system consisting of a sound sensor, a transmitter and a receiver | Auditory hypo-sensitiveness | 20 (17 males, age: 8-15 yo) | Yes | Pre-post | APHAB, CNC word scores (quantitative) | Improved speech recognition in noise and improved attention. |

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| Ringland et al., 2014 | A large display device for multi-sensory environment | Multi-sensory processing issue | 19 (19 males, age: 4-14 yo) | Yes | Pre-post | Semi-structured interview (qualitative) | Improved engagement, attention, and sensory skills. |
| Schafer et al., 2016 | Phonak sound amplification system consisting of a sound sensor, a transmitter and a receiver | Auditory hypo-sensitiveness | 12 (gender ratio: n.d., age: 5-17 yo) | Yes | Pre-post | LIFE-R, CHAPS, CHILD, SSP (quantitative) | Improved speech recognition in noise, memory, and attention. |
| Rance et al., 2017 | Phonak sound amplification system consisting of a sound sensor, a transmitter and a receiver (or a speaker) | Listening-related stress | 26 (20 males, age: 6-16 yo) | Yes | Pre-post | CBCL, TRF, APHAB, CNC word scores, cortisol concentration (quantitative) | Reduced physiological stress levels. |

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| | | | | | | | Increased game scores over time, |
| Mir and Khosla, 2018 | A counting game-based software application using Microsoft Kinect sensor | Sensory and motor issues | 3 (gender ratio: n.d., age: n.d.) | Yes | Time series | Game scores (quantitative) | Improved motor, sensory and academic skills. |
| Schafer et al., 2019 | Phonak sound amplification system consisting of a sound sensor, a transmitter and a receiver. | Auditory hypo-sensitiveness | 15 (10 males, age: 7-21 yo) | Yes | Pre-post | TAPS-3, CELF-5, BKB-SIN, ANL test, LiSN, DWT, RDDT, SP, LIFE-R, CHAPS (quantitative) | Improved processing of general auditory input, and attentional behaviours (e.g., eye contact and paying attention). |

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| Khullar et al., 2019 | An IoT-based system consisting of a gas sensor, a VGA camera, a 3-axis accelerometer, a microphone, a display screen and a speaker | Multi-sensory hyper-sensitiveness | 10 (8 males, age: 8-19 yo) | No | n.r. | n.r. | n.r. |
| Hu et al., 2020 | A matching task-based software application using Leap Motion sensor | Visual processing difficulty | 2 (1 male, age: 9-10 yo) | Yes | Pre-post, time series | Task performance, self-defined social validity survey (quantitative) | Improved task performance over time, more engagement than traditional intervention. |
| Johnston et al., 2020 | A VR game-based software application using Oculus Rift HMD device | Auditory hyper-sensitiveness | 6 (4 males, age: 16-19 yo) | Yes | Pre-post | Self-defined assessment questionnaire (quantitative) | Reduced self-reported stress levels associated with unpleasant noise. |

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| Ali et al., 2020 | A NAO robot | Multi-sensory hypo-sensitiveness | 12 (11 males, age: 4-10 yo) | No | n.r. | n.r. | n.r. |
| Polo Rodríguez et al., 2021 | An IoT-based smart home system using sensors for monitoring user presence, door opening, ambient sound, light, water leak, humidity, temperature, and mattress pressure | Multi-sensory processing issue | n.r. | No | n.r. | n.r. | n.r. |
| Ghafghazi et al., 2021 | An AI-driven ABA system using sensors fusion, AI techniques, and front-end technologies such as VR HMD or tablets | Stereotypical motor movement | n.r. | No | n.r. | n.r. | n.r. |

| Reference | Description of technology elements | Target issue | ASD sample | Evaluating the effects of TBI on the target issue | | | |
|---|---|---|---|---|---|---|---|
| | | | | Empirical evidence presented? | Study design | Measure methods (data type) | Reported effeciency |
| Reis et al., 2021 | An Android software application | Multi-sensory processing issue | n.r. | No | n.r. | n.r. | n.r. |
| Farroni et al., 2022 | Multi-sensory virtual environment using HMD display devices | Multi-sensory processing issue | 2 (1 male, age: n.d.) | No | n.r. | n.r. | n.r. |
| Chevalier et al., 2022 | A Cozmo robot | Joint attention | 36 (31 males, age: 4-6 yo) | No | n.r. | n.r. | n.r. |

yo – years old, n.d. – not defined, n.r. – not reported, SIFTER – Screening Instrument for Targeting Educational Risk, CHAPS – Children's Auditory Performance Scale, APHAB – Abbreviated Profile of Hearing Aid Benefit, CNC – Consonant-Nucleus-Consonant, LIFE-R – Listening Inventory for Education-Revised, CHILD – Children's Home Inventory for Listening Difficulties, SSP – Short Sensory Profile, CBCL – Child Behaviour Checklist, TRF – Teacher Report Form, TAPS-3 – Test of Auditory Processing Skills Third Edition, CELF-5 – Clinical Evaluation of Language Fundamentals Fifth Edition, BKB-SIN – Bamford-Kowal-Bench Speech-in-Noise, ANL – Acceptable Noise Level, LiSN-S – Listening in Spatialised Noise-Sentence Test, DWT – Dischotic Words Test, RDDT – Randomised Dichotic Digits Test, SP – Sensory Profile.

# C Quality assessment of empirical studies which evaluated the effects on the target issue, using Single-Case Experimental Design (SCED) Scale from Tate et al. (2008)

| SCED Scales | | | | | SCED Scores |
|---|---|---|---|---|---|
| Inter-rater reliability | Independence of assessors | Statistical Analysis | Replication | Genenralisation | |
| ✓ | ✓ | ✓ | ✓ | | 10/11 |
| | | ✓ | ✓ | | 8/11 |
| | | | ✓ | ✓ | 7/11 |
| ✓ | ✓ | ✓ | ✓ | | 10/11 |
| | ✓ | ✓ | ✓ | | 9/11 |
| | | | ✓ | | 3/11 |
| | | ✓ | ✓ | | 8/11 |
| | | ✓ | ✓ | ✓ | 10/11 |
| | | ✓ | ✓ | | 8/11 |

| Reference | Clinical history | Target behaviours | Design | Baseline | Sampling behaviour | Raw data record |
|---|---|---|---|---|---|---|
| Schafer et al., 2013 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Rance et al., 2014 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Ringland et al., 2014 | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Schafer et al., 2016 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Rance et al., 2017 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Mir and Khosla, 2018 | | | | | ✓ | ✓ |
| Schafer et al., 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Hu et al., 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Johnston et al., 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

✓: Met the description of the item.

# D ASD specialist advisory panel members

| Panel Member | Qualification and Years of Practice Experience in ASD by the Time of Participation (2020) |
|---|---|
| Ms. Zhang Y | Certified behavioural analyst with 5 years of practice experience |
| Ms. Yang H | Qualified occupational therapist with 6 years of practice experience |
| Mr. Feng D | Director of ASD rehabilitation centre with 14 years of practice experience |
| Ms. Kong I | Qualified occupational therapist with 5 years of practice experience |
| Ms. Zheng X | Qualified special education teacher, director of ASD rehabilitation centre with 14 years of practice experience |
| Dr. Zhang W | Qualified psychiatrist with 20 years of practice experience |
| Ms. Li G | Certified behavioural analyst with 19 years of practice experience |
| Ms. Xu S | Certified behavioural analyst with 10 years of practice experience |
| Mr. Yang Y | Specialist in sensory integration intervention with 3 years of practice experience |
| Mr. Chen G | Specialist in sensory integration intervention with 5 years of practice experience |

# E Online user needs questionnaire (English version)

The author used both English and Chinese versions for people of different cultural backgrounds in the research. Only English version is presented here.

1

What is your relationship to the child with Autism Spectrum Disorder? *

- ◯ Father
- ◯ Mother
- ◯ Other

2

What is your age? *

Enter your answer

3

What is your child's age? *

Enter your answer

4

What is your child's gender? *

- ◯ Male
- ◯ Female

5

Have you ever noticed any sensory preference by your child in terms of vision, sound, touch, taste or smell? Please select your child's behavioural reaction(s) that you have noticed. If you have not noticed any sensory preference by your child, please select 'No'. If you have noticed any other sensory preference not listed below, please specify in the 'Other' blank. (This is a multiple answers question) *

- ☐ Enjoys strange noises/seeks to make noise for noise's sake
- ☐ Prefers to be in the dark
- ☐ Displays unusual need for touching certain toys, surfaces, or textures
- ☐ Will only eat certain tastes (such as the taste of soy sauce)
- ☐ Shows strong preference for certain smells (such as the smell of rubber)
- ☐ No
- ☐ Other

6

Have you ever noticed any sensory limitation by your child in terms of vision, sound, touch, taste or smell? Please select your child's behavioural reaction(s) that you have noticed. If you have not noticed any sensory limitation by your child, please select 'No'. If you have noticed any other sensory limitation not listed below, please specify in the 'Other' blank. (This is a multiple answers question) *

- ☐ Has trouble completing tasks when the TV is on
- ☐ Appears to not hear what you say (for example, does not "tune-in" to what you say)
- ☐ Expresses discomfort with or avoids bright lights
- ☐ Has a hard time finding objects in competing backgrounds
- ☐ Expresses distress during grooming (for example, fights or cries during haircutting, face washing, fingernail cutting)
- ☐ Reacts emotionally or aggressively to touch
- ☐ Gags easily with food textures, or food utensils in mouth
- ☐ Avoids certain tastes or food smells that are typically part of children's diets
- ☐ No
- ☐ Other

7

Have you ever heard of or used any therapeutic approaches which deals with the child's sensory problems, e.g. sensory integration therapy? *

- ◯ Have heard of
- ◯ Have used
- ◯ Neither

8

Have you used any assistive technology designed specifically for children with Autism Spectrum Disorder, for example, Robot like NAO*?

(*NAO is a robot developed by Aldebaran Robotics which has been used to teach autistic children. It has cameras, microphones and tactile sensors which enable it to sense the child's emotion through touch and to play with the child.) *

Alt text: Nao robot

- ○ Yes
- ○ No

9

Could you please give examples on the assistive technologies that you have used?

Enter your answer

Section 2 ...

Assuming there is a mobile application, which is designed to assist children with ASD. It can collect environmental factors surrounding the child, such as light intensity, noise level, temperature, and know potential physiological changes of the child in accordance to the changing environment so that it can provide regulation suggestions for the child and the caregivers in time. For example, Anna is a 6-year-old girl with ASD. When she was playing at home and suddenly there was a clap of thunder, Anna started to become really anxious and screamed. The application may send an immediate suggestion to her mother to put headphone on Anna with music in order to help her calm down.

10

How much do you think that such an App will be helpful for children with ASD? *

| | Not at all helpful | Slightly helpful | Somewhat helpful | Very helpful | Extremely helpful |
|---|---|---|---|---|---|
| Extent | ○ | ○ | ○ | ○ | ○ |

11

What can help children and their caregivers to better understand or follow recommendations given by the App? (Multiple choices) *

- ☐ Display detailed step-by-step instructions
- ☐ Display simple and short instructions
- ☐ Use pictures to display instructions
- ☐ Use video to display instructions
- ☐ Have healthcare workers come and give guidance
- ☐ Offer history records or diaries to keep track of symptoms
- ☐ Other

# F Common questions asked in semi-structured interviews for user needs investigation (English version)

The original version is in Chinese. The version presented below is translated from the Chinese text.

| | Questions |
|---|---|
| For Caregivers | 1. How many years of ASD-related experience do you have?<br><br>2. When did you first notice that your child present unusual symptom, and when did you first seek professional help?<br><br>3. What are the major challenges that you have faced in dealing with your child's condition?<br><br>4. How do your child's conditions impact on his or her and your life?<br><br>5. What service do you usually use?<br><br>6. What technological approaches have you used?<br><br>7. What are the barriers that may prevent you from using an assistive technology, e.g., an application such as *Roomie*, for your child?<br><br>8. Do you think that using a TBI will be helpful for your child?<br><br>9. What kind of TBI do you think that you need urgently?<br><br>10. What particular functions are desired in *Roomie* for the benefits of your child? |

| | Questions |
|---|---|
| For ASD specialists | 1. How many years of ASD-related experience do you have?<br><br>2. When providing services, what evaluation and intervention approaches do you usually use?<br><br>3. Do you know any technologies that can be used to help the evaluation, intervention and treatment of children with ASD?<br><br>4. Do you notice any shortcomings of the existing technologies?<br><br>5. What are the barriers that may prevent caregivers and professionals from using an TBI for children with ASD?<br><br>6. What are the potential clinical impacts of the promotion and application of TBIs on ASD groups?<br><br>7. What kind of TBI do you think that caregivers in China need urgently?<br><br>8. What particular functions are desired in *Roomie* for the benefits of individuals with ASD? |

# G Sensory Profile caregiver questionnaire (English version)

The author used standard Taiwan Chinese version in the research. The attached is the standard English version.

SENSORY PROFILE
Winnie Dunn,
Ph.D., OTR, FAOTA

**SENSORY PROFILE CAREGIVERS QUESTIONAIRE**

**Child's Name:** ______________________
**Date of Birth:** __________ **Age:** __ yrs __mos **Gender:** ______ **Administration Date:** ______________
**Service Provider:** ______________________ **Discipline:** Occupational Therapist

**Completed By:** ______________________ **Relationship to Child:** ______________

**Services child receives:** ______________________

**Conditions:** ______________________

**Comments:** ______________________

A = Always, F = Frequently, O = Occasionally, S = Seldom, N = Never

Sensory Processing

| Item | A. Auditory Processing | A | F | O | S | N |
|---|---|---|---|---|---|---|
| 1 | Responds negatively to unexpected or loud noises (for example, cries or hides at noise from vacuum cleaner, dog barking, hair dryer) | | | | | |
| 2 | Holds hands over ears to protect ears from sound | | | | | |
| 3 | Has trouble completing tasks when the radio is on | | | | | |
| 4 | Is distracted or has trouble functioning if there is a lot of noise around | | | | | |
| 5 | Can' t work with background noise (for example, fan, refrigerator) | | | | | |
| 6 | Appears to not hear what you say (for example, does not "tune-in" to what you | | | | | |
| 7 | Doesn't respond when name is called but you know the child' s hearing is OK | | | | | |
| 8 | Enjoys strange noises/seeks to make noise for noise's sake | | | | | |
| **Item** | **B. Visual Processing** | **A** | **F** | **O** | **S** | **N** |
| 9 | Prefers to be in the dark | | | | | |
| 10 | Expresses discomfort with or avoids bright lights (for example, hides from sunlight through window in car) | | | | | |
| 11 | Happy to be in the dark | | | | | |
| 12 | Becomes frustrated when trying to find objects in competing backgrounds (for | | | | | |
| 13 | Has difficulty putting puzzles together (as compared to same age children) | | | | | |
| 14 | Is bothered by bright lights after others have adapted to the light | | | | | |
| 15 | Covers eyes or squints to protect eyes from light | | | | | |
| 16 | Looks carefully or intensely at objects/people (for example, stares) | | | | | |
| 17 | Has a hard time finding objects in competing backgrounds (for example, shoes | | | | | |
| **Item** | **C. Vestibular Processing** | **A** | **F** | **O** | **S** | **N** |
| 18 | Becomes anxious or distressed when feet leave the ground | | | | | |
| 19 | Dislikes activities where head is upside down (for example, somersaults, roughhousing) | | | | | |
| 20 | Avoids playground equipment or moving toys (for example, swing set, merry-go-round) | | | | | |
| 21 | Dislikes riding in a car | | | | | |
| 22 | Holds head upright, even when bending over or leaning (for example, maintains a rigid position/posture during activity) | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 23 | Becomes disoriented after bending over sink or table (for example, falls or gets dizzy) | | | | | |
| | 24 | Seeks all kinds of movement and this interferes with daily routines (for example, can't sit still, fidgets) | | | | | |
| | 25 | Seeks out all kinds of movement activities (for example, being whirled by adult, merry-go-rounds, playground equipment, moving toys) | | | | | |
| | 26 | Twirls/spins self frequently throughout the day (for example, likes dizzy feeling) | | | | | |
| | 27 | Rocks unconsciously (for example, while watching TV) | | | | | |
| | 28 | Rocks in desk/chair/on floor | | | | | |
| Item | | **D. Touch Processing** | A | F | O | S | N |
| | 29 | Avoids getting "messy" (for example, in paste, sand, finger paint, glue, tape) | | | | | |
| | 30 | Expresses distress during grooming (for example, fights or cries during haircutting, face washing, fingernail cutting) | | | | | |
| | 31 | Prefers long-sleeved clothing when it is warm or short sleeves when it is cold | | | | | |
| | 32 | Expresses discomfort at dental work or toothbrushing (for example, cries or fights) | | | | | |
| | 33 | Is sensitive to certain fabrics (for example, is particular about certain clothes or bedsheets) | | | | | |
| | 34 | Becomes irritated by shoes or socks | | | | | |
| | 35 | Avoids going barefoot especially in sand or grass | | | | | |
| | 36 | Reacts emotionally or aggressively to touch | | | | | |
| | 37 | Withdraws from splashing water | | | | | |
| | 38 | Has difficulty standing in line or close to other people | | | | | |
| | 39 | Rubs or scratches out a spot that has been touched | | | | | |
| | 40 | Touches people and objects to the point of irritating others | | | | | |
| | 41 | Displays unusual need for touching certain toys, surfaces, or textures (for example, constantly touching objects) | | | | | |
| | 42 | Decreased awareness of pain and temperature | | | | | |
| | 43 | Doesn't seem to notice when someone touches arm or back (for example, unaware) | | | | | |
| | 44 | Avoids wearing shoes; loves to be barefoot | | | | | |
| | 45 | Touches people and objects | | | | | |
| | 46 | Doesn't seem to notice when face or hands are messy | | | | | |

| Item | E. Multisensory Processing | A | F | O | S | N |
|---|---|---|---|---|---|---|
| 47 | Gets lost easily (even in familiar places) | | | | | |
| 48 | Has difficulty paying attention | | | | | |
| 49 | Looks away from tasks to notice all actions in the room | | | | | |
| 50 | Seems oblivious within an active environment (for example, unaware of activity) | | | | | |
| 51 | Hangs on people, furniture, or objects even in familiar situations | | | | | |
| 52 | Walks on toes | | | | | |
| 53 | Leaves clothing twisted on body | | | | | |
| **Item** | **F. Oral Sensory Processing** | **A** | **F** | **O** | **S** | **N** |
| 54 | Gags easily with food textures, or food utensils in mouth | | | | | |
| 55 | Avoids certain tastes or food smells that are typically part of children' s diets | | | | | |
| 56 | Will only eat certain tastes | | | | | |
| 57 | Limits self to particular food textures/temperatures | | | | | |
| 58 | Picky eater, especially regarding food textures | | | | | |
| 59 | Routinely smells nonfood objects | | | | | |
| 60 | Shows strong preference for certain smells | | | | | |
| 61 | Shows strong preference for certain tastes | | | | | |
| 62 | Craves certain foods | | | | | |
| 63 | Seeks out certain tastes or smells | | | | | |
| 64 | Chews or licks on nonfood objects | | | | | |
| 65 | Mouths objects (for example, pencil, hands) | | | | | |

| Item | G. Sensory Processing Related to Endurance/Tone | A | F | O | S | N |
|---|---|---|---|---|---|---|
| 66 | Moves stiffly | | | | | |
| 67 | Tires easily, especially when standing or holding particular body position | | | | | |
| 68 | Locks joints (for example, elbows, knees) for stability | | | | | |
| 69 | Seems to have weak muscles | | | | | |
| 70 | Has a weak grasp | | | | | |
| 71 | Can' t lift heavy objects (for example, weak in comparison to same age children) | | | | | |
| 72 | Props to support self (even during activity) | | | | | |
| 73 | Poor endurance/tires easily | | | | | |
| 74 | Appears lethargic (for example, has no energy, is sluggish) | | | | | |
| **Item** | **H. Modulation Related to Body Position and Movement** | **A** | **F** | **O** | **S** | **N** |
| 75 | Seems accident–prone | | | | | |
| 76 | Hesitates going up or down curbs or steps (for example, is cautious, stops before moving) | | | | | |
| 77 | Fears falling or heights | | | | | |
| 78 | Avoids climbing/jumping or avoids bumpy/uneven ground | | | | | |
| 79 | Holds onto walls or banisters (for example, clings) | | | | | |
| 80 | Takes excessive risks during play (for example, climbs high into a tree, jumps off tall furniture) | | | | | |
| 81 | Takes movement or climbing risks during play that compromise personal safety | | | | | |
| 82 | Turns whole body to look at you | | | | | |
| 83 | Seeks opportunities to fall without regard to personal safety | | | | | |
| 84 | Appears to enjoy falling | | | | | |
| **Item** | **I. Modulation of Movement Affecting Activity Level** | **A** | **F** | **O** | **S** | **N** |
| 85 | Spends most of the day in sedentary play (for example, does quiet things) | | | | | |
| 86 | Prefers quiet, sedentary play (for example, watching TV, books, computers) | | | | | |
| 87 | Seeks sedentary play options | | | | | |
| 88 | Prefers sedentary activities | | | | | |
| 89 | Becomes overly excitable during movement activity | | | | | |

| | Item | | A | F | O | S | N |
|---|---|---|---|---|---|---|---|
| | 90 | "On the go" | | | | | |
| | 91 | Avoids quiet play activities | | | | | |
| | Item | **J. Modulation of Sensory Input Affecting Emotional Responses** | A | F | O | S | N |
| | 92 | Needs more protection from life than other children (for example, defenseless physically or emotionally) | | | | | |
| | 93 | Rigid rituals in personal hygiene | | | | | |
| | 94 | Is overly affectionate with others | | | | | |
| | 95 | Doesn't perceive body language or facial expressions (for example, unable to interpret) | | | | | |
| | Item | **K. Modulation of Visual Input Affecting Emotional Responses and Activity Level** | A | F | O | S | N |
| | 96 | Avoids eye contact | | | | | |
| | 97 | Stares intensively at objects or people | | | | | |
| | 98 | Watches everyone when they move around the room | | | | | |
| | 99 | Doesn't notice when people come into the room | | | | | |
| | Item | **L. Emotional/Social Responses** | A | F | O | S | N |
| | 100 | Seems to have difficulty liking self (for example, low self-esteem) | | | | | |
| | 101 | Has trouble "growing up" (for example, reacts immaturely to situations) | | | | | |
| | 102 | Is sensitive to criticisms | | | | | |
| | 103 | Has definite fears (for example, fears are predictable) | | | | | |
| | 104 | Seems anxious | | | | | |
| | 105 | Displays excessive emotional outbursts when unsuccessful at a task | | | | | |
| | 106 | Expresses feeling like a failure | | | | | |
| | 107 | Is stubborn or uncooperative | | | | | |
| | 108 | Has temper tantrums | | | | | |
| | 109 | Poor frustration tolerance | | | | | |
| | 110 | Cries easily | | | | | |
| | 111 | Overly serious | | | | | |
| | 112 | Has difficulty making friends (for example, does not interact or participate in group play) | | | | | |
| | 113 | Has nightmares | | | | | |
| | 114 | Has fears that interfere with daily routine | | | | | |
| | 115 | Doesn't have a sense of humor | | | | | |
| | 116 | Doesn't express emotions | | | | | |

| Item | | M. Behavioral Outcomes of Sensory Processing | A | F | O | S | N |
|---|---|---|---|---|---|---|---|
|  | 117 | Talks self through tasks | | | | | |
|  | 118 | Writing is illegible | | | | | |
|  | 119 | Has trouble staying between the lines when coloring or when writing | | | | | |
|  | 120 | Uses inefficient ways of doing things (for example, wastes time, moves slowly, does things a harder way than is needed) | | | | | |
|  | 121 | Has difficulty tolerating changes in plans and expectations | | | | | |
|  | 122 | Has difficulty tolerating changes in routines | | | | | |
|  | 123 | Jumps from one activity to another so that it interferes with play | | | | | |
|  | 124 | Deliberately smells objects | | | | | |
|  | 125 | Does not seem to smell strong odors | | | | | |

# H Sensory Profile scoring tool, presented by a filled out example from Geyser (2009)

Quadrant Grid

| Quadrant 1 | |
|---|---|
| Registration | |
| Item | Raw Score |
| 6 | 2 |
| 7 | 1 |
| 47 | 4 |
| 50 | 4 |
| 53 | 4 |
| 66 | 4 |
| 67 | 3 |
| 68 | 4 |
| 69 | 3 |
| 70 | 3 |
| 71 | 2 |
| 72 | 4 |
| 73 | 2 |
| 74 | 3 |
| 75 | 4 |
| Quadrant Raw Score Total | 47 |

| Quadrant 2 | |
|---|---|
| Seeking | |
| Item | Raw Score |
| 8 | 4 |
| 24 | 3 |
| 25 | 3 |
| 26 | 4 |
| 27 | 4 |
| 28 | 4 |
| 40 | 4 |
| 41 | 4 |
| 44 | 4 |
| 45 | 4 |
| 46 | 3 |
| 51 | 3 |
| 59 | 4 |
| 60 | 2 |
| 61 | 2 |
| 62 | 2 |
| 63 | 4 |
| 80 | 3 |
| 81 | 3 |
| 82 | 3 |
| 83 | 4 |
| 84 | 4 |
| 89 | 1 |
| 90 | 4 |
| 94 | 4 |
| 123 | 1 |
| Quadrant Raw Score Total | 85 |

| Quadrant 3 | |
|---|---|
| Sensitivity | |
| Item | Raw Score |
| 3 | 3 |
| 4 | 1 |
| 14 | 4 |
| 18 | 4 |
| 19 | 4 |
| 21 | 4 |
| 30 | 3 |
| 31 | 4 |
| 32 | 2 |
| 33 | 4 |
| 34 | 4 |
| 39 | 4 |
| 48 | 3 |
| 49 | 1 |
| 55 | 4 |
| 56 | 2 |
| 57 | 4 |
| 58 | 4 |
| 77 | 1 |
| 78 | 3 |
| Quadrant Raw Score Total | 63 |

| Quadrant 4 | |
|---|---|
| Avoiding | |
| Item | Raw Score |
| 1 | 4 |
| 2 | 4 |
| 5 | 4 |
| 9 | 4 |
| 10 | 4 |
| 11 | 4 |
| 15 | 4 |
| 20 | 4 |
| 22 | 4 |
| 29 | 4 |
| 36 | 4 |
| 37 | 4 |
| 54 | 3 |
| 76 | 3 |
| 85 | 2 |
| 86 | 2 |
| 87 | 4 |
| 88 | 4 |
| 93 | 4 |
| 103 | 3 |
| 104 | 2 |
| 105 | 1 |
| 107 | 2 |
| 108 | 1 |
| 109 | 2 |
| 110 | 3 |
| 111 | 4 |
| 112 | 4 |
| 114 | 4 |
| Quadrant Raw Score Total | 96 |

**Quadrant Raw Scores/Classifications**

| | | ← Less than Others* | | | More than Others → * | |
|---|---|---|---|---|---|---|
| **Quadrants** | **Quadrant Raw Score Total** | **Definite Difference** | **Probable Difference** | **Typical Performance** | **Probable Difference** | **Definite Difference** |
| 1. Registration | 47/75 | ** | 75 -------- 73 | 72 -------- 64 | 63 -------- 59 | 58 ---X--- 15 |
| 2. Seeking | 85/130 | ** | 130 -------- 124 | 123 -------- | 102 -------- 92 | 91 ---X--- 26 |
| 3. Sensitivity | 63/100 | ** | 100 -------- 95 | 94 -------- 81 | 80 -------- 73 | 72 ---X--- 20 |
| 4. Avoiding | 96/145 | 145 -------- 141 | 140 -------- 134 | 133 -------- | 112 -------- 103 | 102 ---X--- 29 |

*See Expanded Cut Score Theory explanation in Sensory Profile Supplement.
**There can be no Definite Difference for this quadrant.

Classifications are based on the performance of children without disabilities ($n$ = 1,037).

# I Sensory regulation strategy online questionnaire (English version)

The original version is in Chinese. The parts presented below are translated from the Chinese text.

1. If the environment becomes less bright (e.g., power outage), the child shows short-term anxiety and distraction, but quickly recovers, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

2. If the environment becomes less bright (e.g., power outage), the child shows extreme anxiety (cannot focus on, or cry), but quickly recover, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

3. If the environment becomes less bright (e.g., power outage), the child shows short-term distraction, but looks relaxed, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

4. If the environment becomes less bright (e.g., power outage), the child shows short-term anxiety (no scream nor cry), but the attention level is normal, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

6. If the environment becomes less bright (e.g., power outage), the child shows long-term anxiety (no scream nor cry), but the attention level is normal, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

7. If the environment becomes less bright (e.g., power outage), the child shows long-term extreme anxiety (cannot focus on, or cry), what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

8. If the environment becomes less bright (e.g., power outage), the child shows long-term distraction, but looks relaxed, what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

9. If the environment becomes less bright (e.g., power outage), the child shows long-term distraction and anxiety (no scream nor cry), what strategy would you recommend the most?

☐ Take no action. (Note: 'Take no action' refers to continuing the class at your own pace, without applying specific intervention for the current incidents.)

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and observe if their atypical responses persist.

☐ Adjust the brightness to a comfortable level (e.g., by opening the curtains, turning on the lights), and immediately show the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Take him or her away from the current environment and change to another comfortable environment.

11. If the environment is getting cold, the child shows a short-term anxiety (no scream nor cry) with normal attention level, what strategy would you recommend the most?

☐ Take no action.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and observe if atypical responses persist.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately give him or her some fidget toys such as balls with texture that the child likes to help reduce tension.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

16. If the environment is getting cold, the child shows a long-term anxiety with normal attention level, what strategy would you recommend the most?

☐ Take no action.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and observe if atypical responses persist.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately give him or her some fidget toys such as balls with texture that the child likes to help reduce tension.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

20. If the environment is too hot, the child shows a long-term anxiety and distraction, cannot pay attention or continue to crying, what strategy would you recommend the most?

☐ Take no action.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and observe if atypical responses persist.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately give him or her some fidget toys such as balls with texture that the child likes to help reduce tension and attract attention.

☐ Adjust the temperature of the room (e.g., by adjusting the air conditioner), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension and attract attention.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

21. If the environment is noisy (e.g., under renovations), the child shows a short-term anxiety (no scream nor cry), and the attention level is normal, what strategy would you recommend the most?

☐ Take no action.

☐ Just remind him or her to pay attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and observe if their atypical responses persist.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to attract his or her attention.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

23. If the environment is noisy (e.g., under renovations), the child shows a short-term distraction with low stress level, but quickly recover, what strategy would you recommend the most?

☐ Take no action.

☐ Just remind him or her to pay attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and observe if their atypical responses persist.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to attract his or her attention.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

30. If the environment is noisy (e.g., under renovations), the child shows a long-term extreme anxiety and cannot pay attention, what strategy would you recommend the most?

☐ Take no action.

☐ Just remind him or her to pay attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and observe if their atypical responses persist.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and immediately reinforce tactile input, such as giving him or her some fidget toys such as balls with texture that the child likes to help reduce tension and attract attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and immediately reinforce tactile input, such as giving him or her a deep pressure, massage, to help reduce tension and attract attention.

☐ Try to block out the noise (e.g., by playing other music or put on noise-cancelling headphones), and immediately reinforce visual input, such as showing the child his or her favourite pictures or videos on mobile phone or other electronic devices.

☐ Immediately take him or her away from the current environment and change to another comfortable environment.

40. If the environment is relatively comfortable and quiet, the child shows short-term anxiety and distraction, but quickly recovers, what strategy would you recommend the most?

☐ There will be no impact. No action.

☐ There will be ignorable impact. Keep observation.

☐ There will be severe impact. Consider whether there are other interfering factors and comfort them immediately.

# J Common questions asked in semi-structured focus group interviews for obtaining user feedback of prototype 1.0 and 2.0 (English version)

The original version is in Chinese. The version presented below is translated from the Chinese text.

| Questions |
|---|
| 1. Are you comfortable with your child being equipped with the current wearable devices which measure their physiological data? |
| 2. Do you think the App for the child easy to use? |
| 3. Is there too much to do in the set up? |
| 4. What other features do you think would be useful to be included in the App? |
| 5. What challenges do you encounter in using the App? |
| 6. Do you think you would be able to use the App yourself at home? |
| 7. Do you have any other feedback? |

# K Autism Spectrum Quotient questionnaire (English version), sourced from Autism Research Centre (2019)

The author used standard Simplified Chinese version in the research. The attached is the standard English version.

NHS
National Institute for Health Research

**AQ-10** **(Child Version)**

**Autism Spectrum Quotient (AQ)**

*A quick referral guide for parents to complete about a child aged 4-11 years with suspected autism who does not have a learning disability.*

***Please tick one option per question only:***

| | | Definitely Agree | Slightly Agree | Slightly Disagree | Definitely Disagree |
|---|---|---|---|---|---|
| 1 | S/he often notices small sounds when others do not | | | | |
| 2 | S/he usually concentrates more on the whole picture, rather than the small details | | | | |
| 3 | In a social group, s/he can easily keep track of several different people's conversations | | | | |
| 4 | S/he finds it easy to go back and forth between different activities | | | | |
| 5 | S/he doesn't know how to keep a conversation going with his/her peers | | | | |
| 6 | S/he is good at social chit-chat | | | | |
| 7 | When s/he is read a story, s/he finds it difficult to work out the character's intentions or feelings | | | | |
| 8 | When s/he was in preschool, s/he used to enjoy playing games involving pretending with other children | | | | |
| 9 | S/he finds it easy to work out what someone is thinking or feeling just by looking at their face | | | | |
| 10 | S/he finds it hard to make new friends | | | | |

**SCORING:** Only 1 point can be scored for each question. *Score 1 point for Definitely or Slightly Agree on each of items 1, 5, 7 and 10. Score 1 point for Definitely or Slightly Disagree on each of items 2, 3, 4, 6, 8 and 9.* If the individual scores **6 or above**, consider referring them for a specialist diagnostic assessment.

**USE:** This is the child version of the test recommended in the NICE clinical guideline CG142. www.nice.org.uk/CG142

**Key reference:** Allison C, Auyeung B, and Baron-Cohen S, (2012) *Journal of the American Academy of Child and Adolescent Psychiatry* 51(2):202-12.

UNIVERSITY OF CAMBRIDGE

autism research centre arc

# L Caregiver-Teacher Report Form (English version), adapted from Achenbach & Rescorla (2020)

The author used standard Simplified Chinese version in the research. The attached is the standard English version.

---

TODAY'S DATE
Mo. ____ Day ____ Year _____

Your role: ☐ teacher ☐ caregiver

Below is a list of items that describe children. For each item that describes the child ***over the past 30 minutes***, please circle the ***2*** if the item is ***very true or often true*** of the child. Circle the ***1*** if the item is ***somewhat or sometimes true*** of the child. If the item is ***not true*** of the child, circle the ***0***. Please answer all items as well as you can, even if some do not seem to apply to the child.

**0 = Not True 1 = Somewhat or Sometime True 2 = Very True or Often True**

| | | | | |
|---|---|---|---|---|
| Anxious or Depressed | 0 | 1 | 2 | 1. Clings to adults or too dependent |
| | 0 | 1 | 2 | 2. Feelings are easily hurt |
| | 0 | 1 | 2 | 3. Gets too upset when separated from caregivers |
| | 0 | 1 | 2 | 4. Looks unhappy without good reason |
| | 0 | 1 | 2 | 5. Nervous, highstrung, or tense |
| | 0 | 1 | 2 | 6. Self-conscious or easily embarrassed |
| | 0 | 1 | 2 | 7. Too fearful or anxious |
| | 0 | 1 | 2 | 8. Unhappy, sad, or depressed |
| Attention Problem | 0 | 1 | 2 | 9. Can't concentrate, can't pay attention for long |
| | 0 | 1 | 2 | 10. Can't sit still, restless or hyperactive |
| | 0 | 1 | 2 | 11. Difficulty following directions |
| | 0 | 1 | 2 | 12. Fails to carry out assigned tasks |
| | 0 | 1 | 2 | 13. Fidgets |
| | 0 | 1 | 2 | 14. Poorly coordinated or clumsy |
| | 0 | 1 | 2 | 15. Quickly shifts from one activity to another |
| | 0 | 1 | 2 | 16. Inattentive, easily distracted |
| | 0 | 1 | 2 | 17. Wanders away |

# M System Usability Scale questionnaire (English version), sourced from Brooke (1996)

The author used standard Simplified Chinese version in the research. The attached is the standard English version.

| | **Strongly Disagree** | | | **Strongly Agree** | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| 1. I think that I would like to use this system frequently. | | | | | |
| 2. I found the system unnecessarily complex. | | | | | |
| 3. I thought the system was easy to use. | | | | | |
| 4. I think that I would need the support of a technical person to be able to use this system. | | | | | |
| 5. I found the various functions in this system were well integrated. | | | | | |
| 6. I thought there was too much inconsistency in this system. | | | | | |
| 7. I would imagine that most people would learn to use this system very quickly. | | | | | |
| 8. I found the system very cumbersome to use. | | | | | |
| 9. I felt very confident using the system. | | | | | |
| 10. I needed to learn a lot of things before I could get going with this system. | | | | | |

# N Copy of the ethical approval letters

## N.1 Ethical approval for user needs investigation

**RE: Research ethics form**

Giampaolo Buticchi [redacted]

Tuesday, May 7, 2019 at 17:58

To: Lingling Deng (20198675); Cc: Prapa Rattadilok; Georgios Kapogiannis; Joanna HUANG

participant-consent-... 116.8 KB

participant-informati... 59.4 KB

research-ethics-che... 851.8 KB

Download All • Preview All

Dear Lingling,

The research can go ahead as planned.

Good luck!

Giampa

## N.2 Ethical approval for data acquisition

**RE: Research Ethics**

Georgios Kapogiannis [redacted]

Monday, June 24, 2019 at 16:33

To: Prapa Rattadilok; Lingling Deng (20198675); Cc: Giampaolo Buticchi; Joanna HUANG

This message is high priority.

Downloading attachments...

Dear All,

On behalf of the team I would like to congratulate you! It is one of most complete and comprehensive forms we have seen!

The ethics panel has approved your application. Please feel free to start when you are ready!

Many thanks
On behalf of the team
Georgios

Dr Georgios Kapogiannis FHEA
**Assistant Professor in Building Information Modelling (BIM)**
**Faculty of Science and Engineering Research Ethics Officer**
**Founder and Leader of the GeoBIM Theme in the Geospatial Research Group**

## N.3 Ethical approval for final evaluation

**RE: Research Ethics Forms**

Faith Chan [redacted]

Wednesday, February 23, 2022 at 02:39

To: Lingling Deng (20198675); Cc: Sherif Welsen; Joanna HUANG

1-research-ethics-c... 528.8 KB

Download All • Preview All

Hi Lingling,

Please find the attached ethics form has been approved.

I Cc Joanna and Sherif for their records.

You may keep this as a record and put in the thesis for your notice if that is necessary.

Good luck for the research.

Best wishes,

Faith

Dr Faith Chan
Associate Professor
Faculty Master (MSc and MRes) Programme Director,
Faculty Research Ethics Officer,
Deputy Head of School, School of Geographical Sciences,
Faculty of Science and Engineering, University of Nottingham Ningbo China

# O Information sheets and consent forms (English version)

The author used both English and Chinese versions for people of different cultural backgrounds in the research. Only English versions are presented here.

### O.1 Information sheet and consent form for the online survey and interviews

An information sheet was always included in the online questionnaire directly, prior to the first questionnaire question. The completion of an online questionnaire is considered implied consent. Participants who complete the questionnaire will be then led to an invitation asking if they are willing to participate in the individual or focus group interview. Positive responses to the invitation will be considered as the consent to take part in the interview.

#### O.1.1 Information sheet

## A survey on the need of a sensory management recommendation system for children with ASD

Thank you for participating in this survey. I am Lingling Deng, a PhD student from the University of Nottingham Ningbo China. This survey is in connection with my PhD research which aims to develop a real-time sensory management recommendation system specifically for children with Autism Spectrum Disorder (ASD).

It is commonly found that children with ASD present some special sensory modality in their lives. Some children may be over-responsive to sound, vision or touch, while some may be under-responsive. For example, a child may be reluctant to touch certain kind of cloth. A child may have a stressful reaction to an approaching stranger. A child may be too under-responsive to the surroundings to play hide-and-seek with their father.

Therefore, we would like to know more about the sensory issues faced by children with ASD, and to develop technology to assist their sensory regulation so that they can live more independently. Your response to the following questions will be appreciated, as it will provide primary data for this research and assist us in understanding the need of a real-time sensory management recommendation system by the children and their caregivers.

This survey will be conducted anonymously. Your participation in the survey is voluntary. To help protect your confidentiality, the data will be stored in a protected format and accessible by the primary researchers only. All the information collected will be used for this academic purpose only and we are committed not to use it for any other purposes.

### O.1.2 Invitation to the interview

## Thank you for your participation and the important feedback!

We are conducting interviews as part of this survey to increase our understanding of the potential need for technologies by children with ASD and their caregivers. Because of your experience with the autistic individuals, we would like to invite you to participate in this interview. If you are willing to participate, please provide us your email address or contact number and suggest a day and time that suits you. Thank you for your contributions!

12

If you are willing to participate, please tell me your email address or contact number, and I will send you the details about the interview in advance

Enter your answer

13

If you are willing to participate, please suggest a day and time that suits you within the next two weeks, and I will do my best to schedule the interview at the day when you are available.

Enter your answer

## O.2 Information sheet and consent form for the data acquisition

### O.2.1 Data acquisition – information sheet

**Participant Information Sheet**

*Using sensors and smart devices to measure the physiological and environmental data: A pilot study for developing a sensory management recommendation system for children with Autism Spectrum Disorder*

Dear Father and Mother,

I am Lingling Deng, a PhD student from the University of Nottingham Ningbo China. This pilot study is in connection with my PhD research which aims to develop a real-time sensory management recommendation system specifically for children with Autism Spectrum Disorder. Your and your child's participation will help me to obtain more reliable data. The outcomes of this study may contribute to the development of a sensory management recommendation system for children with Autism Spectrum Disorder.

Should you agree to allow your child to take part in the study, you will be required to complete the Sensory Profile of Children 3 to 10 Years, Caregiver Questionnaire and give permission for the results of your child's Sensory Profile to be made known to the researcher. In the study, your child will be asked to wear the sensing devices and complete some simple tasks and games in the testing room. Two healthcare professionals will be on-site to keep your child safe during the whole testing.

You are able to withdraw yourself and your child from the study at any time. All the information will be treated confidentially and that neither your name, nor your child's name will be mentioned in the study or any publications of the results.

The research project has been reviewed according to the ethical review processes in place in the University of Nottingham Ningbo. These processes are governed by the University's Code of Research Conduct and Research Ethics. Should you have any question now or in the future, please contact me or my supervisor. Should you have concerns related to my conduct of the study or research ethics, please contact my supervisor or the University's Ethics Committee.

Yours truly,

Lingling Deng

### O.2.2 Data acquisition – consent form

**PARTICIPANT CONSENT FORM**

**Project title** Using sensors and smart devices to measure the physiological and environmental data: A pilot study for developing a sensory management recommendation system for children with Autism Spectrum Disorder

**Researcher's name** Lingling Deng

**Supervisor's name** Dr. Prapa Rattadilok

- I have read the Participant Information Sheet and the nature and purpose of the research project has been explained to me. I understand and agree to take part.
- I agree to allow my child to take part in this study as a research participant.
- I understand the purpose of the research project and my child's and my involvement in it.
- I understand that I may withdraw myself and my child from the research project at any stage and that this will not affect my child's ASD treatment and status now or in the future.
- I understand that all the information will be treated confidentially and that neither my name, nor my child's name will be mentioned in the study or any publications of the results.
- I understand that the data collection will be filmed.
- I understand that data will be stored in accordance with data protection laws.
- I understand that I may contact the researcher or supervisor if I require more information about the research, and that I may contact the Research Ethics Sub-Committee of the University of Nottingham, Ningbo if I wish to make a complaint related to my child's and my involvement in the research.

**Signed** ........................................................................................ (Parent/Guardian)

**Print name** ........................................................................... **Date** ........................................

## O.3 Information sheet and consent form for the system evaluation

### O.3.1 System evaluation – participation information sheet

**Participant Information Sheet for Caregivers**

*Evaluating the Performance of a Sensory Management Recommendation System with Children with Autism Spectrum Disorders*

Dear Father and Mother,

I am Lingling Deng, a PhD student from the University of Nottingham Ningbo China. This study is in connection with my PhD research which aims to develop a real-time sensory management recommendation system specifically for children with Autism Spectrum Disorder. Your and your child's participation will help me to obtain more reliable data to assess the performance of the sensory management recommendation system.

In this study, you will be instructed about how to use the sensory management recommendation system with your child. Should you agree to allow your child to take part in the study, you will be required to complete the registration of the system and a Sensory Profile of Children 3 to 10 Years Caregiver Questionnaire. You shall give permission for the results of your child's Sensory Profile to be made known to the researcher. In the study, your child will be asked to wear the sensing devices and complete three independent sessions with one teacher in the testing room. You need to observe the sessions and report the prediction accuracy and child performance using adapted caregiver-teacher report form. The teacher and the researcher will be on-site to keep your child safe during the whole testing.

You are able to withdraw yourself and your child from the study at any time. All the information will be treated confidentially and that neither your name, nor your child's name will be mentioned in the study or any publications of the results.

The research project has been reviewed according to the ethical review processes in place in the University of Nottingham Ningbo. These processes are governed by the University's Code of Research Conduct and Research Ethics. Should you have any question now or in the future, please contact me or my supervisor. Should you have concerns related to my conduct of the study or research ethics, please contact my supervisor or the University's Ethics Committee.

Yours truly,

Lingling Deng

### O.3.2 System evaluation – consent form for teachers

**PARTICIPANT CONSENT FORM**
**For Teachers**

**Project title** Evaluating the Performance of a Sensory Management Recommendation System with Children with Autism Spectrum Disorders

**Researcher's name** Lingling Deng

**Supervisor's name** Dr. Anthony Graham Bellotti, Dr. Adam Rushworth, Dr. David Daley, Dr. Prapa Rattadilok

- I have read the Participant Information Sheet and the nature and purpose of the research project has been explained to me. I understand and agree to take part.
- I understand the purpose of the research project and my involvement in it.
- I understand that I may withdraw from the research project at any stage and that this will not affect my status now or in the future.
- I understand that while information gained during the study may be published, I will not be identified and my personal results will remain confidential.
- I understand that the data collection will be monitored.
- I understand that data will be stored in accordance with data protection laws.
- I understand that I may contact the researcher or supervisor if I require more information about the research, and that I may contact the Research Ethics Sub-Committee of the University of Nottingham, Ningbo if I wish to make a complaint related to my involvement in the research.

**Signed** ........................................................................................ (participant)

**Print name** ............................................................................ **Date** .........................................

### O.3.3 System evaluation – consent form for caregivers

**PARTICIPANT CONSENT FORM**
**For Caregivers**

**Project title** Evaluating the Performance of a Sensory Management Recommendation System with Children with Autism Spectrum Disorders

**Researcher's name** Lingling Deng

**Supervisor's name** Dr. Anthony Graham Bellotti, Dr. Adam Rushworth, Dr. David Daley, Dr. Prapa Rattadilok

- I have read the Participant Information Sheet and the nature and purpose of the research project has been explained to me. I understand and agree to take part.
- I agree to allow my child to take part in this study as a research participant.
- I understand the purpose of the research project and my child's and my involvement in it.
- I understand that I may withdraw myself and my child from the research project at any stage and that this will not affect my child's ASD rehabilitation and status now or in the future.
- I understand that all the information will be treated confidentially and that neither my name, nor my child's name will be mentioned in the study or any publications of the results.
- I understand that the data collection will be monitored.
- I understand that data will be stored in accordance with data protection laws.
- I understand that I may contact the researcher or supervisor if I require more information about the research, and that I may contact the Research Ethics Sub-Committee of the University of Nottingham, Ningbo if I wish to make a complaint related to my child's and my involvement in the research.

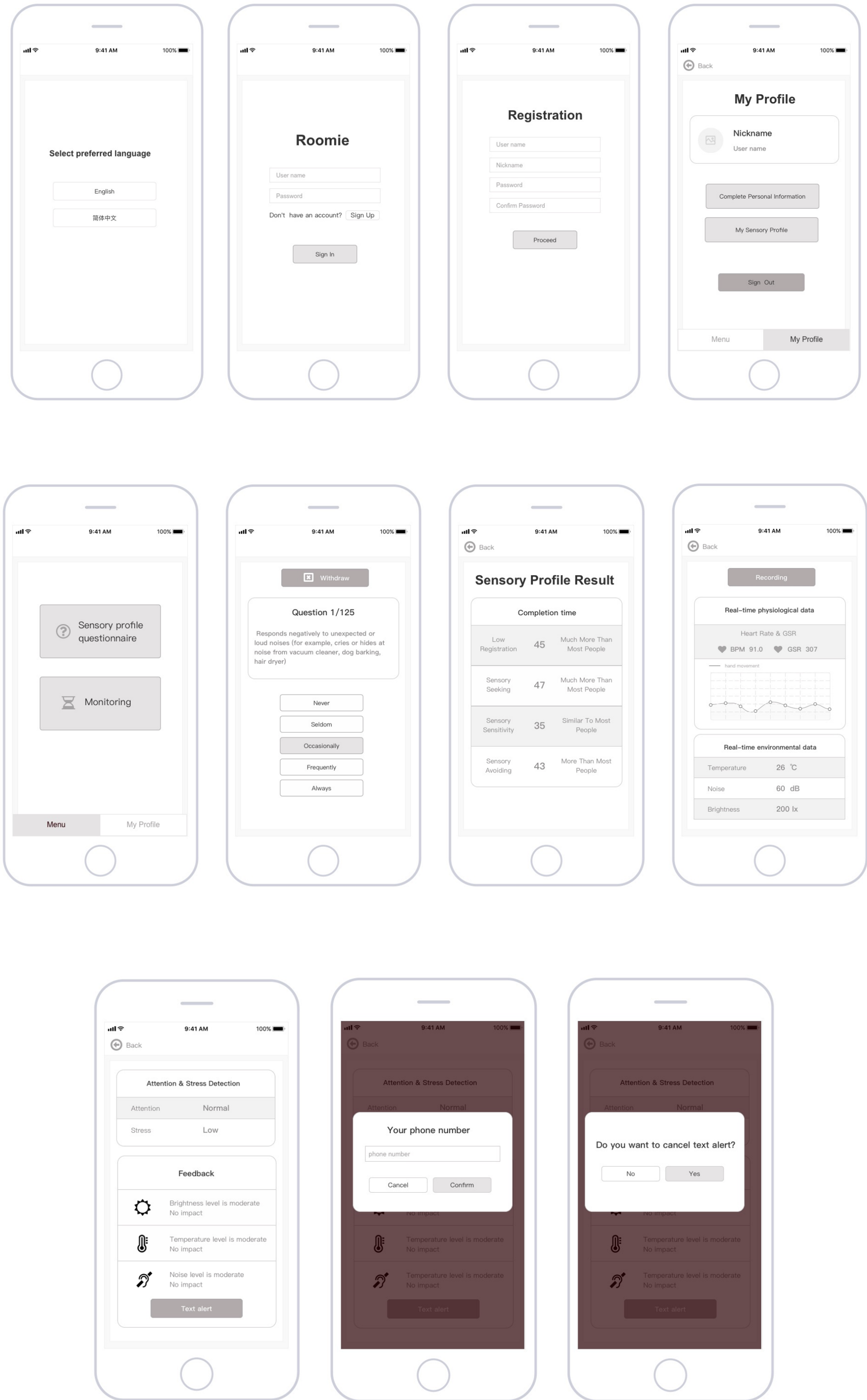
**Signed** ........................................................................................ (Parent/Guardian)

**Print name** ............................................................................ **Date** .......................................

## P Online survey participants' ($n = 93$) nationality, parental or professional information

| | **Parents** | | | **Non-Parents** | | |
|---|---|---|---|---|---|---|
| | | **Num** | **%** | | **Num** | **%** |
| China | Father | 4 | 12.90 | Healthcare professionals | 4 | 57.14 |
| | Mother | 27 | 87.10 | Educators | 1 | 14.29 |
| | Total | 31 | 100.00 | Technology developers | 2 | 28.57 |
| | | | | Total | 7 | 100.00 |
| | Child's age | | | | | |
| | 0-3 years | 5 | 16.13 | | | |
| | 4-6 years | 4 | 12.90 | | | |
| | 7-9 years | 9 | 29.03 | | | |
| | Above 10 years | 13 | 41.94 | | | |
| | Child's gender | | | | | |
| | Boys | 25 | 80.65 | | | |
| | Girls | 6 | 19.35 | | | |
| UK | Father | 4 | 10.53 | Healthcare professionals | 13 | 76.47 |
| | Mother | 33 | 86.84 | Educators | 3 | 17.65 |
| | No mentioned | 1 | 2.63 | Technological developers | 1 | 5.88 |
| | Total | 38 | 100.00 | Total | 17 | 100.00 |
| | Child's age | | | | | |
| | 0-3 years | 1 | 2.63 | | | |
| | 4-6 years | 10 | 26.32 | | | |
| | 7-9 years | 6 | 15.79 | | | |
| | Above 10 years | 21 | 55.26 | | | |
| | Child's gender | | | | | |
| | Boys | 33 | 86.84 | | | |
| | Girls | 5 | 13.16 | | | |
| Total | | 69 | 74.19 | | 24 | 25.81 |

# Q Paper-based prototype design



# R Fuzzy logic rules

Temperature_rule1 = ctrl.Rule(antecedent = (((Temperature['Low'] | Temperature['High']) & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | ((Temperature['Low'] | Temperature['High']) & Duration['Short'] & Attention['Low'] & Stress['Low']) | (Attention['Normal'] & Stress['Low'])), consequent = Outcome['Low Risk'], label = 'Low Risk')

Temperature_rule2 = ctrl.Rule(antecedent = (((Temperature['Low'] | Temperature['High']) & Duration['Short'] &Attention['Normal'] & Stress['High']) | ((Temperature['Low'] | Temperature['High']) & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Temperature['Moderate'] & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | (Temperature['Moderate'] & Duration['Short'] & Attention['Normal'] & Stress['High']) | (Temperature['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['Low']) | (Temperature['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Temperature['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['High']) | (Temperature['Moderate'] & Duration['Long'] & Attention['Normal'] & Stress['Moderate'])), consequent = Outcome['Medium Risk'], label = 'Medium Risk')

Temperature_rule3 = ctrl.Rule(antecedent = (((Temperature['Low'] | Temperature['High']) & Duration['Short'] & Attention['Low'] & Stress['High']) | ((Temperature['Low'] | Temperature['High']) & Duration['Long'] & Attention['Normal'] & Stress['Moderate']) | ((Temperature['Low'] | Temperature['High']) & Duration['Long'] & Attention['Normal'] & Stress['High']) | ((Temperature['Low'] | Temperature['High']) & Duration['Long'] & Attention['Low'] & Stress['Low']) | ((Temperature['Low'] | Temperature['High']) & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | ((Temperature['Low'] |Temperature['High']) & Duration['Long'] & Attention['Low'] & Stress['High']) | (Temperature['Moderate'] & Duration['Long'] & Attention['Normal'] & Stress['High']) | (Temperature['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['Low']) | (Temperature['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | (Temperature['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['High'])), consequent = Outcome['High Risk'], label = 'High Risk')

Noise_rule1 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | (Noise['High'] & Duration['Short'] & Attention['Low'] & Stress['Low']) | (Noise['High'] & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Attention['Normal'] & Stress['Low'])), consequent = Outcome['Low Risk'], label = 'Low Risk')

Noise_rule2 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] & Attention['Normal'] & Stress['High']) | (Noise['Low'] & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | (Noise['Low'] & Duration['Short'] & Attention['Normal'] & Stress['High']) | (Noise['Low'] & Duration['Short'] & Attention['Low'] & Stress['Low']) | (Noise['Low'] & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Noise['Low'] & Duration['Short'] & Attention['Low'] & Stress['High']) | (Noise['Low'] & Duration['Long'] & Attention['Normal'] & Stress['Moderate'])), consequent = Outcome['Medium Risk'], label = 'Medium')

Noise_rule3 = ctrl.Rule(antecedent = ((Noise['High'] & Duration['Short'] & Attention['Low'] & Stress['High']) | (Noise['High'] & Duration['Long'] & Attention['Normal'] & Stress['Moderate']) | (Noise['High'] & Duration['Long'] & Attention['Normal'] & Stress['High']) | (Noise['High'] & Duration['Long'] & Attention['Low'] & Stress['Low']) | (Noise['High'] & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | (Noise['High'] & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | (Noise['High'] & Duration['Long'] & Attention['Low'] & Stress['High'])), consequent = Outcome['High Risk'], label = 'High Risk')

Brightness_rule1 = ctrl.Rule(antecedent=(((Brightness['Low'] | Brightness['High']) & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | ((Brightness['Low'] | Brightness['High']) & Duration['Short'] & Attention['Low'] & Stress['Low']) | ((Brightness['Low'] | Brightness['High']) & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Attention['Normal'] & Stress['Low'])), consequent=Outcome['Low Risk'], label='Low Risk')

Brightness_rule2 = ctrl.Rule(antecedent=(((Brightness['Low'] | Brightness['High']) & Duration['Short'] & Attention['Normal'] & Stress['High']) | ((Brightness['Low'] | Brightness['High']) & Duration['Short'] & Attention['Low'] & Stress['High']) | ((Brightness['Low'] | Brightness['High']) & Duration['Long'] & Attention['Normal'] & Stress['Moderate']) | ((Brightness['Low'] | Brightness['High']) & Duration['Long'] & Attention['Low'] & Stress['Low']) | ((Brightness['Low'] | Brightness['High']) & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Normal'] & Stress['Moderate']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Normal'] & Stress['High']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['Low']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['Moderate']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['High']) | (Brightness['Moderate'] & Duration['Short'] & Attention['Low'] & Stress['High']) | (Brightness['Moderate'] & Duration['Long'] & Attention['Normal'] & Stress['Moderate'])),
consequent=Outcome['Medium Risk'], label='Medium Risk')

Brightness_rule3 = ctrl.Rule(antecedent=(((Brightness['Low'] | Brightness['High']) & Duration['Long'] & Attention['Normal'] & Stress['High']) | ((Brightness['Low'] | Brightness['High']) & Duration['Long'] & Attention['Low'] & Stress['High']) | (Brightness['Moderate'] & Duration['Long'] & Attention['Normal'] & Stress['High']) | (Brightness['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['Low']) | (Brightness['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['Moderate']) | (Brightness['Moderate'] & Duration['Long'] & Attention['Low'] & Stress['High'])),
consequent=Outcome['High Risk'], label='High Risk')

# S Fuzzy logic algorithm test results: Centroid vs Largest of Maximum

| Trial | Temperature (Unit: °C) | Brightness (Unit: lx) | Noise (Unit: dB) | Duration (Unit: second) | Attention | Stress | Expected Results | | | Simulated Results (Defuzzification Method: Centroid) | | | Simulated Results (Defuzzification Method: Largest of Maximum) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Temperature-related risk assessment | Brightness-related risk assessment | Noise-related risk assessment | Temperature-related risk assessment | Brightness-related risk assessment | Noise-related risk assessment | Temperature-related risk assessment | Brightness-related risk assessment | Noise-related risk assessment |
| 1 | 35 | 575 | 71 | 5 | Normal | Moderate | Low | Low | Low | Low | Low | Medium | Low | Low | Low |
| 2 | 10 | 125 | 72 | 6 | Normal | High | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 3 | 35 | 575 | 73 | 7 | Low | Low | Low | Low | Low | Low | Low | Medium | Low | Low | Low |
| 4 | 10 | 125 | 74 | 8 | Low | Moderate | Medium | Low | Low | Medium | Low | Medium | Medium | Low | Low |
| 5 | 30 | 575 | 75 | 9 | Low | High | High | Medium | High | Medium | Medium | Medium | High | Medium | High |
| 6 | 10 | 125 | 76 | 20 | Normal | Moderate | High | Medium | High | Medium | Medium | Medium | High | Medium | High |
| 7 | 30 | 575 | 77 | 25 | Normal | High | High | High | High | Medium | Medium | Medium | High | High | High |
| 8 | 10 | 125 | 78 | 30 | Low | Low | High | Medium | High | High | Medium | High | High | Medium | High |
| 9 | 30 | 575 | 79 | 35 | Low | Moderate | High | Medium | High | High | Medium | High | High | Medium | High |
| 10 | 10 | 125 | 80 | 40 | Low | High | High | High | High | High | High | High | High | High | High |
| 11 | 25 | 350 | 55 | 5 | Normal | Moderate | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 12 | 26 | 355 | 56 | 6 | Normal | High | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 13 | 24 | 360 | 57 | 7 | Low | Low | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 14 | 25 | 365 | 58 | 8 | Low | Moderate | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 15 | 26 | 370 | 59 | 9 | Low | High | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 16 | 25 | 375 | 60 | 20 | Normal | Moderate | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium | Medium |
| 17 | 24 | 380 | 61 | 25 | Normal | High | High | High | High | Medium | Medium | Medium | High | High | High |
| 18 | 25 | 385 | 62 | 30 | Low | Low | High | High | High | High | High | High | High | High | High |
| 19 | 26 | 390 | 63 | 35 | Low | Moderate | High | High | High | High | High | High | High | High | High |
| 20 | 26 | 395 | 64 | 40 | Low | High | High | High | High | High | High | High | High | High | High |
| 21 | 35 | 400 | 60 | 40 | Normal | Low | Low | Low | Low | Low | Low | Low | Low | Low | Low |

Simulated results that do not match with the expected results are marked in red.

# T Apple Developer approval emails for beta testing

**Your app ZDRoomie (1611887844) has been approved for beta testing.**

"App Store Connect" <no_reply@email.apple.com>
Sunday, February 27, 2022 at 10:46
To: Lingling Deng (20198675)

## App Store Connect

Dear Lingling Deng,

Build 1.0 (2) of your app has been approved for TestFlight beta testing.

App Name: ZDRoomie
App Apple ID: 1611887844
Bundle Version Short String: 1.0
Build Number: 2
Platform: iOS
SKU: ZDRoomie

If you haven't already invited testers, go to build 1.0 (2) in the TestFlight section of App Store Connect and select groups or individual testers.

To learn more about adding testers to your developer account, visit TestFlight beta testing overview in App Store Connect Help.

As a reminder, approval for testing through TestFlight does not constitute approval for distribution on the App Store. Apps submitted to the App Store will undergo a full review to make sure they follow the App Store Review Guidelines.

Best regards,
App Store Review

Contact Us | App Store Connect | One Apple Park Way, Cupertino, CA 95014

Privacy Policy | Terms of Service

**App Store Connect: Version 1.0 (4) for ZDRoomie has completed processing.**

"App Store Connect" <no_reply@email.apple.com>
Saturday, April 23, 2022 at 22:17
To: Lingling Deng (20198675)

## App Store Connect

Dear Lingling Deng,

The following build has completed processing:

Platform: iOS
App Name: ZDRoomie
Build Number: 4
Version Number: 1.0
App SKU: ZDRoomie
App Apple ID: 1611887844

You can now use this build for TestFlight testing or submit it to the App Store.

If you have any questions regarding your app, click Contact Us in App Store Connect.

Regards,

The App Store team

Contact Us | App Store Connect | One Apple Park Way, Cupertino, CA 95014

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