Using Mobile Technology for Coordinating Educational Plans and Supporting Decision Making Through Reinforcement Learning in Inclusive Settings

استخدام تقنية الهاتف الجوال لتنسيق الخطط التعليمية ودعم اتخاذ القرار من خلال التعليم المعزز في نظم التعليم الشاملة

by

NUR SIYAM

A thesis submitted in fulfilment

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Abstract

Learners with special education needs and disabilities (SEND) require attention from a large set of a care team that includes parents, teachers, specialists, therapists, and doctors. Good coordination among these stakeholders leads to increased behavioural and academic progress for the learners. However, achieving good coordination in such setting is a challenging task. This is due to the different tasks each stakeholder is attempting, the different backgrounds of the stakeholders, and the lack of face-to-face interaction among them. I call this the intervention coordination problem (ICP). Furthermore, learners with SEND, and specially learners with autism spectrum disorder (ASD), usually show little interest in academic activities and may display disruptive behaviour when assigned certain tasks. Research indicates that selecting a good motivational variable during interventions improves behavioural and academic performance. I refer to this problem as the motivator selection problem (MSP).

This work aims to exploit mobile and artificial intelligence (AI) technologies in order to address the above two problems. Toward this aim, this study follows a design science research approach to develop the IEP-Connect app. This mobile app uses the Individualized Education Program (IEP) as the foundation for coordinating the efforts and supporting the decision-making process of the different personnel who are involved in the IEP of a child with special needs. The proposed work presents four significant contributions, namely identifying the key design principles to inform the design of a coordination mobile app for special education, developing and implementing the IEP-Connect mobile app, modelling the selection of a motivator as a Markov Decision Process (MDP), and proposing a Reinforcement Learning (RL) framework to recommend a motivator to be used with students with SEND in a given learning setting.

To evaluate the effectiveness of the proposed mobile app and RL framework, a series of studies based on participatory design research, mixed-methods usability evaluation, and pre-test/post-test quasi-experimental research methodology were conducted. The evaluation of the app focused on students with ASD as their learning requires sharing information from different distributed sources. Results from the usability questionnaires, interviews, and log data revealed that the app has good usability and that participants were satisfied with the use of the app for recording and sharing IEP information. Moreover, evaluations and data analysis have shown the validity of the proposed RL framework through improving the intervention effectiveness and users' satisfaction.

The implementation of this work provides insights into the future development of technology tools that facilitate information sharing between special education teachers and other stakeholders involved in the intervention of children with special education needs. Moreover, this work expands the interdisciplinary research of machine learning and special education by presenting promising preliminary results for therapy decision-making support.

Keywords: Mobile App Development; Usability; Reinforcement Learning; Markov Decision Process (MDP); Special Education; Autism Spectrum Disorder (ASD); Individualized Education Program (IEP); Motivation

الملخص

يحتاج المتعلمون ذوي الاحتياجات الخاصة إلى رعاية خاصة من مجموعة كبيرة تتضمن أولياء الأمور والمعلمين والمتخصصين والمعالجين والأطباء. ويؤدي التعاون البنّاء بين جميع هؤلاء إلى تطور التقدم السلوكي والأكاديمي للطلاب. ومع ذلك، فإن العمل معا يعد تحديا صعبا. ويرجع ذلك إلى قيام كل منهم بمهام مختلفة، كما أن لكل منهم خبرات مختلفة، وقد يكون أحيانا من الصعب التواصل المباشر فيما بينهم لتنسيق المهام. كما أن الأطفال ذوي الاحتياجات الخاصة عادة ما يظهرون القليل من الاهتمام بالأنشطة الأكاديمية وقد يظهرون سلوكًا مزعجًا عند إسناد هذه المهام لهم.

يهدف هذا العمل إلى توظيف تقنيات الهاتف الجوال والذكاء الاصطناعي لحل مشكلة تنسيق الخطط التعليمية والسلوكية. من أجل ذلك، قمت بتصميم وتنفيذ تطبيق جوالIEP-Connect. يستخدم تطبيق الهاتف المحمول هذا خطة التعلم الفردية (Individualized Education Program) كأساس لتكاتف الجهود وربط عملية اتخاذ القرار لمختلف الأشخاص الذين يعملون مع الأطفال ذوي الاحتياجات الخاصة. يقدم هذا العمل أربع مساهمات مهمة، وهي تحديد مبادئ التصميم الرئيسية التي يجب اتباعها لتصميم تطبيق جوال لتنسيق الخطط التعليمية في نظم التعليم الشاملة، وتطوير وتنفيذ تطبيقIEP-Connect ، ونمذجة اختيار المحفز كعملية قرار ماركوف(Markov Decision Process) ، واقتراح إطار عمل للتعلم المعزز (Reinforcement Learning)لاختيار بمحفز لاستخدامه مع الطلاب ذوي الاحتياجات الخاصة.

ولتقييم فعالية تطبيق الجوّال ومنظومة التعلم المعزز المقترحين، أجريت سلسلة من الدراسات بناءً على منهجية بحث التصميم التشاركي، وتقييم قابلية التطبيق، ومنهجية البحث شبه التجريبية والاختبار القبلي والبعدي. ركز تقييم التطبيق على الطلاب الذين لديهم اضطراب طيف التوحد لأن تعلمهم يتطلب مشاركة المعلومات من مصادر موزعة مختلفة. وكشفت نتائج الاستبيانات والمقابلات قابلية استخدام هذا البرنامج وأن المشاركين كانوا راضين عن استخدام التطبيق لتسجيل معلومات الخطة الفردية ومشاركتها. كما أظهرت التقييمات وتحليل البيانات فاعلية إطار التعلم المعزز المقترح من خلال تحسين تحفيز الطلاب ورضا المستخدمين.

يوفر تنفيذ هذا العمل رؤية حول التطوير المستقبلي لأدوات التكنولوجيا التي تسهل تبادل المعلومات بين معلمي التربية الخاصة وجميع من يقوم بمساندة ودعم الأطفال ذوي الاحتياجات التعليمية الخاصة. علاوة على ذلك، يوسع هذا العمل البحث متعدد التخصصات للتعلم الآلي والتعليم الخاص من خلال تقديم نتائج أولية واعدة لدعم اتخاذ قرارات العلاج.

Dedication

This work is dedicated to the people who shaped my life…

For My Parents

for instilling in me the love for reading and thirst for knowledge

For My Husband

for believing in me and supporting me all the way

For My Children

for being the joy and hope of my life

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Finally, I am forever grateful for my dear husband, my rock. You have always been the star that lights my way and keeps me calm during the roughest of storms.

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ABA	Applied Behavioural Analysis	4
ABC	Antecedents, Behaviour and Consequences	8
ADHD	Attention-deficit/hyperactivity disorder	52
AI	Artificial Intelligence	13
ASD	Autism Spectrum Disorder	2
CAI	Computer Assisted Instruction	37
CAS	Computer Aided Systems	36
CDC	Centres for Disease Control and Prevention	26
CRPD	Convention on the Rights of Persons with Disabilities	22
DSM	The Diagnostic and Statistical Manual of mental disorders	26
DSRP	Design Science Research Process	48
FBA	Functional Behaviour Assessment	76
HCI	Human-Computer Interaction	40
ICP	Intervention Coordination Problem	2
IDEA	Individuals with Disabilities Education Improvement Act	2
IEP	Individualized Education Program	2
LMS	Learning Management System	41
LSA	Learning Support Assistants	52
MDP	Markov Decision Process	14
MSP	Motivator Selection Problem	5
MVP	Minimal Viable Product	74
PECS	Picture Exchange Communication Systems	41
PMLD	Profound and Multiple Learning Difficulty	52
POMDP	Partially Observable MDP	106
RL	Reinforcement Learning	16
SEND	Special Education Needs and Disabilities	1
SENDCO	Special Education Needs and Disabilities Coordinator	56
STEM	Science, Mathematics, Technology, and Engineering	37
SUS	System Usability Scale	41
TAM	Technology Acceptance Model	42
UDHR	Universal Declaration of Human Rights	22
UI	User Interface	40
UN	United Nations	22
UNESCO	UN Educational, Scientific and Cultural Organisation	22
WHO	The World Health Organization	26

Publications

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1. Introduction

Learners with special education needs and disabilities (SEND) require attention from a large care team that includes parents, teachers, specialists, therapists, and doctors (Zablotsky, Boswell & Smith 2012; Strunk, Leisen & Schubert 2017; Jordan, Roberts & Hume 2019). School staff and families play an equally essential role in the education of learners with SEND (Zablotsky, Boswell & Smith 2012). A strong relationship among these stakeholders may lead to increased learning quality and academic success for the learners (Clarke, Sheridan & Woods 2010; Bowman, Suarez & Weiss 2021).

Inclusion requires educators to provide appropriate education for all learners regardless of their abilities or disabilities in general education classes (Foreman & Arthur-Kelly 2017). Inclusive schooling at all levels depends on interdisciplinary care that is individualized according to the learner's specific needs. However, there is a coordination challenge recognized by the stakeholders involved in inclusive education as well as by the research community (Verger et al. 2021).

In this research, I identify two problems related to the intervention coordination and decision-making in inclusive education; the intervention coordination problem (ICP) and the motivator selection problem (MSP). These problems emanate from the need for coordination among all stakeholders to monitor the learner's individual academic and behaviour progress (Woods, Morrison & Palincsar 2018). To solve these two problems, I propose, design, and evaluate a system based on mobile technology and machine learning.

1.1. Statement of the Problem

To facilitate intervention and learning coordination, the care team defines a high-level Individualized Education Program (IEP). The IEP (see Figure 3) describes the main learning objectives for the learner and is considered the core of the Individuals with Disabilities Education Improvement Act (IDEA) (Gartin & Murdick 2005; Rodriguez & Murawski 2020).[1] The IEP is updated through periodic reports that monitor the learners' progress in meeting the specified goals (Siegel 2017). Chapter 22.1 provides a detailed description of the IEP process and components.

While my proposed solution can be applied to a wide range of learners with SEND, my evaluation focuses on learners with ASD. ASD is a complex neurodevelopmental disorder with a prevalence rate between 1% and 2% that constitutes a broad range of conditions characterized by social, communication and behavioural challenges (CDC 2020). Whilst it has been proven that the coordination between all parties involved in the creation of the IEP for learners with ASD is essential for good outcomes (Clarke, Sheridan & Woods 2010; Woods, Morrison & Palincsar 2018), there is a lack of effective mechanisms to support this coordination and to monitor the progress of learning skills (Strunk, Leisen & Schubert 2017; Winterman & Rosas 2017; Bowman, Suarez & Weiss 2021; Sisti & Robledo 2021). Team members work with learners in different times and different context of learning. However, they are usually unaware of other team members' objectives and plans, despite the frequent interaction between the different IEP objectives (Siyam 2018). I refer to this problem as **the Intervention Coordination Problem, or ICP**.

[1] The IDEA act is an American legislation that guarantees learners with special needs are provided with appropriate education that is personalized according to their individual needs

Despite the advances in specialized computer systems and their proven success in improving the conditions of learners with SEND, special education programs are usually reluctant to adopt these advances (Burns 2015). Scarcity of computer skills and motivation are some of the reasons that drive teachers to use primary communication and coordination methods that may rise privacy issues and overload (Siyam 2018). Most importantly, most of the proposed specialized systems act in an isolated manner and ignore the fact that the education of learners with ASD requires the communication of not only academic information, but also social and behavioural information (Zywica 2014). Thus, there is a need for a user-friendly system that generates complete learning plans for the team and that ensures coordination between all members (Amir et al. 2015; Linstead et al. 2015).

The COVID-19 pandemic also imposed new challenges on the coordination process in special education. Many studies reported that the communication and coordination process was impacted during the pandemic, specially affecting families and learners (Yazcayir & Gurgur 2021). Technology offers powerful tools that can make the coordination process more efficient (Dahiya et al. 2021). However, most of the available systems for therapy coordination do not integrate all the IEP objectives, including the academic and behavioural goals.

Another challenge related to special education, is that for learners with severe learning and behavioural problems, therapists are required to make the intervention process systematic for it to be efficient. Therapists are recommended to use a research-based process for individualizing intervention through the methodical use of assessment data and research-based adaptation strategies. During this process, therapists collect and analyse learner-level data, develop and update intervention components when data indicate inadequate response, individualize intervention judged by their clinical experience, and continuously monitor learners' progress (National Center on Intensive Intervention 2013).

Another challenging aspect in early intervention is the lack of learners' interest in academic activities or homework assignments. Learners with ASD may resort to behave in a disruptive manner to avoid academic tasks (Koegel et al. 2010). Such disruptive behaviours are considered major barriers to the attainment of educational goals as described in the IEP of the learner. Disruptive behaviours are likely to worsen if left untreated. However, research indicates that incorporating motivational variables into the intervention of learners with ASD leads to improvements in core symptoms of autism and academic areas (Koegel et al. 2010; Schuetze et al. 2017). The use of motivational variables, often referred to as reinforcement learning, has been refined into a structured treatment system called Applied Behavioural Analysis (ABA). ABA-based treatment approaches use reinforcement learning to promote desired behaviour (such as eye contact) and diminish atypical behaviours (such as repetitive body movements) (Schuetze et al. 2017). To differentiate between Reinforcement Learning as a machine learning paradigm and reinforcement learning as part of the ABA-based treatment approaches, this paper refers to the latter as "the use of motivators".

While the use of motivators is supported by evidence and is broadly used (Browder et al. 2014), how the use of motivators impacts behavioural and cognitive changes in ASD is still unclear. Moreover, it was noted that the extent of response to ABA-based intervention varies between learners (Schuetze et al. 2017). In addition, different learners are motivated by different motivators. For example, not all learners desire praise nor they are all motivated with chocolate (Riden, Markelz & Randolph 2019). Thus, identifying the right motivators for learners with ASD is considered a challenge (Mechling, Gast & Cronin 2006). Different types of motivators have proven effective in the motivation of learners with ASD, such as tangible and edible motivators, social motivators, and the token system (Zager, Cihak & Stone-MacDonald 2004). However, even with successful motivator identification, teachers and therapists often find themselves repetitively using one or two motivators that they found to be successful with a learner, which lessens the effectiveness of the motivator or yields adverse effects when used over a long period of time (Mechling, Gast & Cronin 2006). I refer to this problem as **the Motivator Selection Problem, or MSP**.

Another issue related to the MSP is that many parents struggle at home as certain motivators often become ineffective with their child. This may be impacted by the type and frequency of motivators administered in the school, which require daily communication and coordination between school and home (Marcu et al. 2019). Studies indicated that practices and tools for documenting behaviours in schools are usually implemented without significant consideration toward exchanging information with parents (Marcu et al. 2019). Additionally, children fall out of their routine due to different circumstances, such as travelling, sickness, or not going to the school as during the COVID-19 lockdown, requiring adjustments in plans and the kind and frequency of motivators used (Spiller 2020).

1.1.1. Intervention Coordination Problem (ICP)

To understand the context in which mobile technology can be beneficial, an illustrative case study of Jacob, a seven-years old boy diagnosed with ASD, is introduced. In the school, Jacob has an IEP in place containing the plan for each core subject. The IEP was created in collaboration with people who are central to the learner's educational success, including parents, teachers, therapists, and special education needs and disabilities coordinators (SENDCOs) (Siegel, 2017). Additionally, Behavioural Adjustment Plans, Skills Development Plans, and Speech and Language Plans were prepared. The IEP is considered the curriculum roadmap for the education services Jacob will receive. Jacob's IEP includes his personal information, information about his psychological, social, behavioural, and emotional development, his health condition, the recommended support strategies and accommodations, in addition to both academic and functional goals.

Let us consider a motivating scenario that illustrates missed opportunities for coordination without the proposed mobile app. In the occupational therapy session, the therapist was trying to teach Jacob how to grasp a ball to improve his fine motor skills. However, the therapist was having a hard time motivating Jacob. After some trial-and-error efforts, the therapist discovered that, for that day, playing with a car was a good motivator for Jacob. Knowing this simple, yet crucial, information about Jacob's motivator helped Jacob master grasping the ball.

In the behavioural therapy session, without a system for efficient information sharing, the therapist will not know the information "Jacob acquired the new motor skill of grasping the ball" and therefore will not start teaching Jacob the skill of passing the ball to others in turns.

Similarly, in mathematics, while trying to teach Jacob how to subtract one-digit numbers, the teacher will waste valuable time searching for a good motivator for Jacob. Had the information "playing with car toy is good motivator" been shared, the teaching would have been more efficient. Finally, the English teacher would like to teach Jacob about the prepositions of place. Had she known about his first session in the morning, she could have used a ball to allow Jacob to practice his motor skills by moving the ball "above" or "under" the table.

At home, the information from the school sessions is particularly important since it will make the interaction between Jacob and his parents more productive, which will help to progress his intervention. Parents usually seek such information by contacting teachers and therapists directly, or through some formal communication channels with the school. This is usually accomplished through a weekly report, a daily agenda, or through the school's management system (Siyam 2018).

As it can be seen from this brief simulating scenario, there are a lot of missed opportunities of coordination (see Figure 1), which may slow down the learning process of the learner. This study hypothesizes that by developing a mobile app that facilitates coordination and sharing of information, the education process will be more efficient, and the achievement of learning objectives will improve.

In Chapter 4, the IEP-Connect is proposed to investigate the use of mobile technology for the purpose of coordinating the intervention efforts of involved parties for the ultimate goal of improving the learning of learners with ASD.

Figure 1: The problem of coordinating the multiple parties involved in the intervention of a learner with ASD (images from Freepik.com)

1.1.2. Motivator Selection Problem (MSP)

Identifying and assessing potential reinforcing stimuli for learners with SEND, and evaluating the methods for maintaining the effectiveness of these motivators, have been acknowledged in the literature (Mechling, Gast & Cronin 2006). As one of the main concerns encountered in the therapy of learners with ASD is the lack of motivation, many studies aimed to identify the factors that impact the learners' response to different motivators (Schuetze et al. 2017). ABA-based treatment is a system that uses motivators to promote desired behaviour and diminish atypical behaviours (Schuetze et al. 2017). ABA data is often collected in the form of antecedents, behaviour, and consequences (ABC), which give a good understanding of the learner behaviour. Antecedents are the events that happened right before the behaviour occurred while consequences are a set of protocols that are used to shape the behaviour, such as the use of reinforcers or motivators (Bhuyan et al. 2017; Lill, Bassingthwaite & Cox 2021).

Therapists usually perform motivators analyses to evaluate the effectiveness of a particular motivator for an individual learner in a particular context. During the motivator analysis, the learner access to the motivator is contingent upon engaging in a specific desired behaviour (e.g., completing an academic task). Across trials, the learner is given instructions to perform specific tasks and is informed that she can receive a particular motivator upon completing the task. Over time, patterns may emerge as to which motivator best maintains the learner's compliance to the task. The motivator that maintains the learner's compliance more frequently is considered to have greater motivator value. Therapists also perform functional analyses to identify the antecedent events that precede the problematic behaviour and the consequences that maintain it. Identifying the function of the problem behaviour impacts the treatment efficiency (Lill, Bassingthwaite & Cox 2021).

Learners with ASD do not typically show preference to social stimuli (such as smiles or praise) or affective stimuli (such as a picture of a crying face), which makes it hard to reinforce new behaviours through a natural environment (Schuetze et al. 2017). That is why parents and teachers tend to rely on edible motivators as an alternative. While various studies showed that many skills can be established while using edible stimuli, there are many downsides for delivering edible motivators (Rincover & Newsom 1985). For instance, providers tend to use food as a common motivator in ABA-based treatment. Therefore, food becomes a therapeutic tool that influences eating behaviours occurring even when the child is not responding to a biological need, resulting in a tendency to overeat. Evidence suggests that children with ASD are at a higher risk for unhealthy weight compared to other children (Matheson & Douglas 2017). Despite this fact, therapists, teachers, and parents continue to use calorically dense foods as a motivator to influence behaviour change. Frequent use of food as a motivator has many undesirable side effects that are mostly not found in other motivators. These side effects include long-term health consequences such as weight gain and dental cavities, interruption of activities to administer the motivator, and satiation (Matheson & Douglas 2017).

Satiation is a decrease in the effectiveness of a stimuli as a motivator when used repeatedly or for a long period of time (Murphy et al. 2003). Research indicates that children satiate more often on edible motivators. This resulted in more investigations on the advantages of using other types of motivators such as tokens and sensory stimuli (Rincover & Newsom 1985; Matheson & Douglas 2017). However, satiation is considered a negative consequence of using any kind of motivator repeatedly. To solve the issue of satiation, therapists and teachers are required to continually vary stimuli and introduce motivators from different modalities, vary the schedules of motivators, provide children with choices, and benefit from the use of technology to access preference items to increase motivation (Murphy et al. 2003; Mechling, Gast & Cronin 2006). Many other factors were considered in the literature such as the benefits of sensory stimuli in promoting greater interaction between the child and the environment (Rincover & Newsom 1985), the reinforcing value of providing choice (Mechling, Gast & Cronin 2006), and the effects of using preferred (specially assessed) motivators (Schuetze et al. 2017).

One of the important steps for a successful deployment of ABA-based interventions is the identification of motivator preference for each learner (Koegel et al. 2010). However, evidence suggests the need of conducting frequent assessment to reflect the changes in preferences over time. Motivators for learners with ASD are sensitive to the changing characteristics across time and learners (Dyer 1987), suggesting that a typical motivator that is powerful in one context might not be effective in other settings or with other learners. Thus, there is a need for continuous identification and assessment of effective motivators, which requires time and effort from teachers, therapists, and parents. This research aims to provide an automated system that addresses that need.

The MSP is considered a challenging problem as various factors impact the effectiveness of a motivator, including the learner herself, the teacher, the subject being taught, the time of day, and the type of disruptive behaviour.

Therapists who are trained on ABA-based treatment approaches usually choose a specific motivator considering the history of the learner behaviour, current behaviour, and some internal approximation of the outcome of possible future therapy decisions. They develop reinforcement sampling menus or lists that can help them identify motivators to each problem behaviour (e.g., aggression, stereotypy, non-compliance) according to the antecedents of the behaviour (e.g., change of activity, denied access to preferred item), context variables (e.g., time of day, subject), and the behaviour function (e.g., attention seeking, escape). Additionally, the therapist takes into consideration the learner’s preferred motivator which is usually identified by using motivator assessments (National Center on Intensive Intervention 2016). In academics and behaviour, teachers and therapists use these data to individualize instruction on a learner-by-learner basis according to the learner’s exceptional learning and behaviour needs (Fuchs, Fuchs & Vaughn 2014). Figure 2 shows the steps in the behaviour intervention strategy followed by therapists to devise their plans.

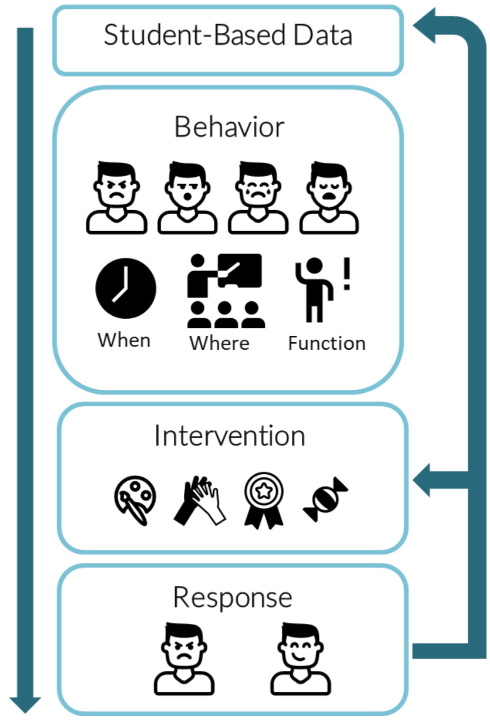


Figure 2: Behaviour Intervention Strategy

However, therapists and teachers face many challenges in developing such plans. First, devising behaviour intervention plans requires training and experience. Whilst therapists and interventionists have the needed knowledge, other teachers, especially those in general education classrooms, rely on behaviour therapists to recommend appropriate intervention plans (Hudson 2020). This requires continuous communication and coordination to prevent the misuse of motivators and to ensure the intervention works as intended. While effective communication is always sought by all parties, it is often lacking due to time restrains or denied access (Siyam 2018). Second, as with most clinical treatments, the effect of the motivator used with the learner is uncertain (non-deterministic). This uncertainty makes it hard to plan ahead as attempting to predict the effect of a series of treatment over time compounds the uncertainty (Bennett & Hauser 2013). The process of navigating learner-based data and plan for the right intervention is not only time consuming, but requires considering various variables and continuous access to research and heuristic investigations (Bennett & Hauser 2013). Moreover, there has been a deal of contradicting evidence regarding the use of “extrinsic” reinforcement to engage and motivate learners. This study follows the popular position in this regard in that the application of planned positive motivation is a critical element of teaching learners with ASD. Teachers, therefore, are required to sustain learners’ motivation using both “intrinsic” and “extrinsic” reinforcement. Motivation is considered an internal “intrinsic” psychological state. Reinforcement, on the other hand, can be intrinsic to the task, extrinsically applied, or both. The challenge is, therefore, in deciding when the use of different types of motivators is effective or even necessary (Healey 2008).

In Chapter 5, I attempt to solve the MSP by modelling it as an MDP, considering the factors that impact the effectiveness of a motivator based on ABA as well as learners’ individual preferences.

1.2. Purpose and Objectives

This thesis aims to exploit mobile and artificial intelligence (AI) technologies to address the ICP and MSP problems. Towards this aim, a mobile app (IEP-Connect) is designed and developed. This mobile app uses the IEP as the foundation for coordinating the efforts and supporting the decision-making process of the different personnel who are involved in the IEP of a child with special needs. In a nutshell, this work aims to achieve the following objectives:

1. Identify the key design principles to inform the design of a coordination mobile app for special education.

2. Evaluate the use of mobile technology for intervention coordination using the IEP as the foundation.
3. Model the selection of a motivator as a Markov Decision Process (MDP) problem.
4. Propose a Reinforcement Learning (RL) framework to select a motivator to be used with learners with ASD in a learning setting.

1.3. Research Questions

This study is fuelled with the need to facilitate the coordination of educational plans, with the ultimate goal of improving the learning and therapy of learners with ASD. With the research objectives in mind, this work aims to answer the following questions:

1. What are the key design principles required to inform the design of a coordination mobile app for special education?
2. How do special education teachers and therapists perceive the use of a mobile app to facilitate the coordination of educational plans in inclusive settings?
3. How can the motivator selection problem in special education be modelled as an MDP?
4. How can Reinforcement Learning (RL) improve the success of the motivators used with learners with ASD in a learning setting?

1.4. Focus and Rationale

The work in this thesis is profoundly interdisciplinary, bridging the gap between special education and computer systems. The key contributions of this thesis are two-fold: firstly, this work contributes to the body of knowledge in Human-Computer Interaction (HCI) for applications designed for special education caregivers, such as teachers, therapists, and parents. Secondly, this work bridges the gap between behaviour intervention in special education and the paradigm of Reinforcement Learning as a machine learning technique.

1.4.1. Mobile Technology for Intervention Coordination

The majority of motivation for developing IEP-Connect comes from the need for a digital tool that facilitates the collection and sharing of data in the area of special education. Data collection in special needs, and especially for learners with ASD, is considered a challenge due to the abundance of information teachers and therapists have to collect about the learners, the heterogeneity of such data, and the number of stakeholders involved in the learning and therapy process. Data sharing is considered a challenge as well due to the lack of proper communication channels between different school staff, and between school and home (Siyam 2018).

Despite the literature containing a myriad of studies on applications for ASD diagnosis and intervention, there is a less focus on applications for data collection, data tracking and data monitoring (Virnes, Kärnä & Vellonen 2015; Sharmin et al. 2018). Moreover, the HCI design principles for special education caregivers is understudied.

This study contributes to the body of knowledge by first identifying the key design principles required to inform the design of a coordination mobile app for special education. To this aim, this study follows a design science research approach (Peffers et al. 2006) to develop the IEP-Connect app, a mobile app that aims to solve the intervention coordination problem in inclusive settings. The IEP-Connect app can prove beneficial in solving the issue of data loss by facilitating data collection and sharing between all stakeholders involved in the learning and therapy of learners with ASD. As the purpose of this study is coordinating educational plans, the focus in this research is on learners with ASD that are aged between 5 and 12. However, the proposed solution is applicable to other types of disabilities and other age ranges. This study refers to students or pupils as “learners” to consider the international reader.

1.4.2. Reinforcement Learning for Motivator Selection

Based on the need to find effective motivators to motivate learners with ASD, this study proposes a therapy decision support system based on Reinforcement Learning (RL). RL is one of the basic machine learning paradigms (van Otterlo & Wiering 2012). In the proposed system, intelligent agents support teachers and therapists in the decision-making process by recommending a motivator to use with a learner in an educational setting. The recommendation is based on the factors that might affect the effectiveness of a motivator (such as the behaviour, time of day, etc.). The intelligent agent then updates the recommendations based on the received feedback. RL is considered suitable for data characterized by uncertainties, heterogeneity, high dimensionality, and incompleteness, which is the case with ASD data (Hall et al. 2012; Gräßer et al. 2017). RL has proven to be a suitable technique for developing solutions in the healthcare domain where decisions or treatments are lengthy and sequential (Yu, Liu & Nemati 2020). Moreover, RL has been widely used in the education domain, where there is a need to develop adaptive learning systems that provide personalized paths and materials based on the learners’ needs (Shawky & Badawi 2019).

Teachers, therapists and parents record details of daily sessions and classes regarding learners’ progress towards the IEP goals, including behaviour monitoring data and motivators used. This information is shared among participating parties to improve learning and therapy outcomes (Siyam 2018). While sharing information is crucial to the learning process, teachers and therapists need to navigate through the data to determine the right motivator to use for the learner in the current session, which may be time consuming and cause overload (Siyam 2019). Additionally, the factors that impact the success of an intervention plan are mediated by other unmeasured or hidden factors, which may not be evident to the teacher or therapist (Shawky & Badawi 2019). Moreover, not all teachers are trained on ABA-based intervention approaches and they have varied skills in conducting Functional Behaviour Assessment (FBA) (Hudson 2020; Lill, Bassingthwaite & Cox 2021), which may result in the repetitive use of the same motivator or the use of motivators that may be harmful on the long run. Field studies showed that the lack of experience for some teachers and the absence of coordination may result in unsuccessful behaviour intervention plans (Siyam 2018). Another challenge is the scarcity and, sometimes contradictory, conclusive evidence on best practices for intervention, especially when attending to children with varied personalities and preferences (Schuetze et al. 2017). The above factors motivate the proposal of a more data-centric approach that systemically evaluates the space of available motivators to determine the best action, which is what is proposed in this research.

The proposed RL model aims to improve the learning activities and sessions for learners with ASD by providing an adaptive decision support system that recommends motivators for teachers and therapists during a learning session. The proposed model is evaluated through the "IEP-Connect" app, where teachers record problem behaviour and the system suggests a motivator to be used with the learner. This study considers contingent rewards, which are used to reward children when meeting a specified goal and provide positive reinforcement when a task is well done (Koegel et al. 2010).

1.5. Key Contributions

The contribution of this thesis can be summarized as follows:

- Identify the key principles required to inform the design of a coordination mobile app for special education.

- Evaluate the use of mobile technology by developing IEP-Connect app to solve the ICP problem.

- Model the selection of a motivator as an MDP problem, considering the factors that impact the effectiveness of a motivator according to ABA-based methods and the trade-off between different motivators.

- Propose an adaptive decision support system that solves the MSP problem using reinforcement learning. The proposed system is implemented and deployed online as an extension to the IEP-Connect app.

- The study confirmed the effectiveness of the proposed system both in terms of improving the success rate of selecting a motivator (from 46% to 89%) and increasing users' satisfaction (from 80.42 to 84.38).

- The use of the app will facilitate the collection of behaviour data, which is considered one of the cornerstones of effective intervention programs (Burns, Donnelly & Booth 2015; Marcu et al. 2019).

1.6. Structure of the Dissertation

This thesis interpolates material from two papers by the author; "A Pilot Study Investigating the Use of Mobile Technology for Coordinating Educational Plans in Inclusive Settings" (Siyam & Abdallah 2021) and "Reinforcement Learning Model for Autism Behaviour Intervention

Therapy”[2], both co-authored with Sherief Abdulla. This introductory chapter as well as chapters 2, 3, and 6 use material from both papers. Chapter 4 is based on (Siyam & Abdallah 2021), while chapter 5 is based on the second paper.

This chapter provided a background on two problems this research aims to address, the ICP and the MSP problems. It also outlined the aims, research questions, rationale and contributions of this study. The remaining chapters are organized as following:

Chapter 2: This chapter provides a detailed background on inclusion, including inclusion in the United Arab Emirates (UAE) context, background on ASD, and the IEP. It also presents a review of related work, including literature related to technology for ASD, coordination and communication in special education, and methods for developing technology for special education. Moreover, it includes literature related to digitized behaviour intervention and RL. This chapter concludes with a statement on the research gap that fuelled the motivation of this study.

Chapter 3: This chapter illustrates the methodology followed in this thesis to design and develop and evaluate the IEP-Connect app as well as the RL framework including modelling the motivator selection problem as an MDP. The chapter outlines the research approach, data collection and sampling methods, and data analysis methods. It also discusses the researcher role, ethical considerations, trustworthiness of the data, and the delimitations of the study.

Chapter 4: This chapter describes the processes followed to design and implement the IEP-Connect app. It first describes the coordination process in special education through an illustrative case study. The chapter then illustrated the design and implementation steps taken to evaluate the

[2] Under review in the International Journal of Artificial Intelligence in Education.

mobile app. Finally, the results of the usability study are discussed and the implications of the study are presented.

Chapter 5: This chapter describes the proposal and implementation of the RL framework to solve the problem of selecting the right motivator for learners with ASD. To this aim, this chapter first outlines RL preliminaries. It then illustrates the process of modelling the task of selecting a motivator as an MDP problem. Finally, it presents the evaluation results resulting from the integration of the RL framework with the IEP-Connect app.

Chapter 6: This chapter provides a summary of the study, the major findings, implications for research and practice, implications for future work, and the study conclusion.

2. Literature Review

Teachers and therapists working with learners with ASD are faced with the challenge of data collection, the unclarity of treatment plans, and the lack of detailed research on best practices (Bhuyan et al. 2017). While therapists and teachers all share the same goal of helping the learner with ASD to make progress by creating appropriate plans and engaging the child in therapy sessions, their path is usually paved with many challenges. The effectiveness of treatment plans created for an individual learner does not only depend on the quality of therapy provided and the resources available, but also on the proper communication between all the caregivers of the child (Winterman & Rosas 2017). Moreover, despite being tailored according to the individual needs of the learner, the treatment plans and IEP goals require continuous adjustments (Linstead et al. 2016). Technology has the potential to transform ASD intervention practices by offering data-driven solutions (Bhuyan et al. 2017). Advanced technology tools such as data mining and machine learning have been leveraged in ASD research. However, the main focus of the research have been on ASD evaluation and diagnosis (Kosmicki et al. 2015), therapy (Stevens et al. 2017), and education (Xanthopoulou, Kokalia & Drigas 2019). Thus, effective data management continues to be a challenge for caregivers of learners with ASD (Linstead et al. 2016).

As this thesis is profoundly interdisciplinary, this chapter first presents a detailed background on inclusion, including inclusion in the United Arab Emirates (UAE) context, background on ASD, and the IEP. Then, it presents a a review of related work on technology applications for ASD, coordination and communication methods in special education, and methods for developing technology tools for ASD. Then, the literature on digitized behaviour intervention and relevant RL applications are explored.

2.1. Inclusive Education

Inclusion is a global movement requiring educators to provide appropriate education for all learners. Inclusion is established when all learners, regardless of their abilities or disabilities, are placed in general education classes and are provided with high-quality education, intervention, and support that allow them to succeed in the curriculum (Gaad & Almotairi 2013; Foreman & Arthur-Kelly 2017).

Through the Universal Declaration of Human Rights (UDHR) adopted by the United Nations (UN) in 1948, children were guaranteed the right to free and compulsory elementary education. This declaration was central to the move towards inclusive education and was followed by various conventions including the UN Convention against Discrimination in Education (UN Educational, Scientific and Cultural Organisation (UNESCO) 1960), the Convention on the Rights of the Child (United Nations 1989), the UNESCO Salamanca Statement (UNESCO 1994), and the UN Convention on the Rights of Persons with Disabilities (CRPD) (United Nations 2006) all which endorsed inclusion as a strategy to attend to the needs of all learners (Cline & Frederickson 2009; Alborno 2017). Specifically, article 24 of the CRPD recommends national legislators to ensure that inclusive education is established at all levels (United Nations 2006). While the UN conventions are not legally binding, they set an international standard and provide guidance for countries to follow. This international movement towards inclusive education has been reflected by policies and legislations in various countries around the world. For instance, the Index of Inclusion adopted by the UK government provides a framework for schools to review and develop the cultures, policies and practices on inclusion (Booth & Ainscow 2002). Similarly, the US Federal Individuals with Disabilities Education Act (IDEA) indicates that special education must be provided to learners, free of charge, through the public education system (U.S. Department of Education 2004).

The term “special education” describes the specialized instruction design to meet the unique learning needs of learners with identified disabilities, in order to ensure they develop to their fullest potential (Kauffman et al. 2018). While inclusion and special education may encounter the same challenges around the world, the way inclusion is addressed differs in each country or region (Battaglino 2007). Therefore, inclusion remains controversial in practice around the world (Warnock & Norwich 2010). The differences are not only evident in the development and adoption of policies and legislations but extends to the terminology used in special education. For instance, the move has been toward placing the person before the disability. Therefore, terms such as “disabled”, were replaced by terms such as “people with disability”. Other terms that are currently being used include “people with special needs”, “people with SEND”, “people with additional needs”, and, as in the UAE, “people of determination” (Gaad 2004; Illes & Lou 2019; The United Arab Emirates’ Government portal 2021).

2.2. Inclusive Education in the UAE

The United Arab Emirates (UAE), founded in 1971, is a federation of seven Emirates located at the southern end of the Arabian Gulf. Oil and gas became the principal source venue in the 1950s, replacing the fishing and pearl diving industries. The UAE is considered to have the most diversified economy, as more recently, tourism, commerce and telecommunications became contributors to the country’s growing economy. The transformation in economy led to the rapid development of all sectors, including health and education. The UAE is considered liberal in its practice of cultural and religious tolerance, accommodating the unique mixture of nationalities and cultures residing in the country. The education sector also serves the diverse national and expatriate population, by offering an Arabic curriculum in public schools, and international curricula in private schools (Alborno 2017).

The move towards inclusive education in the UAE became evident with the issuing of several legislation documents starting with the Federal Law No. 29 of 2006 (Ministry of Social Affairs - UAE 2006). Despite the country's young age, the government invested its efforts to comply with the CRPD (Gaad 2019). Federal Law No. 29 of 2006 is the first law in the UAE that protects the rights of people of determination. According to Article 12, the country guarantees people of determinations equal opportunities in all kinds of education, including vocational training, adult education, and continuing education institutions. According to the law, education should be provided in regular classes or special classes with the availability of appropriate curriculum and methods (The United Arab Emirates' Government portal 2021).

In 2008, the Ministry of Education provided schools with inclusion guidelines and provisions through the "School for All" initiative, which was considered a major step towards the social integration and involvement of people of determination (The United Arab Emirates' Government portal 2021). The "School for All" guidelines require all parties involved in the intervention of learners with SEND to coordinate and collaborate with each other. The guidelines provide a set of recommendations describing the responsibility of all parties involved (Ministry of Education - UAE 2010). However, these guidelines are considered vague and lacking practical details (Alborno & Gaad 2014). The National Project for Inclusion of People with Special needs, launched also in 2008, emphasized the need to provide the required facilities for people of determination to facilitate the practical access to the educational system. Under the slogan "Our Life is Our Integration", the project expanded to all the emirates with the aim of achieving a complete integration of people of determination into the society at all levels (The United Arab Emirates' Government portal 2021). In 2017, the Ministry of Community Development published the National Policy to Empower People of Determination" as part of the UAE efforts to create an inclusive society for people of determination and their families (Ministry of Community Development 2017). It was through this policy that people with special needs were referred to as "the determined ones" or "people of determination". The policy consisted of six pillars; healthcare and rehabilitation, education, vocational training and employability, accessibility, social protection, and family empowerment, and public, cultural and sport life (see Appendix A for the goals and initiatives of the education pillar).

Dubai, which is one of the emirates in the UAE, is one of the main cities that reflect the adoption of inclusive education in the UAE (Gaad 2010, 2019). The Dubai Inclusive Education Policy Framework published by the Knowledge and Human Development Authority (KHDA) (2017) provides guidance on the actions to be taken to ensure the provision of quality inclusive services for learners of determination. According to the framework, schools' leaders and special education needs coordinators (SENDCOs) should ensure effective collaboration methods between parents, teachers, therapists, and medical practitioners to meet the needs of learners with SEND. The framework also requires educators and therapists to collect and analyze data to track learners' progress against the IEP objectives, and share relevant information across stakeholders (Alborno & Gaad 2014). More recently, the KHDA published the "Advocating Inclusive Education" guide for parents, which aims at providing a clear understanding of parental rights, responsibilities and opportunities in the system of inclusive education (KHDA 2021).

While the policies and frameworks in the UAE meet international benchmarks and promote collaboration between all stakeholders involved in the intervention of learners with SEND, it is still unclear how these policies are implemented and adopted in practice (Alborno & Gaad 2014).

2.3. ASD

ASD is a developmental disorder that manifests itself in childhood. The subject heading "Autistic Disorder" was renamed "Autism Spectrum Disorder" in the MeSH[3] database in 2016. The Diagnostic and Statistical Manual of mental disorders (5th edition), or DSM-5, is used by professionals such as paediatricians, psychologists and speech pathologists when diagnosing autism (American Psychiatric Association 2013). The DSM-5 considered a single diagnosis of ASD that replaced the different subcategories previously used, such as "autistic disorder", "Asperger's disorder", "childhood autism", "Kanner Autism", "high functioning autism" and "pervasive developmental disorder – not otherwise specified (PDD-NOS)". According to the DMS-5 criteria, the diagnosis of ASD depends on evidence of involvement in "social communication and interactions", and "restricted, repetitive and/or sensory behaviours or interests" (Alves et al. 2021).

According to The World Health Organization (WHO) and the Centres for Disease Control and Prevention's (CDC) Autism and Developmental Disabilities Monitoring (ADDM) Network, the prevalence of ASD has increased in recent years, estimating that 1 in every 68 children has ASD. Moreover, ASD is more common among boys (1 in 42) compared to girls (1 in 189) (CDC 2020). Based on the remarkable increase of prevalence in recent decades along with the change of the

[3] MeSH (Medical Subject Headings) is the NLM controlled vocabulary thesaurus used for indexing articles for PubMed. https://www.ncbi.nlm.nih.gov/mesh/

ASD descriptor, there became a need for a scientific update on the state of knowledge and the methods of ASD early diagnosis (Alves et al. 2021).

ASD is considered a life-long neurodevelopmental disorder which varies from mild (Level 1) to severe (Level 3) and which is often accompanied by other developmental disorders such as attention, sensory, and language processing disorders. The severity of learning and development special needs at an individual level depends on the combined effects of all the disorders. Additionally, special needs depend on the degree to which the learner is supported by caregivers. One important aspect of support provided for learners with ASD is education, as an effective education can have a significant impact on the outcomes for those on the autistic spectrum (Jordan, Roberts & Hume 2019). A child with ASD usually requires more than one therapist, each focusing on a specific skill (Gaad 2010; Strunk, Leisen & Schubert 2017). For instance, an occupational therapist teaches the skills that help the child become more independent in life skills, such as getting dressed, eating, and relating to people. Occupational therapists also help the child improving fine-motor skills (e.g., holding a pencil) and gross-motor skills (e.g., throwing a ball). A behavioural therapist helps in modifying the child's challenging behaviours, such as repetitive movements and avoiding eye contact, and teaches the child more appropriate ways to communicate her needs. A speech therapist addresses a variety of communication-related issues, such as pronunciation, sentence formation, and listening skills (Politte et al. 2015). Whilst there is no universal accepted cure for ASD, it is widely believed that both intensive behavioural and educational interventions are essential for improving outcomes of children on the spectrum (Koegel et al. 2014).

Once schools were required by law to provide learners with SEND with appropriate education that is personalized according to their individual needs, new intervention approaches started to emerge and become implemented. Nowadays, there is a much better understanding of ASD and the various intervention strategies (Jordan, Roberts & Hume 2019). However, as ASD can manifest itself in various ways, in different children or in the same child on different contexts, the task of formulating an intervention plan to meet the learner's special needs can be challenging (Mahon 2019).

Another challenge schools and parents face is that learners with ASD may show little interest in academic activities and may exhibit disruptive behaviour when required to complete certain assignments. Whilst there is no known cure for ASD, early intervention has proven to be effective in improving cognitive abilities as well as language and adaptive behaviours (Dawson et al. 2012). Research indicates that incorporating motivational variables during interventions results in improvements in behaviour and academic performance (Browder et al. 2014). However, the impact of such motivational variables varies between children. Moreover, parents require a lot of support and guidance to support their children (Gaad & Thabet 2016). Unfortunately, teachers and therapists often stand in need of the time and resources to coach parents on effective behaviour management techniques (Spiller 2020). In the UAE, there has been recently some efforts in providing parents with training to cope with the behavioural and emotional challenges that are related to ASD. However, more studies are required to follow the impact of such programmes in the long run (Gaad & Thabet 2016).

2.4. The IEP

The IEP represents all the steps required to create and articulate a legal document developed by the care team that is critical to the learners' educational success. The IEP process starts when a student is identified as experiencing cognitive difficulties or behavioural problems. After the identification process, the IDEA necessitates that the following participants contribute to the development of the IEP; the parents, the learner (when appropriate), at least one regular education teacher who is or will be working with the learner, at least one special education teacher, a representative from the school that is qualified to supervise or provide special education services, a specialist who can perform or interpret the learner's evaluations, and specialists that have the expertise specific to the learner (e.g., speech therapist, psychologist, occupational therapist). Periodic meetings are held on which all participants develop, agree to, and revise the program and monitor the learner's progress in meeting the specified goals (Siegel 2017). During the IEP meetings, a written description of the educational program is produced.

The IEP document is based on different types of assessments, the learner's strengths and needs, and the observations of parents and other team members (Diliberto & Brewer 2014). For the IEP to be successful, it should include sufficient information that allows someone unacquainted with the learner to understand her. The IDEA (20 U.S.C § 1414(d)(1)(A)) necessitates that an IEP includes (a) learner's present academic achievement and functional performance, which are considered the starting point of the IEP, (b) measurable goals, including academic, functional, long-term and short-term goals, (c) an evaluation mechanism to assess whether the established goals are being achieved to ensure that the learner is involved and progressing in the general curriculum, and to meet other educational needs that result from the learner's disability, (d) special services and accommodations the learner will receive, such as one-on-one aid, low-distraction work area for tests, read-aloud or text-to-speech, and positive reinforcement motivators, (e) the projected date for the beginning of the services and their duration, and (f) an individualized transition plan by the age of 14 or earlier (Gartin & Murdick 2005; Wamba & Dunn 2009; Ruble et al. 2010). Figure 3 illustrates the main components of the IEP document.

IEP goals cover different areas, including academic skills (e.g., reading, spelling, and numeracy skills), cognitive skills (e.g., memory and abstract thinking), emotional skills (e.g., overcoming fears and refining self-esteem), social-behavioural skills (e.g., sharing with peers), speech and communication skills, independent living skills (e.g., using money, using the toilet, getting dressed), physical skills (e.g., improving fine and large motor skills), and transition skills (e.g., work skill development).

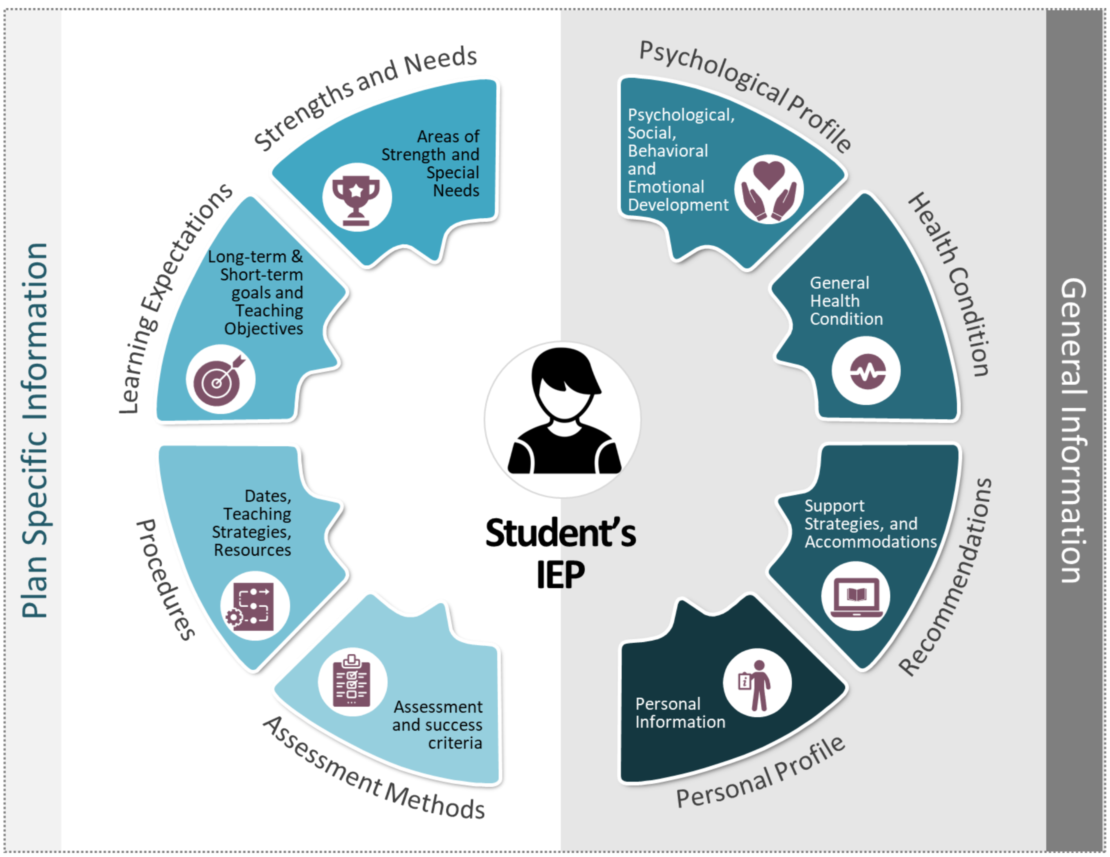


Figure 3: Components of the IEP document

After completing the IEP document and setting the goals and related services, the team agrees on the education setting placement of the learner. The placement refers to the amount of time in each school day that a learner spends in general education classroom, resource, or self-contained classrooms. Inclusion is when learners receive special education and related services in General (or mainstream) education classrooms. Some services that a learner may receive in a general education classroom include a helping teacher, co-teaching, education aides, and modifications or accommodations in lessons. Resource (or pull-out) is a separate setting where a special education program can be delivered for a learner individually or within a small group. Lastly, a self-contained (or separate) classroom (Spencer 2013) is considered when a learner needs to receive special education services for more than half of a school day (Yell & Katsiyannis 2004; McLeskey et al. 2012). According to IDEA, learners with SEND are to be educated in the least restrictive environment (LRE), meaning they are to learn alongside other learners without disabilities to the maximum extent possible.

The IEP should also provide the mechanism by which instructional methods are articulated across all participants (Ruble et al. 2010). Each party receives a copy of the IEP, either printed or electronic. Once the IEP is agreed on, the implementation of the IEP starts. In other words, the learner with SEND starts receiving the education and services listed in the IEP that are necessary for the learner to advance towards the IEP goals. Therefore, all participants involved in the IEP should understand their responsibilities for carrying out the IEP. Moreover, teamwork plays an essential part in implementing the IEP. As many professionals are likely to be involved in the IEP, sharing expertise and insights between all participants facilitates the implementation of the IEP which leads to improving the learner's progress. Schools are encouraged to provide teachers, support staff and professionals with the needed time to plan and work together. Additionally, communication between school and home is essential as parents can share information about what is happening at home and build upon what the child is learning at school. Parents can also provide insights as why the child may be having a certain difficulty at school to explore possible motives and find solutions. An additional key part of the implementation of the IEP is providing regular progress reports that will allow parents and schools to monitor the learner's progress towards the IEP goals (U.S. Department of Education 2019).

Despite the dramatic increase in numbers of learners with ASD, and the growing base of IEP legislation for these learners, reliable information on the content, effectiveness, and outcomes of the IEPs for learners with ASD is missing from the literature (Ruble et al. 2010). Moreover, research examining the quality of IEP for learners with ASD indicates that most of the IEPs do not meet the requirements of the IDEA indicators, with the measurability of IEP objectives being the area in need of most attention. Moreover, it was found that most objectives did not meet the state standards or were adopted without individualization to the learner. Another area requiring attention was the inadequate description of tailored instruction for a specific objective (Ruble et al. 2010). Many issues may occur when designing the IEP because of the overwhelming tasks teachers need to tackle such as new learners' admissions, contradictory educational directives, and pressure from supervisors or others in authority. Other reasons affecting the quality of the IEP include the long time needed to revise and evaluate the IEP and not including inclusion teachers in the efforts made to improve the intervention strategies (Wamba & Dunn 2009). Moreover, not having a clearly defined mechanism to articulate the IEP and share the expertise between participants results in missing data and opportunities.

Paper-based IEP documents were exclusively used before the introduction of electronic IEPs. The move towards electronic IEP has improved the way the IEP data is stored, analysed and shared (Marcu et al. 2013). Although IEPs are still developed and written by hand in some settings, many schools have adopted commercially available software or templates to aid in the development of IEPs, save time, and reduce paperwork (More & Barnett 2014). Most of the electronic IEP software contain an online component that allows the IEP to be accessed by multiple participants at the same time, streamlining the drafting process. The electronic IEP has many advantages in facilitating the writing progress of the IEP. For example, electronic IEPs aid in the procedural aspects of IEP development, such as incorporating demographic information from the school's management system and displaying the learner's name and parents' data on top of each page on the IEP document. Additionally, electronic IEPs can facilitate the actual writing of IEP goals and objectives with goal banks or drop-down menus. Goal banks expedite the writing of the IEP by reducing the time it takes teachers to write the goals, simplifying the process of reports generation, assisting team members with compliance issues, and aligning with state standards (More & Hart 2013; More & Barnett 2014). However, the use of electronic IEPs presents many challenges to writing quality individualized goals. These challenges can be related to issues in wording, content, accuracy, and measurability (More & Barnett 2014). Moreover, while electronic IEP facilitate the writing, accessing and reporting of the IEP, it usually does not have specialized components for sharing the needed information to the required team member on a specific time (Marcu et al. 2019). Current computerized methods of IEP focus on minimal compliance by reducing cost and time, rather than ideal compliance by improving quality of ongoing communication and documentation (Marcu et al. 2019).

The writing of the IEP is one of the most important steps towards the inclusion of learners with SEND. However, without a clear mechanism to coordinate the efforts of all parties involved in the daily intervention of the learner, as well as an efficient way to monitor the learners progress, there might be a lot of missed opportunities for daily coordination. The use of mobile technology can provide various solutions for coordinating the efforts of all people involved with the learning and therapy of learners with ASD.

2.5. Knowledge Sharing in Cross-functional Teams

The learning and therapy of learners with SEND requires the coordination of a group of individuals with different expertise and specialities. In projects, this group of people is called a cross-functional team (Ghobadi & D’Ambra 2013; Pershina, Soppe & Thune 2019). The literature emphasizes on realizing the potential value of cross-functional teams when the knowledge and expertise of an individual is shared with the knowledge and expertise of other team members (Ghobadi & D’Ambra 2012; Morley & Cashell 2017).

However, there are many challenges that impact effective knowledge sharing in cross-functional teams. These challenges include team members or groups considering the knowledge private or having different and superordinate goals. Other challenges include accessibility, physical proximity and formalized rules and procedures (Pinto, Pinto & Prescott 1993). Therefore, there is a cooperative and competitive nature to cross-functional teams communication and knowledge sharing. This mixed-characteristics impacts knowledge sharing practices and is referred to as coopetitive knowledge sharing (Ghobadi & D’Ambra 2012).

Knowledge sharing is important for achieving effective collaborative practices. Still, it is more important to ensure that the shared knowledge is transformed to become an integrated synergized solution (Ganguly, Talukdar & Chatterjee 2019). According to the knowledge transfer literature, knowledge transfer necessitates both the sharing of the knowledge from the source agent, and its learning by the recipient agent (Argote et al. 2000; Ajith Kumar & Ganesh 2009). Therefore, there is a need for sharing high-quality information that is perceived as useful and applicable by the receiver (Ganguly, Talukdar & Chatterjee 2019).

This study is based on the notion that sharing high-quality information between different stakeholders involved with learners with SEND is essentials for good learning outcomes. Subsequently, the use of mobile technology and artificial intelligence is proposed to improve knowledge sharing and provide an effective tool for coopetitive knowledge sharing.

2.6. Technology for ASD

The increased rate of ASD diagnosis in recent years (CDC 2020) has fuelled the research in technology for special education in general, and ASD in particular, with the purpose of improving the life quality of those affected (Yee 2012). The topic has been examined from multidisciplinary approaches to study how technology can benefit autism research in the fields of education, psychology, and technical sciences (Virnes, Kärnä & Vellonen 2015). Another widely studied topic in relation to ASD is mobile health (mHealth) (Istepanian, Laxminarayan & Pattichis 2007). mHealth utilizes emerging mobile networks and devices for the benefit of improving the health and well-being of individuals. mHealth applications include promotion of healthy lifestyles, or monitoring and improving the individual’s health (Alnaghaimshi et al. 2020).

The literature shows a variation in the purpose of using technology for learners with ASD (Virnes, Kärnä & Vellonen 2015; Olakanmi et al. 2020), with a main focus on education (Cheng & Lai 2020), diagnosis and screening (Kosmicki et al. 2015; Desideri, Pérez-Fuster & Herrera 2021), and modelling social and behavioural aspects of ASD (Stevens et al. 2017). Technology for education purposes covered various topics and skills including general education (Xanthopoulou, Kokalia & Drigas 2019), cognitive abilities (Yi et al. 2020), literacy skills (Gobbo, de Barbosa & Mafort 2018; Silva et al. 2020), academic skills (Roman, Mehta & Sajja 2018), communication skills (Fazana et al. 2017), social skills (Hourcade, Bullock-Rest & Hansen 2012), functional skills (Crutchfield et al. 2015), and emotion recognition (Khan, Li & Madden 2018).

Similarly, the literature includes a wide range of technologies developed to serve the aforementioned purposes (Olakanmi et al. 2020). These technologies include computer aided systems (CAS), games, hardware, learning environments, portable devices, robots, tracking solutions (i.e. eyes trackers), facial recognition, computerized assessment, virtual reality, machine learning, and artificial intelligence assisted intervention (Virnes, Kärnä & Vellonen 2015; Jaliaawala & Khan 2020; Valentine et al. 2020).

Wide-ranging research has confirmed other benefits of developing innovative technologies for children with ASD and the people involved with them (Goodwin 2008). For example, technology can provide families access to resources that are usually limited, such as distance clinical healthcare and direct communication with professionals. Moreover, the use of technology to perform autism-related assessment and diagnosis allows the data to be automatically transferred to a centralized location for analysis, interpretation and feedback. Data collected from technology-based assessments and other recording and tracking methods is considered a valuable data repository for research on children with ASD.

Moreover, special educators use a wide range of technologies as part of their teaching and to collaborate more effectively with families (More & Barnett 2014). One application of the use of technology in this field is the computerized IEP. Electronic IEP format does not only facilitate the creation and writing of the IEP, but also provides a more efficient way to monitor learners' progress. Using paper communication and data collection forms may result in a lack of access to information if paper data is not timely and accurately transferred (Vannest et al. 2011). Conversely, electronic IEP can provide schools and teachers with automated graphs that can be used for data-based decision making. Special education teachers and parents also make use of mobile applications designed for learners. These applications usually target specific learning objectives and can be customized according to the learner's level and preferences. For example, some mobile apps use flashcards to help learners with ASD learn skills related to daily activities by creating individualized content adaptable to the learners' level of functioning (Zaffke et al. 2015). Other apps can be used to teach learners with ASD academic skills using computer assisted instruction (CAI) programs and applications (Snyder & Huber 2019). These skills include vocabulary and receptive language skills (Khowaja & Salim 2019; Novack et al. 2019), mathematical skills (Kamaruzaman et al. 2016; Xin et al. 2017), and Science, Mathematics, Technology, and Engineering (STEM) education (Ehsan et al. 2018). Another category of technology used in the classroom is the use of visual scheduling systems. Visual schedules use symbols to represent a series of activities to help learners with ASD recognize, structure and predict their daily activities. Interactive visual scheduling apps allow teachers or caregivers to create visual schedules and monitor learners' progress throughout the scheduled activities (Hirano et al. 2010; Reinert, Higbee & Nix 2020).

Moreover, there has been an increased attention given to the research in the area of machine learning with the purpose of improving the learning experience of learners with ASD. The focus of research has been mainly on developing academic or social skills learning applications (Roman, Mehta & Sajja 2018), improving diagnosis efficiency (Kosmicki et al. 2015), and modelling social and behavioural aspects of ASD (Stevens et al. 2017). For instance, agent-based systems have been found to have immense potential to improve diagnosis and intervention. Milne et al. (2009) used autonomous agents as social tutors for learners with ASD to investigate learners' ability to recognize and respond properly to facial expressions. Similarly, Foster et al. (2010) presented a multi-modal learning environment which integrates autonomous agents into an interactive virtual world to support learners' social interactions and communication skills. In a more recent study, Roman et al. (2018) described an intelligent tutoring system where agents interact with each other to adapt to the learning needs of the learner. However, no research was found that applied reinforcement learning to solve the MSP.

2.7. ASD Care Coordination and Communication

The literature contains a myriad of research on technology for ASD. However, the ways different stakeholders involved with learners with ASD communicate and coordinate are understudied (Woods, Morrison & Palincsar 2018). Moreover, there is little research on the use of digital technology to monitor the progress of learners with ASD (Valentine et al. 2020). While the coordination and monitoring of children with ASD has not been widely targeted for educational purposes, coordination and monitoring for health purposes has received more attention by researchers. For instance, Bangerter et al. (2019) designed a mobile and web-based mHealth app to monitor clinical outcomes in ASD. Caregivers of children with ASD use the app to record their child's treatments, log symptoms and behaviour, and track progress. The advances in mHealth technologies has enabled the development of practical alternatives to retrospective reporting such as the Aberrant Behaviour Checklist (ABC) (Aman et al. 1985). Surveys such as the ABC require recall of specific behaviours over periods of time, which can impact the accuracy of the rating. mHealth technologies can facilitate the recording of behaviours in real time and improve the reliability of the ratings. Moreover, when combined with biometric data and data from other resources, mHealth technologies can enhance the understanding of data and identify patters in behaviours in children with ASD (Bangerter et al. 2019).

Alnaghaimshi et al. (2020) proposed a mobile application that allowed parents to detect signs of ASD, access autism specialists in the region, and access essential educational resources to care for their children. In addition, the app allowed users to connect with other parents to share information and experiences. Moreover, the app aimed to simplify ASD data collection through surveys and interviews via text messages. The use of mHealth apps has the potential of increasing the accuracy of caregiver-reported outcomes compared to paper-based reporting. Moreover, timely recording of behaviour instances can help identify early changes in response to intervention and monitoring of progress (Bangerter et al. 2019).

Other studies researched ASD care coordination in heterogenous settings by taking advantage of artificial intelligence capabilities, such as multi-agent systems. For instance, Amir et al. (2015) described the design of an app that aims to support the creation and monitoring of team-based care plans of children with complex conditions. The main building blocks of the proposed system consisted of the goals, the actions needed to accomplish the goals, and progress monitoring updates. The proposed design allowed a diverse and growing team of care providers to build and maintain a shared plan and to include parents in its design. Similarly, Linstead et al. (2016) introduced the Autism Management Platform, an integrated health care information system for managing data related to the diagnosis and treatment of children with ASD. The authors developed a mobile application to facilitate information and multimedia sharing between parents and clinicians. The system also included a web interface and analytics platforms, allowing specialists to mine patient data in real-time. The analytics platform used machine learning techniques to provide users with personalized data searching preferences.

2.8. Human-Computer Interaction (HCI)

As many studies show the effective impact of using technology to support children and parents with ASD in different aspects, there is a need for guidelines to be followed by developers and researchers for designing, developing and evaluating such technology (Kamaruzaman et al. 2016; Dattolo & Luccio 2017; Sharmin et al. 2018). Many advances were made regarding human-computer interaction (HCI) for learners with ASD and their caregivers (Kamaruzaman et al. 2016; Constain, Collazos & Moreira 2018). Many of the research papers in the literature follow informed design approaches that involve the learner with ASD and other relevant stakeholders in the design process from the start, such as participatory design and user-cantered design approaches (Spiel et al. 2019).

One of the main factors impacting the success of HCI is the user interface (UI). A good UI design allows the users to carry out tasks in an easy and engaging way. When designing applications for children with ASD, UI design should be thoroughly considered to accommodate the varied needs of learners with ASD (Kamaruzaman et al. 2016). Moreover, visual supports should be considered in the UI design of apps targeted at learners with ASD as they were found to reduce anxiety, improve predictability, and support communication (Frauenberger, Good & Alcorn 2012). Picture Exchange Communication Systems (PECS) are examples of effective methods of teaching learners with ASD through visuals that have been embedded into a digital-based medium (Shminan et al. 2017).

The usability of a system is considered one of the fundamental concepts in HCI. Usability can be defined as the degree to which a system can be used by its intended users to achieve defined goals effectively and efficiently and provide satisfaction in a particular context of use (Bevan, Carter & Harker 2015). The definition covers three measure of usability (Brooke 1996; Bevan, Carter & Harker 2015); (1) the level of resources consumed when performing tasks, such as time, money, and mental exertion (efficiency), (2) the ability of users to complete the intended tasks through the system and the quality of the output (effectiveness), (3) and the extent to which users find the system worthy (satisfaction). Other usability measures include the simplicity of performing a task (ease of use) and the intuitiveness of the interface (learnability). These measures apply not only on systems designed for learners with ASD, but also when designing and developing systems for all other users, such as carers, teachers, therapists, and doctors. The System Usability Scale (SUS), developed by Brooke (1996), has been widely used by researchers and systems developers as a quick measure of perceived usability. For instance, the SUS measure has been used in evaluating the usability of educational applications and websites such as learning management systems (LMS) (Orfanou, Tselios & Katsanos 2015) and eHealth applications (Maramba, Chatterjee & Newman 2019).

While usability is related to aspects of HCI and in particular the user interface, system "usefulness" is concerned with the content and services the system has to offer, and how strongly they meet user requirements. When system usability and usefulness are combined, it is possible to determine system satisfaction and usage (Buchanan & Salako 2009). Usability evaluation on its own may lead to systems that are effectively designed, but functionally inadequate (Greenberg & Buxton 2008). Proposed models for systems evaluation that have usefulness as a component or variable include the DeLone and McLean (D&M) model of information system success (DeLone & McLean 1992), and the Technology Acceptance Model (TAM) (Davis, Bagozzi & Warshaw 1989). These models considered usefulness as a variable dependent of other constructs such as system quality, information quality, user satisfaction, individual impact, and organizational impact in the D&M model, and perceived ease of use, attitudes towards using a system, behavioural intention to use the system, and actual system use in the TAM model.

2.9. Digitized Behaviour Intervention

There are many available applications that allow therapists, teachers and parents to monitor the behaviour of learners with SEND (Vannest et al. 2011; Marcu et al. 2013). These applications allow the people involved with the intervention of learners with SEND to track, store and share important information. This information is used to plan for interventions, monitor progress towards IEP objectives, and generate reports. While these applications are very helpful and a good replacement of paper-based data collection, the data collected in special needs settings is usually complex, unstandardized and incomplete (Marcu et al. 2013). Many studies suggested using data mining techniques to support intervention decisions (Thabtah 2019). For instance, Burns et al. (2015) developed a mobile app that employed association rule mining to reveal patterns in behaviour causes and effects to inform the therapists decisions. In the study, parents use a mobile app to collect Antecedent, Behaviour and Consequence (ABC) data. The data mining techniques aimed to identify behaviour causes and effects patterns to enable therapists to improve intervention. Linstead et al. (2016) introduced the Autism Management Platform, an integrated health care information system for managing data related to the diagnosis and treatment of children with ASD. The authors developed a mobile application to facilitate information and multimedia sharing between parents and clinicians. The system also includes a web interface and analytics platforms, allowing specialists to mine patient data in real-time. The analytics platform uses machine learning techniques to provide users with personalized data searching preferences. Bhuyan et al. (2017) studied temporal data to identify factors that aid caregivers in creating an effective intervention plan and predict the right treatment based on the data in other contexts.

Previous studies also focused on using mobile technology to help children with ASD and their caregivers in regulating challenging behaviours. For instance, Crutchfield et al. (2015) evaluated the impact of the I-Connect app on stereotypy in adolescents with ASD in a school setting. Préfontaine et al. (2019) developed the iSTIM app to support parents of younger children with ASD in reducing stereotypy behaviour. The app was evaluated and found successful in regulating stereotypy behaviour when used by trained researches as well as parents who do not have the required ABA training (Trudel, Lanovaz & Préfontaine 2020).

2.10. Reinforcement Learning (RL)

As a subfield of machine learning, RL has been widely implemented, resulting in its increasing applicability in real-life problems and decision-support systems (Yu, Liu & Nemati 2020). For instance, RL has been used to improve the delivery of personalized care by optimizing medication choices, medicine doses, and intervention timings (Liu et al. 2020). In the healthcare and therapy domain, data is characterized by its high dimensionality and complex interdependencies (Gräßer et al. 2017). RL has the potential to automatically explore various treatment options by analysing patient data to derive a policy and personalized therapy without the need of pre-established rules (Liu et al. 2020).

Recommender systems has also been leveraged using RL. Recommender systems based on RL have the advantage of updating the policies during online interaction, which enables the system to generate recommendations that best suit users' evolving preferences (Zhao et al. 2019). Examples include news (Zheng et al. 2018), music recommendations (Hong, Li & Dong 2020) and personalized learning systems (Shawky & Badawi 2019).

RL has proven to be an appropriate framework for interaction modelling and optimization of problems that can be formulated as MDPs. The advantage of such methods is the ability to model the stochastic variation of outcomes as transition probabilities between states and action (Tsiakas et al. 2016). RL has been successfully applied to personalized learning systems (Shawky & Badawi 2019; Sayed et al. 2020), adaptive serious games for ASD (Khabbaz et al. 2017) and robot assisted therapy (Tsiakas et al. 2016). For instance, Bennane (2013) automated the selection of the content of a tutoring system and its pedagogical approach to provide differentiated instruction. Similarly, Shawky and Badawi (2019) used RL to build an intelligent environment to provide learners with suitable content as well as adapt to the learner's evolving states. Khabbaz et al. (2017) proposed an adaptive serious game for rating social ability in learners with ASD using RL. The game adapts itself according to the level of the child by adjusting the difficulty level of the activities. In the field of Robot Assisted Therapy, Tsiakas et al. (2016) proposed an Interactive RL framework that adapts to the user's preferences and refine its learned policy when coping with new users.

2.11. Summary and Research Gap

The overall increased level of ASD research coupled with the extensive proposed technology solutions indicate the interest of research societies in providing novel solutions for learners with ASD. However, there is still a gap between available commercial technologies and the state-of-the-art technologies (Virnes, Kärnä & Vellonen 2015). Moreover, research on technologies for learners with ASD has focused on diagnosis and intervention, with less applications on data collection, data tracking, and progress monitoring (Virnes, Kärnä & Vellonen 2015; Sharmin et al. 2018).

Mobile technology has the ability to provide various solutions for learners with ASD and their caregivers, but has not been leveraged to solve the ICP problem (Marcu et al. 2013; Linstead et al. 2016; Kharbat, Alshawabkeh & Woolsey 2020). Prior HCI research has identified the need to design systems that facilitate the collaboration between home and school to help learners generalize skills they gain in school to more settings, including home (Marcu et al. 2019). Therefore, there is a need to explore the use of mobile technology to coordinate IEP objectives (Linstead et al., 2015). This should include the tracking of academic as well as the behaviour progress of a learner. Additionally, designing a system that enables the automatic sharing of specific information to certain parties according to their needs would allow teachers and specialists to adjust plans and accommodations to increase the learning outcomes of learners (Amir et al. 2015). To reduce the burden on teachers participating in the IEP creation process as well as increase the efficiency of plans, an intelligent system that is able to recommend instructional procedures is much needed.

Moreover, technology in practice should be tailored to meet individual needs. One way of ensuring that is by involving end users of the system in the early stages of the system requirements analysis and design (Parsons et al. 2017). There is a tendency of assuming that expertise lies with the researcher, rather than with specialists and others within the ASD community, which reflects the lack of end-user involvement in the field (Virnes, Kärnä & Vellonen 2015; Parsons et al. 2017).

Additionally, many of the proposed systems within the field of ASD are limited in regards of the methodological quality (Zapata et al. 2015; Valentine et al. 2020), including limited research on: user experiences, randomized controlled trials, longer study periods, larger number of participants, economic evaluation, and qualitative studies (Bangerter et al. 2019; Valentine et al. 2020).

Finally, while there are many studies that support behaviour tracking and regulation in learners with ASD, these studies are often focused on one stakeholder. For instance, research on technology for parents of learners with ASD has focused on recording behavioural occurrences and supporting behavioural intervention in the home, with a lack of technologies focusing on behavioural information sharing (Kientz & Abowd 2009; Nazneen et al. 2012; Pina et al. 2014; Marcu et al. 2019). In school settings, previous research focused on capturing the context of behaviour to support teachers and therapists determining appropriate interventions (Hayes et al. 2008; Marcu et al. 2019). However, none of the studies on behaviour intervention leverages the power of RL to support the decision-making process for solving the MSP.

3. Methodology

This research aims to propose, develop and implement a mobile app for special education that addresses both the ICP and the MSP problems. To this end, the design science research approach is adopted. First, the key design principles to inform the design of the mobile app are identified through participatory design. The processes at play when teachers and therapists collect, use and share data are also considered. Then, various iterations are conducted to deploy and evaluate the usability and effectiveness of the mobile app in addressing the two identified problems. In the first iteration a preliminary assessment on the app is first performed to verify the usability of the system and evaluate its effectiveness in solving the ICP problem. In this phase, the application is presented to three users to assess the user interface and interaction and provide feedback regarding performance and satisfaction through a think-aloud session. In the second iteration, the initial study is extended with a larger group of users to assess usability using the System Usability Scale (SUS) and interviews. Finally, usage and log data are collected to measure the actual use of the system.

In the third iteration, a RL framework is proposed to solve the MSP problem. To this end, the MSP is formulated using MDPs, which has been found to address the challenges faced in clinical decision-making. Then, a Q-learning algorithm with an epsilon-greedy (ε-greedy) policy with linearly decreasing exploration rate is used to solve the proposed MDP problem. The "Motivator Selection" feature is then added to the mobile app. Another usability study is conducted to evaluate the effectiveness of the proposed RL framework.

This chapter provides an overview of the methodology followed in this thesis. Figure 4 summarizes the research methodology followed in this study.

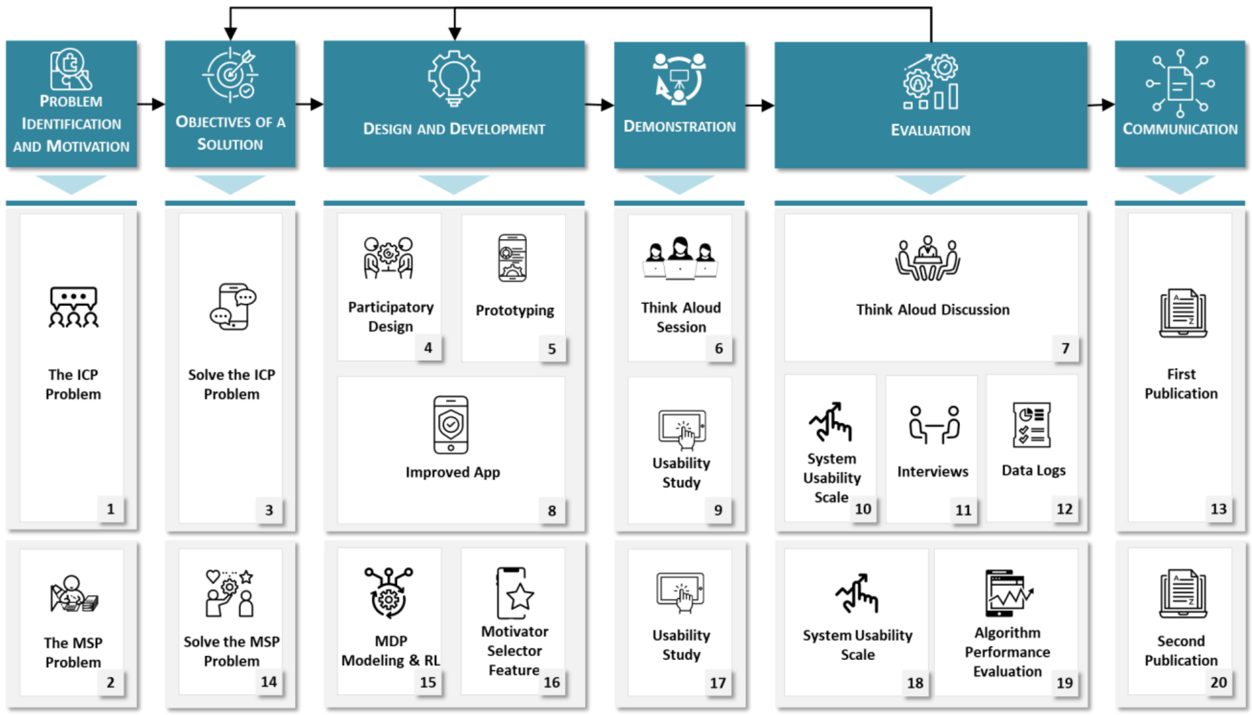


Figure 4: Research Methodology

3.1. Research Approach

This thesis follows the design science research approach. The design science paradigm allows the achievement of knowledge and understanding of the problem domain and its solution by building and employing a digital artifact (Hevner et al. 2004). The design science approach can be realized by following the design science research process (DSRP) model (Peffers et al. 2006). The DSRP includes six main steps as shown in Figure 4: problem identification and motivation, objectives for a solution, design and development, demonstration, evaluation, and communication (Peffers et al. 2006).

In this research, the problem identification, motivation and objectives of the solution are outlined in Chapters 1 and 2.1. In the problem identification and motivation phase, the ICP and

MSP problems are justified and defined. Then, the IEP-Connect app (the artifact) is proposed with the aim of solving the two identified problems (ICP and MSP).

With the aim of solving the ICP problem, this study employs a participatory design research approach in the process of designing and developing the IEP-Connect app, which is detailed in Chapter 4. Participatory design is seen as a design approach with its own techniques distinguished by users' involvement (Spinuzzi 2005; Bratteteig & Wagner 2016).

The mobile app development is followed by the demonstration of the produced artifact in a real context. In this research, the IEP-Connect app is introduced to the stakeholders that participate in the learning and intervention of learners with ASD through a usability study. To evaluate the initial produced artifact, the think-aloud method is used to identify initial use issues.

The feedback from the think-aloud evaluation is then used to inform the design and development of the artifact in the second iteration of the design process, which is evaluated using the System Usability Scale (SUS) questionnaire. The SUS questionnaire is considered a quick measure of the perceived usability of a system (Brooke 1996) and has been proven valid and reliable even for small sample sizes (Bangor, Kortum & Miller 2008; Lewis & Sauro 2009). Structured interviews are then conducted to gain insights on users' perceptions on using the app. Both the questionnaires and interviews are used to identify issues with repeated use and provide insights on users' perceptions regarding the app usability and user satisfaction. While the aim of this research is to perform statistical analysis to obtain statistically significant results regarding the usability of the app, it is usually recommended to use the SUS with other measures to compliment the perceived usability findings (Brooke 2013). The qualitative approach is considered suitable for studies of exploratory nature to pinpoint the issues that need tackling (Maramba, Chatterjee & Newman 2019). Moreover, interviews allow respondents to describe their experience after using the mobile app (Creswell 2015). Many previous studies used qualitative methods to test the usability of different systems, such as schools' websites (Kokil & Scott 2017), special needs assistive technologies (Keshav et al. 2018), and mobile health applications (Lodhia et al. 2016; Ergecer 2017). Finally, all users' interactions with the system are logged. Log data are mainly used to measure the actual use of the system, which is typical for usability analysis (Harrati et al. 2016).

In Chapter 5, the MSP is formulated as an MDP and solved as a Q-learning algorithm with an epsilon-greedy (ε-greedy) policy with linearly decreasing exploration rate. The "Motivator Selection" feature is then added to the IEP-Connect app in the third iteration of the design process. To evaluate the usability of the app after adding the "Motivator Selection" feature, a usability evaluation is conducted and compared to the results of the usability study conducted in Chapter 4 in a one-group pre-test/post-test quasi-experimental research design. Moreover, the success of the motivators is measured before and after using the "Motivator Selection" app feature. The "quasi" design lacks the randomness of assigning participants to different groups. However, this method can be used to conveniently assess an intervention on target participants. Moreover, this design allows for statistical analysis of data using recognized methods (Stratton 2019). To evaluate the performance of the RL proposed model, the data (i.e., rewards) produced by the Q-learning algorithm is analysed over time.

Finally, the results of the design science research must be communicated effectively to the wider research community, including scholarly researchers who will extend the research or practicing professionals who will decide whether the solution can be implemented within their organizations (Hevner et al. 2004). Future research aims to expand the use of the mobile app to a wider and more diverse population to further study the applicability of the mobile app in real contexts.

3.2. Sampling Methods

Sampling refers to the selection of some parts of a large group of people, called population, with the aim of obtaining information about the population (Kothari 2004). Any part of the population is called sample (Price 2016). In this study, the population is considered all the parties involved in the therapy and learning of learners with ASD, including the learners themselves. This also includes teachers, therapists, physician and parents.

Sampling can be either random or convenient (Price 2016). In random sampling, also called probability sampling (Kothari 2004), each member of the population has an equal chance of being selected for the sample (Price 2016). On the other hand, in convenient sampling, or non-probability sampling, the sample consists of individuals who are approachable and willing to participate (Price 2016). This study uses purposeful convenient sampling, in which a pre-set criterion is used to choose participants (Creswell 2015).

All data collected in this study through various methods (except the literature review examination) was collected from a private K-12 school in the UAE. The school teaches the American curriculum for Math, Science, English, and Computer Science, and the UAE Ministry of Education curriculum for Arabic Islamic and Social Studies. During the academic year of 2019-2020, the school had around 1,500 learners, mostly Emiratis (70%). Out of the total number of learners, 70 learners were learners with SEND studying in general education classes and 50 learners studying in special education classes (self-contained classes (Spencer 2013)). The special education section was led by a special education coordinator (SENDCO), who is also a psychologist. The section included special education teachers (n=10), therapists (n=4), subject teachers for special education classes (n=15), and learning support assistants (LSA) (n=20). Twenty learners in this section were learners diagnosed with ASD. Other learners were diagnosed with different disabilities including Profound and Multiple Learning Difficulty (PMLD), Attention-deficit/hyperactivity disorder (ADHD), hearing disabilities, muscular dystrophy, cerebral palsy, or general learning difficulties.

3.3. Participants

Parents of learners with ASD who's ages ranged between 5 and 12 and studied in the self-contained classes in the school were first invited to participate in the study. Consent was obtained from four parents to participate in the study by using the learners' data in the system. These learners were diagnosed with a middle-range (Level 2) to severe (Level 3) form of ASD and their ages ranged from 6 to 10 years (see Table 1). Teachers and therapists of those students were invited to participate in the study. This resulted in the participation of ten teachers and two therapists (see Table 2). The twelve teachers and therapists were first part of the mobile app development phase and then participated in the usability of the mobile-app study with the data of the four participating students. Additionally, the SENDCO in the school participated in the think-aloud study. The participating therapists have extensive experience in the use of behavioural therapy techniques with learners with SEND in general, and with learners with ASD in particular. On the other hand, participating teachers did not receive any formal training in the use of behavioural therapy techniques but had varied experience dealing with learners with ASD in terms of tracking behaviour and using motivators inside the class.

Table 1: Learners' demographics

2019-2020	N	**2020-2021**	N
Participants		**Participants**	
Learners	4	Learners	12
Parents (Using the app)	1	Parents (Using the app)	0
Learners' Gender		**Learners' Gender**	
Female	1	Female	1
Male	3	Male	11
Learner's Age		**Learner's Age**	
6	1	6	3
7	1	7	5
8	1	8	2
9	0	9	2
10	1	10	0
Level of ASD		**Level of ASD**	
Level 2	2	Level 2	5
Level 3	2	Level 3	7

However, after completing the first usability study and before starting the RL algorithm evaluation, WHO declared COVID-19 as a global pandemic in March 2020 (World Health Organization 2020). This caused all the schools in the UAE to move online. Therefore, the study was postponed until the new academic year of 2020-2021. During the new academic year of 2020-2021, the number of students studying in the special education section decreased to 30 students. Consents were sent again to parents of learners with ASD. Although the number of registered students was less compared to the previous academic year, consent was obtained from more parents, resulting in the participation of twelve students. All participating learners met the following criteria: (1) were diagnosed with a middle-range to severe form of ASD, (2) attended self-contained classrooms for learners with SEND, (3) had an IEP, and (4) had a comprehensive behavioural plan.

Two of the twelve students were students participating from the previous academic year (an eight-years girl and an eleven-years boy). Again, teachers and therapists of those students were invited to participate in the study. All of the teachers participating from the previous academic year consented to participate in the new academic year, resulting again in the participation of twelve special education teachers and therapists, and a SENDCO.

Table 2: Teachers, therapists and SENDCO demographics

Category	**N**
Gender	
Female	12
Male	1
Nationality	
Egyptian	8
Jordanian	3
Syrian	2
Job Description	
SENDCO	1
Subject Teacher	10
Occupational Therapist	1
Behaviour Specialist	1

3.4. Data Collection

Data in this study is obtained through various methods, including classroom observation, documents examinations, workshops, think-aloud session, questionnaires, interviews, users' data entry through the mobile app, and literature review examination.

The first data collection method used was unstructured observation, as the main goal of the observation was exploratory, rather than descriptive. Moreover, the observation in this study was participant observation. In this type of observation, the researcher observes by making herself a member of the group she is observing to experience their practice (Kothari 2004). Also, a non-controlled observation is when observation takes place in a natural setting. While observation is considered an expensive method and provides limited information, it has many benefits such as eliminating subjective bias and allowing the researcher to describe current events. Moreover, participant observation allows the researcher to gather more information compared to the non-participant observation. Additionally, it allows the researcher to verify data collected by other methods such as interviews and questionnaires. Non-controlled observation also allows the observer to get an unprompted picture of the tasks and individuals being observed without using precision instruments (Kothari 2004). Data resulting from the classroom and sessions observations was first recorded using unstructured observation forms and then was coded to find common themes.

The second data collection method used was documents analysis, which included examining ongoing records of the special education department in the participating school, including IEP documents, behaviour modification plans, learners' journals, and teachers' notebooks (see Appendix B). Both observations and documents analysis in this study aimed at understanding the methods teachers use to collect, record, and share data. Document analysis is considered a form of qualitative research that incorporates coding document content into themes similar to how interviews transcripts are analysed (Bowen 2009). Document analysis serves various functions, one of which is to verify findings or support evidence from other sources. In this thesis, document analysis is used in combination with observations and workshops as a mean of triangulation. Triangulating data allows the researcher to validate findings across data sets and reduce the impact of potential biases (Bowen 2009). Documents were collected in two forms; paper and electronic. Electronic copies were kept on the researcher's laptop and will be removed after five years following final approval of the research committee. Copies were made from paper documents and were immediately returned to teachers as they included learners' journals that were in use at the time of the study. Documents were then annotated using Microsoft Word for word documents, Acrobat Reader for PDF documents, and Paint 3D for images.

The aim of the workshops data collection tool was also exploratory. Workshops allow the researcher to identify and explore relevant factors and understand knowledge processes (Ørngreen & Levinsen 2017). The participation mode in this study was contractual, where a SENDCO, a behaviour therapist, and a math and science teacher were contacted by the researcher to participate in inquiries regarding the possible components and information they perceive as essential to be added to the mobile app interface design. Workshops bring forward knowledge that is considered different from observations and documents analysis. Observation provides first-hand evidence of what participants do, and documents analysis provides insights on procedures followed and information deemed necessary. On the other hand, workshops facilitate the organization of data gathered through previous methods and provide a place for collaborative negotiation of meaning (Ørngreen & Levinsen 2017). Samples of the workshop activities conducted in this study can be found in Appendix C. The workshop session took place in the school were participants worked. Files of the activities were copied to three laptops, each handed to one of the participants. Participants were asked to complete the activities and save their work. Then, files were moved from the three laptops into the researcher laptop. Output of the workshop activities were then compared, analysed and triangulated with results from the observations and documents analysis. This process allowed the researcher to identify the different users' personas as well as the basic information different stakeholders considered essential when communicating and coordinating plans.

The observations, document analysis and workshops data collection instruments aimed at informing the design of the IEP-Connect app. On the other hand, the think-aloud, questionnaires, interviews, and users' data entry aimed at evaluating the usability and performance of the proposed mobile app and RL algorithm. Data collected from the think-aloud session allowed to investigate users' first impression of the app and whether they think it can be used by the wider population of users. Users during this session were asked to verbalized their thoughts while performing specific tasks (Ericsson & Simon 1993). The session was recorded after obtaining verbal informed consent of the participants and later were transcribed verbatim and analysed to identify patters using Microsoft Word.

Both the questionnaires and the interviews aimed to identify issues with repeated use and provide insights on users' perceptions regarding the app usability and user satisfaction. Questionnaires and interviews were administered after the participants used the mobile app for two weeks. The System Usability Scale (SUS) (Brooke 1996) questionnaire was first administered to teachers and therapists to study general app usability and users' satisfaction. Electronic questionnaires were sent to teachers and therapists who used the mobile app. The same questionnaire was administered to the same participants after introducing the "Motivator Selection" feature to the mobile app to compare usability scores. Questionnaires as a method of collecting data are considered very common as they are low in cost, free of the bias of the researcher, allow enough time for respondents to give well thought answers, and allow the researcher to reach a big number of respondents, which in return make the results more dependable and reliable (Kothari 2004). Results of the SUS were analysed using Microsoft Excel.

Structured interviews were conducted after the administration of the questionnaires (Appendix D). All interviews were conducted in-person in the school. Each interview lasted from 20 to 30 minutes. Interviews were recorded after obtaining informed verbal consent of the participants. While interviews are more time consuming than questionnaires, they allow the researcher to obtain more in-depth information. Moreover, misinterpretation of the questions can be avoided as the researcher can adapt the language of the interview as needed (Kothari 2004). Interviews were transcribed using the computer assisted qualitative analysis software "QDA Miner".

Data was also collected through the mobile app. This data collection method aimed first to report additional usability analysis based on the actual usage of participants. Second, it aimed to evaluate the proposed RL algorithm. All the data entered to the mobile app by users, as well as their activity logs were directly saved to a hosting server. This data could be accessed only through login credentials available only for the researcher. Data collected through the mobile app was analysed using Microsoft Excel and SPSS.

Lastly, data was collected by reviewing the literature with the aim of investigating the factors that impact the selection of a motivator for learners with ASD and model the problem as an MDP. Reviewing the literature is a useful data collection approach when the purpose is to combine perspectives to create new models (Snyder 2019). During this phase, the literature was reviewed to determine the factors that represent the state space as well as the actions the agent can make in the MDP.

Table 3 summarizes the data collection methods used in this work as well as the research questions they aim to answer. More details about each collection method are specified in the mentioned sections.

Table 3: Data collection methods used in the study

Research question	**Data Collection Method**	**Aim**	**Section**
RQ1: What are the key design principles required to inform the design of a coordination mobile app for special education?	Observation	Understand the methods teachers use to collect, record, and share data.	4.1
	Documents Examination		
	Workshops	Inform the user interface design process.	
RQ2: How effective can mobile technology be in facilitating the coordination of educational plans in inclusive settings?	Think-Aloud	Investigate users' first impression of the app	4.2.1
	Questionnaires	Investigate users' perceptions regarding the app usability and user satisfaction.	4.2.2
	Interviews		4.2.3
	Data Entry and Logs	Measure the actual use of the system.	4.2.4
RQ3: How can the motivator selection problem be modelled as an MDP?	Literature Review Examination	Investigate the factors that impact the selection of a motivator for learners with ASD.	5.2.1
RQ4: How can Reinforcement Learning (RL) improve the success of the motivators used with learners with ASD in a learning setting?	Questionnaires	Investigate users' perceptions regarding the app usability.	5.4 and 5.5
	Data Entry and Logs	Evaluate the performance of the RL algorithm.	

3.5. The Role of the Researcher

The researcher holds a Bachelor of Science in Computer Information Systems and a Master of Arts in Education Leadership, Management and Policy. The researcher worked in the education field for 15 years and was the Learning Technologies Coach at the school where the study was conducted. However, no participant had a direct relationship with the researcher that signified a conflict of interest or may have imparted bias on the study. The participants did not have any employment or reporting relationship with the researcher.

The researcher's role as a Learning Technologies Coach was fitting as the study required that participants are trained on using the mobile app. Moreover, the researcher had been trained on how to conduct qualitative research through two distinct qualitative research courses at the British University in Dubai in both the Education and Computer Science disciplines.

The researcher was available at the school the whole period of the study, providing support to teachers using the mobile app. Moreover, all the workshops, focus groups and interviews were conducted by the researcher in the school.

3.6. Ethical consideration

Throughout the study, it was ensured that ethics remained a top priority. Ethical considerations in this study were directed by the University's ethical guidance. A Research Ethics Form was filled by the researcher and submitted to the academic program office. Research was conducted only after receiving a signed approval from the Research Ethics Committee.

Informed consent forms were first obtained from the school's principal (Appendix E.1), parents (Appendix E.2), and teachers and therapists (Appendix E.3). Informed consents are an essential requirement prior to any research involving human being participants in the study (Creswell 2015). The informed consent letters follow the guidelines outlined by Price (2016) in that they should include the purpose of the study, procedures to be undertaken, the foreseeable risks and benefits of participation, extent of confidentiality and identification of personal data and demographics, foreseeable consequences of declining or withdrawing, and contact information for questions about the study.

This study asks a group of caregivers, including teachers, therapists and parents, to use a mobile app to record academic and behavioural details related to learners. This data may contain progress information, achievement of learning objectives, and behaviour monitoring data. The data can be in the form of text, images, videos, and documents. Parents' consent form includes information about how this data will be used. Only information of learners whose parents signed the informed consent were used and entered into the mobile app database. The data used in the application complies with the school's policies of data collection, as all the data entered to the system is collected by teachers and therapists through other methods (notebooks, emails, instant messaging, clouds). Since the mobile app includes sensitive students' data, each user of the app had a personal account secured with a password. Each teacher or therapist was only able to preview the data of the learners he/she is working with. Parents were only able to preview the updates of their own kids. Administrative rights, such as assigning students to teachers, editing objectives, and editing users were only granted to the SENDCO as well as the researcher.

There are no associated risks to participating learners outside of normal daily risks as the use of the app does not require caregivers to change any of the normal learning activities and environments where participating learners usually engage.

One challenge for applying RL in experimental settings is exploration. In other domains, such as game playing and movies recommendations, experiments can be repeated as many times as needed. In our clinical setting, the RL agent has to learn online with limited previously collected data. Using trial and error to explore all possible states may conflict with therapy and education ethics (Liu et al. 2020). However, when using the “Motivator Selection” feature in the app, the caregiver has the ability to dismiss any suggested motivator, either because of its unavailability, or because of the caregiver belief that the motivator suggested will not be effective. Moreover, the process of ABA-based therapy requires that the therapist varies between the motivator choices. This sometimes requires the therapist to try motivators that may not work. As the caregiver maintains the control of what motivators to use, this study does not pose any identifiable or foreseeable risk to any participant outside of normal daily risks.

There is also no associated risk to teachers as the use of the app tries to mimic teachers’ and therapists’ daily tasks in recording data. Parents have the choice to use the app to record their child’s progress data, use the app only to monitor their child progress, or not use the app at all.

Data resulting from the use of the app was stored in the cloud and could not be accessed without authentication. Moreover, interview recordings were kept on a hard drive on the researcher laptop. The recordings will be kept for a period of five years following final approval of the research committee and will be erased afterwards. Any information that could identify the participants was removed from the transcripts and documents before analysing them.

3.7. Trustworthiness

In quantitative research, validity, reliability and objectivity are methods used to establish trustworthiness of the data. On the other hand, credibility, transferability, dependability, and confirmability are methods used to establish trustworthiness in qualitative research (Pitney 2004). These methods are used to ensure data accuracy, results applicability to other contexts, consistency of results if the study is replicated, and neutrality. Table 4 summarizes the methods used to establish data trustworthiness in both quantitative and qualitative research.

Table 4: Methods of establishing data trustworthiness

Criteria	**Quantitative Research**	**Qualitative Research**
Truth Value	Internal Validity	Credibility
Applicability	External Validity	Transferability
Consistency	Reliability	Dependability
Neutrality	Objectivity	Confirmability

As this thesis integrates various methodologies, trustworthiness is established through different methods during each phase of data collection and analysis. Internal validity and credibility are established when research findings capture what is really happening and allow the researcher to learn what was intended from the research (Pitney 2004). Credibility in this study was established through various ways. First, the researcher's prolonged engagement with participants due to the proximity and the workplace dynamics allowed the participants to build trust and feel comfortable during observations, workshops, think-aloud sessions, and interviews (Pitney 2004). Second, participants were carefully chosen through purposeful sampling to ensure that they have the adequate experience and knowledge required for the research (Lincoln & Guba 1986). Third, data gathered through observations, documents analysis, and interviews were ensured to be sufficient to provide credibility by demonstrating saturation (Charmaz 2006). Lastly, data for each research question was gathered through multiple sources and multiple data-collection methods (see Table 3). Triangulation is essential to ensure that a thorough and accurate understanding of the phenomenon is achieved (Pitney 2004). Though also referential adequacy is a method used to ensure credibility by storing research raw data to be examined later and compared with future studies, the unavailability of the data after five years of the final approval of the research committee causes potential limitations to the credibility of this study in the future.

To establish transferability, this thesis attempts to provide descriptive information about the context, participants, instruments, and procedures in order for readers to assess whether the results apply to their situation or experience and whether it can be generalized (Pitney 2004). While some data collected in this study apply to the wider population, such as the mobile app design principles, other data such as usability and users' satisfaction may require further investigation before generalizing the results to other contexts (Pitney 2004).

Confirmability is achieved by ensuring that the findings of this study are objective and are not based on biases and beliefs of the researcher (Pitney 2004). One main pitfall of qualitative methods is biased and subjective interpretation. For instance, uncontrolled observations impose the danger of assuming knowing more about the observed phenomena than what is actually observed (Kothari 2004). Similarly, bias, both in the creator of the document as well as the researcher, can be an issue when beginning document analysis (Bowen 2009; O'Leary 2017). Moreover, observer influence is a concern related to the level of guidance the researcher gives to participant during data collection phases such as workshops, think-aloud sessions and interviews (Kothari 2004; Ørngreen & Levinsen 2017). While it may seem implausible that participants will not be impacted by the presence of the researcher (and in some cases the audio recorder), the value of data collected through qualitative methods cannot be negated (Cotton & Gresty 2006). The researcher made sure to minimize bias by creating a positive atmosphere, providing minimal prompting, and being sensitive to verbal and non-verbal communication.

For quantitative data, internal validity is established by controlling the variables that impact the dependent variable. This thesis uses first the SUS, which is a questionnaire that demonstrated validity and reliability for different platforms even for small sample sizes (Bangor, Kortum & Miller 2008; Lewis & Sauro 2009). However, this study does not follow a randomized control methodology, which was a result of the settings of teachers' assignment to classes. As most participating teachers and therapist taught all of the participating students, it was hard to conduct control trials and avoid spill-overs. Spill-overs occur when a treatment affects those in the control group (Baird et al. 2017). In this study, there was no way to assign the participants randomly into two separate groups. First, students who are in a group may have a teacher who is teaching students in both groups, which prevents measuring the true usability value of the feature. On the other hand, if teachers are assigned to either group, they may teach students who have teachers from both groups, which prevents measuring the impact of the RL policy on the learner motivation.

One way to minimize threats to internal validity related to having no control group is to follow a one-group pre-test/post-test design, and comparing scores after the treatment to before the treatment for the same participants and on the same measure. However, this method is still susceptible to many threats to internal validity, especially those related to observing the same participants over time. Without a control group, it cannot be concluded with a certain degree that the treatment is what caused the change in scores (Stratton 2019). One category of alternative explanations is called "history", where it could be possible that another event triggered the change of the scores. Another category is called "maturation", where participants might have changed between the pre-test and post-test because of learning and growth. "Regression to the mean" is also considered an alternative explanation for a change in the scores. Regression to the mean refers to the statistical fact that a participant with an extreme score on one occasion will tend to score less extremely on the next occasion. Another important explanation in psychological research is "spontaneous remission", where there is a tendency for many medical and psychological issues to improve over time without a form of treatment (Price 2016). The lack of randomized experiment design limits generalization of the results of the study to a general target population (Stratton 2019).

Another issue concerning applicability is that RL-based policies face many challenges before they can be deployed to inform clinical decision-making. One of the most common limitations is the challenge in obtaining training data, both in terms of time and cost. Thus, the number of trajectories obtained is limited compared to those resulting from simulations. Besides the number of trajectories limitation, other factors that impact the estimation of the value function is that the type of data collected on different learners can be extremely variable, both across learners and within a learner over time (Shortreed et al. 2011).

3.8. Limitations and Delimitation

In this study, various prominent limitations and delimitations should be highlighted to better inform the readers. First, the number of participants in this study may be considered limited and homogenous, which limits the degree to which the findings can be generalized. Moreover, while the aim is to facilitate the coordination of learning between all stakeholders involved with learners with ASD, this study is limited on teachers and therapists' use of the app and their perceptions without including parents and learners themselves. First, learners did not use the mobile app in this study. Therefore, their perceptions regarding the mobile app were not studied. On the other hand, the main aim of this study is to use mobile technology to improve the learning and therapy of the learners. Longitudinal studies may reveal the impact for learners with ASD when using the mobile app for a long time. Second, parents' consent was obtained for this study to allow for the use of their children data in the study. Additionally, some parents participated by using the mobile app to share data with teachers and therapists. However, all parents refused to participate in formal interviews and questionnaires.

Additionally, while coordination and communication between stakeholders is an essential component for effective learning for all learners with SEND, this study focuses only on learners with ASD. This is due to the high prevalence of ASD as well as the social and behavioural challenges that ASD impose on learners affected. These challenges result in the need of a diverse care team that communicate and coordinate information regularly. Additionally, all learners who participated in this study were learners with a middle-range (Level 2) to severe (Level 3) form of ASD placed in self-contained classrooms, which may be considered a limitation as learners in general classrooms and with less severe forms of ASD were not included.

Moreover, while the RL system presents a contribution to the learning and therapy of learners with ASD, it has deliberated omissions of aspects of the system for the sake of simplicity, interpretability and computability. First, the state space was limited by both the features considered and the number of values considered for each feature. For example, the number of values for the time of day were grouped into three timings and behaviours were grouped into seven categories (Table 10). Moreover, actions (motivators) that the agent can choose from were grouped into six categories rather than using specific motivators (e.g., the agent suggests "Edibles" rather than "strawberries"). While this may be considered a limitation, it was a deliberated decision as it allows the user to choose from the available or preferred items rather than narrowing the choice to one particular motivator.

Another delimitation is that the system does not consider learner-specific Q-learning algorithms. Rather, it treats all learners as one while considering the values of the state as what distinguish one child from another. The proposed model represents the first step towards the development of an agent-based system that coordinates the therapeutic efforts of both caregivers and specialized computer systems for the well-being of a learner with ASD. The proposed model has been simplified to be able to verify and validate the results. Using data mining techniques to give each child a specific model can be considered in future iterations of the system (Lei & Li 2019).

Lastly, one notable limitation of this work is that the system does not explain the choices it makes to the user. Explaining why a particular motivator was selected ensures the users understand and trust the system and helps them make better decisions (Wang et al. 2018; Kusters et al. 2020).

In light of these limitations, conscious decisions were made to increase the value of the study's results. For instance, this work was constructed as a mixed-method study by integrating both qualitative and quantitative data collection methods as well as integrating multiple data sources. As this work contains exploratory stages, it was essential to gather data regarding participants practices to understand more completely the current state of practice as well as their perceptions regarding the implementation of new technology-based methods for coordinating learning and therapy. This allowed results to provide a more holistic picture of the topic under study.

3.9. Summary

The aim of this chapter was to outline the research methodology used to answer the research questions. This chapter outlined the procedures as well as the research approach followed in this study. It also summarized the sampling and data collection methods used, the role of the researcher, the ethical considerations, the reliability and validity of the data, and the scope of the study.

With the aim of developing a coordination mobile app and a RL framework for motivators recommendations, this work integrates various methodologies including participatory design research methodology, mixed-methods usability study, and pre-test/post-test quasi-experimental research methodology. Chapters 4 and 5 present a detailed account of the two studies; the mobile technology for solving the ICP and the decision-support system for solving the MSP. These two following chapters detail how the methodology described in this chapter was followed and provide the study's results.

4. Mobile Technology for Intervention Coordination

To solve the ICP, the IEP-Connect mobile app is proposed, which aims at coordinating the intervention efforts of involved therapists, teachers, and parents for the ultimate goal of improving the learning and therapy of learners with ASD. IEP-Connect allows teachers, therapists and parents to record the details of learning and therapy sessions using IEP as the foundation.

For illustration, we can revisit the case study in Section 1.1.1 using the proposed app. The SENDCO or an admin enters all Jacob's personal information through the admin interface of the IEP-Connect system. This information will include Jacob's personal information, academic grade level, preferences, learning styles, motivators, strengths, and skills, among others. IEP objectives are also entered to the system and assigned to the corresponding teacher or therapist. Data is updated daily as every teacher, therapist, and parent enters new information by recording session details, activities, IEP objectives achievement, behaviour issues and motivators used.

In a school day, as Jacob's therapist tries several motivators, the therapist will record which motivator worked best, e.g., "playing with cars", through the mobile app. Jacob is now motivated and the therapist is able to achieve the objective of the session, which is improving Jacob's fine motor skills of grasping a ball. Jacob's new skill will also be recorded in the system and shared with other users.

In the behavioural therapy session, the therapist wants to teach Jacob how to "take turns". As the behaviour therapists has access to the information from the operational therapy session, she will use the activity of "passing a ball" as she knows that Jacob had acquired the fine motor skills needed to grasp an object.

Knowing that “playing with cars” is a motivator that has been working with the previous therapists and teachers on that day will save valuable time. The English teacher may also allow Jacob to practice his motor skills by moving the ball “above” or “under” the table to learn using the prepositions of place.

As it can be seen from this example, the mobile app can facilitate the coordination and sharing of information, which may result in a more efficient learning and therapy process.

In this chapter, the design process of the IEP-Connect mobile app is described while considering the processes at play when teachers and therapists collect and share data. Usability analysis is then conducted to gather teachers and therapists’ feedback. Finally, the results of the usability study are discussed and summarized.

4.1. Mobile App Development

This research aims to examine the use of mobile technology to solve the ICP. To this aim, the IEP-Connect mobile app is developed. The mobile app development in this research follows a participatory design approach, where users are a main part of the research process.

In the initial two steps of the DSRP, a set of interviews and questionnaires were conducted to identify the research problems. The interviews in the first baseline study (Siyam 2018) aimed at understanding the ways special education teachers communicate and coordinate between each other as well as with parents and therapists. It also aimed at exploring how special education teachers use and perceive technology tools for communication and coordination. The study found that the use of technology for communicating learners progress was minimal. While many teachers were content with current communication methods, some believed that technology can improve this process and provide more accurate, secure, and complete data tracking opportunities. As many teachers where reluctant to adopt new methods of communicating learners' progress, a second baseline study was conducted to explore the factors that impact special education teachers perceptions and actual use of technology (Siyam 2019). The results highlighted self-efficacy, time and access to technology as factors that significantly impact special education teachers attitudes towards using technology.

With the implications of the baseline studies in mind, various techniques were employed to better understand users' priorities and requirements. The methods followed in this stage included classroom and therapy sessions observation, documents examinations and workshops.

Teachers and therapists' observation during the school day aimed at closely understand the methods teachers use to collect, record, and share data. For this aim, unstructured, participant, non-controlled observations were conducted. The researcher observed classes and therapy sessions for two days, resulting in the observation of three academic classes and two therapy sessions. In addition to that, the researcher observed the daily interaction between teachers and therapists. Observations indicated that in a typical school day, teachers and therapists juggle additional responsibilities including attending, writing, and updating IEPs, communicating with parents, tracking learners' progress on IEP goals, and tracking learners' behaviour. With all these tasks to manage, teachers' way of communication and coordinating with other teachers was usually done informally in teachers' lounges or hallways.

The second data collection method used was documents analysis, which included examining ongoing records of the special education department in the school, including IEP documents, behaviour modification plans, learners' journals, and teachers' notebooks. Observations aimed at understanding the methods teachers use to collect, record, and share data. The examination of documents indicated that in spite of the large amount of data collected and recorded, the methods in place resulted in missing or incomplete information.

The aim of the workshops data collection tool was exploratory. The participation mode in this study was contractual, where a SENDCO, a behaviour therapist, and a math and science teacher were contacted by the researcher to participate in inquiries regarding the possible components and information they perceive as essential to be added to the mobile app interface design. Table 5 summarises the methods used to inform the design of the IEP-Connect app.

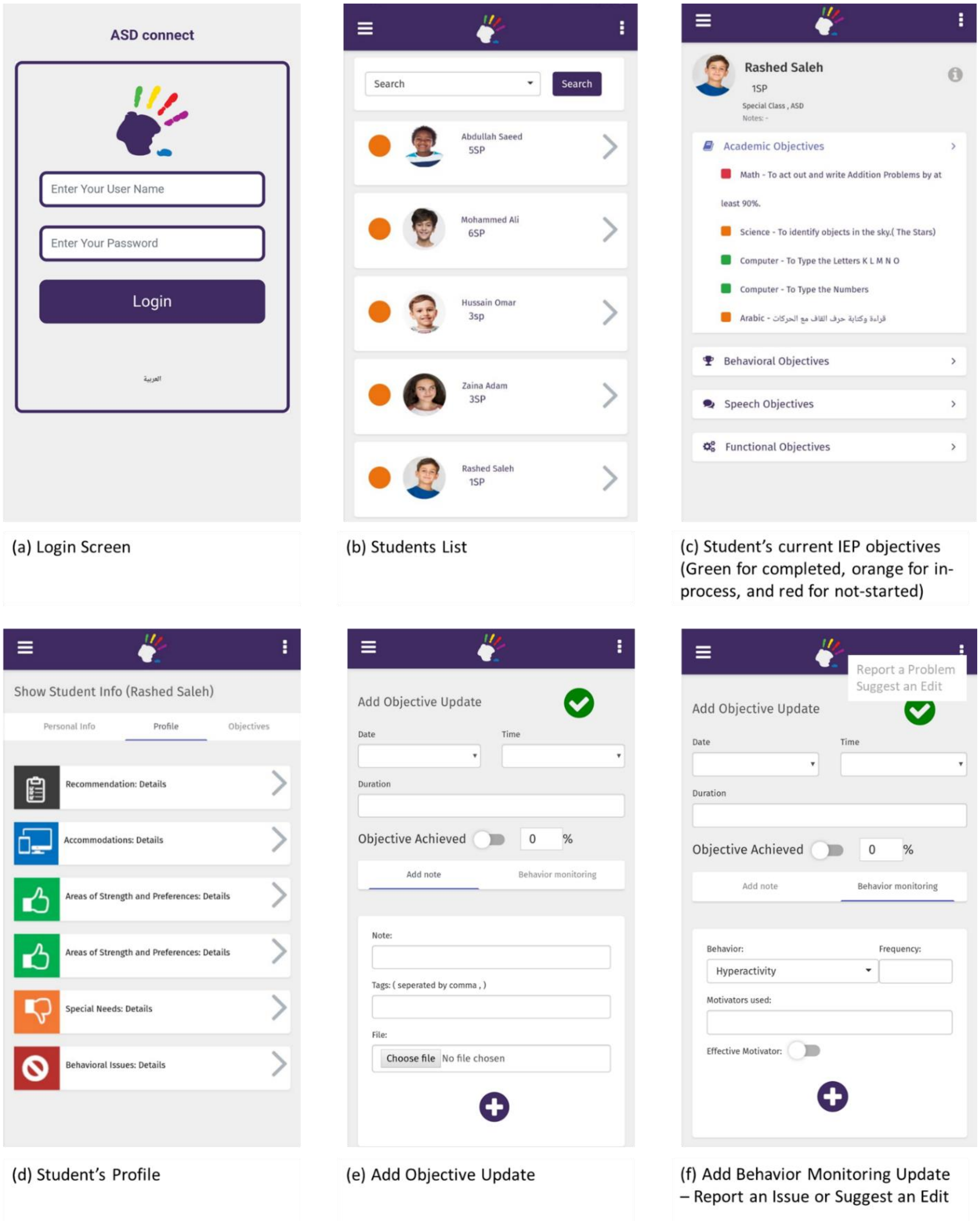
Table 5: Summary of methods used to inform the design of the IEP-Connect app

Classroom Observation	
Methods	- Unstructured, participant, non-controlled observations
Procedures	- Classroom observation for two days, resulting in 5 visited classes and the observation of communication between teachers - Recorded using unstructured observation forms
Analysis	- Manually coded to find common themes.
Findings	- Various teachers' responsibilities - Limited time - Informal communication methods
Documents Examination	
Methods	- Paper and electronic documents analysis
Procedures	- Collected and examined IEP documents, behaviour modification plans, learners' journals, and teachers' notebooks
Analysis	- Documents annotated and coded
Findings	- Big amount of data to be collected and shared - Missing or incomplete information
Workshop	
Methods	- Contractual participation

Procedures	- Activities file copied to three laptops	
	- Laptops handed to participants (teachers, therapist and SENDO)	
	- Participants completed the activities and saved the files	
Analysis	- Output of the activities were compared	
Findings	- Users' personas	
	- Essential information needed for good coordination includes (theme of lessons, achievement of goals, behaviour monitoring data)	

In the last stage of the mobile app development process, a Minimal Viable Product (MVP) was developed. The MVP is a version of a product that provides the maximum possible amount of feedback from users with the least effort (Münch et al. 2013). Through the first two stages of the mobile app development process, the following design principles were identified: the need for all information to be available in one place, the ease of transitioning from currently used methods to new ones, the ability to collect data through minimal effort and time consumption, the ability to maintain and share data securely, and the support of flexibility and scalability. The MVP was designed while taking into consideration all the aforementioned designed principles. Moreover, the mobile app included from the early stages a hosted web-based control panel to facilitate analytical tracking. Data tracking is an essential feature of the program as it allows the quantifying of the actual usage of the system and keep track of error logs. During the MVP deployment, users' feedback was collected to create new iterations of the app.

Figure 5 shows the main screens of the MVP version of the IEP-Connect app. Moreover, the design principles identified and considered in the mobile development process are detailed in the following subsections.



(a) Login Screen

(b) Students List

(c) Student's current IEP objectives (Green for completed, orange for in-process, and red for not-started)

(d) Student's Profile

(e) Add Objective Update

(f) Add Behavior Monitoring Update – Report an Issue or Suggest an Edit

Figure 5: Main Pages of the IEP-Connect App

4.1.1. Availability of all information in one place

The need of this principle was identified in a previous research (Siyam 2018), and confirmed by the field observations of the current study. Teachers complained that they find it hard to access all the needed information to plan for their lessons. It was also observed that SENDCOs, therapists and teachers collected data from different resources. These data include the learner's personal information, academic level, preferences and learning styles, motivators, strengths, and skills (see Figure 5-d). Moreover, the data include diagnostic and assessment reports such as IQ tests, Functional Behaviour Assessment (FBA), and speech diagnosis. All this information is essential for the development and revision of IEP plans as well as lessons and therapy planning. In the IEP-Connect app, each user is able to see the learner and IEP information as required (see Figure 5-c and Figure 5-d). For example, the SENDCO can see the profile IEP of all the learners, parents can see the profile and IEP of their child only, while teachers can see the profile and IEP for the learners and subjects they teach. Additionally, data is updated in real-time as teachers, therapists, and parents enter new information by recording session details, activities, IEP objectives achievement, behaviour issues and motivators used (see Figure 5-e and f).

4.1.2. Ease of transition from old tools to new ones

This design principle emerged when some teachers voiced their reluctance in adopting new methods for coordinating and sharing information (Siyam 2018). Moreover, the workshop data showed that teachers and therapists prefer to maintain the naming conventions they normally use (see Appendix C). To acknowledge this concern, the design of the app maintained the fundamental methods of collecting and sharing data by following the structure of current IEP plans, maintaining all the naming conventions the teachers and therapists are used to, and allowing teachers to choose their preferred interface language. Matching user interfaces to the design of old tools eases the transition from conventional to digital tools and increases system usability (Hirano et al. 2010; Marcu et al. 2013).

Moreover, the app was designed in a way that resembles standard mobile applications such as the Email and Messages apps, which users are familiar with. Figure 5-b shows the main page of the application. This page contains the work list for each user. In addition to the simple design, the application uses icons and images to represent functions, which makes it easier for the user to navigate through functionalities.

4.1.3. Collect and share information through minimal effort

One of the main goals of this research is to facilitate information sharing between all stakeholders involved in the therapy of learners with ASD. While observing teachers' daily methods in recording and sharing data, it was possible to propose a tool that will improve these practices. As time was an important factor, the efficiency and ease of use of the app was one main focus in the design process. This is consistent with my previous studies about special education teachers perceptions of current coordination practices (Siyam 2018), and the factors that impacted teachers' adoption of new technologies (Siyam 2019).

The IEP-Connect app was designed in a way that allows teachers to record learners' activities and progress in less time and with less effort. For example, the app allows teachers to create new objective updates or reuse previous ones. Drop-down menus and radio buttons were provided, when possible, for easier data entry. Moreover, information is presented to the user according to the priority and time-frame. For example, teachers will see first the objectives that need addressing at the moment. Additionally, objectives are color-coded, showing objectives not worked on yet in red, objectives being addressed but not completed in orange, and completed objectives in green (see Figure 5-e and f).

4.1.4. Maintain and share data securely

One of the main challenges identified through interviews in my previous study was the privacy of information (Siyam 2018). Moreover, through observations, it was noted that the IEP document is usually created as one file, containing all information about the learner. This file is shared with the staff members involved with the intervention of the learner, causing confusion and privacy issues. Moreover, cloud folders are usually shared with various users, giving access to all learners' information to teachers that are not involved with them. To overcome this issue in the IEP-Connect app, users are required to log in to the application through a given username and password. Users have only access to the information they require and for the learners they teach. Once logged in to the app, a session is created. All requests and access to data should be performed with a valid session that identifies the user and her/his permissions. Moreover, all sensitive stored data is encrypted. Data transfer between different users through the Internet is performed over the HTTPS protocol.

4.1.5. Design for Extensibility

As the design of the app follows the iterative software development cycle, the feedback of users on each iteration informs the design of the next one until the end product is produced (Munassar & Govardhan 2010; Ruparelia 2010). Therefore, the IEP-Connect app design uses modular components that can be modified and updated over time, providing flexibility, adaptability and scalability. One important feature of the IEP-Connect app is the feedback option available on every screen of the application (see Figure 5-f). This feature allows users to report any issue faced on a certain screen or suggest an edit, with the ability to attach a screenshot or a file for clarification.

4.2. Mobile App Usability Study

The participatory design research methodology contributed to the recognition of five main design principles that informed the design of the first iteration of the IEP-Connect app. To evaluate the IEP-Connect app, usability tests were used by allowing a group of users to interact directly with the system. The IEP-Connect app is evaluated using four distinct empirical approaches to usability evaluation; Think-aloud method, questionnaires, interviews, and log data. The think-aloud approach identifies the issues encountered from initial use. The System Usability Scale (SUS) questionnaire and the interviews are used to identify issues with repeated use and provide insights on users' perceptions regarding the app usability and user satisfaction. Moreover, all users' interactions with the system were logged. Log data were mainly used to measure the actual use of the system.

While it is referred to the evaluation phase as "Usability Study", the aim is to evaluate both usability and usefulness. When system usability and usefulness are combined, it is possible to determine system satisfaction and usage (Buchanan & Salako 2009). Usability evaluation on its own may lead to systems that are effectively designed, but functionally incompetent (Greenberg & Buxton 2008).

There are many measures of usability categorized as either objective (such as completion time and error rate), or subjective (such as satisfaction and ease of use) (Al-Gahtani 2016). This study adopts the ISO 9241– 11 (Bevan, Carter & Harker 2015) main aspects of usability; efficiency, effectiveness and satisfaction. Efficiency encompasses the resources consumed when performing a task on the app, including time and mental effort. Effectiveness considers the ability of users to complete the intended tasks using the app, quality of the output, and the error rates. Satisfaction, which is considered a subjective measure of usability, is defined as the extent to which users find the system worthy as well as their positive attitudes towards using it (Kokil & Scott 2017). According to the Technology Acceptance Model (TAM) (Davis, Bagozzi & Warshaw 1989), perceived ease of use and perceived usefulness are the two aspects of user satisfaction, and therefore their intention to use the app. While all the approaches used in this study are intended to evaluate usability in general, some methods focus on some usability aspects more than others (see Table 9).

4.2.1. Think-Aloud

The think-aloud study was conducted to investigate users' first impression of the app and whether they think it can be used by the wider population of teachers as an app to record and coordinate the learning and therapy data of learners with ASD. The think-aloud usability assessment method is commonly used to determine users' views and opinions while they perform a set of authentic tasks with a system (Ericsson & Simon 1993). Think-aloud method asks the users to talk aloud during their interaction with the system and verbalize what they are thinking while performing the specific tasks. The tasks are done by the user with minimal intervention from the researcher, as this evaluation method aims to capture users' experience with the system and the usability issues with the users' own words.

For this phase, a SENDCO, a behavior therapist, and a math/science teacher from the participants sample used the MVP using mock students' data. The IEP-Connect app was downloaded on the participants' mobile phones. Login credentials to access the app were also sent via email. The MVP included most of the basic features required for recording learners learning progress. These features were included in the usability tasks. Users were asked to interact with the system by completing authentic tasks related to information recording and communication. Users were asked to perform these tasks in a room in the presence of the researcher. Before starting the tasks, the researcher briefly described how the application works. Then, each user was handed a list of tasks to be performed. The tasks included (1) logging in (Figure 5-a), (2) choosing language preference (Figure 5-a), (3) choosing a learner from the working list (Figure 5-b), (4) viewing learner information and profile (Figure 5-d), (5) choosing an objective to work with (Figure 5-c), (6) viewing learner data from the objective page, (7) creating a new session (Figure 5-e), (8) recording session date and time, (9) typing a note, (10) attaching a photo or video from the camera roll, (11) saving the note, (12) adding a new note to the same session, (13) attaching a document to the note, (14) saving the new note, (15) adding a behaviour issue and its frequency (Figure 5-f), (16) adding the motivator used and whether it was effective, (17) saving the session, (18) repeating tasks 7 to 12 for the same IEP objective, (19) deleting a note from any session, (20) deleting a session, (21) marking an objective as completed by editing a session, (22) reporting an issue (Figure 5-f), and (23) suggesting an edit. All users performed each task at the same time. While completing each task, participants were asked to express their thoughts. The session was recorded and the researcher took notes and encouraged the users to say what they are thinking if they fell silent. At the end of the session, participants were asked to express their general thoughts regarding the app.

After the think-aloud session, many of the comments and suggestions proposed by the users were addressed. These features included the ability to edit the objective notes (which users were only able to delete), adding custom behaviour (instead of just choosing from a predefined list), and the automatic saving of the session.

4.2.2. Questionnaires

The System Usability Scale (SUS) (Brooke 1996) questionnaire was administered to teachers and therapists after using the mobile app for a period of 2 weeks to measure the perceived usability of the IEP-Connect mobile app. The SUS questionnaire was developed in 1996 by Brooke as a quick measure of the perceived usability of a system (Brooke 1996). Analysis of results in numerous studies and surveys demonstrated the validity and reliability of the SUS for different platforms even for small sample sizes (Bangor, Kortum & Miller 2008; Lewis & Sauro 2009). For instance, in a study comparing questionnaires for assessing usability, it was found that even with twelve participants, the SUS achieved the same results as a larger sample size in at least 90% of the cases studied (Tullis & Stetson 2004).

The SUS questionnaire is composed of 10 questions with a 5-point Likert scale to measure the agreement level. The rate of each question ranges from 1 for “Strongly Disagree” to 5 for “Strongly Agree”. The questions are divided into two groups; positive (questions 1, 3, 5, 7 and 9) and negative questions (questions 2, 4, 6, 8 and 10) (Brooke 1996). The questionnaire in this study was presented to participants in two forms, an English version and an Arabic version. For the English version, the term “this/the system” from the original paper by Brooke (1996) was replaced with term “the IEP-Connect app”. Moreover, for item 8, the word “cumbersome” was replaced with the word “awkward” as suggested for non-English speakers (Finstad 2006; Lewis & Sauro 2009). The Arabic version (A-SUS) is a customization of the SUS original form intended as a standard usability measure on native Arabic-language speakers (AlGhannam et al. 2018). The term “this system/هذا النظام” was also replaced in the Arabic questionnaire with the term “ برنامجIEP-Connect”. Table 6 shows the questionnaire items used in this study in both English and Arabic.

Table 6: SUS Questionnaire Items in English and Arabic

Item Number	English SUS Version	Arabic A-SUS Version
1	I think that I would like to use the IEP-Connect app frequently	اظن انني أحب ان استخدم برنامج IEP-Connect باستمرار
2	I found the IEP-Connect app unnecessarily complex	وجدت برنامج IEP-Connect معقدا أكثر من اللازم
3	I thought the IEP-Connect app was easy to use	اظن برنامج IEP-Connect سهل الاستخدام
4	I think that I would need the support of a technical person to be able to use the IEP-Connect app	اعتقد بأنني احتاج مساعدة شخص من تخصص تقني لاستخدام برنامج IEP-Connect
5	I found the various functions in the IEP-Connect app were well integrated	وجدت الوظائف المتعددة في برنامج IEP-Connect منسجمة فيما بينها
6	I thought there was too much inconsistency in the IEP-Connect app	ظننت ان هناك الكثير من التضارب في استخدام برنامج IEP-Connect
7	I would imagine that most people would learn to use the IEP-Connect app very quickly	اتخيل بان كثير من الناس سوف يتعلمون استخدام برنامج IEP-Connect بسهوله
8	I found the IEP-Connect app very awkward to use	وجدت برنامج IEP-Connect غريب للاستخدام
9	I felt very confident using the IEP-Connect app	شعرت بالثقة التامة عند استخدام برنامج IEP-Connect
10	I needed to learn a lot of things before I could get going with the IEP-Connect app	يجب معرفة امور كثيرة لتسهيل استخدام برنامج IEP-Connect

To allow participants to use the app, the data of the four participating students was first entered to the system. This data included learners’ personal information, their diagnostic profile, and the IEP objectives. Each participant was assigned the corresponding IEP objectives according to the learners and the subjects she/he teaches. Parents were able to view the data and the IEP objectives of their kids only. Participants were briefly trained on how to use the app. Moreover, participants were reminded that the objective of the study is to evaluate the system usability, not their technical skills. A screen recording video including the steps on how to use the app was also created and sent via email to all participants. Teachers and therapists were asked to use the IEP-Connect mobile app for two weeks to record all the learning and therapy session outcomes, upload related images and videos, add comments to the parents or recommendations for practice, record learner behaviour and motivators used, and mark objectives as completed. Parents were asked to check the notes added by teachers on a daily bases, add behaviour issues and motivators used, and add comments to the objectives' sessions. All users were asked to report any issue or suggest edits using the feature in the app, as shown in Figure 5-f. This feature allows the users to take screenshots from their screen to be attached to their comments. The researcher was available in the school for the whole period of the study to assist the participants if needed.

After the participants had a chance to interact with the IEP-Connect app for two weeks, the SUS questionnaire was administered. The SUS is recommended to be used after the participants had a chance to use the system being evaluated, but before any discussion takes place (Lewis & Sauro 2009). The link to the electronic questionnaire was sent to participants via email, including the two languages option. It was clarified at the beginning of the questionnaire that all items should be checked. If a participant felt that they cannot respond to a particular item, the centre point of the Likert scale should be marked. Also, participants were asked to record their immediate response to each item, instead of thinking about a question for a long time (Brooke 1996). Responses were collected electronically and saved in a spreadsheet for analysis.

4.2.3. Interviews

Structured interviews were conducted to gain insights on users' perceptions after using the app for two weeks. It is usually recommended to use the SUS with other measures to compliment the perceived usability findings (Brooke 2013). The qualitative approach is considered suitable for studies of exploratory nature to pinpoint the issues that need tackling (Maramba, Chatterjee & Newman 2019). The interview questions asked the twelve participants to describe their overall experience with the IEP-Connect app, mention parts of the app that were easy or hard to use, describe functionalities that they found useful, describe whether the app facilitated sharing information between staff and between teachers and parents, whether they think the app will help in improving students' achievement of IEP objectives, and whether they intend to keep using the app. All interviews were conducted in the school and each interview lasted for 20 to 30 minutes. All interviews were recorded.

4.2.4. Usage and Data Logs

During the study period, teachers and therapists recorded the details of the session outcomes using the mobile app. All users' interactions with the system, such as page views and duration, were logged to measure the actual usage of the system, which is typical for usability analysis (Harrati et al. 2016). This process aids in reporting additional usability analysis based on the actual performance of participants.

4.3. Analysis

To evaluate the usability and usefulness of the IEP-Connect app and its effectiveness in solving the ICP problem, data collected from various usability evaluation approaches is analysed. First, participants' comments during the think-aloud session were transcribed verbatim and analysed to identify patters. Since the number of participants for the think-aloud session was low, analysis was done first according to the task, and then for the whole experience to investigate users' first impression of the app and whether they think it can be used by the wider population of teachers as an app to record and coordinate the learning of learners with ASD.

Second, the SUS score is calculated by considering the score contribution for each item. The score contribution for the odd questions is the scale position of the item minus 1. The score contribution for the even questions is 5 minus the scale position of the item. For each response, the scores of the 10 items is summed and multiplied by 2.5. The average score of all participants responses is the value of the system usability (Brooke 1996). Despite it being a unidimensional measure, it was also found that the SUS can be decomposed into Usability and Learnability components. Learnability can be measured by using items 4 and 10. Even though item 7 is about learnability, it did not align with the Learnability factor. This could be attributed to its focus on considering others' skills rather than the respondent's own skills (Lewis & Sauro 2009).

The SUS is a score that ranges from 0 to 100, with 0 being the absolute worst and 100 being the absolute best. However, the SUS is not a percentage and can be difficult to interpret by itself. The study of normative data provided the basis for situating SUS scores as percentiles, proposing a more meaningful way for interpreting SUS scores (Bangor, Kortum & Miller 2008; Sauro 2011; Brooke 2013). The average score for SUS is 68, representing the 50^{th} percentile (Brooke 2013).

Another way to judge the SUS scores is based on the usual grading scale used in schools, known as the "university grade analogue" (Bangor, Kortum & Miller 2008). According to this judgment, grades range from A for superior performance, to F for failing performance, and C for average performance. This is considered a useful interpretation that is based on subjective correlation between tasks success rates, subjective users' remarks, and the value of the SUS scores being reported. Even though this judgment has not been scientifically validated, this grading scale can be distributed to match the normalization process for percentiles (Lewis & Sauro 2009; Sauro 2018).

Bangor et al. (2008) associated 212 scores with an additional 7-point adjective rating question aimed to inquire about the overall experience of the participant by asking "Overall, I would rate the user-friendliness of this product as”, with the options Worst Imaginable, Awful, Poor, Ok, Good, Excellent, and Best Imaginable. For example, scores above 85 were found to be associated with “Excellent”, while Good was just above average at 72.75. Similarly, Bangor et al. (2008) used another word variation to describe the SUS in terms of what is “acceptable” or “not acceptable”. Scores above the average of 68 are considered “Acceptable”, while scores below 50 are considered “Unacceptable”. Scores between 50 and 70 are considered “Marginally Acceptable”. **Table 7** summarized the proposed ratings that are used to describe the SUS scores (Bangor, Kortum & Miller 2008; Sauro 2018).

Table 7: Proposed Rating Correlating with SUS Scores (Bangor, Kortum & Miller 2008; Sauro 2018)

Score	Percentile	Grades	Adjective	Acceptable
84.1 – 100	96-100	A	Best Imaginable	Acceptable
80.8 – 84.0	90 – 95	B	Excellent	Acceptable
78.9 – 80.7	85 – 89	B	Good	Acceptable
77.2 – 78.8	80 – 84	C	Good	Acceptable
74.1 – 77.1	70 – 79	C	Good	Acceptable
72.6 – 74.0	65 – 69	C	Good	Acceptable
71.1 – 72.5	60 – 64	C	Good	Acceptable
65.0 – 71.0	41 – 59	D	Ok	Marginal High
62.7 – 64.9	35 – 40	D	Ok	Marginal Low
51.7 – 62.6	15 – 34	F	Ok	Marginal Low
25.1 – 51.6	2 – 14	F	Poor	Not Acceptable
0 – 25	0 – 1.9	F	Worst Imaginable	Not Acceptable

Third, interviews were transcribed verbatim and analysed to identify patters regarding the system usability. Interviews transcripts were analysed using both inductive and deductive analysis approaches. In inductive analysis, interview data is read with the purpose of deriving themes and concepts. Deductive analysis aims to test whether the interview data is consistent with prior results derived from the quantitative analysis and from the literature. Thus, inductive analysis is used to identify patterns, deductive analysis is used to structure patterns, and explain and evaluate categories (Schadewitz & Jachna 2007). Data was open coded by assigning identifying labels to chunks of text. Labels were compared and grouped to identify emerging themes and categories.

Lastly, log and usage data were analysed and compared to the data collected during classes observation and documents examination to measure the use of the system.

4.4. Results

4.4.1. First Impression

To understand users' first impression of the IEP-Connect app, participants' responses and comments during the think-aloud session were analysed and grouped into three themes; features that participants found well designed or useful, features that they found in need of improvement or unnecessary, and participants general attitudes towards the app. Participants voiced their thoughts after performing each of the assigned tasks.

Tasks that participants found easy to perform were logging in, creating a new objective session, and reporting issues and suggesting edits. Features that participants found useful were the ability to change the interface language, viewing the learner data from the objective page, attaching a photo or video from the camera roll, adding a behaviour issue and its frequency, adding the motivator used and whether it was effective, adding more than one session to the same objective, marking an objective as completed, and reporting issues.

On the other hand, participants found it hard to view learners' information and profile and return back to the learners' main page, save the session note, and add a new note to the same session. For example, Participant 1 remarked that it was confusing to differentiate between an objective update and an update note, and that some more clarification was needed to get the idea. Also, participants voiced the importance of auto-saving sessions as not to lose recorded data. Additionally, the only feature that participant found unnecessary is recording the session time and duration. For instance, Participant 1 mentioned that *"[recording the session time and duration] feels like an extra task if I need to do this after every class"*.

Moreover, participants suggested some features that they thought are necessary, such as retrieving a forgotten password, adding custom behaviour and editing a note. For example, Participant 3 affirmed that *"[...] it is important that [teachers] can write their own observed behaviour that may not be in the list"*. Also, Participant 2 exclaimed that he was able to delete a note but was not able to edit it.

Finally, participants' general attitudes towards the app were positive, expressed by comments on the easiness of use, and on the design simplicity. For instance, Participant 1 said that "*the app is very easy to use even without training. The screens are clear"*. Participant 3, on the other hand, mentioned that *"teachers and parents will need some training before using the app [as] they are all used to using notebooks for progress tracking and writing comments"*. Another aspect the participants discussed is the usefulness of the app. All participants agreed that the use of the app will be very useful for teachers and parents and will benefit the learning of the learners. For instance, Participant 2 said "*an important part of our job is to record and track progress. I believe this app will be very useful for that"*.

4.4.2. Usability

The average SUS score for the IEP-Connect app was 80.42 while the learnability score extracted from items 4 and 8 only was 80.2, indicating good satisfaction among the app users. Both scores fit within the same range of usability making the app “acceptable” and “good”. Both scores fit in the 85-89 percentile range and can be given a “B” grade (Figure 6).

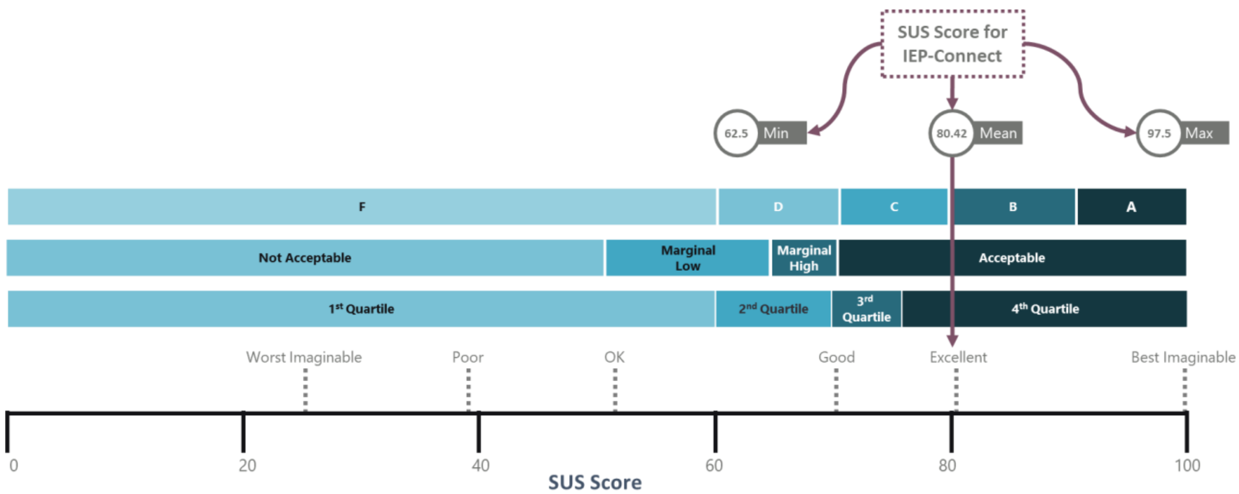


Figure 6: SUS Score and Rating (Bangor, Kortum & Miller 2009) for IEP-Connect

4.4.3. Efficiency, Effectiveness, Satisfaction, Ease of Use, and Usefulness

Participants’ responses to the interview questions were analysed and grouped into five categories of system evaluation derived from the literature; efficiency, effectiveness, satisfaction, ease of use, and usefulness (Davis, Bagozzi & Warshaw 1989; Brooke 1996; Bevan, Carter & Harker 2015). Themes and subthemes that emerged from the interviews coding process were grouped under these five categories (Table 8).

Table 8: Categories, themes and sub-themes emerging from interview data

Category	Themes	Subthemes
Efficiency	User Interface	Organization
		Looks
	Personalization	Language
		Sorting and Filters
	Navigation	Many Steps Required
		Information not available in all screens
	Functionality	Adding information
		Adding information perceived as insignificant
Effectiveness	Maintaining fundamental methods in data collection	Multi-session tracking
		Multi-behaviour tracking
	Improving quality of output	Multimedia content & attachments
Satisfaction	Intent to use	Perceived ease of use
		Perceived Usefulness
	Missing features	Improving the app
Ease of Use	Performing Tasks	Adding Information
		Previewing Information
	General	General Ease of Use
Usefulness	Recording and Tracking	Objectives Progress
		Behaviour
	Share Data	With Teachers
		With Parents
	Quality of Content	Attaching multimedia content

4.4.3.1. Efficiency

Efficiency encompassed the resources consumed when performing a task on the app, including time and mental effort. As discussed previously, one of the main design considerations was to allow users to collect and share information through minimal effort. Four themes were coded under the efficiency category; user interface, personalization, navigation, and functionality. For the user interface theme, two sub-themes emerged; organization and looks. Many participants commended on the way the app is organized and information is presented. For example, one feature that users found attractive was the color-coding of the objectives, which indicated the status of the objective. Another efficiency aspect commented on was personalization. Participants found that selecting their preferable language (English/Arabic) was a good feature as most apps they use do not have this option. On the other hand, participants felt they need more personalization options to make the app more efficient, such as including an option to search, sort and filter learning objectives. Additionally, participants thought that moving between different learning objectives required many steps, which was considered a navigation issue. Even though access to information is considered an aspect of system usefulness, participants commented that the missing option to view IEP information in one of the mobile app pages required them to navigate back to access the needed information. Finally, while participants found that adding and recording information to the system to be more efficient in terms of saving time compared to the traditional methods (paper or electronic IEP), most of the participants commented on having to enter information that they deemed unnecessary, such as the time and duration of the session.

4.4.3.2. Effectiveness

Two main themes emerged under the effectiveness category; maintaining fundamental methods and improving the quality of output. The first theme was one of the main points considered in the design process, which is the ease of transition from old tools to new ones, and maintaining the ability of users to complete the intended tasks they used to perform using other methods. These tasks included the ability to track multiple sessions for the same objective and observe the progress, and the ability to track learners' behaviour. However, few of the participants complained that the system allowed them to add only one behaviour in each session, and requested that multiple behaviour instances could be tracked in one session. In addition to maintaining fundamental methods, the use of the mobile app should provide the users with additional tools to improve the quality of the output, which improves in return the effectiveness of the mobile app. Most of the users found that the ability to add multimedia content to the session's updates improved the quality of their notes.

4.4.3.3. Satisfaction

Satisfaction is the extent to which the users find the system worthy. While efficiency and effectiveness can be quantified using the time taken to complete a task and the quality of the output, satisfaction is usually evaluated by considering the SUS score (Brooke 1996) or by exploring the two aspects of user satisfaction according to TAM (Davis, Bagozzi & Warshaw 1989); perceived ease of use and perceived usefulness, which impact the behavioural intention to use the app and the actual use. Thus, to be able to gain more insights into satisfaction during interviews, participants were asked a direct question; whether they are willing to continue using the app in the future, and why. Consistent with the TAM (Davis, Bagozzi & Warshaw 1989), two sub-themes emerged under the intention to use the app theme; perceived ease of use and perceived usefulness. As these two aspects were considered main themes in this study, the codes were categorized under the perceived ease of use and perceived usefulness sub-themes to answer the direct question regarding the users' willingness to use the app in the future. All users affirmed that they would like to use the app in the future as they found it easy to use and very useful. Some participants believed that the app can replace the IEP in its traditional form. However, some of them made this affirmation a conditional one, stating that some features should be added to the app to make it more useful and easier to use. This is consistent with the definition of satisfaction considering it the gap between the expected gain from using the system and the actual gain (Harrati et al. 2016).

4.4.3.4. Ease of Use

Ease of use can be defined as the simplicity of performing a task. This was considered by designing the app in a way that mimics other mobile applications. Ease of use was regarded in terms of the tasks users mainly performed; adding and previewing information. Users found these tasks easy to use. Moreover, many participants commented on the ease of use of the application in general.

4.4.3.5. Usefulness

Usefulness was considered in regards of users' requirements. This resulted in three main themes; recording and tracking data, sharing data, and the quality of content. Participants found the ability to track academic and behavioural progress in one place very useful. Moreover, the ability to share data with other teachers as well as with parents was considered a very useful and important functionality, as this facilitates following up and monitoring learners' progress. Quality of content, represented by the ability to attach multiple-format files, was also considered a feature that improved usefulness. In addition to improving the quality of the output and improving the effectiveness of the app, participants believed that using this feature to share video recordings of the sessions, practice papers, and pictures of the learner's work provided parents with resources to help their kids practice the same taught skills at home, which in return improved learners' progress and their achievement of IEP objectives.

4.4.4. Actual Usage: Effectiveness and Efficiency

System usage according to the usage logs was high, indicated by the number of objective updates and notes that were added and compared to the average number of notes written in the student journal when not using the app. For instance, a total of 155 IEP objectives were added to the app during the study period by the SENDCO. Teachers and therapists added a total of 222 updates to those IEP objectives, resulting in an average of 1.4 update per objective. Using the previous tracking system through shared document, teachers only added one update to each objective to indicate the final progress of the student. Additionally, during the two weeks of the study, 100 behaviour updates were added. Out of those, 54 updates included a motivator that worked.

The number of logins to the app were 202, indicating that participants added more than one objective update per login. Participants spent an average of 7 minutes per visit. The most frequently visited page after the home page that contains the list of learners was the objective update page, with a total of 315 visits. Surprisingly, another frequently visited page was the edit objective update page, with a total of 70 visits, indicating that one of four times, participants felt the need to edit their notes. After discussing this data with participants after the study period, they have explained that before attaching a video of photo of a learner to be shared with parents, they had to get an approval of the SENDCO. Moreover, they indicated that on many occasions, they couldn’t finish writing the objective update data on one setting and had to come to it later to edit it and add all the information, especially the behaviour tracking updates. Most logins to the app were recorded during the weekdays and working hours, with only 10% of visits recorded during the weekend, and 15% of the visits recorded after school hours during weekdays.

Additionally, participant suggested some features that they thought are necessary using the “Suggest an Edit” function on each screen in the app (Figure 5-f). These features included retrieving a forgotten password, setting the session default time, recording directly from the phone’s camera when attaching a multimedia file, being notified before deleting a note or a session, and marking an objective as completed by comparing the written percentage with the success criteria of the objective in the IEP. On the other hand, no errors were reported during the time of the study using the “Report and Issue” feature available on each page of the app.

4.5. Discussion

The think-aloud session, the SUS questionnaire and the interviews data indicated that participants had positive attitudes towards using the app. In the think-aloud session, participants expressed their positive attitude by comments on the usefulness of the app and its ease of use. The SUS indicated that the app was acceptable in terms of usability and learnability, with a score that can be described as “good”. The interviews indicated positive attitudes in terms of efficiency, effectiveness, satisfaction, ease of use and usefulness. Albeit the general positive attitudes, some concerns regarding navigation, access to information, and the need to record information perceived as insignificant arose from the interviews. However, participants expressed their preference to using the app compared to the previously used paper system or through word documents shared in the cloud. Moreover, system usage according to the usage logs was high, indicated by the number of objective updates and notes that were added. Table 9 provides a summary of usability evaluation findings.

Table 9: Summary of usability evaluation findings

Usability Evaluation	Usability Aspects Focus	Findings
Think-Aloud	First impressions on usability	Easy to use: log in, create a new objective session, report issues and suggest edits. Useful: change the language, view student data, attach multimedia files, ass a behavior problem, ass the motivator used and its effectiveness, ass more than one session to the same objective, mark an objective as completed, and report issues. Hard to use: view students’ information and profile and return back to the students’ main page, save the session note, and add a new note to the same session. General attitudes: positive attitudes, expressed by comments on the easiness of use, and on the design simplicity.
Questionnaire	App usability and users’ satisfaction	SUS score was (80.42), indicating that the app is acceptable in terms of usability and learnability, with a score that can be described as “good”.
Interviews	Efficiency	The app was found efficient in terms of organization and looks of the user interface.

		Recording session details was found to be more efficient in terms of saving time using the app compared to the traditional methods. Some navigation issues were reported.
	Effectiveness	Most of the participants found that the ability to add multimedia content to the session's updates improved the quality of their notes.
	Satisfaction	All users affirmed that they would like to use the app in the future as they found it easy to use and very useful.
	Ease of Use	Many participants found the app generally easy to use. Specifically, adding and previewing information was found easy to perform.
	Usefulness	The app was found useful in terms of the ability to track academic and behavior progress, share data with other teachers and parents, and the ability to attach multiple-format files.
Usage and Data Logs	Efficiency	Average time spent on adding an objective update is less than seven minutes.
	Effectiveness	No errors were reported during the time of the study using the "Report and Issue" feature. No crash reports were reported.

The contribution of this study is not only to test the usability of the IEP-Connect app, but to understand the ways in which a coordination app could be made easy and rewarding to use. This section discusses the results of the usability study in terms of efficiency, effectiveness, satisfaction, ease of use and usability.

4.5.1. Efficiency

Efficiency in this study referred to the resources consumed in performing tasks on the IEP-connect app. Specifically, time was considered as one of the main resources impacting efficiency. Time and effort needed to learn to use the app were also considered. The four usability tests in this study included some aspects of efficiency. The think-aloud session included comments on the intuitiveness of the interface as being "straight forward". The "learnability" score of the SUS indicated good acceptability. The interview data as well as some of the think-aloud comments included both positive and negative perceptions on efficiency. While the participants found that the app is easy to use and believed it will save them time compared to the traditional methods, they still expressed their dislike of having to enter additional information to the session details, such as the time and duration of the learning session. This piece of information was not required when not using the app. Asking participants to enter additional data was considered a burden, especially when they cannot see the benefits of such practice.

Despite addressing some issues that arose during the think-aloud session before the start of the second study, participants that used the app for longer times and with multiple learners reported some issues in navigation, such as having to navigate through many pages to switch between objectives or to find information about the IEP. However, the usage data from entry logs shows that the average time spent on adding an objective update is low (less than seven minutes).

4.5.2. Effectiveness

Effectives encompassed the quality of output when using the IEP-Connect app. This was mainly represented by the quality of data collected, denoted by the IEP objectives updates, including session and behaviour updates. Interview data indicated that users were satisfied with the data collection methods, as it maintained the fundamental approaches used in traditional data collection methods while allowing the addition of multimedia content not previously possible. Data logs show that the majority of participants added session notes in the right places, filled in all the data fields, and marked the objective as “achieved” once the percentage was attained. Moreover, data logs indicated that the app did not crash during the study period and did not no errors were produced by the system or reported by users.

4.5.3. Satisfaction

The SUS allows to measure the usability of the interface and the user satisfaction (Bangor, Kortum & Miller 2008). The SUS score for the IEP-Connect app was 80.42, indicating good acceptability and user satisfaction. This correlates with the interview data indicating that participants found the app worthy and were willing to continue to use the app in the future. While the SUS and interviews data indicate high satisfaction, there is always room for improvement. The SUS score can be improved by addressing users concerns that arose in the interviews and the feedback option within the app. For example, users discussed the need for more automation, reporting features, connection with other apps, and more flexibility in sharing data with others. As satisfaction is a subjective measure, including users in the design process is essential to provide them with tools that are tailored to their needs (Spiel et al. 2019).

4.5.4. Ease of Use

Comparing the think-aloud and interviews studies, it was clear that the confusion participants had in the first study was not present in the second study. First, some features were edited before the second study, such as the automatic saving of sessions. Second, participants in the second study worked on the app for two weeks compared to the first study where participants worked only for less than two hours. The repeated use of the app for the participants of the second study may have resolved any confusion they had on how to use the app.

Moreover, most participants during the interviews said that they found it easy to add and preview information. According to the usage reports, the add and edit objective update pages (Figure 5-e) were among the most frequently visited page. Considering the aim of the app, these pages are regarded as the core of the app, allowing teachers, therapists and parents to communicate with each other by recording the progress against an objective. Additionally, the average of time spent on each visit to the app was around 7 minutes per visit. Usage data indicates that teachers recorded more than one objective update per log in. This information is consistent with users' comments indicating that they found the app easy to use.

According to TAM (Davis, Bagozzi & Warshaw 1989), ease of use impacts participants perceptions of, and intention to use a certain technology. In this study, ease of use meant for the participants that entering information should be easy, somewhat automated, and not time consuming. According to TAM, ease of use not only impacts the attitudes and intensions to use a technology, but also impacts the perceived usefulness of the technology. That is why, when designing any technology, it is of utmost important to make it easy to use, without overwhelming the user with additional or unnecessary requirements.

Moreover, participants' comments included the attractiveness of the interface and the use of colour codes to indicate the status of the objectives. On the other hand, they complained about some difficulty in navigating through different objectives. The model resulting of the combination of the TAM and the Information Systems (IS) Success Model (DeLone & McLean 2002) assumes that the quality of the system leads to the ease of use of the system (Wessa et al. 2008). Quality of the system refers to the technical stability, reliability, navigational functionality, and attractiveness of the user interface.

4.5.5. Usefulness

Perceived usefulness in this study can be defined as the extent to which participants believe that using the IEP-Connect app is beneficial and would enhance their work performance (Davis, Bagozzi & Warshaw 1989). Participants remarked that they found the app beneficial in terms of collecting and displaying data, and tracking learners' progress.

Information quality and availability is also an important aspect impacting the perceived usefulness of the system. Information quality is a multi-dimensional notion that encompasses different dimensions such as the clarity, the relevance, the completeness, and the effectiveness of the information provided in the system (Wessa et al. 2008). Participants commended on the availability of learner's information and data within the system. However, they complained that this data is not available on the page where they have to record the session information and the learners' progress. Such details should be taken into consideration when designing a coordination app, where data and information are central to the success of the process.

Other features that participants found useful were the ability to monitor academic performance, monitor behaviour, and receive parents' comments and feedback. All these aspects are considered at the core of the coordination process in special education. As it was mentioned in previous sections, the coordination between all the people involved in the therapy and learning with learners with SEND, and particularly learners with ASD, is essential for good progress (Clarke, Sheridan & Woods 2010; Woods, Morrison & Palincsar 2018).

4.6. Summary

This chapter described the development and evaluation of IEP-Connect, an app for coordinating educational plans in inclusive settings. The main aim of the app is to facilitate information sharing between different parties involved in the intervention of learners with SEND, with the aim of addressing the diversity and complexity of data collection needs in special education. To this aim, a participatory design and iterative software design processes was employed to create the mobile app. The usability and usefulness of the app using various empirical measures were then evaluated.

Results from the usability evaluations indicated that the app has good usability rate and user satisfaction. Moreover, the app was found to be efficient, effective, easy to use and useful. Users commended on particular features such as the ability to easily find information regarding a learner, record and share session updates with parents and receive their feedback, attach multimedia content, and monitor learner behaviour. Moreover, users suggested to add certain features to the app such as the ability to sort and filter data, report and graph information, and connect the app with other educational apps. Looking at the features the users praised, it can be concluded that the IEP-Connect app achieved what it was intended to, which is providing a tool that facilitates the communication and coordination of learning of SEND learners with different stakeholders.

Chapter 5 describes the process of modelling the “Motivator Selection” problem as an MDP and solving it using RL. After the introduction of the problem, the chapter presents a preliminary on RL. It then explains the MSP in special education and models the problem as an MDP, considering the states, actions and rewards. It then describes how the MDP can be solved using Q-Learning. The experiment parameters are then detailed before describing the deployment and evaluation processes. The evaluation results of the usability study and the RL algorithm performance are then presented and discussed, with concluding notes on the implication of the results.

5. Decision Support System for Motivator Selection

In this chapter, a Reinforcement Learning (RL) framework is proposed to solve the MSP problem by adapting to the most influential factors impacting the effectiveness of the contingent motivator used. The task of selecting a motivator is first modelled as a Markov Decision Process (MDP) problem. The states, actions and rewards design consider the factors that impact the effectiveness of a motivator based on ABA as well as learners' individual preferences. A Q-Learning algorithm with an epsilon-greedy policy is applied to solve the modelled problem. To evaluate the performance of the proposed framework, the "Motivator Selection" feature is deployed in the IEP-Connect mobile app developed for special education plans coordination. A group of teachers and therapists are asked to use the "Motivator Selection" feature in the app to aid them in the decision-making process of selecting a motivator. The evaluation results of the usability study and the RL algorithm performance are then presented and discussed.

5.1. Reinforcement Learning: Preliminaries

The RL paradigm resembles the fundamental ways in which humans learn; by interacting directly with their surroundings and observing cause and effect. In RL, an agent continuously interacts with and learns from a stochastic environment to achieve a certain goal. Supervised machine learning, which dominates most of the recent machine learning research, consists of learning from data labelled by a knowledgeable external supervisor. Unsupervised learning, on the other hand, is about finding structure hidden in collections of unlabelled data. RL differs from both supervised and unsupervised learning as it does not rely on labelled data nor on examples of correct behaviour. Instead, RL relies only on feedback in the form of a reward signal as a way to consider an action better than another. One key feature of RL is that the reward is delayed for most tasks with some degree of complexity. This means that the impact of an action may not be sensed until several time steps into the feature (Sutton & Barto 2018; Zhang, Lu & Jin 2020).

One challenge in RL, which does not arise in supervised and unsupervised learning, is the trade-off between exploration and exploitation. To maximize the reward, the agent must choose an action that it was trued in the past and received the highest reward. However, this will prevent the agent from trying other actions that may yield higher reward. Thus, the agent is faced with the exploration-exploitation dilemma, where it has to exploit already known actions to obtain reward, or explore new actions to make better action selections in the future. While the exploration-exploitation dilemma has been intensely studied over the last decades, it remains unsolved (Sutton & Barto 2018). However, despite this challenge, the generality of RL and its ability to consider a holistic, goal-directed approach to learning, and innately capture uncertainty in observations, makes RL widely appealing for planning in various aspects and domains.

5.1.1. Elements of Reinforcement Learning

In addition to the agent and the environment, a RL system consists of four other elements; a policy, a reward signal, a value function, and a model of the environment, if available. The policy is what defines the agent's actions at a given time according to the state. Policies can be a simple lookup table or more complex functions requiring extensive computations. A reward signal is what defines the goal of the agent. The agent aims to maximize the reward signal it receives from the environment after every action it takes. However, the main objective of the agent is to maximise the reward it receives over the long run, which is specified by the value function. The value of the state is the accumulative reward the agent can expect to receive over the future, starting from that state. While the agent seeks actions that bring about states with highest value, not highest reward, it is much harder to determine values than to determine rewards. That is because rewards are obtained directly from the environment, while values must be continuously estimated from the sequence of observations the agent makes over its entire lifetime. Efficient value estimation is considered the most important component of almost all RL algorithms. The final element of some RL systems is the environment model. The model allows the agent to make inferences about how the environment will behave in terms of next states and rewards, given a state and action. Models are used for planning, allowing the agent to decide on a course of action by considering potential future situations before they are actually experienced. However, some methods for solving RL problems are model-free, as opposed to model-based, in where the agent learns by trial and error (Sutton & Barto 2018).

5.1.2. Markov Decision Processes (MDP)

An MDP is a standard formalization of sequential decision making, which is widely used for applications where an autonomous agent interacts with its surrounding environment through actions. An MDP can be defined as a four-tuple; $(\mathcal{S}, \mathcal{A}, P, \mathcal{R})$, where $\mathcal{S}$ is a set of states called the state space, $\mathcal{A}$ is a set of actions called the action space, P is the state transition function, which is the probability of transitioning between every pair of states given an action, and $\mathcal{R}$ is the reward function that assigns an immediate reward after transitioning to a new state due to an action (Figure 7).

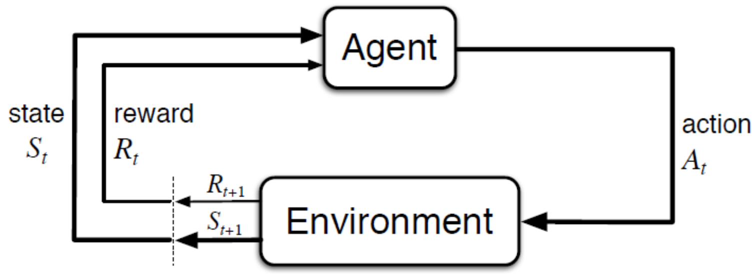


Figure 7: The agent–environment interaction in an MDP (Sutton & Barto 2018)

To maintain the Markov property, future state and reward depends only on the current state and action. However, the assumption of perfect information encapsulated by the current state can often be idealistic in practice (Prasad 2020). One way to relax this assumption is through the popular Bayesian approach known as Partially Observable MDPs (POMDPs). In POMDPs, observations are considered noisy measures of the true underlying state of the environment, and are used to model the probability distribution over the state space given an observation. In POMDSPs, the agent does not have direct access to the environment. Thus, the agent must make decisions under uncertainty by interacting with the environment, receiving observations, and update its belief by updating the probability distribution of the current state (Sutton & Barto 2018). However, the inference process is often challenging and computationally unfeasible, especially for large problems. Therefore, carefully incorporating relevant information in the design of the state in an MDP is considered more effective in practice (Prasad 2020).

5.1.3. Solving an MDP

To solve a RL task, the agent aims to learn a policy function $\pi : \mathcal{S} \rightarrow \mathcal{A}$ that maps the distribution over actions for each possible state, in such a way that this policy maximizes the expected cumulative sum of rewards received by the agent over time, known as the expected return. This optimal policy is denoted as π^*,

$$\pi^* = \underset{\pi \in \Pi}{\operatorname{argmax}} \mathbb{E}_{s_0 \sim P_0} \left[\lim_{T \to \infty} \sum_{t=1}^{T-1} \gamma^t \, r_{t+1} | \pi \right] \tag{1}$$

for an infinite horizon MDP, where γ ($0 \leq \gamma \leq 1$) denotes the discount factor which determines the relative importance of immediate and future rewards. If $\gamma = 0$, the agent will be completely myopic, caring only about actions that produce immediate rewards. As γ approaches 1, future rewards increasingly contribute to the expected return. The use of discounted sum of rewards when solving an MDP is considered mathematically feasible, ensuring finite returns when $\gamma < 1$. Moreover, it is considered a practical model for most tasks, as immediate feedback reflects the current action taken, while distant rewards become increasingly uncertain.

5.1.4. The Bellman Optimality Equation

A value function, denoted as $\mathcal{V}^{\pi}(s)$, determines how good it is for the agent to be in a particular state. This is determined by the action the agent will take according to the policy it follows. $\mathcal{V}^{\pi}(s)$ of state s is defined as the expected return when starting from s and following π:

$$\mathcal{V}^{\pi}(s) = \mathbb{E} \left[\lim_{T \to \infty} \sum_{t=0}^{T-1} \gamma^t \, r_{t+1} | \pi, s_0 = s \right] \tag{2}$$

An essential property of value functions is that they can be written recursively. Thus, the value of the current state s can be written as the sum of the immediate reward $r = R(s, a, s')$, where a is the action taken and s' is the resulting next state. This can be represented using the Bellman (Bellman 1966) recursive equation for value function $\mathcal{V}^{\pi}(s)$:

$$\mathcal{V}^{\pi}(s) = \mathbb{E}[r + \gamma V^{\pi}(s')] \tag{3}$$

Therefore, an optimal policy π^* is one where $V^*(s) = max_{\pi} V^{\pi}(s)\ \forall_s \in S$. The Bellman optimality equation can be obtained by substituting the recursive definition above:

$$\begin{aligned} V^*(s) &= \max_{\pi} \mathbb{E}\ [r + \gamma V^{\pi}(s')] \\ &\leq \max_{a \in A} \sum_{s' \in S} P(s,a,s')[R(s,a,s') +\ \gamma V^{\pi}(s')] \\ &= \max_{a \in A} \sum_{s' \in S} P(s,a,s')[R(s,a,s') +\ \gamma V^{*}(s')] \end{aligned} \tag{4}$$

Thus, the value of a state under an optimal policy is essentially the discounted return when taking the best possible action from that state (Sutton & Barto 2018). In fact, $V^*(s)$ is a unique solution to Bellman's optimality equation, which follows that the deterministic policy is optimal:

$$\pi^*(s) = \operatorname*{argmax}_{a \in A} \sum_{s' \in S} P(s,a,s')[R(s,a,s') +\ \gamma V^{*}(s')] \tag{5}$$

A deterministic policy is one that maps any given state to one action, $\pi_d : S \rightarrow A$. On the other hand, a stochastic policy is one that maps a state to a family of conditional probability distributions over the action state, $\pi_s\ (S|A)$.

5.1.5. Value Function Approximation

The action-value function for optimal policies is denoted as $Q^*(s,a) = max_\pi\ Q^\pi(s,a)$, where $Q^\pi(s,a)$ is the expected return in state s when taking action a and following policy π where $V^*(s) = max_a\ (Q^*(s,a))$. The corresponding Bellman optimality equation for $Q^*(s,a)$ is given by:

$$Q^*(s) = \sum_{s' \in S} P(s,a,s') \left[R(s,a,s') + \max_{a \in A} \gamma V^*(s') \right] \tag{6}$$

This equation captures the result of one-step lookahead searches for the value of each action at a given state, which simplifies the process of choosing optimal actions. This is considered the basis of the popular value-based methods in RL, such as Q-learning. Q-learning (Watkins & Dayan 1992), is an off-policy and model-free RL algorithm that uses one-step bootstrap on current estimates for the value of each state-action pair. Q-learning is considered off-policy because it learns from actions that are outside the current policy, such as taking random actions. It is also considered model-free because it does not require prior knowledge of the transition or reward dynamics of the environment.

Given an initial state $Q\ (s,\ a)$, an update is performed using the observed reward r and the estimation of the maximum reward that can be obtained by taking an action in the new state s'. This update is based on Bellman's optimality equation and is denoted as:

$$Q(s,a) \leftarrow Q(s,a) + \ \alpha\ (r + \ \gamma \max a'\ \ Q(s',a') - Q(s,a)) \tag{7}$$

where α is the learning rate and $Q\ (s', a')$ is the estimation of the maximum reward that can be obtained by taking some future action in the state s'. This process is repeated over a set number of iterations or until both sides of Equation (7) are almost equal. This procedure has been found to guarantee convergence to the true values of Q in the tabular setting, given that all pairs in a discrete state-action space are repetitively sampled and updated (Prasad 2020).

Finally, the optimal policy π^* is simply the action that maximizes Q at each state:

$$\pi^*(s) = \underset{a \in A}{\operatorname{argmax}}\, Q(s, a)\ \forall_s \in S \tag{8}$$

5.2. Solving MSP using RL

The aim of this work is to leverage the power of RL to solve the problem of selecting the best motivator for each intervention session (the MSP problem). These motivators are personalized based on the evolving needs and the characteristics of the learner. RL has the ability to effectively learn complex behaviour-motivator interactions in the presence of high temporal variation and uncertain outcomes (Zheng et al. 2021).

In this chapter, the MSP is first modelled as an MDP problem. By using MDPs, the proposed model can explicitly model future rewards, which will benefit the motivator recommendation accuracy significantly in the long run. MDPs can address many of the challenges faced in therapy decision-making. Then, RL is applied by using Q-Learning to solve the modelled problem.

5.2.1. Modelling MSP as an MDP

The MSP can be formulated as an MDP. The agent, which is situated in the therapists or teacher mobile application, interacts with the environment at discrete time steps. In our example, a time step is considered each time a therapist records a behaviour in the mobile application. At each time, the agent receives a state S_t from the environment from a set of possible states, $\mathcal{S}$. Based on this state, the agent selects an action A_t from a set of valid actions $\mathcal{A}$ in state S_t. Actions in our example are motivators the therapist can use to motivate the learner. Based in part on the agent's action, the agent finds itself in a new state S_{t+1} one time-step later. The environment also provides the agent a scalar reward R_{t+1} from a set of possible rewards, $\mathcal{R}$. The reward in our example will depend on whether the learner became motivated and to which degree, among other factors that are explained in the next sections. The transition (s_t, a_t, r_{t+1}, s_{t+1}) is stored in memory M. The ultimate variation of this system aims at enhancing the learning and therapy experience of the child by recommending the right motivator (Sutton & Barto 2018).

The agent-environment interaction produces a trajectory of experience consisting of state-action-reward tuples. The state is considered the behaviour of the child along other context features such as the time of day, the subject being taught, the last motivator used, and the number of times a certain motivator was used in a specific time-frame. An action is the suggested motivator that the therapists, teacher or parent will introduce to the child to reinforce a certain behaviour. Actions influence immediate rewards as well as future states and, therefore, future rewards. When the agent takes an action in a state, the transition dynamics function $p(s', r \mid s, a)$, formalizes the state transaction probability. This produces the probability of transitioning to state s' with reward r, from state s when taking action a.

The research suggests that, in various clinical settings, modelling treatment decisions through MDPs is effective and can yield better results than therapists' intuition alone (Bennett & Hauser 2013). Careful formulation of the problem and state/action space is essential to obtain satisfactory results and satisfy the Markov assumption that the current timepoint (*t*) is dependent only on the previous time point (*t-1*) (Sutton & Barto 2018). The following sub-sections describe how each component of the MDP is used to model the MSP problem.

5.2.1.1. State

One of the most challenging and critical issues in designing the MDP model is to properly identify the factors that influence the effectiveness of a motivator, especially when these factors may differ from one child to another. The personalization of intervention can be achieved by carefully determining these features that represent the state space (Shawky & Badawi 2019). Through careful investigation of the research that investigates motivation stimuli for learners with ASD, the following features were considered:

Table 10: Features representing the state space

Feature	Description	Number of values	Reference
Contextual features			
Antecedent event (trigger)	Event or activity that immediately preceded a problem behaviour (alone, given a direction or demand, transitioned to new activity, denied access to an item)	4	(Stichter et al. 2009; Bhuyan et al. 2017)
Time of Day	Time of the day the problem behaviour occurred (morning, noon, evening)	3	(Burns, Donnelly & Booth 2015)
Subject	The aim of this feature is to account to the place and person the problem behaviour occurred with (academic subjects, therapy sessions, home)	8	(Burns, Donnelly & Booth 2015)
Behaviour			
Behaviour	The problem behaviour that requires intervention, grouped into seven categories (aggression, self-injury, disruption, elopement, stereotypy, tantrums, non-compliance)	7	(Stevens et al. 2017)
Behaviour Function	The reason the behaviour is occurring (sensory stimulation, escape, access to attention, access to tangibles)	4	(Alstot & Alstot 2015)
History			
Last unsuccessful motivator	The ID of the last motivator used that was not successful in motivating the learner within an episode, including an option for "none".	7	

Motivator past usage	The number of times each motivator was used within a week grouped in categories of <5, 5-10, >11. This factor is composed of six features according to the number of motivators (actions) available (edibles, sensory, activities, tokens, social, choice).	3^6	(Çetin 2021)

Therapists and teachers aim to identify appropriate intervention for multiple settings. However, these interventions may fail if no attention is given to contextual differences (Stichter et al. 2009). Contextual features such as antecedent events, time of day, and location (where and with whom) all impact the child response to a proposed intervention, therefore informing optimal motivators. Moreover, while interventionists aim to track and remediate problem behaviours, the ability to understand the reason behind the occurrence of a behaviour is essential as the behaviour itself for creating appropriate behaviour plans (Schaeffer 2018).

Problem behaviours in special education are numerous and diverse. In this study, challenging behaviours are grouped into eight widely observed behaviours (Stevens et al. 2017); aggression (e.g. hitting, biting), self-injury (e.g. head-banging, hitting walls), disruption (e.g. yelling, knocking things over), elopement (e.g. wandering, escaping), stereotypy (e.g. rocking, hand-flapping), tantrums (e.g. crying, screaming), non-compliance (e.g. whining, defying orders), obsession (e.g. constantly talking about same topic).

Keeping track of the last ineffective motivator used is essential in our problem definition to maintain the Markov property where future state and reward depend only on the current state and action (Sutton & Barto 2018). Therefore, this feature is considered a part of the state to prevent suggesting the same motivator repeatedly. Moreover, the number of times a motivator group was used is tracked to prevent satiation (Rincover & Newsom 1985; Matheson & Douglas 2017). While studies have shown that extrinsic reward does not directly harm a child’s intrinsic motivation

(Cameron & Pierce 1994), repeated long-use of tangible rewards, such as edibles or tokens, is considered to have a negative impact when not carefully administered, and therefore should be limited (Witzel & Mercer 2003).

5.2.1.2. Actions

There has been a controversy regarding what type of reward to use to best motivate learners with ASD to follow routines and complete academic tasks without negatively impacting their future behaviour. Nevertheless, there is a strong evidence that rewarded learners report higher intrinsic motivation than the nonrewarded ones (Cameron & Pierce 1994).

However, the dilemma regarding which motivator is best suited for each intervention withstands. There are many factors that impact the choice of the right contingent reward (motivator) during a therapy or academic session. According to ABA techniques, there is a need to address what happens before the behaviour, what is the behaviour itself, and what is done immediately after the behaviour. In this study, the goal is to recommend an action (contingent motivator) that can be given to the learner after completing a certain task or complying to a certain command. The teacher or therapist needs to decide on which motivator to use from a list of six motivators categories (see Table 11); edibles, sensory, activities, tokens, social, and choice (Çetin 2021). For example, if a learner is yelling to get the teacher's attention, the teacher may promise the learner a favourite food item (edible) if the learner stops yelling and completes her task. Alternatively, the teacher may assign a leadership role (social) as a motivator to the learner once she is done with the activity. If another learner is wandering to escape a task, the teacher may promise extra computer time (activity) once the learner completes the task in hand. Therapists also consider the long-term effect of the motivator. For example, edible items, especially unhealthy choices, should be avoided. Repetitive use of the same motivator should be avoided as well to prevent satiation. Experienced interventionists sometimes use the same motivator for a specific period of time to stablish a routine but change it later to prevent the learner dependency on that particular reward to complete the tasks.

Table 11: Motivators Categories

Motivator	Description
Edible	Food items, such as fruits, snacks, and juice.
Sensory	Items or activities that realizes pleasure to the senses of the child, such as listening to music, sitting in a rocking chair, or playing with sand.
Activity	Activities may include drawing, playing with the computer, or jumping on a trampoline.
Token	Tangible items that the child values, such as stickers, money, or stars on an honour chart.
Social	Attention or interaction with another person, such as high-fives, smiles, and praise.
Choice	Giving the child the chance to choose between two different items or methods, such as asking whether she prefers to use a pencil or crayons to write.

5.2.1.3. Rewards

One of the main challenges of RL in practice is specifying the agent's reward. Wrongly specified rewards can introduce unexpected effects and irreversible changes in the environment. The challenge therefore is to combine multiple requisites for desired behaviour into a single scalar feedback (Shortreed et al. 2011). Approaches for representing this scalar reward have been proposed in healthcare tasks such as taking reward to be sparse, or rewards based on a single functional variable (Prasad 2020).

The reward in the problem definition of this study is the measure of learner motivation after introducing the motivator. In this study the subjective measure of responsiveness proposed by Koegel and Egel (1979) is adopted, as shown in Table 12. The teacher or therapist rates the learner's responsiveness after introducing a motivator and carrying out an activity.

Table 12: Scale of child's responsiveness

Output	Description	Reward
Negative	Child continues problem behaviour (tantrums, kicking, screaming) or does not comply with instructions and engages in behaviour unrelated to the activity (rocking, yawning, tapping).	-1
Neutral	Complies with instructions but tends to get restless or loses attention.	+2
Positive	Performs task readily. Attends to task quickly, smiles while doing the task, and presents appropriate behaviour.	+4
Rejected recommendation	The user rejects the motivator recommendation and does not introduce it to the child.	-0.25
Edible item	The motivator selected was an edible item.	-1
Token item	The motivator selected was a token item.	-0.5

Each learner responsiveness category results in the agent receiving a reward, as shown in Table 12. The agent receives a reward of -1 if the motivator did not work or the learner response was negative. Alternatively, it receives a +2 if the response was neutral, or +4 if the response was positive. If the caregiver chooses not to follow the recommendation, the reward is -0.25. In formulating the problem, we also aim to balance two competing objectives; receiving positive responsiveness from the learner, and limiting long-term exposure to unhealthy items. The definition of "safe Reinforcement Learning" has been proposed in the literature, especially for recommender systems that aim to balance user's satisfaction and the avoidance of recommending harmful items like violent movies (Heger 1994). Therefore, the agent receives a penalty of -1 when recommending edibles and -0.5 for recommending tokens.

5.2.2. Q-Learning

To solve the proposed MDP problem, a Q-learning algorithm with an epsilon-greedy (ε-greedy) policy with linearly decreasing exploration rate is used. Q-learning is an off-policy, value-based RL algorithm that aims to find the best action to take according to the current state. Q-learning seeks to learn a policy that maximizes the total reward. Q-learning is considered off-policy as the

Q-learning function learns from actions chosen according to a behaviour policy that differs from the updated policy. A policy is equivalent to an ABA-based intervention protocol with the advantage of capturing more individualized details of learners. In the case of this study, the agent choses an action according to an ε-greedy policy, while learning the optimal policy. ε-greedy is a method used to balance exploration and exploitation, where epsilon (ε) refers to the probability of choosing to explore (i.e., choosing a random action) rather than exploit (i.e., choosing the optimal action). The policy is represented by a table that maps all possible states with actions. While following the ε-greedy policy, the agent exploits with a probability of (1-ε) and with a probability of exploring of (ε). This probability (ε) decays over time by some rate as the agent learns more about the environment. The agent will become "greedy" in terms of exploiting and the probability of exploration becomes less. If the agent becomes "well-trained", it is possible to select the best action given the state. This process is described as acting according to an optimal policy (Sutton & Barto 2018).

The reward is an estimation of the scores the state *S* receives under the action *a*, which is denoted as *Q (s, a)* and updated based on Equation (7), outlined in section 5.1.5. The Q-learning algorithm is given as follows:

Algorithm 1: Q-learning

Initialize Q-table values *Q (s, a)* as "zeros" for all *s, a*
Get initial state *s*
for *episode* = 1, …, K **do**
    for *t* = 0, …, *T* – 1 **do**
        Select action *a* using ε-greedy policy
        Execute action *a*
        Observe reward r_{t+1}
        Observe next state s_{t+1}

Store transition (s_t, a_t, r_{t+1}, s_{t+1}) in memory M
$Q(s,a) \leftarrow Q(s,a) + \alpha\ (r + \gamma \max a'\ Q\ (s', a') - Q\ (s, a))$
$s \leftarrow s'$
End
End

The learning process can continue for any number of episodes. T is the time step where the state is terminal. In this study, the end of the episode is considered when the learner becomes motivated.

5.2.3. Parameter Settings (Experiment Settings)

While it seems straightforward to apply standard learning algorithms to learn the agent's optimal policy and then use it to recommend motivators to the user, this approach cannot be applied in practice to the problem of this study. Unlike traditional reinforcement tasks such as Atari games (Mnih et al. 2015), therapy recommendation tasks cannot benefit from the possibility of interacting with the user repeatedly to obtain any amount of experience to update the policy towards an optimal one (Lei & Li 2019). Moreover, there is no previously collected data to train the algorithm offline before the online interaction. Therefore, the experimental parameters are fixed in this study. On the other hand, online learning is beneficial for therapy recommendations due to the highly dynamic nature of learners' preferences and responses to intervention. Moreover, online learning allows us to obtain user's feedback by tracking whether the suggested motivator was used or not.

Each episode starts when a caregiver records a behaviour on the mobile app. Then, it is terminated by reaching the final state in which the learner becomes motivated. A learning rate α of 0.1 and a discount γ of 0.95 are used. ε-greedy policy that starts with a high ε of 0.9 is applied to encourage state exploration. Then, it decays exponentially with a rate of 0.9 until it reaches 0.05. Table 13 shows the detailed settings of the experiment.

Table 13: Parameter Settings

Parameter	Setting	Reference
Future reward discount γ	0.95	Equation 7
Step (learning) rate α	0.1	Equation 7
Explore probability ε	0.9	ε-greedy policy
Explore decay rate	0.9	ε-greedy policy
Episode length	Until the learner state is "motivated"	Algorithm 1

As shown in Figure 9, on each time step *t*, the therapist or teacher records a behaviour instance and requests a motivator recommendation. The agent takes the feature representation of the current state and recommends a motivator using ε-greedy policy. The caregiver then administers the intervention and provides feedback by rating the response of the learner. Alternatively, the caregiver can choose not to use the recommended motivator if deemed inappropriate. Moreover, the caregiver can skip the recommendation if the item is not available (e.g., edible items) or cannot be applied to the current activity (e.g., choice).

When the agent chooses to exploit, it selects an action by selecting the highest *Q(s,a)* for the observed state from the Q-table. Otherwise, the agent "explores" by selecting a random action.

The agent then waits until receiving the feedback from the caregiver. The agent receives a reward of -1 if the motivator did not work or the learner response was negative. Alternatively, it receives a +1 if the response was neutral, or +2 if the response was positive (see Table 12). If the caregiver chooses not to follow the recommendation, the reward is -0.25. In addition to the previous rewards, the agent receives a penalty of -1 when recommending edibles and -0.5 for recommending tokens. The agent then waits to receive the next state (next recorded behaviour by the caregiver) to update the Q-value according to Equation 7.

5.3. Deployment

To evaluate the proposed model, participating teachers and therapists (Table 2) continued to use the app to maintain behavioural monitoring data for an additional four weeks. In this phase, caregivers decided what motivator to use for each case according to their knowledge and experience and recorded this information along with the success of the motivator in the app (see Figure 8). Then, the “Motivator Selection” feature was added to the IEP-Connect app and participants were asked to use it for four weeks to select a motivator during a learning or therapy session (see Figure 9). To test the usability of the IEP-Connect app after adding the “motivator selection” feature, the SUS is administered and its score is compared to the score obtained in the precious iteration of the system. Then, the performance of the Q-Learning algorithm is evaluated by conducting statistical analysis to compare learners’ motivation before and after using the app, as well as to evaluate the performance of the algorithm over time. The evaluation in this study follows a one-group pre-test/post-test quasi-experimental research design, in which the same variables (i.e. usability of the app and learners motivation) are measured in one group of participants before and after using the “Motivator Selection” app feature (Kirk 2012). The term “quasi” indicates that the design resembles experimental research. However, since participants are not randomly assigned to different groups, quasi-experimental design is considered a non-experimental research.

This study relies on online learning rather than on previously collected data. While online learning does not benefit from the offline repetitive training period, it allows the model to adjust the polices to match the non-stationary environment and individuality of each child with ASD.

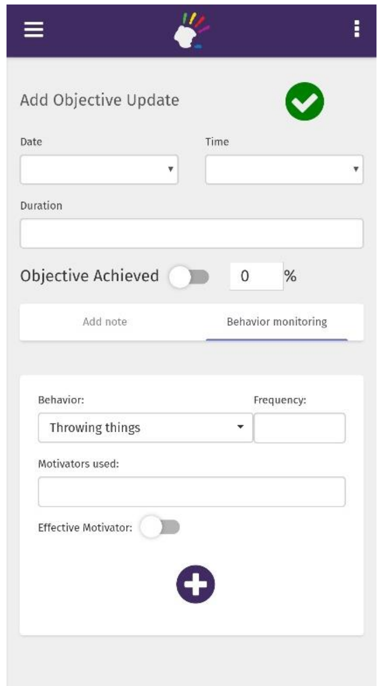


Figure 8: Behaviour monitoring without the “Motivator Selection” feature

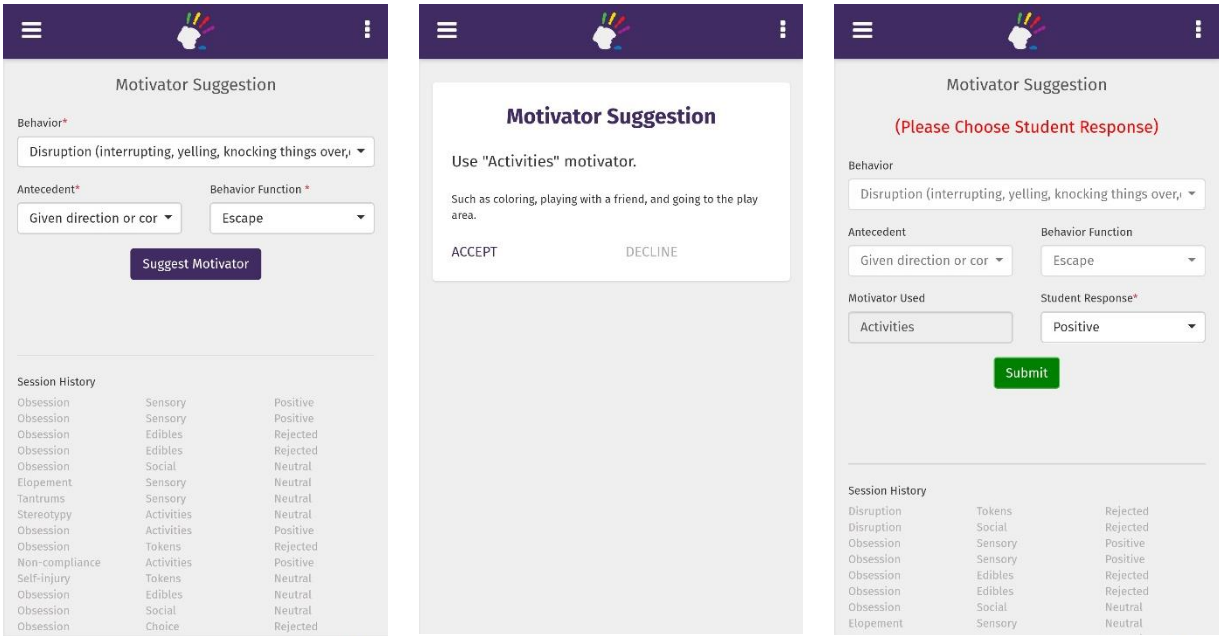


Figure 9: The “Motivator Selection” Feature

5.4. Usability Evaluation

To evaluate the performance of the of the applicability of the application and RL algorithm, the SUS questionnaire was re-administered to the same participants. This resulted in an average SUS score for the IEP-Connect app of 84.38. This score makes the app fall in the “acceptable” and “excellent” criteria range. Compared to the previously obtained SUS score in the previous study (Section 4.2.2), which was 80.42, the score is considered to have improved, as shown in Figure 10. This is considered a significant result as the introduction of new features in a technology tool usually results in an initial drop on usability score as users become accustomed to the new introduction (Bangor, Kortum & Miller 2008).

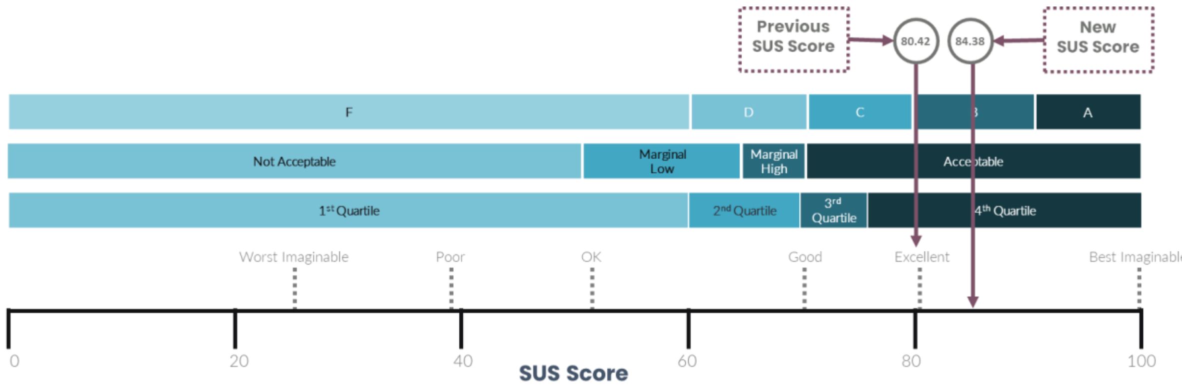


Figure 10: New SUS mean score compared to the SUS mean score of the previous iteration

5.5. Q-Learning Algorithm Performance Evaluation

Compared to other machine learning algorithms, there is an absence of an agreed upon performance evaluation standards for RL (Liu et al. 2020). While this problem is not unique to RL, it is harder to address compared to other machine learning algorithms that rely on accuracy and precision recall as a performance indicator. Calculating the precision and accuracy of an algorithm usually requires an offline dataset to be divided into training and testing sets. As this study does not benefit from an offline dataset, the effectiveness of the proposed algorithm is evaluated through statistical analysis (Stratton 2019). The Q-Learning algorithm is evaluated by answering the following questions:

1- Does learner motivation significantly increase when using the "Motivator Selection" feature compared to the traditional motivator selection methods?

2- When using the RL algorithm for the "Motivator Selection", does reward significantly increase over time?

3- When using the RL algorithm for the “Motivator Selection”, does the episode length (number of steps) significantly decrease over time?

5.5.1. Descriptive Summary

During the first four weeks, participants manually recorded the use of motivators through the behaviour monitoring page in app. In this phase, teachers and therapists presented learners with motivators according to the treatment approaches they usually follow. They also recorded whether the motivator was effective or not (Figure 8). During this period, teachers and therapists entered 490 behaviour monitoring entries. Out of those entries, 223 (45.5%) contained motivators that worked and 267 (54.5%) contained motivators that did not work. Table 14 presents the descriptive summary for the dataset collected before using the RL algorithm.

Table 14: Descriptive summary for "no-algorithm" dataset variables

Variable	Total	Per	Mean	SD	Min	Max
Users	12	Research				
Students	12	Research				
Days	30	Research				
Entries	490	User	40.833	40.653	6	141

In the following four weeks, participants were asked to use the “Motivator Selection” feature in the app rather than manually choose the motivators. In this phase, teachers and therapists recorded the behaviour problem, the antecedent, and the behaviour function (Figure 9). Then, the app would select a motivator to be used. Once using the motivator, the user would record the learner response to the monitor. Each entry is an instance where the app suggested a motivator to be used. An entry ends when the user either “declines” the motivator (i.e., choose not to use it), “accepts” the motivator (i.e., uses the suggested motivator) and the motivator works, or “accepts” the motivator but the motivator does not work (i.e., the learner does not become motivated). To compare the effectiveness of selecting motivators with and without using the "motivator selection" feature, the entries that include a motivator that was actually used are considered. This results in 671 entries. Out of those entries, 602 (89.7%) were motivators that worked and 69 (10.3%) were motivators that did not work. Figure 11 compares the percentage of motivators used and were effective before and after using the motivator selection feature.

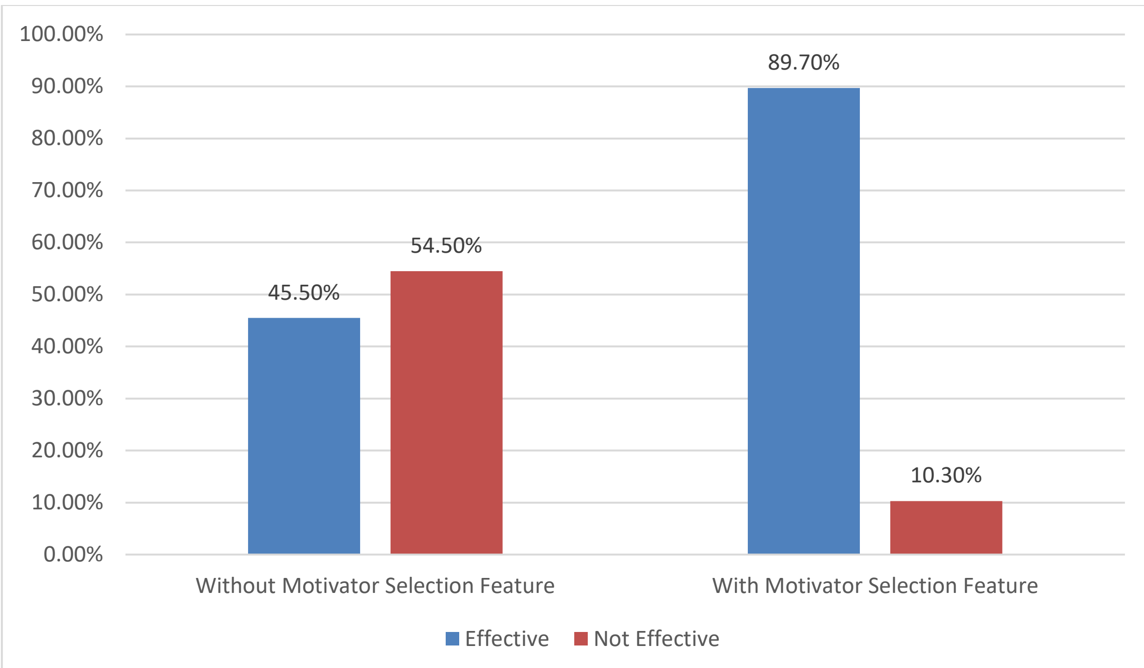


Figure 11: Percentage of effectiveness of motivator with and without using the motivator selection feature

Teachers and therapists were asked to decline the suggested motivator when the item suggested is not available (e.g., food). On the other hand, other items might have been declined when the teacher or therapist believed that the suggested motivator will not work or is hard to administer at the moment. The number of entries that were "declined" was (560).

Table 15 presents the descriptive summary for the dataset collected after using the RL algorithm. An episode considers all the steps until the learner becomes motivated, including the motivators that were dismissed and not used. This resulted in 598 episodes, with an average of 2.06 steps per episode. Figure 12 shows the percentage of steps taken in episodes. The figure indicates that for most episodes (65.7%), the first motivator selected was effective.

Table 15: Descriptive summary for the "algorithm" dataset variables

Variable	Total	Per	Mean	SD	Min	Max
Users	12	Research				
Students	12	Research				
Days	32	Research				
Entries	1231	User	102.58	98.72	8	376
Episodes	598	Day	38.469	26.39	1	91
Steps (Episode Length)		Episode	2.06	2.35	1	22
Reward					-2.00	4.00
Reward Sum		Episode	2.68	1.478	-4.50	4.00

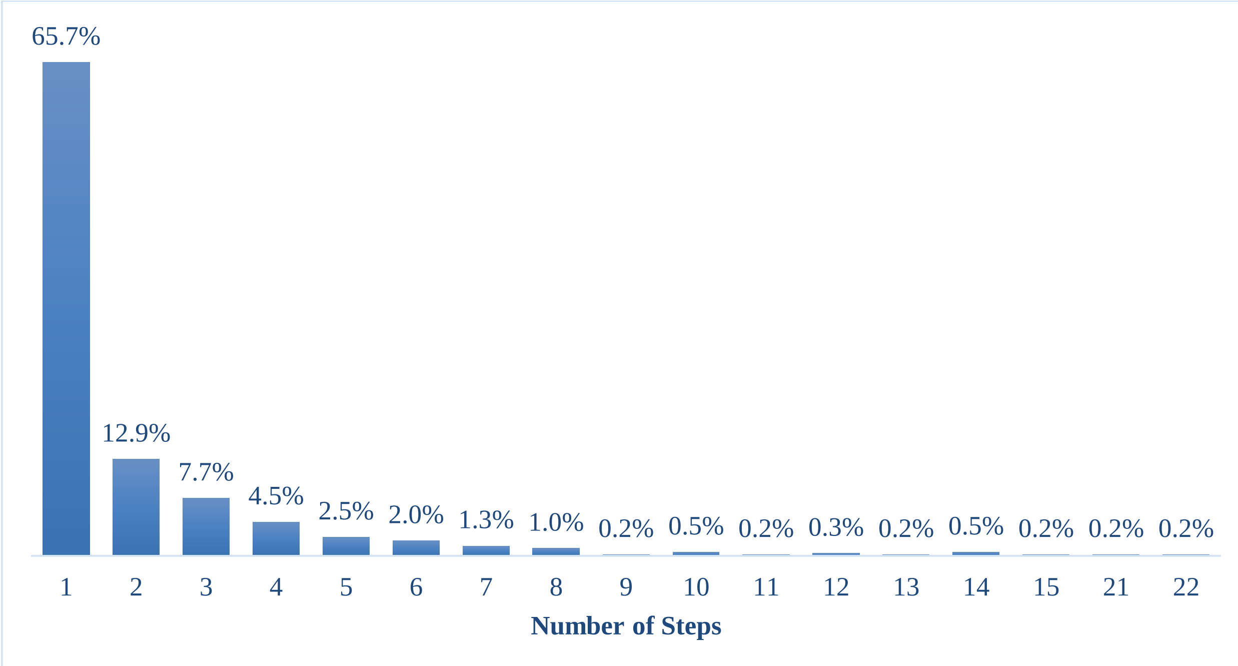


Figure 12: Percentage of episode steps

5.5.2. Algorithm Evaluation

Three statistical techniques were applied to evaluate the performance of the Q-Learning algorithm: Chi-square test, Correlation, and Regression analysis. Significance level was set at $\alpha = 0.05$.

5.5.2.1. Does learner motivation significantly increase when using the "motivator selection" feature compared to the traditional motivator selection methods?

In order to answer this question, a chi-square test of independence was conducted to test whether or not the application of the algorithm has a significant effect on motivating learners. The test revealed that applying the algorithm is significantly associated with more motivated learners, *Pearson* $\chi^2 = 265.16$ and $p < 0.001$. The crosstabulation in Table 16 indicates that 45.5% of learners were motivated without applying the algorithm, while 89.6% were motivated with algorithm being applied. The contingency coefficient was 0.432, $p < 0.001$, indicating that learners being motivated is significantly associated with the algorithm application, and that this association is relatively strong.

Table 16. Crosstabulation of Algorithm vs. Status

		Status		Total
		Not Motivated	Motivated	
Algorithm	Without	267	223	490
		54.5%	45.5%	100.0%
	With	69	594	663
		10.4%	89.6%	100.0%
Total		336	817	1153
		29.1%	70.9%	100.0%

Pearson $\chi^2 = 265.16$, $p < 0.001$. Symmetric Measures: Contingency Coefficient = 0.432, $p < 0.001$. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 142.79.

5.5.2.2. When using the RL algorithm for the "motivator selection", does reward significantly increase over time?

The reward data for the applied algorithm was plotted against time so that it would be easy to observe the pattern of reward data, as shown in the scatterplot in Figure 13. Correlation analysis revealed that there is a significant positive association between reward and sequence, $r = 0.081$, $p = 0.036$. Although the association is weak (in magnitude), it is positive and statistically significant, indicating that reward significantly increases over time. This allows to proceed to regression analysis that shows how reward increases over time.

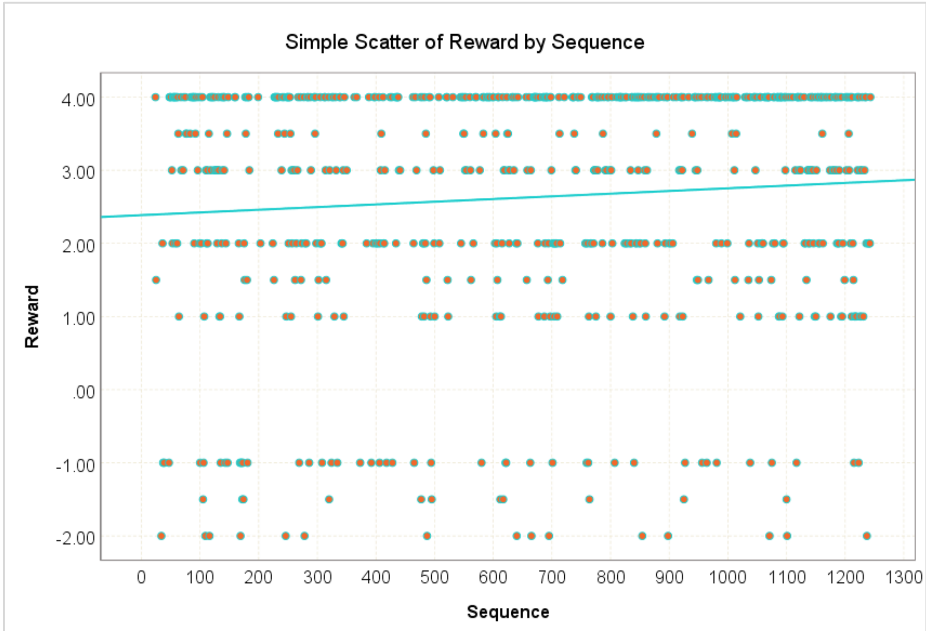


Figure 13. Scatterplot of Reward over Time

5.5.2.2.1. Regression Analysis of Reward

A simple linear regression analysis was conducted to investigate how reward is predicted over time. The results of regression analysis, reported in Table 17, shows that the regression mode is significant, $F(1,661) = 4.412$, $p = 0.036$, and explains 0.7% of the variance in Reward. The t test of the regression coefficient shows a significant predictor, $t = 2.101$, $p = 0.036$. That is, time that refers to each step taken to apply the algorithm, is a significant contributor to the positive change in reward. In other words, each one step taken to apply the algorithm would cause an increase in reward by 0.00037 (or from 0.000024 to 0.00071).

Table 17. Regression Analysis Summary for Sequence Predicting Reward

Variable	**B**	**95% CI**	**β**	**t**	**p**
(Constant)	2.386	[2.125 , 2.647]		17.944	< .001
Sequence	.000367	[.000024 , .000710]	.081	2.101	.036

R^2 = .007, R^2adj. = .005, CI = Confidence Interval for B.

5.5.2.2.2. Deeper Regression Analysis of Reward

Considering that a reward higher than 2 is already high, a simple linear regression analysis was conducted using data for reward below 3. The analysis produced a significant regression model, $F(1,257) = 7.519$, $p = 0.007$, with $R^2 = 0.028$. The correlation coefficient between reward and sequence is equal to 0.169, which is a stronger value than 0.081. Moreover, investigating the regression coefficient of 0.001 indicates that low rewards significantly increase over time; that is, for each new step, reward increases by 0.001. The regression line is shown in Figure 14.

Table 18. Regression Analysis Summary for Sequence Predicting Reward (< 3)

Variable	**B**	**95% CI**	**β**	**t**	**p**
(Constant)	.475	[.136 , .813]		2.764	.006
Sequence	.000627	[.000177 , .001077]	.169	2.742	.007

R^2 = .028, R^2adj. = .025, CI = Confidence Interval for B.

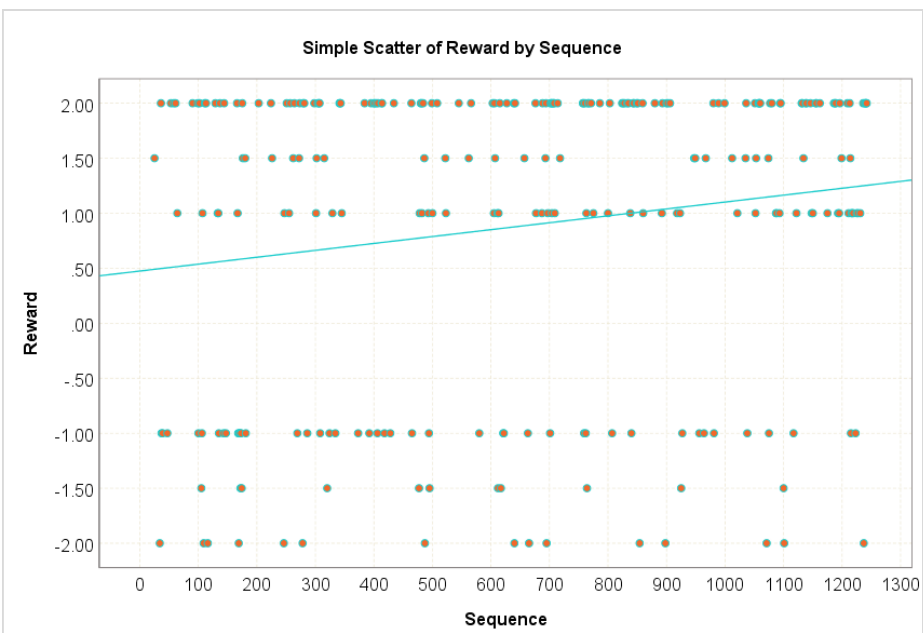


Figure 14. Scatterplot of Reward (< 3) over Time

5.5.2.3. When using the RL algorithm for the "motivator selection", does the episode length (number of steps) significantly decrease over time?

In order to answer this question, scatterplot of episode length against time is investigated first to check whether there is a negative pattern on length over time (see Figure 15). The scatterplot shows a negative pattern of episode lengths over time as the fit line is moving downward. A correlation analysis revealed that there is a significant negative association between episode length and sequence, $r = -0.161$, $p < 0.001$. This encourages to run regression analysis to discover how length decreases over time.

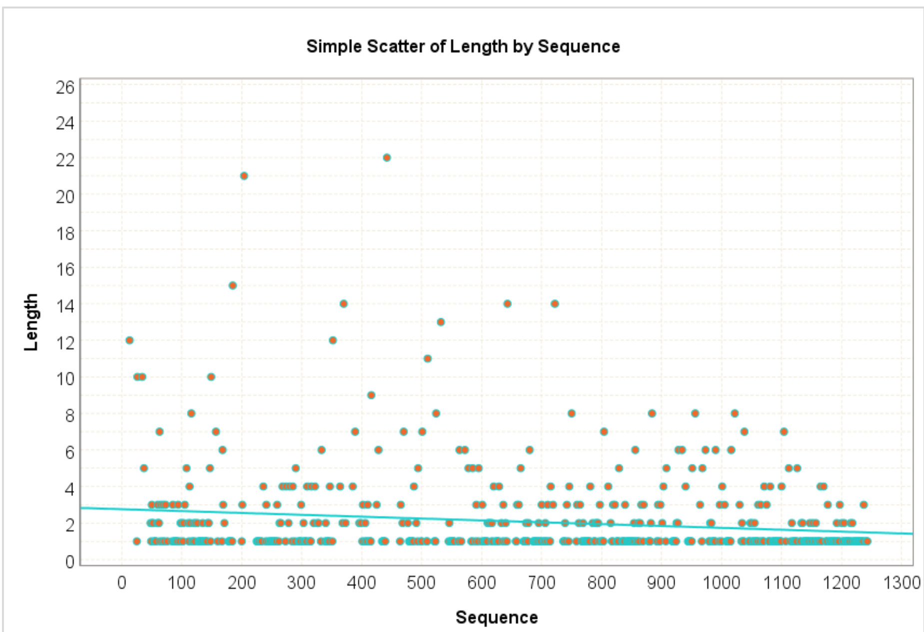


Figure 15. Scatterplot of Episode Length against Time

5.5.2.3.1. *Regression Analysis of Episode Length*

A simple linear regression analysis was conducted to investigate how episode length changes based on sequence. A significant regression equation was found, $F(1,596) = 15.917$, $p < 0.001$, with an R^2 of 0.026. The predicted episode length is equal to 2.758 – 0.001(sequence) steps for each episode. That is, episode length decreases by 0.001 (or between 0.000518 and 0.001524) steps for each episode. This indicates that an episode would need a smaller number of steps over time.

Table 19. Regression Analysis Summary for Sequence Predicting Episode Length

Variable	**B**	**95% CI**	**β**	**t**	**p**
(Constant)	2.758	[2.366 , 3.149]		13.841	< .001
Sequence	-.001021	[-.001524 , -.000518]	-.161	-3.990	< .001

R^2 = .026, R^2adj. = .024, CI = Confidence Interval for B.

5.5.2.3.2. *Deeper Regression Analysis of Episode Length*

As number of steps per an episode of 1 or 2 steps is already a small number, regression analysis was conducted using data of episodes with a number of steps greater than 2. The analysis revealed that the association between episode length and sequence is stronger. The produced regression model was significant, $F(1,126) = 4.951$, $p = 0.028$, with $R^2 = 0.038$. Moreover, the regression coefficient $B = -0.002$ indicates that for each new episode, the number of steps significantly decreases by 0.002. This causal relationship can be seen in Figure 16.

Table 20. Regression Analysis Summary for Sequence Predicting Episode Length (> 2)

Variable	**B**	**95% CI**	**β**	**t**	**p**
(Constant)	6.482	[5.312 , 7.652]		10.965	< .001
Sequence	-.001903	[-.003596 , -.000210]	-.194	-2.225	.028

R^2 = .038, R^2adj. = .030, CI = Confidence Interval for B.

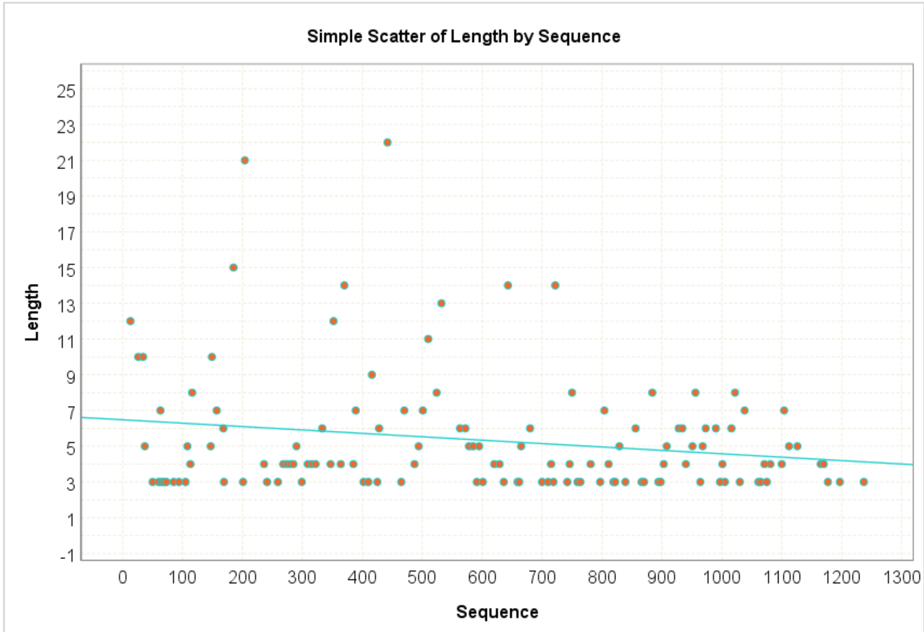


Figure 16. Scatterplot of Episode Length (> 2) against Time

5.6. Summary

This chapter presented how the motivator selection problem (MSP) can be solved with RL by adapting to the most influential factors impacting the effectiveness of the contingent motivator used. The task of selecting a motivator was first modelled as an MDP problem. Then, a Q-Learning algorithm with an epsilon-greedy policy was applied to solve the modelled problem. The usability study and the RL algorithm performance evaluation demonstrated the feasibility of RL to support the decision-making process of caregivers of learners with ASD in regards of the MSP. The adaptation of RL technology by special education stakeholders has the potential of increasing the efficiency of learning and therapy. Moreover, RL in the form of learning and predictive analysis can gain insights into the learners' data and make conclusions or recommend solutions, which can be hard to realize manually.

The next final chapter of the thesis provides a summary of the study and a discussion of the major findings and their implications for research, theory and practice.

6. Conclusion

The purpose of this study was to propose the IEP-Connect mobile for coordinating the efforts and supporting the decision-making process of the different stakeholders involved in the IEP of a learner with ASD. This last chapter includes a summary of the study and a discussion of the major findings. Also included are recommendations and implications for research, theory and practice. The chapter concludes with a discussion of areas of future research, and a concluding note.

6.1. Summary of the study

This research first reported the development and evaluation of IEP-Connect, a mobile app for coordinating educational plans in inclusive settings. The main aim of the app is to facilitate information sharing between different parties involved in the intervention of learners with ASD. The design of the mobile app focuses on data used broadly in inclusive classroom settings and IEP coordination, without limiting it to a particular discipline or therapy, with the aim of addressing the diversity and complexity of data collection needs in special education. To this aim, a participatory design and iterative software design processes were employed to create the mobile app. Then, the usability and usefulness of the app were evaluated using various empirical measures, including a Think-Aloud session, SUS questionnaires, interviews, and usage data.

This research then tackles the problem of selecting the right motivator to use for learners with ASD in learning settings by proposing a RL algorithm. The task of selecting a motivator was first modelled as an MDP. The states, actions and rewards design consider the factors that impact the effectiveness of a motivator based on ABA as well as learners' individual preferences. A Q-Learning algorithm with an epsilon-greedy policy was applied to solve the modelled problem. To evaluate the performance of the proposed framework, the “Motivator Selection” feature was deployed in the IEP-Connect app. A usability study and a RL algorithm performance evaluation were then conducted.

6.2. Key findings

With the aim of facilitating the coordination of educational plans, and with the ultimate goal of improving the learning and therapy of learners with ASD, this study reported the work of developing and evaluating a mobile app for coordinating educational plans and the development of a RL framework to solve the problem of motivator selection. This work aimed to answer four research questions. The major findings of this study are presented by answering the research questions.

6.2.1. What are the key design principles required to inform the design of a coordination mobile app for special education?

As discussed in Chapter 4, a participatory design methodology was followed to identify the design principles prior to the development of the IEP-Connect app. To identify the problems, two baseline studies that included interviews and questionnaires involving special education teachers and therapists were conducted (Siyam 2018, 2019). The results of the interviews and questionnaires revealed the challenges special education teachers face when coordinating their effort as well as the obstacles that may hinder their use of technology. The main factors that impacted teachers attitudes towards technology were self-efficacy and time. Considering the implications of these two baseline studies, various techniques were employed to better understand teachers and therapists’ priorities and requirements. Through classroom and therapy sessions observation and documents examinations, it was noted that teachers and therapists usually communicated and coordinated with each other through informal ways. Moreover, documents analysis revealed that in spite of the large amount of data collected and recorded, the methods in place resulted in missing or incomplete information.

Through these studies, the following design principles were identified:

1. The need for all information to be available in one place.
2. The ease of transitioning from currently used methods to new ones.
3. The ability to collect data through minimal effort and time consumption.
4. The ability to maintain and share data securely.
5. The support of flexibility and scalability.

6.2.2. How do special education teachers and therapists perceive the use of a mobile app to facilitate the coordination of educational plans in inclusive settings?

To answer this research question, a mobile app (IEP-Connect) was developed considering the designed principles identified. The IEP-Connect app allowed teachers, therapists and parents to record and share learners’ progress against IEP academic and behavioural goals. As detailed in Chapter 4, a series of usability evaluations indicated that the app has good usability rate and user satisfaction. Moreover, the app was found to be efficient, effective, easy to use and useful. Participants indicated that the mobile app facilitated finding information about a learner, recording and sharing updates with parents and receive their feedback, and monitoring learner behaviour.

These results suggest that the use of a mobile app can facilitates the communication and coordination of learning of learners with special needs between different stakeholders.

6.2.3. How can the motivator selection problem (MSP) be modelled as an MDP?

Selecting the right motivator for a learning setting is one of the main parts of the intervention process for learners with ASD. This is considered a challenging process as various factors impact the effectiveness of a motivator. To model the MSP as an MDP, careful formulation of the state/action space and the reward function should be considered. This is achieved by first identifying the factors that influence the effectiveness of the motivator.

As detailed in Chapter 5, contextual features such as antecedent events, time of day, and location (where and with whom) were found to impact the child response to a proposed intervention (Schaeffer 2018). In addition to the behaviour itself, understanding the reason behind the occurrence of the behaviour is considered essential for planning appropriate behaviour interventions. Moreover, the history of motivators previously used with a child are considered during intervention to prevent satiation as well as to maintain the Markov property where future state and reward depends only on the current state and action (Matheson & Douglas 2017; Sutton & Barto 2018). Therefore, the state space was designed considering the following features: antecedent event, time of day, subject, problematic behaviour, behaviour function, and history of motivators used. The action space consisted of six contingent motivators categories: edibles, sensory, activities, tokens, social, and choice. Finally, the reward function considered the feedback of the therapist or teacher as whether the motivator had a positive, negative or neutral impact on the motivation of the child according to Koegel and Egel (1979) measure of responsiveness.

Moreover, the reward function considered limiting the long-term exposure to unhealthy items by assigning a smaller reward to edibles and tokens.

6.2.4. How can Reinforcement Learning (RL) improve the success of the motivators used with learners with ASD in a learning setting?

A Q-learning algorithm with an epsilon-greedy (ε-greedy) policy with linearly decreasing exploration rate was used to solve the MDP formulated for the MSP. To evaluate the proposed RL model, the feature of selecting a motivator was added to the IEP-Connect app. This feature was used by teachers and therapists during a learning or therapy session to select a motivator to use. As detailed in Chapter 5, statistical analysis indicated that when using RL, the motivation of learners increased. Furthermore, the analysis of the Q-Learning data indicated that the episodes reward increased over time, signalling that the agent was able to learn to maximize its reward earned.

6.3. Implications

The findings of this study have many implications for theory, software development, practice, and research. While the literature shows that information technology does not guarantee knowledge sharing among organizational members (Yoo 2015), this study indicates that mobile technology and artificial intelligence can improve knowledge exchange and provide an effective tool for coopetitive knowledge sharing. This can be done by providing tools that allow and encourage users to share relevant and useful information in an easy and effective manner.

This study also emphasizes on including users in the design process as it is essential to provide them with tools that are tailored to their needs (Spiel et al. 2019), which will in return ensure users' satisfaction and increase their intention to use the proposed technology. Innovative technologies hold great promises for improving the research and treatment of autism. Therefore, increased support for interdisciplinary collaboration is much needed. Moreover, this research highlights design principles that can be considered as guidelines for future research on mobile app development for education.

As the aim of this study is to facilitate the communication and coordination process, the efficiency of the app was one big focus area. Special education teachers have worked so hard to make the coordination process work for them, which makes it hard and stressful to consider other alternatives (Marcu et al. 2013). As time is always a major concern for special education teachers, they should be presented with tools that do not require additional time and resources and are easy to learn (Siyam 2018). This can be done by reducing and specifying the data entry requirements, providing teachers with personalization and optimization options, and ensuring minimal navigation requirements to access tasks and information (Hasan & Abuelrub 2011; Bangerter et al. 2019).

While efficiency and effectiveness do not necessary correlate (Frøkjær, Hertzum & Hornbæk 2000), there is no doubt that the interface usability impacts the effectives of the app. Providing special education teachers with the right tools to collect and share data will result in high quality content and more frequent communication between different stakeholders. This study shows that when creating new tools for special education teachers, it is very important to preserve the fundamental methods used while taking advantage of the features that technology can add to the traditional methods.

Data is positioned at the core of special education practices. Though, current coordination methods make it hard to manage individual and groups' progress data as all information is managed by hand, which is a burdensome process. However, at the end of each term as well as the end of the academic year, teachers and therapists need to provide evidence for the completion of the IEP objectives. Moreover, in the case of learners with ASD, the behaviour of the learner needs to be monitored daily to measure the impact of certain interventions. To address these challenges, new technologies should allow teachers to add and retrieve data easily. They should also provide data mining capabilities and data visualization in different forms, such as line and pie graphs. This analysis and representation of data will allow teachers to provide evidence on objectives completion. It will also allow teachers to identify trends and gain insights on their learners' behaviour.

This study took place during the COVID-19 pandemic, which resulted in disruptions such as schools closing or shifting to distance learning. This unique context highlighted the issues in information sharing and collaboration between school and home regarding learners' academic and behavioural plans (Spiller 2020). Moreover, it was reported that during distance learning, learners in general, and learners with SEND in particular felt less motivated and engaged with their lessons (Beulah 2020). Additionally, behavioural plans had to change according to whether the learner is in a distance learning, blended learning, or on-site learning program. However, the challenges in behaviour management coordination are not exclusive to distance learning settings. Many studies reported issues in coordination between school and home, where the communication is often one-sided (Siyam 2018). Moreover, teachers and therapists often lack the time and resources needed to train parents on effective behaviour management techniques (Spiller 2020).

With so many challenges in place, it became more apparent that an innovative and dynamic way of communication and progress monitoring should be adopted. Moreover, as parents' responsibility in managing their children behaviour increased, the need for specialized decision support systems for parents or caregivers without the needed experience became increasingly apparent. The use of the IEP-Connect app with its "Motivator Selection" feature can address the inconsistency in behaviour management techniques between home and school.

The results shown in this study demonstrate the feasibility of RL to support the decision-making process of caregivers of learners with ASD in regards of the motivator selection problem. Despite its early stages of development, the proposed RL framework performs significantly better than current traditional motivator selection methods. A distinct advantage of RL over other machine learning approaches is that users' preferences guide the choice of the RL algorithm, which in return optimizes the reward function, resulting in higher reward values over time. The results indicated that the episode rewards increased over time, which indicates that the agent learnt to maximize its total reward earned. However, the episode reward did not level out at a high reward per episode value, meaning that the agent is not yet behaving optimally at every state. This is due to the large state space compared to the number of episodes the agent experienced. However, with the continued use of the algorithm through the app, the performance of the algorithm will continue to improve until it acts optimally at every state.

The results of this study also show that Machine Learning research can go beyond predicting outcomes towards decision-making support and finding new patters through exploratory studies (Kusters et al. 2020).

The proposed RL algorithm was based on scientific research which considered ABA practices, health concerns, and satiation. Moreover, the algorithm encouraged caregivers to incorporate motivational components in academic tasks and give the learners a choice, which resulted in higher motivation rates. These results add to the existing literature regarding the use of motivators for behaviour management. Moreover, the results indicate that the introduction of the "Motivator Selection" increased the usability score of the app. The modelling approach using MDP can be further improved to provide more accurate and personalized motivator selections.

A key challenge of RL- based systems, especially those that are multi-disciplinary, is to ensure that non-RL experts are engaged in the design process, and are able to evaluate the performance of the model and decide whether to trust the results (Thieme, Belgrave & Doherty 2020). The literature shows that evaluation of RL-based algorithms is mostly done in laboratory settings, with few studies done in clinical settings. However, there is little known about the effects RL has on healthcare and people's wellbeing. Moreover, a significant concern with decision support systems is what is called "automation bias", where users tend to over-rely on the output the system produces, rather than being cautious. As with any technology, RL will also come with its undesired effects that may pose risks to people. Therefore, the benefits of RL cannot be reached safely unless RL is reliably and effectively integrated into the decision-making of the processes it intends to support (Magrabi et al. 2019).

Evaluating RL algorithms in sociotechnical settings is not a one-off activity but requires continuous evaluation to monitor the developing behaviour of the algorithm and its response to users. Therefore, evaluating RL-based systems requires continues algorithm improvement using newly generated evidence to inform practice changes (Magrabi et al. 2019).

The data collected in this study will provide valuable data repository for research on learners with ASD behaviour and how they are motivated in different settings (Burns, Donnelly & Booth 2015). Data mining techniques can be used to uncover fundamental patterns regarding the optimal motivator magnitude and to predict the likelihood of the child response to intervention. For example, learners with inconsistent or reduced response to motivators may require additional training or therapeutic sessions (Bennett & Hauser 2013; Schuetze et al. 2017). Moreover, patterns can be extracted from such data to understand and explain problematic and reoccurring behaviour or antecedents, which will help in return minimize the situations where such behaviour occurs. Using data mining techniques can offer capabilities beyond human comprehension, such as considering numerous contextual features (Burns, Donnelly & Booth 2015).

While RL has the potential to offer significant contribution in the area of therapy decision-making for special needs, there are certain key issues that need to be addressed, such as clinical implementations and ethics (Liu et al. 2020). Since the proposed RL algorithm is run in a real scenario without the benefit of a training period, the large number of possible state-action pairs has to be considered to avoid coverage problems. The RL models in clinical settings require iterative refining to include new data from various resources as well as longer training periods to increase the system's knowledge-base. Using data from limited resources may result in biased algorithms that do not apply to all scenarios. Thus, RL research must be complemented by explainable decisions and dataset bias transparency (Kusters et al. 2020). Additionally, among the raised ethical concerns of AI algorithms is the ownership of generated data and the right to benefit from them (Shawky & Badawi 2019; Alkashri, Siyam & Alqaryouti 2020).

The Reinforcement Learning approach followed in this study is fairly unique as the training was conducted within the experiment. This allowed the exploration to be executed in a real context which prevented large variance and bias in data.

6.4. Scope for further study

Data collected in this study is considered homogenous, both in terms of data collected regarding the learners or regarding teachers and therapists' perceptions. This limits the degree to which the findings can be generalized. However, while the current algorithm has been trained on data from one specific context, it can be still scaled to other contexts and used with other learners. Yet, there is a need for a dynamic adaptation mechanism that allows the agent to efficiently refine its policy towards a new child (Tsiakas et al. 2016). Other possible directions for future work include modelling the RL algorithm as a partially observable MDP where data are mapped to some state space that truly represents learners' behaviour and context features.

While the one-group quasi experimental design was the possible choice for this work, more credibility could be given to this study if randomized control trials could be employed. Moreover, a longitudinal study could be done to better evaluate the impact of mobile technology on the learning of learners with ASD through facilitating the coordination between all stakeholders. Additionally, a longitudinal research can be beneficial to study the performance of the algorithm and whether it will act optimally at every state in the long run.

Moreover, future work should consider the interpretability of produced recommendations (Kusters et al. 2020). The system should be able not only to suggest suitable motivators, but to explain such choices to the user. “Explainable” AI systems have been proven to increase users trust and acceptance of the system (Abdi et al. 2020).

The proposed RL framework can be integrated into a multi-agent ecosystem that aims to improve the coordination among the stakeholders of an IEP. The agents in the system will be able to “learn” over time and adapt to the real-world variation. Such systems can aid in the decision-making process of education providers while developing updated knowledge about effective special education practices (Bennett & Hauser 2013; Bulling 2014).

6.5. Concluding note

The main goal for the development of the IEP-Connect was to facilitate communication and collaboration and to support the decision-making process for those involved with a child with ASD. Through the system’s development and implementation, it was found that the IEP-Connect app has the potential to do just that. Through a series of usability studies, it was found that the IEP-Connect app is usable and useful. Furthermore, the development and employment of the motivator selector feature to the IEP-Connect app demonstrated the feasibility of RL to support the decision-making process of caregivers of learners with ASD.

While the results of this study are positive, the development of the IEP-Connect app can benefit from continuous improvements. As this study indicates, the IEP-Connect app has successfully been through three iterations, as the system was design for extensibility. Therefore, users’ feedback can continue to drive future iterations.

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Appendices

Appendix A Education Pillar of the National Policy to Empower People of Determination

Goal: Enhancing the inclusion in education (public, vocational and higher education)

Initiatives:

- Providing a clear education track for people of determination through all stages
- Redesigning and adapting the curricula to respond to the needs of people of determination
- Providing additional resources, tools and technologies to support the education of people of determination
- Providing treatment support services (speech, functional, behavioral…)
- Empowering and engaging communities and families in educational, entertainment, arts, sports and cultural activities
- Launching awareness campaigns targeting the community and school students on the importance of inclusion
- Launching home schooling programs for certain disabilities

Goal: Providing highly qualified teachers and experts in education for people of determination across different learning stages

Initiatives:

- Inaugurating specializations in education for people of determination in universities and colleges (such as education in the cases of autism and severe disabilities)

- Ensuring that universities introduce the teachers in the pre-service stage, to the principles of teaching and assessing students with disabilities and learning difficulties
- Launching a training program for Emirati nationals working in the elds of disabilities, including teachers and education specialists

Stakeholders:

- Ministry of Education
- Ministry of Community Development
- Local Education Authorities
- Education councils
- Schools
- Federal, Local and Private Disabled Centers
- Universities and higher education institutions
- Associations
- Parents of disabled children

Appendix B **Documents Analysed**

Table 21: Sample of Documents Analysed

Document	**Data Analysed**
IEP documents	Components (objectives, accommodations, recommendations), hierarchy of objectives, objectives details.
Behaviour modification plans	Components, sample data.
Students' journals	Information communicated between school and home.
Teachers' notebooks	Information and data teachers and therapists considered essential.

Appendix B.1 Sample IEP Document

Student's Name: **Teacher's Name:** **School Year:**

Subject: **Term: One**

Learning Expectations		Procedure	Date		Teaching Strategies and Resources Required	Assessment Methods
			From	To		
Long-Term Goals: (During the year)	Short-Term Goals: (During the term)					

Teaching Objectives for the Scholastic Year 2018/2019

Short-Term Goal (1)		Date	
		From --/--/2019	To --/--/2019
Teaching Objectives	1	From --/--/2019	To --/--/2019
	2	From --/--/2019	To --/--/2019
	3	From --/--/2019	To --/--/2019
	4	From --/--/2019	To --/--/2019
	5	From --/--/2019	To --/--/2019
	6	From --/--/2019	To --/--/2019
	7	From --/--/2019	To --/--/2019

Figure 17: Sample Page of IEP Template (Learning Objectives)

Appendix B.2 Sample Behaviour Modification Plan

استمارة خطة العلاج السلوكية :

م	التاريخ	اليوم	السلوك المُشكل	المثير السابق	المثير اللاحق	المدعم	ع م تكرار السلوك
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							

ملاحظات :

Figure 18: Sample Page of Behaviour Modification Plan

Appendix B.3 Sample Student Journal

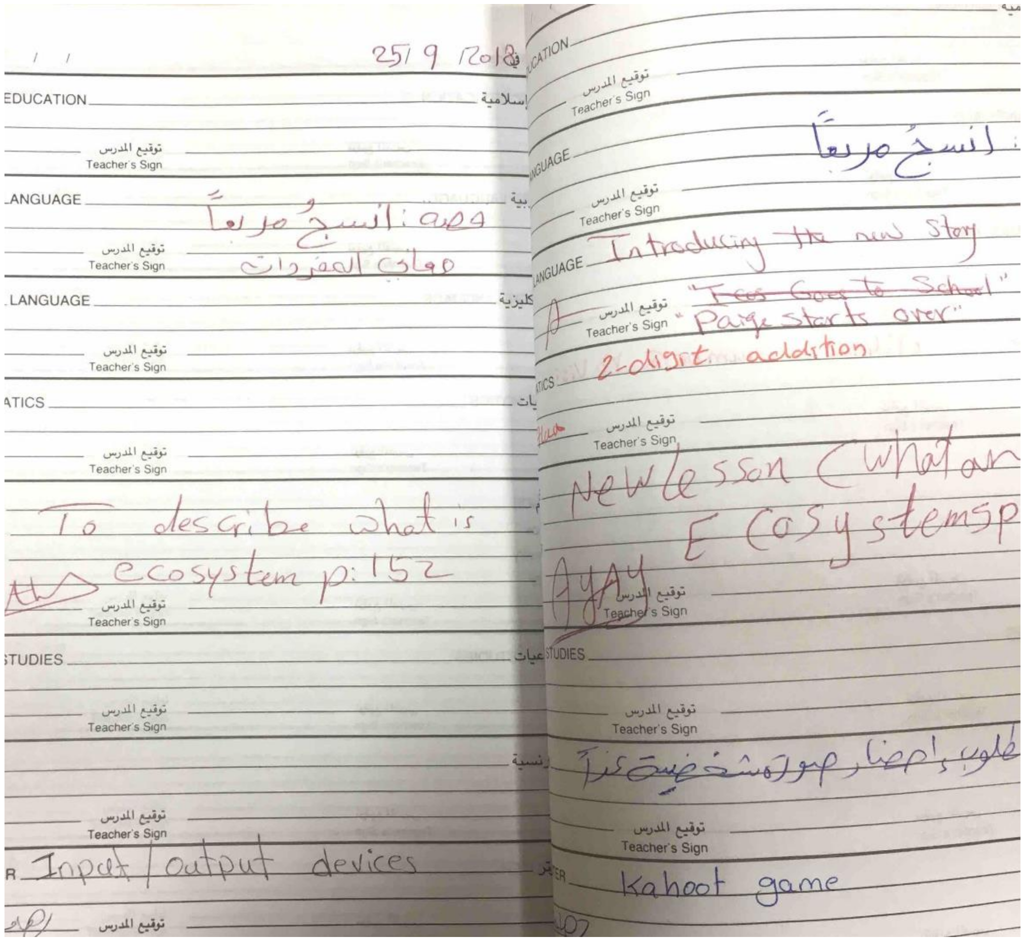
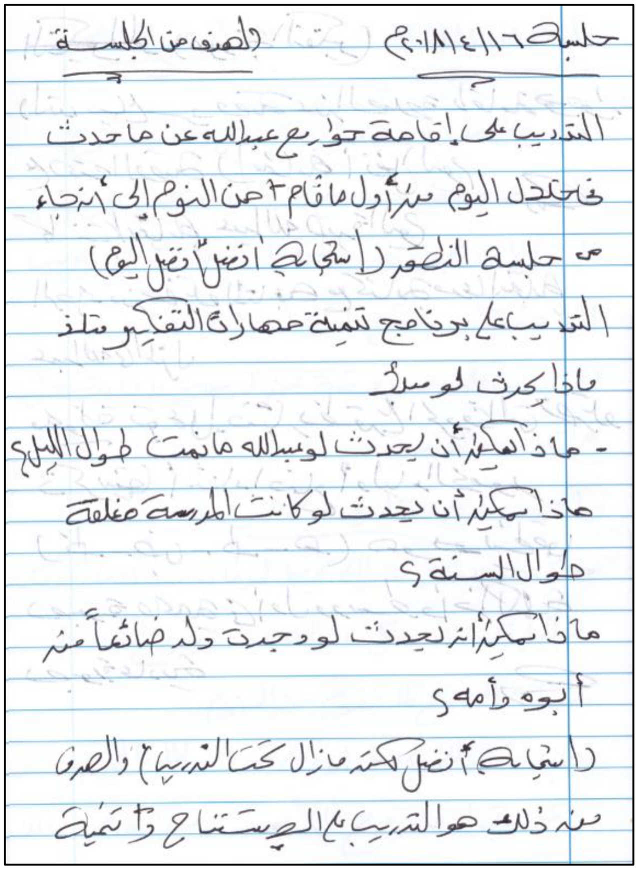


Figure 19: Sample Page of Student’s Journal

Appendix B.4 Sample Teacher's Notebook


جلسة ١٦/٤/٢٠١٨م (الهدف من الجلسة)

التدريب على إقامة حوار مع عبدالله عن ما حدث
في خلال اليوم منذ أول ما قام من النوم إلى انتهاء
من جلسة النطق (استجابة أفضل تقبل اليوم)
التدريب على برنامج تنمية مهارات التفكير مثل
ماذا يحدث لو سألك
- ماذا أمكن أن يحدث لو عبدالله ما نمت طول الليل؟
ماذا يمكن أن يحدث لو كانت المدرسة مغلقة
طوال السنة؟
ماذا يمكن أن يحدث لو وجدت ولد ضائعاً من
أبوه وأمه؟
(استجابة أفضل لكنه مازال تحت التدريب) والهدف
من ذلك هو التدريب على الاستنتاج و تنمية

Figure 20: Sample Page of Teacher's Notebook

Appendix C **Workshop Activity Sample**

Complete the User Personas According to Your Own Perception

Teacher

Needs	Pain Points
• create and edit IEPs academic objectives • update students' academic progress • keep track of students' academic progress • keep track of completion of IEPs academic goals • share academic information with other staff and parents • receive information from other staff and parents	• IEPs are hard to read and understand. • no experience in special education • IEPs operational objectives are hard to transform to academic objectives without specialists help • medical and therapeutic information not always available • Lack of channel of daily communication with parents

Figure 21: Workshop Task - Completing users' personas

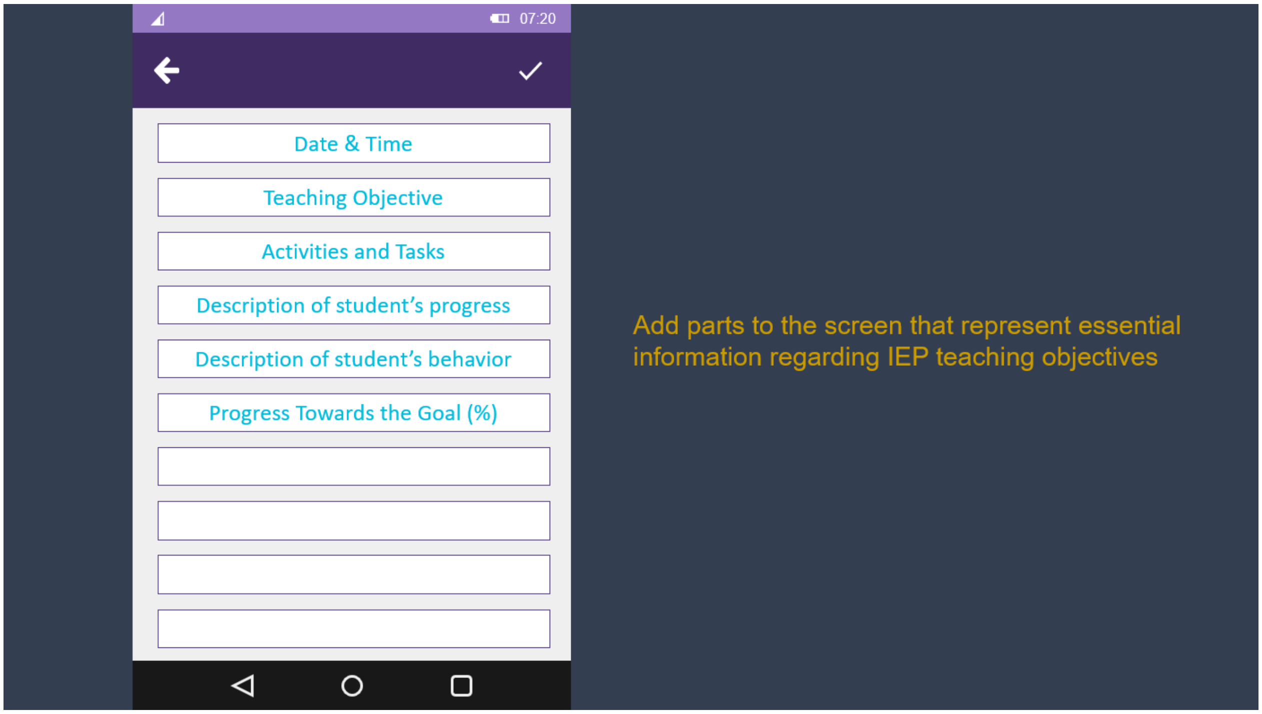


Figure 22: Workshop Task - Adding Components to the Mobile App Interface

Appendix D **Open-ended Interview Questions**

(1) How can you describe your overall experience using IEP-Connect?

(2) What parts of the app were hard to use?

(3) What parts of the app were easy to use?

(4) What parts of the app were useful to your practice?

(5) Did the app facilitate information sharing between you and other staff?

(6) Did the app facilitate information sharing between you and parents?

(7) Do you think the app has improved students' achievement of IEP objectives?

(8) What can be added to the app to improve it?

(9) Do you intend to use the app in the future?

Appendix E Research Consent Forms

Appendix E.1 Principal Consent Form

Project Information Statement - Invitation to School Principals

Dear _______________,

My name is Nur Siyam and I am a student in the British University in Dubai. I am currently studying the benefits of using a mobile app to share therapy and learning information of the students with ASD as well as track their progress in achieving the IEP objectives. As the principal of the school on which I would like to conduct the research, I would like to invite you to participate in this study. This study will meet the requirements of the Research Ethics Committee of the university.

Aims of the Research:

This study aims to improve the achievement of IEP objectives by facilitating information sharing between different parties involved in the intervention of ASD students. This will be achieved by developing a mobile app to be used by teachers and therapists to record the learning outcomes of each class or therapy session.

Benefits of the Research to Schools

The use of the mobile application will replace the paper-based system in the school, as well as the electronic IEP documents that are usually hard to read to accommodate the different needs of students, teachers and therapists. This is expected to result in improved achievement of IEP objectives for students with ASD.

Research Plan and Method

For this research, IEP data for students with ASD will be collected and entered into the mobile app. Teachers and therapists will be asked to enter daily the learning outcomes of the classes and/or therapy sessions into the mobile app. Teachers will be asked to use the app for a period of three months. Permission will be sought from the teachers, therapists, and parents of the participating students prior to the participation in the research. Only those who consent will participate. All information collected will be treated confidentially and neither the school nor the individual students and teachers will be identifiable in any reports that are written. Participants may choose to withdraw from the study at any time without penalty. The role of the school is voluntary and the school principal may decide to withdraw the school's participation at any time without penalty.

School Involvement:

Once I have received your consent to approach teachers and parents to participate in the study, I will

- arrange for informed consents to be obtained from teachers and therapists
- arrange for informed consents to be obtained from parents of participating students
- arrange for a timeframe for data collection to take place

Attached for your information are copies of the Teachers and Parents consent forms.

Invitation to Participate

If you would like your school to participate in this research, please complete and return the attached form.

Thank you for taking the time to read this information.

Research: A Mobile App for Coordinating Educational Plans and Supporting Decision Making

Consent Form: School Principal

I give consent for you to approach teachers and parents of students with ASD to participate in the above-mentioned research.

I have read the Project Information Statement explaining the aim of the research project and understand that:

1. The school's participation in this study is voluntary.
2. I may decide to withdraw the school's participation at any time without penalty.
3. Only students whose parents consent will participate in the study.
4. All information obtained will be treated in strictest confidence.
5. The identity of teachers and students will be reported anonymously.
6. Your identity will be reported anonymously.
7. The school will not be identifiable in any written report about the study.
8. Participants may withdraw from the study at any time without penalty.
9. A report of the findings will be available to the school.

Principal: ____

Email: ____

Phone number: ________________________________

Signature ______________________________

Date _____________

Nur Siyam

nur.siyam@gmail.com

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Appendix E.2 Parents' Consent Form

Research: A Mobile App for Coordinating Educational Plans and Supporting Decision Making

Consent Form: Parents/Guardians of Research Participants

Dear Parent,

My name is Nur Siyam and I am a student in the British University in Dubai. I am currently studying the benefits of using a mobile app to share therapy and learning information of the students with ASD as well as track their progress in achieving the IEP objectives. As a parent of one of the chosen students to participate, I would like to ask for your consent for your child to participate in this study.

If you choose to provide your consent, your child records and information will be added to a mobile app developed for this study. This information includes your child profile data, the IEP objectives and accommodations, and the learning outcomes of each class or therapy session. Data recorded may also include images or videos of your child during a learning session, with what complies with the school's policy of data collection. You will be able to use the mobile app to view the information related to your child's progress. The app will be used for a period of three months. All the collected data will be kept securely. Only assigned teachers and therapists will be able to view your child's data and add new information.

The results of the study may be published but your child's identity will remain confidential and anonymous. For example, we might refer to a school as School A, and a student as Student A.

Even though there may be no direct benefit to you or your child from this study, a possible benefit of your child's participation is identifying possible ways of improving information sharing among different parties involved in the learning of ASD students, which in return may increase the achievement of IEP objectives of your child.

If you have any questions concerning the research study, please contact me. If you choose to provide your consent, you should note the following:

1. Your child's participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, you can do so without any consequences to you or your child.

2. The researcher will have access to your child's IEP.
3. Your child's identity will be reported anonymously.
4. All data will be saved and transferred securely.
5. The research results will be used for publication.

By signing this form, you acknowledge that you understand the nature of the study, and the methods by which your identity will be kept confidential. Your signature on this form also indicates that you agree that your child, whose name is mentioned herein and for whom you are a guardian, may take part in the above-mentioned research project.

Child's name: ____

Parent/Guardian's name:

Parent/Guardian's Email: ____

Parent/Guardian's Phone number: ________________________________

Parent/Guardian's Signature ______________________________

Date _____________

Nur Siyam

nur.siyam@gmail.com

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Appendix E.3 Teachers and Therapists Consent Form

Research: A Mobile App for Coordinating Educational Plans and Supporting Decision Making

Consent Form: Teachers and Therapists

Dear Teacher,

My name is Nur Siyam and I am a student in the British University in Dubai. I am currently studying the benefits of using a mobile app to share therapy and learning information of the students with ASD as well as track their progress in achieving the IEP objectives. As a teacher and/or therapist working with a child with ASD, I would like to invite you to participate in this study. If you choose to participate, you will be asked to use the mobile app to record the outcomes of every class or therapy session for a period of 3 months. You will also be asked to participate in a face-to-face interview with the researcher as well as to fill in a short questionnaire.

The results of the study may be published but your identity will remain confidential and anonymous. For example, we might refer to a school as School A, and a teacher as Teacher A. Interviews might be audio-recorded, but all recordings will be deleted once transcribed. You may also request that no audio recording shall be used. Your answers to the questionnaire will be also anonymous.

Even though there may be no direct benefit to you from this study, a possible benefit of your participation is identifying possible ways of improving information sharing among different parties involved in the learning of ASD students, which in return may increase the achievement of IEP objectives.

If you have any questions concerning the research study, please contact me. If you choose to participate in this study, you should note the following:

1. Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, you can do so without any consequences.
2. Your identity will be reported anonymously.
3. The information from the interview recordings will be transcribed. The researcher will use a coding system to ensure your confidentiality is protected.
4. The research results will be used for publication.

By signing this form, you acknowledge that you understand the nature of the study, and the methods by which your identity will be kept confidential. Your signature on this form also indicates that you give your approval to voluntarily serve as a participant in the study described.

Interviewee name: ____________________________________

Email: ____

Phone number: _______________________________

Signature _____________________________

Date _____________

Nur Siyam

nur.siyam@gmail.com

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