SEQUENTIAL MIXED-METHODS STUDY TO IDENTIFY FACTORS PREDICTING PARENTAL PREPAREDNESS FOR INTRODUCTION OF CHILD ARTIFICAL INTELLIGENCE LITERACY INITIATIVES IN PRIMARY SCHOOLS IN THE UNITED KINGDOM

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Dedication

To all the women out there….Break barriers and accomplish all that you have ever desired. If you can dream of it, you can realize it!

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Abstract

This dissertation used Sequential exploratory and subsequently sequential explanatory approach to answer a single research question to assess various predictors of parents' preparedness for introduction of Child Artificial Intelligence Literacy (CAIL) initiatives in primary grades in UK schools. Study 1 comprises of initial qualitative exploration of the research question and identifying key variables of interest to predict parental CAIL preparedness. Study 2 tests the hypotheses using quantitative survey. 438 parents of primary kids in the UK participated. The outcomes of quantitative study were then further explained through qualitative Study 3 where 5 qualitative interviews were conducted. Stakeholder collaboration (parent-child, parent-teacher), a new variable thus far not fully used to assess parents within research context was developed. Together innovativeness, attitudes, collaboration predicted parents preparedness for CAIL while concerns did not predict CAIL well. Overall, the study model used new adapted scales and developed a new scale to assess collaboration. The study is the first of its kind to assess predictors of preparedness for CAIL among parents in the UK and provides a model that can be used to further research preparedness for CAIL or other new technologies. The results will help inform policy, researchers, educators as well as developers and curriculum design for CAIL.

Key words: *Artificial Intelligence literacy, parents, teachers, primary school, mixed-methods design, preparedness, attitudes, concerns, collaboration, innovativeness*

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LIST OF ABBREVIATIONS

AI- Artificial Intelligence

AI HLEG- High level expert group on artificial intelligence

AIK12-AI for K12

ANN- Artificial Neural Network

ANOVA- Analysis of Variance

CAIL- Child Artificial Intelligence Literacy

CSTA- Computer Science Teachers' Association

DIT- Diffusion of Innovation

DSW- Digital story writing

EV- Eigen Value

H1-Hypothesis 1

H2-Hypothesis 2

H3-Hypothesis 3

H4-Hypothesis 4

ICT- Internet Communication Technology

ISTE- International Society for Technology in Education

K-12- Kindergarten to 12th grade.

MCAR- Missing completely at random

MIT- Massachusetts Institute of Technology

ML- Machine Learning

OECD- Organization for Economic Cooperation and Development

PCA- Principle component Analysis

PEU- Perceived ease of use

PhD Doctor of Philosophy

PU- Perceived usefulness

P1- Participant 1

P2- Participant 2

P3- Participant 3

P4- Participant 4

P5- Participant 5

RQ- Research Question

SDG- Sustainable development goals

SPSS- Statistical Package for Social Sciences

SSBM- Swiss School of Business & Management

STEM- Science Technology Engineering Mathematics

TAM- Theory of Acceptance Model

TPP-Theory of Planned behavior

TR- Technology readiness

TRA- Theory of reasoned action

TRI- Technology readiness Index

TTF- Theory of Task-technology fit

UK- United Kingdom

UN- United Nations

UNESCO- United Nations Educational, Scientific and Cultural organization

UNICEF- United Nations

US- United States

USA- United States of America

UTAUT- Unified Theory of acceptance and use of technology

CHAPTER I:

INTRODUCTION

1.1. Introduction

Artificial intelligence (AI) is altering several aspects of humanity in the current times. AI technologies are helping revolutionize industries (Liu et al., 2018), enabling efficient decision-making processes and even impacting day to day life of individuals. In that sense AI is ubiquitous and impacts how individuals live and work today. While broad concepts of AI have been around since the 1950s (Bush, 1945; TURING, 1950) it is only after big data (Diebold, 2012) revolution that the technology has seen remarkable progress. So far, the focus of both the AI industry players and governments and research has been towards industrial application of the technology and a large chunk of investment is allocated towards it. Within education sphere courses were and still to a great extent are largely designed for university level studies for computer and software students alone. But slowly the importance of AI Literacy for all including those that do not have a technical education background is being recognized (D. T. K. Ng et al., 2022a). According to an independent document titles “Ethics Guidelines for Trustworthy AI” prepared by a High-Level Group on Artificial Intelligence for the European Commission (AI HLEG, 2019) AI literacy refers to the understanding and proficiency in concepts, applications, and implications of AI. AI literate individuals will be capable of critically analysing AI-powered systems, assessing their ethical implications as well as application of AI tools responsibly which in turn can enable active participation, ability to make informed decisions as well as address challenges posed by AI technologies both in work and general life scenarios (AI HLEG, 2019). To that effect transformative courses to enable easy entry of the new workforce as well as upskilling courses for the existing workforce are gaining purchase. With AI technology being in its own evolutionary growth phase it is also being realized that the future workforce needs to be made AI ready today (Larson and Miller, 2011) and researchers are now beginning to focus on how to introduce AI at school levels starting from kindergarten all the way to 12 standard just as it was done to enable computer literacy a few decades ago. Early exposure to AI literacy can lay the foundation for a child's digital literacy and technological competence. Integration of AI education into the primary school (child artificial intelligence literacy-CAIL) curriculum can help a child develop enhanced computational thinking, problem-solving skills, sensibilities towards ethical considerations related to AI (Bers et al., 2022; Casal-Otero et al., 2023; Huang and Qiao, 2022; Ma et al., 2021; Wong, 2024). It can empower young minds to become responsible creators as well as consumers of technology and prepare them for the future workforce, which will heavily rely on AI-Powered tools and applications. CAIL can also help reduce misconceptions that people and children hold on such technologies.

1.2. Research Problem

As such various existing studies conducted thus far inform us that several factors including technology adoption and innovativeness of individuals (Liu et al., 2018; Mauch, 2001; Midgley and Dowling, 1978; Rogers et al., 2003), attitudes (Busch, 1995; Gherheş, 2018; Morahan-Martin and Schumacher, 2007) of not only children but those of parents and teachers may impact preparedness for CAIL initiatives. However, most of these studies were conducted in other countries and so far, no studies have explored predictors of preparedness for CAIL among parents of primary school children. Additionally, there was no recent research found on CAIL that focused on The United

Kingdom (UK) even though an agency that counsels The Government of UK has acknowledged the importance of AI Literacy (UK AI COUNCIL, 2021) and lack of investment in the area, in its report and the government has recently announced its increased focus on integrating AI Literacy in school education (Waterfield Sophia, 2023). Having said that, how preparedness of AI is impacted by various other factors in the UK among parents of primary school going children remains unexplored. This study aims to bridge this gap in literature by studying various factors that impact preparedness of parents for introduction of CAIL initiatives in primary schools in the UK.

1.3. Purpose of Research

This research aims to explore the variables that predict preparedness of UK parents, towards the introduction of CAIL at the primary school level. By inspecting these factors, the dissertation endeavours to provide an understanding into the perceptions and expectations of stakeholders regarding the integration of CAIL in primary school curriculum. Understanding the attitudes of parents towards CAIL is of importance as parental influence plays a significant part in a child's development as well as learning (Druga et al., 2022a; Halim et al., 2018; Hammer et al., 2021; Hoover-Dempsey and Sandler, 1995; Jipson et al., 2016; Lawrence and Fakuade, 2021; Long et al., 2022; Shao and Kang, 2022; Thomas et al., 2020). Understanding their views on AI literacy will provide valuable insights into their expectations, concerns, and willingness to support and engage in AI-related activities outside of school which may prove beneficial in enhancing their child's AI learning ability and experience. This knowledge will help in developing effective strategies for parental involvement and collaboration to make CAIL initiatives a success. Findings of the study will provide a holistic picture that can inform education policy, curriculum design as well as future research.

1.4. Significance of the Study

Studies show that society depends on parents to prepare children for changes caused by education and technology and also for protecting them and preventing them from online risks (Livingstone et al., 2017). Further another study has suggested that parents can influence children's perceptions and enable them to differentiate between what may be harmful and what may be useful when encountering online situations (Cabello-Hutt et al., 2018). Hence parents play a crucial role in child's access, learning ability and use of digital environments and also in shaping children's perceptions and learning. The reasons due to which parents may choose to get involved with their child's learning and education were explained in a much cited study (Hoover-Dempsey and Sandler, 1995). Based on the model, the engagement of parents has an impact on the development and educational achievements of children through various means such as demonstrating, reinforcing, and instructing, which are influenced by the parent's use of activities that are suitable for the child's age and the alignment between these home-based parental activities to engage children in learning and school requirements. The main educational results of the engagement process encompass the enhancement of children's skills and knowledge, along with fostering a personal belief in their ability to enhance academic achievement. Another qualitative study also discussed the role of parents in influencing children's interest in learning science in schools (Halim et al., 2018). Yet another study found that other than teachers, parents own beliefs and attitudes played a pivotal role in shaping a child's beliefs pertaining to digital media and their efficacy in the subject (Hammer et al., 2021). Further a study showed that collaboration between parents and teachers to facilitate supportive informal learning for children involving coding and robotic technologies proved beneficial (Relkin et al., 2020). Within AI Literacy domain a recent study has shown that family plays a critical role in a child's adoption and learning of AI technologies (Druga et al., 2022a) outside of school environment. In addition to this past research has also recognized the importance of parent-teacher partnership in enhancing child's learning and development (Epstein, 2018; McLanahan and Sandefur, 2009). Further another case study based research has posited that parental engagement in children's learning in home based environment contributes in a big way towards student achievement (Harris and Goodall, 2008). So far parental involvement in child's AI learning has remained largely neglected in literature. This makes studying impact of collaboration between various stakeholders (parents-teachers, parents-children) crucial to gain insights on collaboration as a predictor for parents' preparedness for CAIL in UK schools. All of the above also will significantly contribute towards better understanding of various factors impacting parent's readiness for CAIL. In addition, demographic variables may have an impact on parents' preparedness for introduction of CAIL initiatives in primary schools in the UK. Thus, it is important to assess parents' affinity towards technological innovativeness, attitudes, favourability to collaborate with other stakeholders such as children and teachers and parents' concerns alongside demographic variables to predict their readiness levels for introduction of CAIL initiatives in primary classes in the UK

1.5. Research Purpose and Questions

For initial investigation in this research, we have limited the research question to one.

RQ: What are the various factors influencing parental preparedness for introduction of CAIL initiatives in Primary schools in the UK?

This research question allows for a broad exploration of various variables including the key variables of innovativeness, attitudes towards AI, willingness to collaborate with other stakeholders (children and teachers), concerns as well as other demographic variables impacting parents' preparedness for introduction of CAIL initiatives in primary schools in the UK, thus allowing for a detailed assessment of our study topic.

1.6. Overview of the Method

This dissertation has adopted a sequential mixed methods approach whereby the research will be conducted in three phases under three studies (Study 1., Study 2, Study3). Study 1 will focus on initial inductive qualitative enquiry of the broad research question, using the sequential exploration design to identify key themes and further categorise these themes under variables of interest. Literature review was thus conducted in two phases. The initial literature review focused on understanding the AI landscape and gaps within research in order to define the first research question. The second literature review was conducted simultaneously with Study 1 where a qualitative interview with an AI expert helped answer the research question and also identify important themes. These themes were then used to develop variables of interest for further investigation. Relevant Theoretical frameworks were thus part of the second literature review which was conducted in combination with the qualitative study 1. Hypothecation happened at the end of study 1 and was further tested in study 2 which used a quantitative survey approach. The quantitative outcomes from study 2 were then further explained using sequential explanatory design where a deductive qualitative investigation was undertaken to explain the quantitative findings as part of Study 3.

While a more detailed explanation of the research design is presented in the Methodology section of this dissertation, here is a synoptic description of the research design used. A sequential mixed-method research design (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017; Sandelowski and Barroso, 2003; Teddlie and Tashakkori, 2003a) has been used in this dissertation to first identify the various factors that predict parental preparedness for the introduction of CAIL initiatives in primary schools in the UK. These variables are then further assessed quantitatively to measure how well they predict parental preparedness for introduction of CAIL initiatives in primary schools in the UK. Further the outcome of the quantitative data is explained using another round of qualitative data gathering in study 3 of the dissertation.

Many researchers support the use of multiple methods to triangulate and validate information. They argue that combining qualitative and quantitative data leads to a deeper comprehension of any research problems, particularly when studying complex phenomena (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017; Onwuegbuzie and Teddlie, 2003). This approach of data gathering has been adopted and has been in existence since 1959 (Campbell and Fiske, 1959) and was first adopted in the field of psychological research. Numerous studies have employed such approaches of research (Campbell and Martinko, 1998; Di Pofi, 2002; Edmondson, 1999; Jehn, 1995; Vitale et al., 2008).

1.6.1 Study 1- Qualitative exploration

A qualitative study was conducted ahead of quantitative study. Semi-structured interview with an AI expert to provide more insights in order to develop initial themes and then further identify key variables of interest was undertaken in this phase of research. The broad line of questioning is included in Appendix A. In addition, past research literature, news articles, reports and informal discussions were included in the qualitative analysis. Qualitative themes were developed using Thematic analysis. These themes were further classified under appropriate variables of interest and in order to study those, hypotheses were developed for further investigation. The specific research question for study 1 derived from the initial literature review was:

RQ: ***What are the various factors influencing parental preparedness for introduction of CAIL initiatives in Primary schools in the UK?***

1.6.2 Study 2-Quantitative exploration and confirmation

This part of the dissertation utilized a quantitative approach based on a survey designed to understand relationships between all the variables of interest and how they predicted the dependent variable parental preparedness/readiness (Readiness/preparedness) for introduction of CAIL in primary schools in the UK. 438 participants responded to the survey questionnaire. Study 2 served to quantitatively explore the identified factors and their relationships.

Data were collected anonymously through an online survey. Scales were developed for key variables of interest and were further examined using exploratory factor analysis in SPSS version 25. Table 1 below presents a summary of main hypotheses examined within this dissertation in Study 2.

Table 1 – Study 2 Hypotheses

Hypotheses
H1: Innovativeness predicts preparedness for CAIL in parents
H2: Attitudes predict preparedness for CAIL in parents
H3: Collaboration predicts preparedness for CAIL in parents
H4: Concerns predict preparedness for CAIL in parents

1.6.3 Study 3-Qualitative explanation

The outcomes of study 2 were further explained following sequential explanatory design. Semi-structured qualitative interviews with five parents were conducted, three of whom also participated in the quantitative survey. Deductive approach was used to assess the data and explain the findings from previous studies in-depth.

CHAPTER II:

REVIEW OF LITERATURE: PHASE ONE

2.1 Introduction

In order for us to understand the topic of our study it is imperative that we first introduce the universe within which our topic resides. This literature review is aimed at arriving at our research topic and research question and hypotheses therein, through a process of first defining what AI means and its genesis and also describe the current AI capabilities and misconceptions held by people due to lack of knowledge on what AI can and cannot do presently. Subsequent sections will touch upon the importance of AI, its current usability in businesses and day to day life. The literature review will then elaborate on recognition of AI Literacy as an important step towards equitable, responsible and informed use and development of AI technology and how it is transitioning into a required study field for all. From there using literary references we will approach the topic of AI Literacy and its role in preparing future generations to live and work in what is predicted to be an AI driven world. Various initiatives being incorporated at K-12 school levels to introduce child Artificial Intelligence Literacy (CAIL) will be discussed and the constraints and barriers to the same will be highlighted. Thereon a microscopic view of literature that highlight factors that predict preparedness of individuals for new technologies such as AI will be discusses. The Literature review will also discuss how various countries are attempting to introduce AI literacy in their schools or any other initiatives to this effect. We will then proceed to understand how The UK fares on AI Literacy and understand the gaps in research to justify the importance of our study.

2.1.1 Definition of AI

The genesis of AI goes back several decades, to 1950s when computer scientists commenced development of algorithms to attempt mimicking how human way of thinking. However the idea of machine being used for the function of organization were in fact introduced in the 1940s (Bush, 1945). Bush, (1945) presented an idea of machines in the future organizing books. The field has since grown rapidly and has become an important area of research in computer science and engineering. The term Artificial Intelligence (AI) over the years has been defined by various scientists and researchers in several different ways since the technologies that fall under AI are evolving since AI technology itself is rapidly evolving (Dobrev, 2012; European Commission. Joint Research Centre., 2020; Kok, 2009). And it can be said that there is no standard definition of AI. One of the initial definitions of AI came into being in 1956, when AI was defined as the scientific and engineering mechanism used to create intelligent machines (McCarthy, 2017). Several researchers and scientists have also suggested that AI could be viewed as intelligent machines that can exhibit human like behaviour or exhibit intelligence which is one of the human traits (Albus, 1991; Bellman, 1978; Fogel, 1995; Gardner, 2011, 1987; Luger, 2005; McCarthy, 1998; McCarthy et al., 1955; Minsky, 1969; Newell and Simon, 1976; Nilsson, 1998; Russel and Norwig, 1995; Winston, 1992). However intelligence as a trait is subjective and abstract and as such is not quantifiable and cannot be precisely explained or measured even for humans (Kaplan, 2016) and hence these definitions have been argued against. Intelligence in reference to machines was explained as a rationality (Russell et al., 2010) where the authors suggested that a system can be considered rational if it does the ‘right thing”, within the limitations of knowledge it possesses. More recently a technical definition of AI explained it as the scientific and engineering mechanism used to create intelligent machines that have the ability to solve varied problems using natural language processing, Artificial neural network and machine Learning (ML) (Mondal, 2020). Whilst AI does not have a standardized definition it has been found that all the various definitions attribute some common traits to AI namely Acuity of the existing environment and real world complexities (AI HLEG, 2019; Albus, 1991; Fogel, 1995; Nakashima, 1999; Newell and Simon, 1976; Nilsson, 1998; Poole et al., 1998; Tsinghua University, 2018; Ulnicane, 2022; Wang, 2019), ability to process data/information or ability to collect and interpret data inputs (AI HLEG, 2019; Kaplan and Haenlein, 2019; Nakashima, 1999; Nilsson, 1998; Poole et al., 1998; Tsinghua University, 2018; Ulnicane, 2022; Wang, 2019); ability to adapt and respond to changes in the environment by utilizing reason and thought in order to (partially) freely arrive at decisions/ Decision making to perform a designated job (AI HLEG, 2019; Albus, 1991; Fogel, 1995; Kaplan and Haenlein, 2019; Newell and Simon, 1976; Nilsson, 1998; OECD, 2021; Poole et al., 1998; Tsinghua University, 2018; Ulnicane, 2022; Wang, 2019) and ability to achieve designated aims (AI HLEG, 2019; Albus, 1991; Fogel, 2006, 1995; Kaplan and Haenlein, 2019; Newell and Simon, 1976; OECD, 2021; Poole et al., 1998; Ulnicane, 2022). AI can thus be defined as a collective term used to identify a computer-based programming system which has the ability to perform a task using thinking abilities just as seen in humans. Human brain is equipped to executing tasks by using certain skills like pattern recognition, learning from existing experiences and scenarios, logically reasoning, problem solving and others aspects that utilize sensory perception, motion etc. and even innovative and creative abilities. Machines that can emulate such qualities to accomplish designated tasks may thus be dubbed as AI. However given that the human brain and its abilities are a constant area of research and new findings emerge on a regular basis when it comes to its capabilities and AI definition is informed by all our collective knowledge of how the human brain works we can say that the definition of AI itself has been evolving and may continue to do so over time (Maini and Sabri, 2017). It finds purpose in several fields today from medicine to psychology, science and even public policy and is transforming these fields immensely at the global and regional level (Xu et al., 2021). AI is ubiquitous in the current world. Consciously and unconsciously, we are all using AI in one form or another. Computer games, navigation devices, voice enabled virtual assistants, cruise control or driver assist devices in motor vehicles and robots are all powered by AI albeit to varying degrees. AI based programs are also being used to create memes, for various social media platforms by users. AI is also being used in robots that can act like companions and teachers to humans (Causo et al., 2016) and such robots are developed to behave more like humans and have more human like traits than deployed in the other systems mentioned above.

2.1.2 AI history

Even though humankind's pursuit of developing machines that could exhibit human traits started in the 1940s (Bush, 1945), AI as a term was first introduced around 1950 when a mathematician and electrical engineer of British Origin named Alan Turing designed a test that would help distinguish humans and intelligent machines which was appropriately named The Turing Test (TURING, 1950). The Turing Test (TURING, 1950) became the first of its kind test where humans were made to interact with machines without them knowing whether their interactions were happening with humans or machines. The core purpose of the test was to understand whether machines could think. And the Turing Test would be considered passed if humans were unable to make out that they were interacting with a machine and not a human being. As such the original Turing Test, was passed (Warwick and Shah, 2016), which led to other scientists creating their own versions of test and in-depth study of artificial intelligence commenced and several versions of the test were used to understand whether machines could behave like intelligent human beings so much so that the humans may not be able to differentiate whether they were actually interacting with a machine or a human being. Two other individuals namely Marvin Minsky the founder of Massachusetts Institute of technology (MIT) Artificial Intelligence Lab and Frank Rosenblatt contributed significantly to the field of AI research and in fact Rosenblatt is the first to mention a probabilistic model which tried to theoretically bring the field of biophysics and psychology by hypothetically discussing how the brain senses the physical world, and in what form it stores this sensory information in order to remember it and how this information retention or memory in recognition and behaviour or in other words how the brain's cognitive system uses stored memory in order to identify and predict behavioural patterns. He explained this ability using a term, 'perceptrons' which was the combination of perception and neurons (Rosenblatt, 1958). This theory model brought together two fields of knowledge namely biophysics and psychology and today we know that it is possible to predict learning curves from neurological variables and vice versa. And in fact this theory today forms the core of a field of AI research that is designing neural network algorithms to try and develop AI that can make complex decisions similar to human brain using knowledge from the field of psychology and neuroscience also known as Artificial Neural Network (ANN) (Chen et al., 2019; Mehrotra et al., 1997; Priddy and Keller, 2005; Silver et al., 2016; Towell and Shavlik, 1994; Valko et al., 2022) The 'perceptron' theory was further elaborated by Minsky and Seymour Papert in their published work titled 'Perceptrons' (Minsky and Papert, 1969), and that has also contributed towards conceptualizing today's ML and deep learning technology (Chen et al., 2019; Mehrotra et al., 1997; Priddy and Keller, 2005; Silver et al., 2016; Towell and Shavlik, 1994). But as mentioned earlier the definition of AI is evolving with our ever growing understanding of the capabilities of the human brain and as new and advanced AI are being developed new versions of Turing Test need to be passed (You, 2015). It is also important to note that even though broad concepts of AI were being explored way back in the 1950s real progress in the field began in the 1980s, when computers became more common place and their potential was assessed immensely. With the development of supercomputers and computers gaining more demand in businesses and penetrating the households the cost of storage devices decreased allowing for more scientific research in the area on how these machines could be enhanced to bring in better consumer experience and ease of use. In 1997 concept of big data a term coined by John Mashey (Diebold, 2012) began to emerge. Big data is large data sets comprising of non-binary (language used by computers) data such as textual content, images etc which changes rapidly and could not be managed with the then existing software technology. Come early 2000s there has been increased focus on development of AI owing to the availability of large data sets that are an essential ingredient for development of enhanced AI systems. The worldwide availability of internet triggered the need to find more innovative ways to store data and that's how big data came into being. Big data sets helped software engineers evaluate various aspects of human behaviour and also understand behavioural patterns which made it possible to make progress in the field of AI. This big data has not only enabled but accelerated the advancement in the field of AI since it provides AI systems with large information sets that can be utilized to not only educate but also enable AI to perform at superior levels than previously possible. AI research and development benefitted a great deal from these developments and helped scientists and software developers study the application of AI in several areas of business (Liu et al., 2018; Peres et al., 2020). And the result is that today we use AI enabled systems in day-to-day life without even realizing it. From over the top (OTT) platforms that suggest programs basis individual's preferences to shopping experience both online and in-store, to navigation while driving and even on social media platforms where past post views guide the AI systems to suggest more similar posts on the individual's personal page. These are just a few examples. AI is also becoming an extremely useful tool in the field of science, manufacturing, medicine, pharma and scientific research to name a few more. In addition, AI is also becoming very useful in the educational field.

2.1.3 AI Market Globally: Current and Future Perspectives

According to various reports AI market globally in 2022 was estimated to be at US Dollar (USD) 387.45 billion and is projected to grow to USD 1,394.39 billion by 2029 (Fortune Business Insights, 2023) and add USD 15.7 trillion to global GDP (World Economic Forum, 2022). Within the next two years until 2025 the overall AI market will be valued at US 190 billion (MarketsandMarkets.com, 2022; World Economic Forum, 2022). Another research portal predicted that AI Market is set to grow by 37.3% from

2023 to 2030 (Grand View Research, 2022). Whilst the data on market size of AI varies from source to source there is consensus that AI market size is bound to grow significantly in the coming years. In addition AI has the ability to play a pivotal role in achieving 134 of the total 169 Sustainable Development Goals (United Nations, 2015) set by the United Nations (Vinuesa et al., 2020; World Economic Forum, 2022). The industrial sectors and business areas that AI is currently having a significant impact on include but are not limited to Healthcare, Engineering, Automotive, Agriculture, Retail, Security, Human Resource, Marketing, Law, Financial Tech. etc. (MarketsandMarkets.com, 2022) . AI tools market is set to grow tremendously owing to AI applications becoming an inherent part of all businesses. All countries have realized the potential and importance of AI and are facilitating substantial investment in the sector. Within The UK the AI will prove to be one of the most significant commercial opportunities which will enable UK's Gross Domestic Product (GDP) to grow to 10.3% by 2030, which means AI sector will contribute an additional £232 billion to The UK economy (PWC, 2017). However according to an entity that counsels the UK Government's AI Strategy, the investment in AI education remains low and needs to become a focus area of the UK Government and Education department (UK AI COUNCIL, 2021). It is noteworthy that AI Literacy/AI education for all, figures prominently in the United Nations Educational, Scientific and Cultural Organization's (UNESCO) Global Education 2030 Agenda as well (UNESCO, 2020). The reasons for lower investment in this area is attributed to the lack of funding due to low monetary gains for developers. However UK AI Council (2020) in its report has also recommended that The UK Government make strong commitments towards attaining AI and data literacy for all UK citizens so as to ensure that the people can develop an understanding of the risks and benefits of AI and become more confident and informed consumers of AI technologies (UK AI COUNCIL, 2021). This according to The UK AI Council (2021) can be achieved by setting up an online academy equipped with trusted content and information on AI which can be used by both teachers and students to facilitate lifelong learning.

2.1.4 Categorizing AI- Current AI abilities and future potential

To begin with AI systems and innovation within this field was initially guided by requirements within certain fields of studies like economics, math, neuroscience and psychology as well as computer science (Russell et al., 2010) and the terminologies used to describe AI such as intelligence, autonomy, learning and memory are borne out of these fields. However, these terms when used to describe AI have a distinctly different meaning from when they are used to describe human attributes. To cite an example by (Aleksander, 2017) the term intelligence used to describe AI can at best be understood as cognitive computing while it means a higher more evolved way of thinking when used to describe human intelligence. Field of neuroscience identifies AI as a ‘human thinking’ lens (Marr, 1977) which essentially means AI acts and thinks like humans and also acts and thinks rationally (Russell et al., 2010). However, the fields of mathematics and computer science view AI as a subcategory or a field within the sphere of mathematics or computer science that is useful to develop tools and approaches and techniques such as ML, vision, process optimization, speech, natural language processing, expert systems and robotics. Further, AI basis its capabilities currently and in the future can be categorized in three different classes- Narrow or weak AI, General or strong AI and

Singularity or Superintelligence. At present AI operates in the Narrow or weak category. This essentially means that AI is capable of performing a single or focused task that it was created for and no other job on its own. Narrow or weak AI can further be categorized under two heads namely AI that comprises of limited memory meant for select tasks and reactive AI that refers to existing data to perform the defined task (Hintze, 2016). To explain reactive AI one can, look at examples of AI used to play and beat world chess champions. Such AI has been fed data from several decades of chess games which comprise of several chess board formations and moves selected by chess champions in each case to win the games. It is developed using robust algorithms and fast computing speed that helps it make decisions faster than humans but only within the defined sphere of chess and from within the data it has been fed. Additionally reactive AI does not rely on memories, past experiences etc to operate and instead refers to the fed data to inform its next move and in that sense is not self-learning and given a particular scenario (specific input), will keep making the same decision or provide the same output. Where it supersedes human ability is in its computational speed, which enables it to refer to the fed data and pick the most optimum move based on the chess formation on the board and execute the next move (Chase and Simon, 1973). However, it is incapable of performing any other tasks outside of its defined area or find creative solutions. Which means that the AI will react the same way each time and not learn from experience or make an unpredictable decision based on past experience or memories or learning from them which is inherent in humans who have adaptive thinking. The chess master may not always use the same moves in the same board formation each time because she/he was successful with that the previous time. She/he may assess the opponent and use a different move in a similar board formation in each contest. In that sense the AI lacks creativity or out of the box thinking which its human opponents possess. Limited memory AI on the other hand does have adaptive capabilities. It can learn from its past memories and experiences and arrive at a creative and unique solution. In that sense it possesses similar adaptive capabilities to humans. Where such AI is superior to humans is in its computational skills and ability to recall and calculate encoded data faster to arrive at the most optimum solution. Its memory stores past data in easily retrievable language. Human brain whilst highly capable of storing memories does not have the ability to recall all past experiences in a detailed manner at an instance and retrieving past experience and data to inform current decisions is more constructive (Loftus and Palmer, 1974; Roediger and McDermott, 1995) than computational. Self-driving cars, chatbots are two examples of Limited memory AI. But again, unlike humans that perform multiple tasks spread over multiple domains everyday Limited memory AI is capable of performing only focused tasks they have been designed for. Which means they can adapt and arrive at a creative solution based on their self-learning capabilities but only for their own defined task. An AI designed for a self-driving car cannot for example go ahead and play chess whilst its human counterpart is both capable of driving and playing chess if she/he chooses to. Limited memory AI thus is still inadequate in its capabilities and cannot perform like a human with all human attributes. In addition, this form of AI has a limited world view since it is based on memories and experiences it has been pre-programmed for. Within the fed data over time this form of AI is capable of adapting and making efficient decisions and self-learn. So whilst both these forms of AI within the Narrow or weak AI category do not have capabilities to exhibit all human traits, within the designated task both forms of AI have the ability surpass any human's capabilities to perform the task they were designed for in terms of efficiency and effectiveness (Silver et al., 2016). It is noteworthy that currently AI is capable of operating only within the Narrow AI category unlike common misperception that all AI operates or is capable of operating in a Super intelligent way as depicted in several science fiction movies and books like the various fictional works of Isaac Asimov such as The Foundation series as well as short stories where he talks about a car capable of expressing jealousy, a super computer that is capable of running the entire galaxy and the universe, the Star Wars franchise that has C3PO an android capable of exhibiting human like emotions but with superior intelligence. The Terminator franchise where machines have learnt to disguise as humans etc. to name a few. All these depictions in media and entertainment are nothing more than a work of fiction at the moment (Broadbent, 2017). Currently there is no one AI system that possesses the abilities to outperform humans in all domains or behave like a human being in all aspects of life and researchers cannot clearly predict if it is even possible and if it is possible by when it may realize (Aleksander, 2017; Müller and Bostrom, 2016). Both these categories namely General or Strong AI and Superintelligence or Singularity AI are based on futuristic assumptions basis our current capabilities of developing AI. Nevertheless, advancements in AI are being met with aversion and fear globally. The reasons as many have found out are lack of understanding, anxiety related to new technology, fear that AI will replace jobs and cause unemployment issues, fear that AI can cause further racial discrimination and make the society more unequal, Super Intelligence will be the doom of humankind (Gherheş, 2018; Schmelzer, 2019). There are even arguments made that whilst AI attaining superintelligence may be one of the best things to happen, it may also pose risk of apocalyptic proportions for humankind if not mitigated (Bostrom, 2014; European Parliament. Directorate General for Parliamentary Research Services., 2018; Häggström, 2016; Tegmark, 2017). Another author stated that once AI technology evolves to reach General AI category it may become self-aware and may create superintelligent entities based on its own form, which may possess human intelligence (Primiero, 2017). But as mentioned earlier this is currently not the level at which AI operates and as such fear incited against AI is due to science fiction movies and series and by media in general which do not portray the true current picture of AI capabilities (Pinkwart, 2016). The fear of AI and the benefits of the technology are separated by a chasm of fear and mistrust that comes from lack of proper understanding and knowledge of AI. Another term that is often heard these days when speaking about AI is Machine Learning (ML) (Bell, 2022; El Naqa and Murphy, 2015; Faggella, 2020; Jordan and Mitchell, 2015; Maini and Sabri, 2017; Mitchell et al., 2007; Zhou and Liu, 2021). ML is a sub-field of AI (Maini and Sabri, 2017) an area of research where focus is on figuring out how to create self-learning machines and algorithms to support such machines to assess their environment, identify information and by way of experience teach itself (Jordan and Mitchell, 2015), which is similar to human way of learning by experiencing. And just like human beings keep learning throughout their lives these machines are being designed to become independent thinkers within the context of the data fed into them which comprises of observations and interactions from actual world scenarios (Faggella, 2020). This allows for the computer or machine to assess the fed information on its own to create its own models and observations. Algorithms of ML help computers pick patterns and trends from fed data of general and predictable fashion. The more data the computer is fed, the more accurate its predictions and identification of patterns becomes, but its predictions and pattern identification will still be based on the data it has been fed. The algorithm usually has two features, ‘classifier’ and ‘learner’. Using the example of spam sorting tool that works on ML let’s understand this better. The Spam filtering classifiers utilize email headers, words in the email body etc to categorize or classify emails as spam or not spam. Similarly, A disease diagnostics machine uses symptoms, blood test report findings etc to assess whether the said patient suffers from heart disease or another ailment. In order for the classifier to make more accurate categorizations the , ‘learner’ algorithm must be provided test data to train with. The classifier then uses weight matrix from the training to classify new data that is fed into the system (Burrell, 2016). Training data at the beginning must comprise of pre categorized emails identified as spam and not spam to educate the classifier. Similarly existing reports and diagnosis for diseases could be used as training data for Machines used for disease diagnosis to educate them initially. Field of ML is evolving at a fast pace owing to availability of Big data. ANN, decision trees, and logistic regression are common ML models. ML can enable humans in decision making. However, there are several concerns around this technology. Privacy concerns are the first and foremost issue. Since ML relies on big data inputs, often times this data is collected using web scraping which does not involve informed consent of the individuals and entities it scrapes data of and that has been under criticism for bypassing ethical obligations of AI tools and their application. The matter is further complicated as algorithms used are proprietary in nature and as such there is no way of knowing if the machine is making biased decisions die to algorithm bias. Further Deep ML like Artificial Neural Networks is highly complex and cumbersome to comprehend (Burrell, 2016), which has even left the scientists and developers that created the algorithm in the first place perplexed on how the Machine is arriving at its decision making. Which is a cause for worry as ML can lead to further increasing inequalities in society and impact humans especially those in the vulnerable category, which is undesirable and violation of Human Rights (Char et al., 2020; Greene et al., 2019; Yates et al., 2013). Currently AI technology is able to only base its predictions/outcome/results basis the data it is fed. So, if the fed data is skewed in any way, chances are the outcome will also be skewed or biased. Not only this, but also how the AI algorithm was designed can play a role in what outcomes are generated by the AI or what the Machine learns. Such factors increase the risk of bias and are becoming an issue of ethics in AI. In addition data privacy is becoming concern as AI technology is becoming common place in daily life via user-interfacing services and products (Lau et al., 2018; Yang et al., 2019). Responsible and accountable AI development is hence essential for continued growth in AI technology field (Busuioc, 2021; Dignum, 2021, 2017). Having said this AI has the potential to remain an integral part of our personal and professional life in the near future and the most optimum path to ensure AI technologies are used and developed responsibly in the future is to educate individuals on what AI is and its existing and future capabilities. The same can help allay fears to do with its deployment as well as also ensure responsible and ethical use of AI (Dignum, 2021, 2017; Greene et al., 2019; UNESCO, 2020). A well cited paper also suggests that 'explainability' of how AI operates can be useful in making AI adoption easier amongst people (Miller, 2019), as humans find it easier to comprehend scenarios when they are deconstructed and explained simplistically. Miller (2019) suggests that if AI tools are equipped to answer and explain their own functioning and logic behind why a certain output was generated by the AI tool, it will help humans understand. Hence in order to make the world population future ready AI education/Literacy may play a vital role.

2.1.5 AI education/literacy

Importance of technology education was first talked about in the 1970s (Papert, 1981) when young students were introduced to LOGO programming and Turtle robot with a focus to enhance their computational thinking competencies, however it is said that due to focus being on programming concepts AI education had not yet come into the picture at that time. It was not until 1995 that AI was introduced to university going computer science students in textbook format and explained AI's problem solving, reasoning, learning, decision making, communication, perception and acting abilities (Russel and Norwig, 1995; Russell et al., 2010). However lack of availability of appropriate teaching tools and mechanisms led to no work being done to introduce AI education as part of digital literacy initiatives at that time (Martins and Gresse, 2022; WANG et al., 2020; Wang et al., 2021). Now with the rapid progress in the AI field, AI education is gaining traction albeit slowly. It is becoming an area of focus for countries and governments (UNICEF, 2018) who have realized that AI education may pose as a bridge that can help AI averse individuals to cross over and adopt AI as well as get current and next generation, future ready to operate in an AI world. Despite this all pervasive technology existing in day to day life people do not understand and even lack awareness about the basic concepts of AI, how it works and also the ethical challenges pertaining to AI (Burgsteiner et al., 2016; Ghallab, 2019). Further fear that AI may render individuals jobless, increase cyber security threats (Yamin et al., 2021) cause mass destruction to humankind if weaponized or in general take control of the world, adds to people’s AI aversion (Schmelzer, 2019). Studies have also shown that AI may render millions of current jobs redundant causing (Davenport and Ronanki, 2018; James Manyika et al., 2017; Manyika, 2017) to many by automating several job functions of which secretarial jobs and bookkeeping jobs that are largely held by women in developed economies may see excessive decline by 2030 (James Manyika et al., 2017). However, another study claimed that AI will help generate new jobs across industries albeit for those that are AI technology savvy. Hence in order for individuals to remain suitably employed and remain part of the evolving societal ways of functioning it is imperative that they transition into the new AI embedded world by upskilling or becoming AI Literate. AI Literacy as a term remained unused until 2016 and when used for the first time it was defined as the skill to comprehend the elementary functioning and concepts of AI technology (Kandlhofer et al., 2019). The former definition of literacy found basis in other definition pertaining to the term ‘Literacy’ itself, which meant an individual’s ability to read and write (McBride, 2015; Wang et al., 2015) and was expanded to include digital literacy which meant acquiring basic computer literacy (Bawden, 2008; Lankshear and Knobel, 2008) and is now being further expanded to include AI literacy (Kong et al., 2021) which is being considered the technology of the future workplace. AI Literacy has since seen the definition evolve further. AI Literacy is defined as the ability to collaborate and communicate with the help of AI (Long and Magerko, 2020; D. T. K. Ng et al., 2022a). The term ‘Literacy’ has since been ascribed by researchers owing to the fact that the term is used widely to define skill-sets across several disciplines. Thus AI Literacy has also been defined as the change in ability of digitally savvy individuals to live, work and communicate with other individuals as well as machines (Long and Magerko, 2020). In that context AI literacy could be defined as the critical abilities that people need to acquire and equip themselves with in order to thrive both personally and professionally in the current AI-driven wolrd (Steinbauer et al., 2021). Having said that AI is still evolving and its potential is still to be fully tapped and in that sense the definition of AI Literacy remains partially defined and ever evolving (Long and Magerko, 2020) as new way to develop and apply AI keep emerging corresponding skills will need to be learnt to keep pace with this technological progress. The definition has been further revised by the (Davy Tsz Kit Ng et al., 2021a, 2021b; D. T. K. Ng et al., 2022a) who using Bloom's Taxonomy framework of three hierarchical models used to classify learning objectives in education (Knowledge, Comprehension, Application, Analysis, Synthesis & Evaluation) (Bloom, 1956) conceptualized AI Literacy as a tool where learners no longer can be viewed as only end users of AI technology but also need to attain advanced cognition levels to play a pivotal role in communicating, collaborating and even developing using AI technology (Long et al., 2021). But there is consensus on AI Literacy being a critical technological skill that needs to be acquired to thrive in the 21st century (D. T. K. Ng et al., 2022a). but also AI Literacy is thus of great importance today if an individual desires to work in any given job across industries (Davy Tsz Kit Ng et al., 2021a, 2021b; D. T. K. Ng et al., 2022a; Touretzky, 2020). But AI Literacy is not only about upskilling to ensure job security. It can serve as a way to prepare future generations to thrive (by developing advanced thinking abilities as well as acquiring multidisciplinary skills, learning to collaborate, create and cultivate life-long learning abilities) in this new world

(Davy Tsz Kit Ng et al., 2021a, 2021b; D. T. K. Ng et al., 2022a, 2022b, 2022c) where AI may be part and parcel of life.

2.1.6 AI Education for K-12 (From Kindergarten up till 12th standard studies in schools)

Studies have shown that students that possess advanced computer skills or AI knowledge may be capable of utilizing technologies and computers in innovative manner to expand their knowledge as well as skill-sets with their contemporaries (Bell, 2010; Griffin and Care, 2014; Larson and Miller, 2011). Piaget’s education theory (Piaget, 1952) inspired the first book “Mindstorms: Children, Computers, and Powerful Ideas.” The book broadly discusses the importance of AI education and how young children can develop superior thinking abilities when allowed to naturally interact with their environments (Papert, 1981). And presently researchers emphasize introducing AI literacy/education at K-12 levels in schools so that young children can benefit by learning how to engage with AI tools and technologies in the appropriate fashion early on (Zhou et al., 2020). This becomes especially pertinent when it comes to ML, since ML exhibits more evolved decision-making skills as a technology. Machines are able to learn from experience and make more complex models and decisions over time. Students need to be taught about how ML works and how machines are able to develop such evolved thinking. But this is easier said than done. There are several challenges to teaching ML in particular and AI in general at K-12 levels in schools currently. Firstly, there is the problem of designing age-appropriate curriculum. A child aged 5 will have a significantly lower ability to grasp complex computational thinking concepts than a child aged 10 or 16. Secondly there is not enough research available to offer guidance on how to teach children such complex topics. Thirdly AI technologies tend to evolve at a fast pace and in each era different topics within AI have gained importance in terms of AI topics that need to be taught and as such AI education for students has focused on teaching students about the most important and current (for each era) technologies (Hitron et al., 2018a, 2018b). Of these projects a substantial chunk focuses on teaching students how to create modest AI applications using block based programming (Bishop et al., 2020); teaching students the essentials of object identification and providing interactive data conception coaching (Gresse von Wangenheim et al., 2021); and a series of classes bundled into a course where students can learn the basic principles of AI and their application. The problem of what needs to be taught at each level of K-12 to students however still remains largely unsolved (Srikant and Aggarwal, 2017). At Kindergarten levels teaching children about AI may require teachers to begin with engaging students to develop basic reading and math skills, whilst high school level students may require a more evolved approach where they are taught advanced problem-solving skills and mathematical modelling so as to prepare them for higher university level studies. K-12 levels comprise of students in various age-groups from kindergartners to higher secondary students and each of these levels have different learning levels and are at different comprehensibility levels hence the goals pertaining to education also need to be designed basis their age and learning abilities. For Kindergarteners, focus is on enhancing their reading as well as math skills. Simultaneously, high school seniors frequently apply advanced problem-solving skills to prepare for college. So, depending on the age and grade level of a student the teaching methodology as well as course content will vary significantly. Given such variation in what needs to be taught and how it needs to be taught depending on the age of the child, researchers have begun focusing on the what and how aspects of AI education to offer solutions. A pilot project targeting high school students between grades 9-11 attempted to introduce basic concepts of computer science and AI through an AI course that covered both theoretical as well as applied components of AI to teach children about data structuring, planning, search, agent systems, automata, graphs, problem-solving as well as ML (Burgsteiner et al., 2016). And this project resulted in students successfully learning about many of the taught topics and concepts (Burgsteiner et al., 2016). In addition to this study another study post investigation identified several barriers to teaching AI at K-12 levels and further recommended that computer instructors/teachers must broaden their approach towards teaching by first realizing that technical or programming knowledge is not an imperative for future generations to develop computational thinking (Srikant and Aggarwal, 2017). Further another study aimed to resolve the issue of teachers' dilemma on what and how to teach AI and ML in schools using a systematic review (Sanusi et al., 2022). This study identified 20 free to use web based tools as well as presented a resource catalogue for teachers to use to find the most optimum path to teach important ML principles to students in classes (Sanusi et al., 2022). Another study recommended a collaborative approach between schools and the private sector to motivate students to learn AI concepts outside of the school, through programming activities that could be provided to them (Zimmermann-Niefield et al., 2019). It was found that students were more inclined to use and learn about AI technologies that were demonstrated to them. In addition, it was found that students' possessed different levels of mathematical knowledge, which impeded the process of learning as well as the pace of learning. Further it was discovered that students were unable to comprehend why it was important for them to learn about AI since learning activities pertaining to AI were not a part of the core curriculum. Owing to all these issues the study stated that integrating AI into the existing school curriculum needs to be given importance and how the integration needs to happen must be studied (Zimmermann-Niefield et al., 2019).

2.1.7 AI Education evolution for K-12 Level

Whilst AI education for K-12 levels was mentioned initially in the 20th century around the 1970s (Papert et al., 1971) initiatives and research in this area have gained momentum only in the last few years (Long and Magerko, 2020; Marques et al., 2020). Initially AI Education/Literacy was primarily concerned with teaching technical aspects of AI to undergraduate and graduate level students. However AI Literacy at university levels for non-computer science students (Kong et al., 2021) has also become a focus area. Researchers have begun adopting different approaches such as fun ways to engage undergraduate students to learn about different aspects of AI (Dodds, 2008); using Java based simulations to introduce AI (McGovern et al., 2011). Another study researched strategies to teach undergraduate students about algorithms and AI (Torrey, 2021). Further a study used Pac-man a popular age old video game to teach undergraduate students about AI concepts (DeNero and Klein, 2010) where students used general purpose AI and domain knowledge of the game environment to complete the 4 designed stages/projects. Another study introduced first year undergraduate students to various themes such as history and evolution of AI, current state of the art- power negotiations, political implications of technological progress and cultural response. Basis the information provided on the various themes students prepared a conceptual map that could help understand the implications of technological advances on society (Keating and Nourbakhsh, 2018). In addition a study also investigated the effectiveness of AI Literacy courses in developing conceptual AI knowledge among university students across various disciplines (Kong et al., 2021) showing that AI Literacy is achievable for even those without a technical background. Such research has been possible in part due to availability and ease of use of AI-powered teaching tools such as Tensorflow Playground, Teachable Machine as well as AI for Ocean in Code.ord (Wangenheim et al., 2021) many of which enable students from non-technical educational disciplines to develop machine learning models with significant ease. Such successes in research also suggests that AI Literacy is no longer a difficult task as was thought earlier. And due to this researchers and educators are feeling more encouraged to collaborate to assess how AI Literacy can be introduced to students from non-technical backgrounds at university level as well as to all students at the K-12 levels (Chai et al., 2021; Chiu et al., 2021; Kandlhofer et al., 2016; Long et al., 2021; Xia et al., 2022). As mentioned earlier it is noteworthy that AI Literacy at K-12 levels has gained importance only recently (Long and Magerko, 2020; Marques et al., 2020). However until 2020 literature largely comprised of only Conference Papers (Yue et al., 2022). Journal articles on the topic have begun emerging only since 2021 (Yue et al., 2022). Hence it would be appropriate to say that AI Literacy is making its way to K-12 level students albeit slowly (Wong et al., 2020). Students are no longer being considered as mere consumers of AI applications, but also being viewed as future architects of smart solutions which may require educating them on AI concepts (e.g., how to develop image recognition models) (AIK12, 2019; D. T. K. Ng et al., 2021, 2022a, 2022b, 2022c; Ng and Chu, 2021; Touretzky, 2020) in order for them to effectively both use, create and apply AI technology in their day to day life.

2.1.8 AI literacy frameworks

A few initiatives (such as ISTE, UNESCO, DigComp) to conceptualize AI Literacy in accordance with contemporary education standards as well as design guidelines have commenced globally (DigComp, 2022; ISTE, 2022; UNESCO, 2021). Each of these frameworks offers a different perspective on AI Literacy. So far eleven countries have incorporated AI into the existing curricula for Science, Technology, Engineering and Mathematics (STEM) as well as computing courses (UNESCO, 2021) so as to promote inclusiveness and competitiveness as also preparing young children for the AI driven future work environment. In age appropriate AI Literacy frameworks one that proposed five big ideas (perception, representation and reasoning, learning, natural interaction and societal impact of AI) has by far been the most useful (AIK12, 2019; Touretzky, 2020) for researchers to develop and test curricula on. The framework draws inspiration from the Computer Science Standards developed by the Computer Science Teachers Association (CSTA, 2017) which outline a core set of learning objectives revolving around key concepts and designed to offer the framework to create and implement computer science curriculum for K-12 level. These standards suggest Algorithm and Programming, Computer Systems, Data & Analysis, Impacts of Computing and Networks and the Internet as the core ideas teachable in schools. The AI Literacy framework designed by AIK12 (2019) follows a similar approach and has aims to simplify AI concepts to make them easy to understand by parents, teachers and children alike and also suggests how to impart this knowledge at various grade levels to children in schools basis their learning abilities, as is done for all other subjects. For example, a child learning English as a subject, first learns the alphabet and then learns how to form a word and subsequently learns how to string words together to form a sentence, a paragraph an essay and so forth. All this is taught to the child at different grade levels starting from low (alphabet) to higher more complex (Essay on a certain topic). This framework suggests that a similar low to complex levels approach can be used to teach children about core concepts of AI starting from K-2 levels in schools (AIK12, 2019; Touretzky, 2020; Touretzky et al., 2019b, 2019a). The five big ideas essentially state that computers utilize several sensory inputs to form perception of the environment; agents are responsible and provide accurate representation of the environment; computers possess the ability to learn from data that has been fed into them; in order for AI to engage with individuals on a regular basis in the most effective manner AI must possess a wide variety of knowledge and; AI has the ability to impact the society positively or negatively (Touretzky et al., 2019b). In other words, on the technical side of AI, it is important to know that computers observe the world using artificial sensors, can learn and use data provided to them to create models for reasoning. On the ethical side, it is important to know that AI is not capable of interacting with humans easily and as such AI can both help and harm society. (AIK12, 2019; Touretzky, 2020). Bearing in mind these ideas the researchers suggest that AI knowledge can be offered at K-12 levels starting from elementary level upwards, using several different age-appropriate tools and techniques (K–2, 3–5, 6–8, and 9–12). This has thus proved to be a foundation for several researchers and academicians to design curriculums for K-12 level (Touretzky et al., 2019a). Another framework developed an AI project guideline and proposed seven standards to enable learning, knowledge construction, computational thinking, innovative designing and collaborating among students to make them global digital citizens of the future. It is suggested that with appropriately designed curricula teachers may find it easier to teach students about AI and related competencies, and build appropriate attitude and readiness, to communicate with learners, solve authentic problems, design and develop ideas and theories as well as innovative solutions in a collaborative manner

(ISTE, 2022). Another framework was developed by (DigComp, 2022) by incorporating AI technologies to enable teachers and instructors to suggest six categories to improve their professional dealings with various entities using AI, strengthen the teacher's instructional skills including digital resource management, teaching and learning, assessment, and teaching strategies that benefit learners, and thereby facilitate learners' AI competency. These frameworks facilitate the comprehension and implementation of AI literacy in order to assist educators, researchers, and governments in designing appropriate techniques and initiatives to promote digital competency in terms of skills and attitudes among learners. In addition to the above a framework of 4As (Druga et al., 2023) consisting of asking, adapting, authoring, and analysing was recently introduced which helps families learn and teach children AI concepts in the home setting using creative techniques (Druga et al., 2022a, 2023; Druga and Michelson, 2020).

2.1.9 Developing Educational Resources as Part of a Course

The above-mentioned guidelines and frameworks have provided useful direction towards curriculum development suitable for K-12 levels. Study to assess school level AI education and the various AI disciplines being taught in classes was first published in 2010 (Fok and Ong, 1996; Heinze et al., 2010). Another study was conducted in Australia, as part of the "Scientist-in-Schools" program, Australian AI researchers collaborated with K-6 instructors to develop a three-year curriculum covering fundamental AI principles, AI terminology, and AI history (Heinze et al., 2010). Their curriculum encompassed both the history and fundamentals of artificial intelligence. However, another study pointed out that Fok and Ong (1996) and Heinze et. al., (2010) studies were limited in that they did not cover several aspects of AI within the curriculum (Burgsteiner et al., 2016). The researchers hence came up with a more comprehensive course that included several other aspects of AI as well as computer science encompassing robotics, algorithm search, ML, problems-solving etc and named it “iRobot” (Burgsteiner et al., 2016). Another study in China introduced an AI+ course curriculum in elementary and secondary schools in Qingdao (Han et al., 2018). The study aimed to provide students a more comprehensive understanding of the AI by engaging them in a project-based learning experience which offered technical training as well as practice in designing and implementation of AI. Other than these MIT institute has introduced several free to use educational courses for teachers teaching K-12 students as well as students in K-12 level classes among others on their website as part of the MIT RAISE (Responsible AI for Social Empowerment and Education) initiative which aims towards social empowerment. For instance researchers have designed an AI curriculum for K-8 level which provides an understanding about AI ethics alongside AI basics as well as creative thinking (Ali et al., 2019). Another platform engages young children using PopBots, three practical AI exercises and assessments based on the exercises to teach children AI concepts (Williams et al., 2019b; Williams and Breazeal, 2020; Williams et al., 2022). This platform helps teachers teach AI concepts and ethics to middle school (Williams et al., 2019b; Williams and Breazeal, 2020; Williams et al., 2022). Private companies such as Google, IBM, Microsoft, Intel etc are also developing resources (curriculum) and instructional tools to assist in AI education. Several experiment-based learning exercises and tools (Quickdraw, Teachable Machine) are available on Google Lab website (https://labs.withgoogle.com/) to teach children about AI concepts and use. Similarly a study used a project based approach to provide practical training, on ML to help students in The UK understand AI concepts as well as impact of

AI on people’s lives (Rodríguez-García et al., 2021). Whilst these additional resources and avenues to learn about AI are proving useful, the fact that these tools and platforms use algorithms and technology to ensure users stay on the platform and generate revenue for the companies that run and develop these platforms raises ethical concerns pertaining to their motives and teachers must be mindful of the business and financial motivations of the companies that are designing these tools and platforms for AI education (Loreggia and Sartor, 2020) before using them or encouraging their students to use them. It may be noted that ISTE (2020) is using General Motors support to create curriculum frameworks whilst AIK12 (2019) is using support from Google. In addition lead author for AIK12, Touretzky is creating curriculum named Calypso (Touretzky et al., 2019b; Touretzky, 2023, 2017; Touretzky and Gardner-McCune, 2018) as part of ReadyAI’s AI-in-a-Box kit which is also an AI education tool.

2.1.10 AI Curriculum and educational resources related progress worldwide

UNESCO in 2019 conducted a workshop to identify the various essential elements that could help both teachers’ as well as learners’ develop and enhance competencies for AI use (UNESCO, 2020, 2019). Since then, several countries have initiated work in this direction. UNESCO report (UNESCO, 2021) shows that at least 11 countries have geared up to introduce AI Literacy at K-12 levels in schools. Government approved AI curriculum are being implemented in Armenia, Austria, Belgium, China, India, Republic of Korea, Kuwait, Portugal, Qatar, Serbia and United Arab Emirates. Other countries like China and The US have progressed further with China having introduced AI course as a compulsory subject at primary and secondary schools in 2017 (Chen et al., 2020), as part of China’s New Generation of Artificial Intelligence

Development Plan (Roberts et al., 2021). Canada too is a front runner in that it became the first country to declare its National Level AI Strategy in March of 2017 (Butcher and Beridze, 2019) and currently The Ontario Curriculum Grades 1-8: Science and Technology has made AI part of its content with the aim to teach young students about the development of AI systems as well as daily life impacts and application of AI. Other countries such as The United States, UK, Finland, Canada, Turkey and Argentina have also witnessed a rise in K-12 AI education programs (Touretzky et al., 2019a). The UK too set up an AI Committee in 2017 to assess the impact of AI technologies in life and work within The UK (House of Lords, 2018). The AI Committee within a year published a report stating the AI would have a significant impact on the lives of future generations and thus education systems need to work towards preparing the future generations to live and work in an AI driven environment by educating them on how AI technologies they engage with work. The report further elaborated that such education will help motivate future generations of AI researchers and engineers as well. Providing training to next generation of experts has also been emphasized as a way to ensure ethical development of AI tools and technologies across industries such as medicine, automobile and finance etc (Oxford Insight, 2020). However currently K-12 level schools have not yet received any mandates from the UK Government or the Education board regards how and what to teach in schools as part of AI education.

2.1.11 After School Programs for Diverse Learners

According to academicians and experts, developing effective AI learning tools and techniques that prepare young individuals to both see themselves are future AI developers as well as responsible users of AI is of critical importance and must be designed with curriculum guidelines and resources in mind (Williams and Breazeal, 2020; Williams et al., 2022). In the US a middle school introduced a an AI curriculum spanning over three weeks using a company developed tool named AI-in-a-Box by ReadyAI, in an AI education pilot project (Wong et al., 2020). The course introduced students to various career opportunities in AI field, helped them gain hands on experience by way of engagement with general AI technologies as well as offered them insight into existing ethical concerns pertaining to AI development and application. Other researchers introduced a 36 week long open-source AI course for Norwegian middle school students (Sabuncuoglu, 2020a). The same authors also developed programming tools for visually impaired children by creating an accessible tangible music platform where children can be taught basics of programming via music creation, and this tool was developed in collaboration with visually impaired developers which was a key effort in the direction of offering equitable learning opportunity for children with visual impairment (Sabuncuoglu, 2020b). However, AI education for K-12 level is still in its infancy and very few institutions have adequate resources to offer such courses or incorporate AI knowledge into existing subjects, hence a majority of work being done on AI education for K-12 level students resides outside of schools. Several different settings are hence being explored to teach AI to these students. And significant research has emerged from Stefanio Druga a PhD graduate (and her team and co-researchers) from University of Washington (Druga, 2018, 2017; Druga et al., 2023, 2022a, 2022b, 2019, 2017; Druga and Ko, 2023, 2021; Druga and Michelson, 2020; Druga and Otero, 2023). Her studies have focused on creative AI education and there are several important findings in her studies, including the following: To assist families in developing a critical awareness of smart technologies that are ingrained in their lives, (Druga et al., 2022a; Druga and Ko, 2023) developed a framework of AI literacy known as the 4As (Druga et al., 2023), which consists of asking, adapting, authoring, and analysing. Through participation in seminars lasting between one and two hours, Druga et al. (2019) investigated how children ages 7 to 12 in the United States, Germany, Denmark, and Sweden perceive current AI technologies and envision future smart devices and toys (Druga et al., 2019) . Children from the United States, Germany, Denmark, and Sweden were recruited for this study. Other than this another study investigated how essential AI principles can be effectively communicated through informal settings in families (Long et al., 2022).

2.1.12 Education in the Ethics of Artificial Intelligence

AI Ethics education has remained a neglected area within AI education courses either by way of exclusion when teaching technical aspects of AI or by teaching about AI ethics as a separate subject instead of making it a part of the existing course (Fiesler et al., 2020; Garrett et al., 2020). Concerns over child rights and privacy have also been raised by UNICEF as part of ethical concerns pertaining to AI (UNICEF, 2018). A study it was found that K-9 students in China's Qingdao city were ignorant on AI ethics and how AI could impact society since AI ethics were sparingly discussed in the class (Gong et al., 2020). AI ethics signify responsible development and use of AI technologies based on values, principles and techniques which guide moral conduct and help create ethical, fair and safe AI applications (Leslie, 2019; Leslie et al., 2021). In order to address such issues governments are establishing organizations to address AI related ethical concerns globally. In The UK, Institute for Ethical AI in Education has developed an ethical governance framework for AI in education (The Institute for Ethical AI in Education, 2021). Similarly a paper was published in Australia by Analysis and Policy Observatory pertaining to development of AI ethics framework for Australia (Zawacki-Richter et al., 2019). Already, researchers have begun devising educational programs to teach younger students about the moral implications of AI. Apart from government initiatives in recent times AI education frameworks and researchers too, are giving required attention to inclusion of AI Ethics as part of the overall AI education curriculum framework (Ali et al., 2019; Char et al., 2020; Garrett et al., 2020; Leslie, 2019; Siau and Wang, 2020; Stahl and Wright, 2018; Touretzky, 2020; Touretzky et al., 2019b; Williams et al., 2022). A program on AI known as AI + ethics is teaching middle school students about biases related to algorithms written for AI technologies as part of its AI ethics education (Ma et al., 2019; Williams et al., 2022). Williams et al. (2022) presented their middle school AI plus ethics curricula which incorporates ethics into technical course content and explains ethical issues pertaining to bias, deepfakes, disinformation and environmental concerns using experiments, discussion as well as real world case studies. This is their approach to teaching ethics in their curricula. Currently AI education itself is in its infancy, hence ethical considerations remain even less researched and as such are a relatively unexplored area within AI education (Garrett et al., 2020) which merits increased focus and research especially on aspects of educating young students about how AI can impact their lives, and also to equip them with the skills to maximize the benefits of AI while minimizing its potential drawbacks so they can be responsible AI users and producers.

2.1.13 Educational Pedagogies for Artificial Intelligence

AI knowledge and skills development for students has been applied in various ways through government and university activities. AI literacy initiatives from K-12 to higher education have been recognized by governments (UNESCO, 2020) and several countries, notably the United States, China, and Germany, have also designed AI Strategies to be implemented nationally (Laupichler et al., 2022). And studies are being conducted both at secondary and primary levels in schools to gather empirical data on informed learning initiatives (Lee et al., 2021; D. T. K. Ng et al., 2022c; Williams et al., 2019a) and effectiveness of formal curriculum (Xia et al., 2022). Among key prototype schemes to develop AI literacy for secondary pupils are, 'AI for the Future' introduced in Hong Kong (Chiu et al., 2021) and the 'Daily Curriculum' in the United States (Lin and Van Brummelen, 2021). Further, several approaches such as digital narrative writing (D. T. K. Ng et al., 2022d), engaging with AI with the help and use of toys and robotics (Yang, 2022), and visualization tools have been introduced by some researchers, to assist young children in learning about the various aspects of AI and also the possibilities of AI use. Additionally, institutions have begun to introduce AI to non-computer science university students, such as medical, business administration, and teacher education, in order to prepare them for their future workforce (Laupichler et al., 2022). A systematic review of Pedagogical designs utilized in AI Education at K-12 levels (Yue et al., 2022) since 2010 shows that there are several teaching and learning frameworks used within AI education and very often they are used in combination with each other. Here's a brief description of each of the approaches: Direct instruction is an approach whereby knowledge is imparted by way of lectures, audio visual routes and or demonstrations. Hands-on activity approach offers children a chance to personally use and explore the tools and how they work but do not allow them to play a part in building or creating the tools. Interactive learning approach on the other hand also allows students to take part in some way in developing the AI or ML process as part of AI learning. However, this approach does not allow for children to identify their own projects or problems to solve. Collaborative learning approach entails children working in groups of two or more. Inquiry base learning approach allows students to choose their own learning aims, seek answers to their own questions as well as make attempts to resolve their own identified problems. Inquiry based approach however does not allow for students to construct their own artifacts and or products. Game based learning approach allows students to learn in a fun game setting. Participatory learning approach allows students to indulge in role play and interaction with their peers. Students shift from developer, to user of AI and so forth in order to understand various aspects of AI and from various different roles perspective. Project based learning approach in general involves construction of an artifact or solving a real-world problem in a project-based setting. Design-oriented learning approach encompasses children designing their own projects and finding solutions to open ended problems instead of working with instruction based defined goals. Finally, there is experiential learning approach which allows children to not only experience but also reflect, think as well as act during the learning process. However all frameworks are constructivist in nature(Papert, 1981; Papert and Harel, 1991). Here are a few examples of the recent studies that have used the various approaches. A study in Belgium Middle school and primary school held role playing games in one session with children spanning over 2 to 4 hours where children alternated between playing the roles of developers, tester and AI (Henry et al., 2021) The children were then asked to define AI to assess their understanding and knowledge of AI. Collaborative learning approach entails students working in groups to achieve a certain assigned task. This approach has been used by several researchers with students sometimes in combination with another pedagogical approach. A few examples would be a study in Finland (Fernández-Martínez et al., 2021) which targeted children between ages 12 and 13 using 3 sessions of 8 to 9 hours where collaborative learning approach was combined with design-oriented approach and students were observed through the process to assess their AI knowledge and understanding. Another study in Romania used collaborative learning approach in a single session of 2 hours with students aged 13 to 19 and assessed them on their AI knowledge using questionnaires and self-assessment of their competence levels (Mariescu-Istodor and Jormanainen, 2019). A study in Spain focused on students aged 16 to 17 in a single session of 2 hours using Direct Instruction, hands-on practical training in combination with collaborative learning (Estevez et al., 2021, 2019), however they did not assess these students on how their AI knowledge and competence was impacted post the session. Williams et al (2019a, b) conducted two different assessments post conducting a designed session of 2 hours over 2 to 4 days with young children aged between 4 to 6 years where they used a combination of Interactive learning and collaborative approach. A questionnaire to assess children's perception of robots was conducted and further a theory of mind assessment and a multiple-choice questionnaire was circulated to assess their AI knowledge. In another crucial study collaborative learning approach in combination with interactive learning and participatory learning approaches was used with middle school children studying in grade 7 to 9 spanning over 25 hours (Zhang et al., 2022). This study focused on three domains to develop holistic AI Literacy in middle school children which were teaching technical concepts and processes, teaching ethical and societal implications pertaining to development and application of AI, and prospective career opportunities in the field of AI in the future for students. The study approached AI education in a different manner bearing mind the children today will be the future implementors and users of AI technology and providing them age-appropriate learning on all three domains will help make them responsible users, and developers of AI in the future. Further the aspect of future career opportunities in AI field helped provide necessary motivation to the students to acquire knowledge on AI concepts even from minority groups in the society, which are generally being neglected albeit unintentionally. The study found that such an approach helped students understand concepts and processes of AI and students were able to detect bias and mitigate it in ML and began to seriously evaluate the ethical implications and impact of AI in society and in career. Post the session students were also able to view AI as not merely a technical topic but were able to relate to it in as a subject that has implications for them personally as well as in their future career prospects as well as on a societal level at large. Thus integrating ethical and career aspects of AI alongside imparting technical knowledge of AI to students in middle school was found beneficial (Zhang et al., 2022). Other studies used collaborative approach in combination with game based learning and problem solving exercises with students aged 8 to 11 (S. Lee et al., 2021) and Project based approach in 6 sessions of 10 hours with students aged 17 to 20 (Kaspersen and Kj, 2022). While Lee et al., (2021) used a pre and post session assessment to gauge students' knowledge in AI concepts, ethical implications of AI Kaspersen et al., (2021) used observational assessment during sessions. Another study in The USA used collaborative approach in combination with design oriented learning approach with data visualization and hands-on practical exploration in a 3 hour session with students aged 15 to 17 and assessed their AI knowledge using a questionnaire (Wan et al., 2020). Another study in the USA targeted secondary school students using a combination of collaborative approach with objective/conceptual knowledge of AI leading to a more constructive project based approach where the sessions were spread over a month (Norouzi et al., 2020). The students were assessed on their conceptual knowledge of AI using questionnaires as well as through self-assessment of their perceived AI knowledge. Interactive learning approach was used a study in the US where 1 session of 2 hours with children aged 8 to 10 were assessed using open questions as well as through self-assessment questionnaire to gauge their AI knowledge (Lin et al., 2020). Interactive learning approach was also used in a study which focused on students aged between 7 and 9 as well as 10 and 12 across multiples countries namely USA, Denmark, Germany and Sweden (Druga, 2018). The researchers conducted a single 2-hour session with children post which the children were asked to fill a questionnaire to determine their perception of AI. Further two Israel based studies also used the interactive learning approach with students aged between 10 and 12 (Hitron et al., 2019) and aged 12 (Shamir and Levin, 2021). Whilst Hitron et al., (2019) conducted a single session where artifacts were used and post the session students were asked to analyse the artifact Shamir (2021) conducted a six-day course and combined interactive approach with participatory learning. Interactive learning approach was used in combination with collaborative learning approach in another study in the US where 1 session of 2 hours with children aged 8 to 10 were assessed using open questions as well as through self-assessment questionnaire to gauge their AI knowledge (Lin et al., 2020). Two other studies combined interactive approach with direct instruction approach and focused on grade 8 and 10 (Fernández-Martínez et al., 2021) and age 10 to 14 (Melsión et al., 2021). Melsión et al., 2021 conducted the study with ML knowledge as their focus. Design based learning approach was used by multiples studies in Finland and focused on children between the ages of 12 and 13 (Fernández-Martínez et al., 2021; Toivonen et al., 2020; Vartiainen et al., 2020; Wan et al., 2020). 3 session of 8 to 9 hours were conducted and students were assessed using by observing them during the process. Further a US base study also used cooperative codesigning approach with 7 to 12 year olds (Woodward et al., 2018). Similarly a Denmark based study focused on students aged between 16 and 20 and used design based approach towards teaching (Bilstrup et al., 2020) and used artifact analysis as their assessment of students' AI knowledge. In addition to these participatory learning approach (Kaspersen and Kj, 2022; Sakulkueakulsuk et al., 2018; Vartiainen et al., 2020; Zhang et al., 2022) as well as direct instruction approach (Fernández-Martínez et al., 2021; Melsión et al., 2021; Tseng et al., 2021; Van Brummelen et al., 2021) to learning have been used in some studies either in isolation or in combination with other learning approaches. Project based learning approach has also been used by some researchers (Druga and Ko, 2021; Kaspersen and Kj, 2022; Tseng et al., 2021). Some other studies that used game based learning approach in combination with other learning approaches like experiential learning were conducted with grade 5 and grade 7 students respectively (Hsu et al., 2022, 2021). The studies provided 9 weeks of sessions and 6 weeks of sessions respectively and assessment of students' AI knowledge was conducted using questionnaires and tests. Another key study was conducted using digital story writing exercises (D. T. K. Ng et al., 2022d) for primary level students in Hong Kong. The study comprised of 7 sessions where researchers used inquiry-based learning consisting of five phases- orientation, conceptualization, investigation, conclusion and post that discussion. Children were then tested on their AI knowledge to assess the effectiveness of the study approach. A systematic study suggests that participatory, design based and collaborative learning approaches have been used most commonly and effectively in various studies (Sanusi et al., 2022). Whilst these approaches have been found successful in various setting and world regions, there is need for more research with bigger samples and roles of teachers and instructors and their own understanding and attitude towards AI is critical for CAIL initiatives to be successfully implemented. Further only one study with grade 6 to 12 students has been conducted within The UK using direct instruction approach over 5 sessions of 13-15 hours (Van Brummelen et al., 2021). The study assessed these middle school students using questionnaires and assessing students' artifacts post learning. It can be said that educational pedagogies used must be engaging and fun so as to motivate students to learn. Further studies that offered multiple sessions over a longer period of time are more effective. Post learning assessments are essential to gauge how much the study approach has benefitted the students in learning and gaining knowledge about AI. Further a more well-rounded approach towards teaching is preferrable so children not only learn the technical aspects of AI but also become ethically aware and responsible users and developers of AI technology.

2.1.14 Parental Role in Child's Learning in Relation to CAIL

Studies show that society depends on parents to prepare children for changes caused by education and technology and also for protecting them and preventing them from online risks (Livingstone et al., 2017) . Further another study has suggested that parents have the power to impact their children's perceptions and enable them to differentiate between what may be harmful and what may be useful when encountering online situations (Cabello-Hutt et al., 2018). Hence parents play a crucial role in child's access, learning ability and use of digital environments and also in shaping children's perceptions and learning. The reasons due to which parents may choose to get involved with their child's learning and education were explained in a much cited study (Hoover-Dempsey and Sandler, 1995). Based on the model, the engagement of parents has an impact on the development and educational achievements of children through various means such as demonstrating, reinforcing, and instructing, which are influenced by the parent's use of activities that are suitable for the child's age and the alignment between these home-based parental activities to engage children in learning and school requirements. The main educational results of the engagement process encompass the enhancement of children's skills and knowledge, along with fostering a personal belief in their ability to enhance academic achievement. Another qualitative study also discussed the role of parents in influencing children's interest in learning science in schools (Halim et al., 2018). Yet another study found that other than teachers, parents own beliefs and attitudes played a pivotal role in shaping a child's beliefs pertaining to digital media and their efficacy in the subject (Hammer et al., 2021). Further a study showed that collaboration between parents and teachers to facilitate supportive informal learning for children involving coding and robotic technologies proved beneficial (Relkin et al., 2020). Within AI Literacy domain a recent study has shown that family plays a critical role in a child's adoption and learning of AI technologies (Druga et al., 2022a) outside of school environment. In addition to this past research has also recognized the importance of parent-teacher partnership in enhancing child's learning and development (Epstein, 2018; McLanahan and Sandefur, 2009). Further another case study based research has posited that parental engagement in children's learning in home based environment contributes in a big way towards student achievement (Harris and Goodall, 2008). So far parental involvement in child's AI learning has remained largely neglected in literature. This makes studying impact of collaboration between various stakeholders (parents-teachers, parents-children) crucial to gain insights on collaboration as a predictor for parents' preparedness for CAIL in UK schools. All of the above also will significantly contribute towards better understanding of various factors impacting parent's readiness for CAIL. In addition, demographic variables may have an impact on parents' preparedness for introduction of CAIL initiatives in primary schools in the UK. Thus, it is important to assess parents' affinity towards technological innovativeness, attitudes, favourability to collaborate with other stakeholders such as children and teachers and parents' concerns alongside demographic variables to predict their readiness levels for introduction of CAIL initiatives in primary classes in the UK.

2.1.15 UK AI education landscape

On June 12th, 2023, British Prime Minister Mr. Rishi Sunak, while speaking at the London Tech Week in the presence of personnel from media and Tech companies like Google and Microsoft said that the Artificial intelligence (AI) could be useful in providing "personalized learning" at school ("AI could be used to provide 'personalised learning' to schoolchildren, Rishi Sunak says," 2023), and has the potential to transform and its addition into the school systems will assist teachers in lesson planning and marking assignments and help reduce teacher's workloads. Notably teachers in The UK have raised issues with Generative AI (ChatGPT, Google Bard, Open AIs). Generative AI is capable of generating new audio, text, visual, simulated or even codes in terms of content basis the big data sets fed in to train these systems. Generative AI are capable of generating essays, speeches, on a wide variety of topics etc. Thus, with the appropriate prompts these AI tools can easily deliver an assignment which will be difficult for teachers to assess. The teachers pointed out that one of the biggest concerns to do with Generative AI is that there are no regulations in place in The UK as to their safe and responsible use by students and no proper guideline on their application and adoption in schools and have demanded that the government and the Education Department take necessary steps to address these issues. Another written evidence suggested to the house of lords suggested that UK's AI literacy policy must aim to create an equitable future ready population by including a holistic approach towards education, workforce development ethical guidelines and programs to create public awareness (Kumar, 2024).

On its part the Department for Education issued a white paper in March 2023 on its position on use of Generative AI (Department for Education, 2023) and has further set up a Foundations Model Task Force that will look into UK's adoption of safe AI models. Further AI education and a robust curriculum for the same was again emphasized as the most optimum way to ensure students make informed decisions on use of all AI technologies including Generative AI (Department for Education, 2023). It was suggested that education sector must ready students and young children to responsibly and securely use emerging AI technologies so as to equip them to thrive in evolving workspaces. Such teaching could mean understanding limitations, reliability, and potential bias of generative AI, issues pertaining to online safety so as to protect against harmful or misleading content (Lynch, 2023). However, both teachers, parents and children's attitudes, perceptions, and readiness for CAIL in schools remains unstudied to a large extent. Given that there is evidence that children's learning is influenced by the attitudes of their teachers as well as their family environment- their parents in particular in early years, it merits studying various factors that influence parental preparedness for change (such as introduction of CAIL initiatives in primary schools) which can have an impact on how and what their children learn.

Thus, a single research question (RQ) was developed:

RQ: ***What are the various factors that influence parents' readiness for introduction of CAIL initiatives in primary schools in The UK?***

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

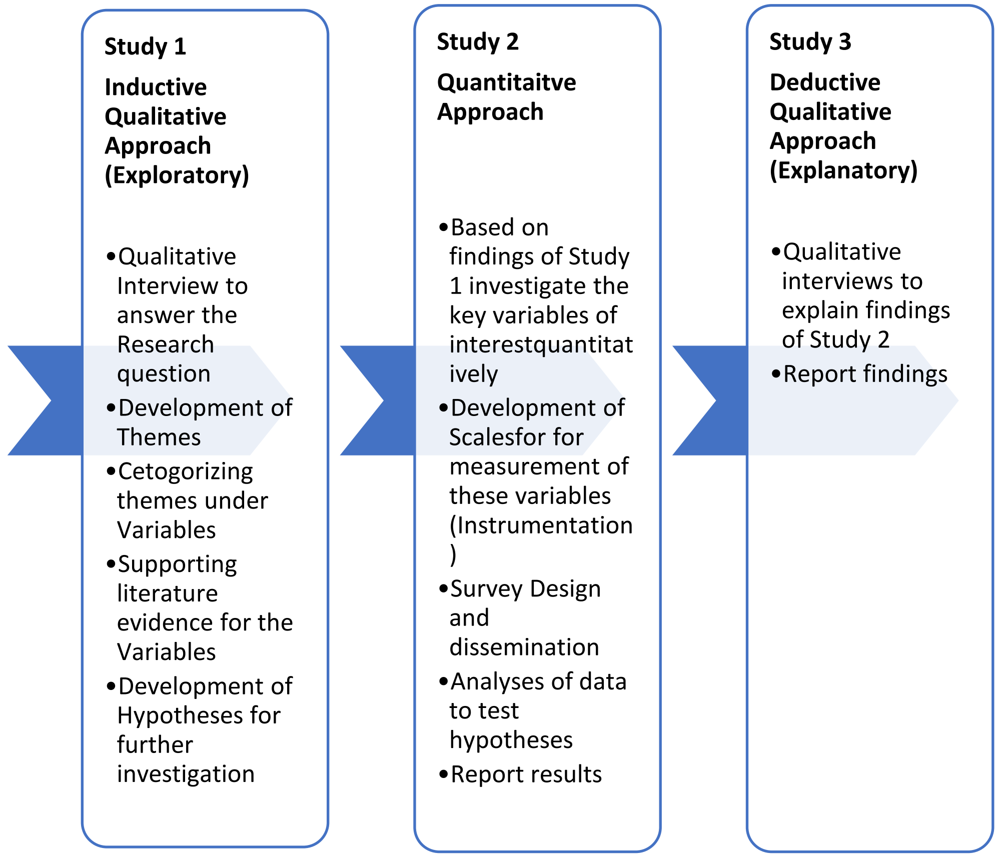
While AI literacy is being considered an imperative for all in order to create an equitable society globally, research is lacking on how and what to teach. It is also being acknowledged that AI literacy is an imperative for future generations and that children must be initiated into it as early as within primary classes in schools. Some countries have already started running courses in schools for all students in secondary classes. Experimental studies have also been conducted with primary class children although not to a large extent and the sample sizes are small. However, most research within AI literacy is focused on children and teachers. Further there are not enough studies from within the UK. Parents have an influence over child's learning especially in early years. However, there is no research that has focused on how prepared parents of primary class children in the UK are for the introduction of CAIL initiatives in their children's learning. This study focuses on the various factors that assess parental preparedness for CAIL in primary schools in the UK to bridge this gap in research.

3.2 Research Design

This research employed a two-phase mixed methods design, specifically an Exploratory Sequential Design followed by an Explanatory Sequential Design (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017). The design thus consists of three studies (Study 1, Study 2, Study 3), the first being inductive qualitative exploration (Study 1), the second being quantitative confirmation of the findings of Study 1 (Study 2) and the third being qualitative explanation of quantitative findings (Study 3).

A sequential mixed methods strategy involves the use of both qualitative and quantitative procedures to investigate a research subject. This approach allows for a more comprehensive understanding of the problem compared to utilizing only one method, either quantitative or qualitative (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017). Distinct characteristics of quantitative and qualitative research are well-known within scientific research. While quantitative research methodologies involve researchers employing positivistic claims to produce knowledge, qualitative approaches develop knowledge claims based on a constructivist stance that recognizes different individual views. Several academics emphasize the need of employing a mixed method approach in research (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017; Onwuegbuzie and Teddlie, 2003; Sandelowski and Barroso, 2003; Shah and Corley, 2006; Teddlie and Tashakkori, 2003a). Further, numerous research projects have effectively integrated qualitative inquiry to develop theory and quantitative assessment to evaluate hypotheses (Shah and Corley, 2006). Figure 1 describes how the research Design will be implemented in this research.

Figure 1- Sequential mixed methods approach



3.3 Research Design rationale

The key features of classic qualitative research are induction, discovery, exploration, the researcher serving as the primary instrument in data gathering, qualitative analysis, theory development, and proposition formulation. Quantitative research is characterized by several key features, including deductive reasoning, verification, testing of theories or hypotheses, explanation, prediction, standardized data collecting, and statistical analysis.

Mixed methods research refers to the practice of integrating quantitative and qualitative research methodologies, methods, approaches, concepts, or language within a single study. This type of research integrates the investigative techniques of induction (identifying patterns), deduction (testing theories and hypotheses), and abduction (formulating and relying on a set of explanations for comprehension). The core premise of mixed methods research entails comprehending the merits and drawbacks of each approach in order to create a more advanced study design compared to single methodological investigations. This is achieved by combining the complementary strengths and non-overlapping weaknesses of different methods (Johnson and Christensen, 2019). An example could involve incorporating qualitative interviews into quantitative experiments as a means of doing a manipulation check. Another option could involve incorporating a quantitative survey into a qualitative study to systematically assess constructs that are deemed essential to the resultant theory.

Advocates on both sides of the qualitative (Lincoln and Guba, 1985) and quantitative divide (Maxwell et al., 2017; Schrag, 1992) support the incompatibility thesis (Howe, 1988), which asserts that the two research paradigms cannot and should not be merged. Opposing this viewpoint are proponents of integrating the two approaches, leveraging their respective advantages and mitigating their limitations in a singular research investigation or over multiple studies.

The methodologies approach serves as a compromise between the contrasting perspectives in the quantitative versus qualitative debate.

Campbell and Fiske (1959) were the first to apply the use of mixing procedures in their study on psychological trait validity.

Subsequently, some researchers have acknowledged the significance of including both qualitative and quantitative data collection methods into their range of techniques. They understand that relying exclusively on either of these approaches would result in an inadequate perspective (Di Pofi, 2002).

A multitude of scholars are currently publishing literature on mixed approaches, including (Brewer and Hunter, 1989; Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017; Greene et al., 1989; Johnson and Christensen, 2019; Newman and Benz, 1998; Reichardt and Rallis, 1994; Teddlie and Tashakkori, 2003b, 2003a). Qualitative research has the potential to be precise, but it can also become excessively intricate. Collecting quantitative data is highly beneficial for the purpose of testing theories. Research proposes that the resolution to making trade-offs is not to discover a single approach that encompasses all three aspects of accuracy, generalizability, and simplicity (Weick, 2015). Instead, it involves cycling between different data sets that offer one or more of these features and supplementing them with additional study. By integrating qualitative and quantitative methodologies, it is possible to mitigate the limitations of each method, as previously highlighted by other researchers (Gioia and Thomas, 1996; Jick, 1979; Van Maanen, 1979; Webb et al., 1975). Both qualitative and quantitative data collecting are highly regarded by many managers and consultants for their importance in providing a comprehensive perspective. Relying only on either approach is considered inadequate by experts (Di Pofi, 2002).

3.4 Research Steps and Timelines

Study 1 adopted an inductive, exploratory approach, involving gathering and analysing qualitative data, to answer the research question, and further design a quantitative survey instrument based on the qualitative findings. Thematic analysis and narrative analysis were used to answer the research question. The exploration led to identifying themes that were further categorised under four key variables. Quantitative survey was then designed for the next phase of research incorporating findings of the qualitative study. Further the findings of quantitative data from Study 2 were explained using study 3 comprising qualitative interviews. The data for Study one was gathered over a period of 7 months (March 2023-October 2023), for study around three months (October 2023-January 2024) and for study 3 for around 1 and a half months (January 2024-February end 2024). A more detailed timeline is presented in Table 2.

Table 2 - Timeline for Studies 1, 2 and 3

Study 1	
Dates	Action
03/03	Initial unstructured scoping of literature, news articles, reports pertaining to the RQ
15/07-31/08	Informal chats with some parents of primary class children
1/09-1/10	Designing interview questions and identifying the appropriate expert for interview
08/10	Interview with the AI expert
08/10-15/10	Analysis of qualitative data
Study 2	
15/10-20/10	Development of scales
25/10	Finalized questionnaire

04/11/23	Survey disseminated
04/11-12/12	Messages, WhatsApp texts, Facebook posts, web posts inviting participants
12/12/23	Survey closed
12/12/23-05/01/24	Data cleaning and Analysis
10/01/24	Final report of results

Study 3	
10/01/24-12/01/24	Qualitative questions in survey assessed
15/01/24	Semi structured interview questions designed
16/01/24-31/01/24	Lining up interviews
03/02/24-05/02/24	Qualitative interviews
05/02/24-29/02/24	Assessment of qualitative data

The developed variables were then tested using quantitative survey (Study 2). Thereafter the findings of the quantitative assessment were further explained using qualitative interviews (Study 3).

3.5 Limitations of Research Design

Mixed methods research is an influential strategy that integrates qualitative and quantitative methodologies to achieve a more profound comprehension of intricate phenomena. Nevertheless, like to every study methodology, it possesses inherent constraints. An important constraint is the heightened intricacy. Proficiency in qualitative and quantitative approaches is essential for doing mixed methods research. Additionally, the process of collecting, analysing, and integrating data can be more intricate compared to utilizing only one method. Further, mixed methods investigations require a significant number of resources. They frequently entail numerous phases of data collecting and distinct data processing, rendering them more time-consuming in comparison to utilizing a single method. Integration issues also emerge, as researchers must meticulously contemplate how to amalgamate diverse forms of data to construct a cohesive narrative. Moreover, the divergent philosophical and paradigmatic perspectives of qualitative and quantitative research might provide difficulties, requiring researchers to skilfully manage these disparities while formulating and analysing mixed methods studies.

3.6 Advantages of Mixed-methods Design

Mixed approaches offer several advantages, such as triangulation, complementarity, initiation, development, and expansion. Triangulation of results refers to the use of many methods and designs in a mixed method approach to validate and strengthen the study findings, providing greater confidence and assurance (Jick, 1979). Using various approaches enhances the validation process by ensuring that the observed differences are a result of the feature being examined, rather than the specific data collection method employed (Campbell and Fiske, 1959). Utilizing numerous perspectives can enhance understanding by enabling the examination of a study subject from many vantage points (Cunningham et al., 2002). Triangulation is a useful approach in the research process as it allows for the integration of results from different methods. This can enhance the overall understanding and validity of the study findings (Creswell and Clark, 2017, 2011; Creswell and Creswell, 2017; Greene et al., 1989). Complementarity refers to the ability of researchers to enhance their understanding and provide more detailed explanations of their findings by utilizing diverse data obtained from various methodologies.

Initiation refers to a situation where researchers encounter apparent contradictions and paradoxes that compel them to redefine their study topics in order to achieve clarity. Development refers to the process in which the information obtained from one approach is used to inform another method. Expansion refers to the researchers' objective of seeking to broaden the scope and diversity of knowledge generated through research by selecting an infrequently utilized strategy to determine if it yields distinct information.

Another benefit of employing a qualitative approach is that it enables individuals to provide detailed accounts of specific occurrences (such as events, incidents, processes, or issues) happening within the organization. These may not be captured by standardized scales that primarily focus on overall attitudes towards a job or organization. By enabling respondents to articulate their schemata using their own language, researchers can acquire a more comprehensive comprehension of the subjects and worries that have the most significance for each respondent. Every participant can recognize the topics that are most individually significant to them, without any influence or prejudice. An enhanced comprehension of the perspectives of respondents, obtained through open-ended responses, decreases the probability of bias when identifying an organization's problems (Gregory et al., 2007).

As data is collected, distinct problems might be discovered. However, data obtained from a prefabricated instrument may lack the level of detail and depth of analysis found in other sources (Gregory et al., 2007). Although certain prefabricated instruments were designed to be comprehensive, it is important to exercise caution and thoroughness when evaluating whether a particular instrument accurately reflects an organization's pertinent concerns (Moates et al., 2005). Data collected from a pre-made instrument that measures satisfaction with a supervisor (Scarpello and Vandenberg, 1987) may reveal that subordinates are unhappy with their supervisor. However, this data may not pinpoint specific behaviours, such as yelling at employees or spreading rumours about them, that have led to this dissatisfaction. Conversely, these particular actions might easily be recorded through interviews.

Including a qualitative method in the collection of specific concerns has a third advantage: it helps save time in identifying the specific challenges that need to be addressed. If the results of a pre-made instrument only show that there is an undesirable state, such as low supervisor satisfaction, researchers would need to gather more information from employees in order to better understand the specific factors that are influencing the survey responses. Acquiring extra data would necessitate a greater investment of time and resources.

Another benefit of an empirical survey derived from a qualitative technique is that it offers data that can be used to produce a quantitative survey that is highly face-valid. This quantitative survey may then address particular and important organizational issues that have been identified by the respondents. A quantitative survey of this nature is more likely to be perceived as personally meaningful to members of the organization compared to a pre-made instrument designed for broad usage. A personalized and well-informed quantitative survey is more likely to motivate employees to fully and accurately complete the survey due to its increased personal significance.

Given the lack of existing research on AI literacy in the UK context, this design is particularly suitable as it allows for initial exploration of the topic, followed by a quantitative analysis, and then a deeper exploration of the quantitative results. This approach will provide a comprehensive understanding of parents' preparedness for the introduction of AI literacy in primary schools in the UK, thereby addressing the identified gap in the literature.

Subsequent chapters of this dissertation will sequentially focus on Study 1, Study 2, and Study 3 and the outcomes of each. Chapter VIII will discuss the full research and outcomes thereof and Chapter IX will summarize the research, elaborate on implications of findings and recommend future research directions.

CHAPTER IV:

STUDY 1 – QUALITATIVE EXPLORATION

4.1 Introduction

In line with the research design the first step was to refine the research question and further answer the same. Inductive qualitative approach was adopted here. Thematic analysis was used to assess data. The following sections will detail out the various steps of the study. Variables of interest will be identified through exploration of qualitative data in this section supported by second phase of literature review. These variables will provide a foundation for next step of the research pertaining to understanding how these variables predict parents' preparedness for child artificial intelligence literacy (CAIL) initiatives in primary schools in the UK.

4.2 Research Purpose and Questions

The purpose of this research is to identify the various factors that influence parental preparedness for CAIL in primary schools in the UK. A single research question based on the initial literature review is presented below:

RQ: What are the various factors influencing parental preparedness for introduction of CAIL initiatives in Primary schools in the UK?

4.3 Research Design: Study 1

Since this study aimed at deriving key themes and designing variables of interest based on themes, a qualitative approach was adopted for this part of the research. Thematic analysis was used to analyse data since it allows to uncover underlying meanings, explore participants' perspectives, and gain insights into the phenomenon being studied and is a flexible approach that can be easily adapted to a variety of research questions and contexts (Clarke and Braun, 2017).

Inductive thematic analysis (Braun and Clarke, 2006; Clarke and Braun, 2017) approach was used to cull out themes, which were further categorised under key variables of interest for further study. Thematic analysis conducted in a bottom-up manner, is known as inductive thematic analysis. The qualitative data, consisting of semi-structured interview of the AI expert was analysed using an inductive approach known as the six-stage method (Braun and Clarke, 2006; Clarke and Braun, 2017). The steps of this method include becoming familiar with the data, generating initial codes, identifying themes, reviewing and refining the themes, defining the themes, and conducting a final analysis. It is stated that debriefing and external checking should be used to ensure a thorough evaluation and justification of the themes created (Norwell et al., 2017). However, in order to provide more accuracy and reliability, the concept of "confirmability" (Norwell et al., 2017) is further supported by providing examples of coding.

Data triangulation is a valuable method for ensuring mutual validity. In this case, both news articles, reports and interview data were collected and analysed simultaneously, and then combined. Nevertheless, it is important to note that these procedures require multiple rounds of analysis that involve some level of interaction between the two sets of data. Therefore, although a clear and linear approach is useful for explaining things, the actual reality is inevitably more intricate. This complexity is termed as “mess” in social science research (Law, 2004).

The inductive analysis revealed several themes that emerged from the interview and other data. These themes were further categorised basis their commonality to arrive at key variables of interest for further investigation. These variables identified were innovativeness, attitudes, collaboration and concerns. The intention was to understand how all these variables and demographic data generated variables impact parental readiness for CAIL. The key factors associated with professionalism were autonomy, collegiality, professional trust, sense of vocation, and professional wellbeing. The sub-themes of managerialism encompassed judgement, burden of proof, and the management class.

Quantitative analysis via survey research only reflects preconceived conceptual categories (Schein, 2010). Collection of quantitative data alone without narrative support will inevitably cause difficulty in explaining interesting relationships (Mintzberg, 1979) and assuming that only quantitative data can be viewed as evidence is a misconception, since good qualitative data can also help hypothesise, supplement quantitative research and also help in uniting people who will be affected by a change (Pfeffer and Sutton, 2006).

Although theory development is highly regarded, it is rarely put into practice. When it is implemented, it primarily involves a quantitative and deductive approach, using existing theories as the basis for creating hypotheses that can be tested (Shah and Corley, 2006). Several scholars argue that the process of constructing theories necessitates more than just gathering and analysing data through cross-sectional surveys (Echambadi et al., 2006). Alternatively, detailed explanations of patterns can be obtained qualitatively using "soft data," which can contribute to the development of theory (Shah and Corley, 2006).

Qualitative approaches are focused on the process, rooted in the specific context, prioritizing experiential data, and give significance to the findings. These strategies derive significance by endeavouring to comprehend the viewpoints of the individuals who are actively involved in the issue being investigated. The current situation involves examining an organizational transformation to uncover the intricate operations of intricate systems, novel factors, and unforeseen connections (Miles and Huberman, 1994).

4.4 Instrumentation

Semi structured qualitative interview was used to collect data for this study. Additionally, the findings were supplemented with focused research of literature.

4.5 Population and Sample

The target population for this stage of the study was parents or guardians of primary school going children residing within the UK. Since the aim of the research is to understand the various factors influencing parental preparedness for CAIL in primary schools in the UK, it was an imperative that parents and guardians of at least one primary going child remain the focus of this study.

4.6 Participant Selection

A single AI expert residing in the UK and also a parent to a young primary school going child was interviewed. Single interviews are intentionally employed as a strategic approach for inductive analysis in qualitative research. Instead of depending on large sample sizes, researchers deliberately engage in detailed talks with a single person. This technique provides multiple justifications. Initially, the abundance and complexity of data acquired from a solitary interview facilitate a detailed investigation of a particular event. Unexpected patterns and ideas that were not initially planned for can arise from these informal exchanges. Further, individual interviews offer a comprehensive comprehension by collecting personal experiences, contextual intricacies, and real-life tales pertaining to the research subject. These preliminary interviews function as an early step, producing initial hypotheses or theoretical conceptions.

Within the framework of sequential exploratory designs, which involve the integration of qualitative and quantitative methodologies, conducting an in-depth interview with a single expert is of utmost importance. In this context, the attention is directed towards an individual expert who possesses highly specialized knowledge and distinct perspectives. Performing a comprehensive interview can assist in identifying crucial aspects that are pertinent to the study question. These discoveries act as a connection to the following quantitative step. Expert-driven interviews provide a high level of accuracy, which enables the fine-tuning of research questions, the development of hypotheses, and the direction of quantitative study designs. The combination of expert views and quantitative data improves the overall validity and depth of understanding in research activities. Many researchers have successfully utilized a solitary interview in their published studies (Boddy, 2016). Research has revealed that even sample sizes consisting of only one instance can provide valuable and significant information, as evidenced by examples from management and medical studies. Research that utilizes a single sample or case but explores new topics or discoveries that are potentially very significant can be considered deserving of publication (Boddy, 2016).

4.7 Data Collection Procedures

For this dissertation initially only one broad research question was intentionally designed in order to capture several factors that influence parental preparedness for CAIL in primary schools in the UK. This research question was designed post conducting an initial online search to identify news articles and reports pertaining to the study topic. The AI expert was also initially invited to have informal chats about the study topic. A thorough investigation of online data, news articles, reports along with a detailed semi-structured interview were conducted subsequently. The detailed interview was conducted using Google Meet chat tool and the data was transcribed using Simon Says transcription tool. Study 1 spanned over seven months approximately.

Themes were culled out of the combined data and further classified under themes that were later converted into key variables of interest.

Initial data collection involved informal discussions and conversations with the AI expert who is a parent to a primary school going child in the UK. The expert is in the age-group of 40-45 and as an AI scientist ranks among the top 2000 scientists in the world in the Stanford list. The discussions largely focused on AI literacy, its importance in an individual's life in today's world, perceptions towards AI and general UK AI landscape. The information gathered during these in person sessions allowed for more detailed and focused research of literature to find out about AI perceptions within UK. News articles and reports were studied to understand these aspects in more detail.

Post this the AI expert was contacted formally to provide time for a semi-structured interview. The interview was conducted in October 2023. The interview happened in three sessions one of which was online on Google meet and the other two were in-person. While the online session was conducted using Google Meet and the content was transcribed using Simon Says transcription tool, the in-person meetings were recorded on paper with copious notes being taken alongside. Simultaneously online research was continued to supplement the findings.

4.8 Data Analysis and Theme Development

For data analysis Thematic approach was adopted. The thematic analysis approach, was established by Braun and Clarke (2006). Reflexive thematic analysis acknowledges the inherent subjectivity of the analysis process, and acknowledges that the researcher actively generates codes and themes.

Therefore, the researcher's values, talents, and experiences have a direct impact on the topics and codes used. Reflexive thematic analysis occurs at the point when the researcher, the dataset, and the many contexts of interpretation intersect. The specified text is located between lines 5 and 6. In this approach, the coding process is characterized by a lesser degree of structure and a more natural and spontaneous nature. Braun and Clarke have expressed criticism towards the term 'emerging themes' commonly used by academics to denote topics that arise from the data itself, rather than being derived from a deductive approach.

This terminology implies that meaning is inherently clear and exists inside the data, waiting to be uncovered. It also says that the researcher acts as an impartial channel via which this meaning is exposed. On the other hand, we define analysis as a process that takes into account the specific circumstances and interactions involved, including the data being analysed, the researcher's perspective, and the overall research context. It is misleading to suggest that themes simply arise on their own, rather than being actively created through collaboration between the researcher, the data/participants, and the context.

There are numerous approaches to carry out reflexive thematic analysis, however, the procedure can be summarized into six key steps. It should be noted that this procedure is not linear, prescriptive, or based on strict rules. Instead, it is an approach that helps researchers systematically and effectively explore their data.

Step one is acquaintance or familiarity with data. This entails thoroughly reading and reviewing transcripts to ensure the researcher becomes fully immersed in the data. The researcher records their preliminary observations, interpretations, and insights for each individual transcript as well as for all the transcripts or data sources collectively. Second step is coding. Coding is the act of assigning concise labels (codes) to data in a manner that accurately represents the meaning and attributes of the data that are pertinent to the research topic. The complete dataset is encoded in multiple iterations; however, unlike the sequential coding process in grounded theory, or the segmentation of data in applied thematic analysis, not all data parts require coding. After several iterations of coding, the codes are organized and pertinent data is extracted.

From the codes initial themes are generated in the next step. The researcher generates early themes by analysing the collected codes and extracted data to identify patterns of meaning. The researcher thereafter reviews the codes and data in order to extract pertinent information for the initial topics and assess the feasibility of each theme.

Next step is evaluating and revising themes. This essentially means comparing the initial themes with codes and the complete data set to determine if they accurately represent the data and address the research question. During this stage, the topics are frequently revised through the process of combining, splitting, or rejecting. In the context of reflexive thematic analysis, a theme is specifically defined as a recurring pattern of shared meaning that is supported by a central concept or idea.

Next comes the process of refining, defining, and naming themes which involves determining the extent and limitations of the topic, constructing the narrative surrounding the theme, and assigning a descriptive name to the theme.

The final step is writing up which is an essential component of the analysis process. It entails crafting a narrative that encompasses the themes, including the data, and establishing the contextual foundation for the topics within the existing literature.

Following these steps themes were generated from the data set. One more step was however added to further suit the next section of the research (Study 2). This involved combining similar themes to identify if they can represent a variable that has been found relevant in other studies as a predictor of preparedness. Broad Interview questions are presented in APPENDIX A.

Table 3, 4, 5, 6,7 show how themes were developed. And figures 2, 3,4,5 show how these themes were combined basis their relations with each other to formulate variables

Table 3 - Themes development for Innovativeness

INNOVATIVENESS			
QUOTES	**KEY WORDS**	**CODE**	**THEME**
One of the most important things about acceptance for new technology or	change, willingness to	Open	Openness to Innovation

technology related change is that the individuals show a willingness to embrace new ideas, processes, products, or services easily. They are active seekers who are on the lookout for new innovative solutions and are open to change.	embrace		
These people are curious and like to explore technology even if it is not of immediate or direct use to them. They are by nature experimenters who like to fiddle with technological tools to see how they function.	curios, experimenters, explore	Explore	Curiosity & Exploration
Such people are quick to adapt technology related changes. They are people who have no problem with continuously learning, unlearning, and relearning as they like to remain updated and relevant.	Adapt, technology, change, learning, unlearning, relearn, update, relevant	Adapt	Adaptability and Learning agility
These people are good at taking calculated risks. They are willing to try new technologies, even if they do not understand what the technology would evolve into in the future. So, uncertainties don't bother them as much.	calculated risk, willing, new technologies, evolve, future facing	Risk	Risk appetite
So, parents or individuals that use technology as a tool to solve problems in their day-to-day life. They find it easy to spot problems and also use technology to solve those problems in their work or personal life.	technology use, problem-solving, real-world scenarios	Problem-solving	Problem-solving mindset
These people connect with others to exchange ideas and knowledge.	connect, exchange ideas,	Cooperation	Cooperation & networking

They participate in tech communities, attend conferences, and cooperate on projects.	knowledge, participate, collaborate		
They can imagine and envision how technology can transform lives and industries.	imagine, envision, technology, transform, change lives, industries	Vision	Vision & imagination
However, it doesn't mean that they do not give any importance to ethical aspects of technology use. In fact, they could be people who weigh all technology against how it may impact aspects like privacy, security, and impact on society	ethical aspect, technology impact, privacy, security, society	Ethics	Ethical cognizance

Table 4 - Themes development for Attitudes

ATTITUDES			
QUOTES	**KEY WORDS**	**CODE**	**THEME**
People with positive attitudes eagerly embrace technological advancements. They look at technology as an opportunity for progress and improvement.	positive attitude, eager, embrace, technology advancement opportunity, progress, improvement	Enthusiastic	Enthusiasm & embrace
If people have negative attitudes, they tend to be sceptics and resist new technology. They fear about their privacy, security, or disruption and this can lead to resistance.	negative attitudes, sceptic, resist, new technology, fear, privacy, security, disruption	Fearful	Resistance & Scepticism
Attitudes are formed on the basis of how individuals perceive technology	Perceptions, technology	Impact	Perceived

can impact their daily life. Positive impact would mean technology will make things efficient and convenient Negative impact could be that they think technology use will make them over dependent on technology or cause unnecessary distraction.	use, impact, positive impact, convenience, efficiency, negative impact, over dependent, distraction		impact on daily life
Cultural factors influence attitudes. Societal norms, values, and expectations shape how individuals perceive change	cultural, societal, norms, values, perception, change	Values, society	Cultural context and Norms
Positive or negative experiences with technology can also shape a person's attitudes towards technological change So, if personally an individual has seen more success stories, then they will perceive technology change positively. But if they have seen more failures of technology then they will be negative towards it.	Personal experience, exposure, new technology, positive perception, negative perception	Experience	Personal experience and exposure

Table 5 - Themes development for Collaboration

COLLABORATION			
Research Paper (Druga et al., 2022a)	**KEY WORDS**	**CODE**	**THEME**
Family engagement helps children learn about AI better outside of school.	Family, engagement,	Engage	Family engagement
Parents' involvement impacts a child's learning in early years. If they take interest in how the child is learning they will be able to provide good support to the child.	parental involvement, child learning, early years, interest, support	Interest	Involvement & Interest
Involvement in school is also an important aspect. Parents that take active role in their child's learning at school	participation, learning, child	Participate	Active role and participation

Another aspect is parent-teacher interactions. If parents are regularly in touch with the teachers chances, are they are going to be able to understand how to help the child learn about new things at home to support what the teachers are teaching ins school.	Parent-teacher, interactions	Interact	Parent-teacher interactions and support

Table 6 - Themes development for Concerns

CONCERNS			
QUOTES	**KEY WORDS**	**CODE**	**THEME**
The biggest worries individuals have are about their personal data being collected, stored, and potentially misused by technology companies or malicious actors. Concerns include data breaches, surveillance, and lack of control over personal information.	Worry, personal data, security, misuse, technology companies, malicious actors, data breaches, surveillance, lack of control personal information	Privacy, safety,	Data Privacy and Security
Fear of losing jobs due to automation and artificial intelligence (AI) is a common concern. Individuals worry about their skills becoming obsolete and the impact on their livelihoods.	Job loss, AI, automation, impact on livelihood	Replacement	Job Displacement and Automation
When it comes to their children most parents are concerned about excessive screen time, digital addiction, and mental health issues. Also, social isolation is a worry where parents feel that children will forget to engage with the real world and lose social skills required to live a fulfilling life.	Screen time, digital addiction, mental health, social isolation, social skills loss	Social isolation, aloofness	Health and well-being
Ethical issues pertaining to AI are also a concern for many. For example, AI can be biased, and	AI bias, algorithms, society, harm	Mistrust	Ethical Dilemmas

algorithms can be designed to cause harm to the society at large.			
Unequal access to technology creates concerns. Individuals also worry about exclusion. This is especially true for socio-economically weaker sections of the society who do not even have internet access. They will be left behind as compared to others from more affluent backgrounds and with good education.	Unequal access, worry exclusion, socio-economic groups, internet access, resource access access to education	Access	Digital Divide and Accessibility
Many fear that technology can lead to reduced face-to-face interactions. They worry that children will grow up in loneliness, get into shallow relationships, and may not be able to form community bonds that are important for them to live in the real world.	Face-to face, interaction, isolation, children, relationships, community bonds, real world, social skills loss	Isolation	Loss of Human Connection
Again, the fear of becoming overly dependent on technology bothers many. Many parents feel that children will lose their ability to think critically with such reliance.	Technological dependence, loss, critical thinking, children	Dependence, loss	Overreliance and dependence
Many are also worried about AI technology controlling all aspects of their lives. For example, smart homes raise concerns about surveillance and loss of control over their own lives. This can make them anxious. So, the problem is of losing the power to decide for oneself instead of being told what and how to do or live. Individuals want to retain agency over their decisions.	AI, loss of control. Surveillance, smart homes, anxious, decision-making ability	Control	Lack of Control and Autonomy

Table 7 - Themes development for Demographic factors

DEMOGRAPHIC FACTORS			
QUOTES	**KEY WORDS**	**CODE**	**THEME**
Age is also a factor. Older people are generally more closed to changes of any kind while younger people are more open to change.	age, older, closed to change, younger, open	Age	Generational differences
Education as I mentioned earlier is also a big divider. Those with good education are more likely to be more predisposed to new technological changes such as AI than others.	Education, technological predisposition	Education	Educational disparity
Then of course socio-economic status is also a factor. The poor do not have access to all the resources and facilities like the rich do and they may hence find it more difficult to prepare themselves or their children	Socio-economic status, access, facilities, difficult, prepare, children	Societal status	Socio-economic disparity
Gender differences are also important to look at. Women are less inclined towards technology. They are also the primary parent for children. So, their own perceptions and attitudes can impact what they allow the child to get exposed to.	Gender, women, technology	Gender	Gender Gap

Themes were then categorized to assess if they fit under any identifiable variables for further investigation.

4.9 Results: Study 1

Main themes largely fell under four key terminologies Innovativeness, attitudes, collaboration and concerns. These became the key variables that answered our research question.

The same are presented in Figure , Figure, Figure and Figure below

Figure 2 - Innovativeness

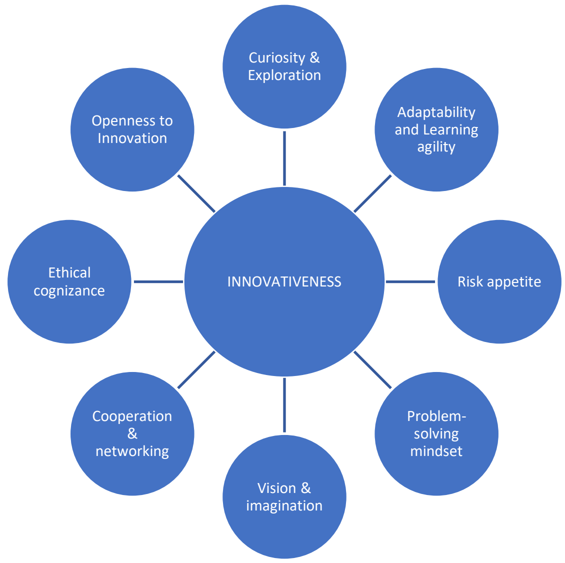


Figure 3 - Attitudes

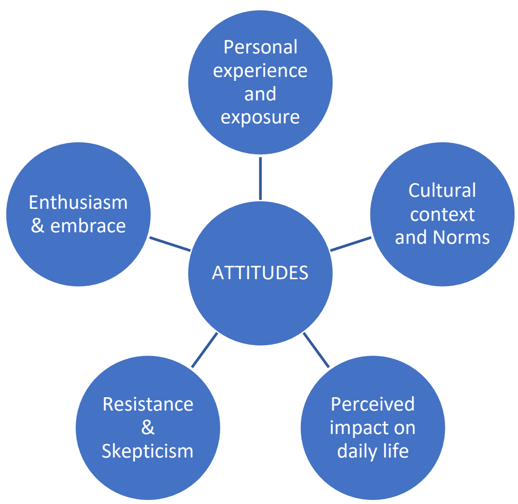
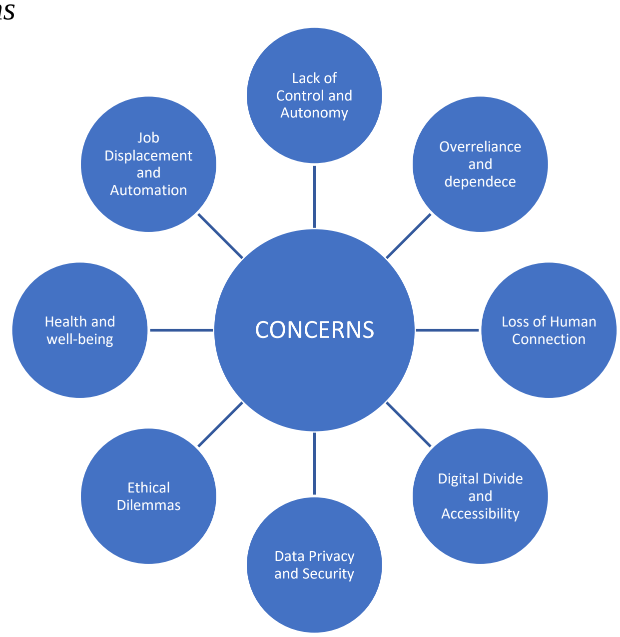


Figure 4 - Collaboration

Figure 5 - Concerns



Basis these findings literature was reviewed further to find support for the identified variables. The aim is to develop a model to assess preparedness for AI (CAIL in this context). There is evidence in literature that supports each of these variables as having influence on preparedness for technological change among individuals. The following section views these variables in detail with the support of theoretical frameworks where possible.

4.9.1 Literature support

The aim of this dissertation is to identify the various factors that predict preparedness of parents for introduction of CAIL initiatives in primary schools for their children in order to develop a model for preparedness predictors. There currently is no single model framework that can fully assess parental readiness for what will be introduced in their child's learning. Hence the focus for this part of the dissertation was on identifying literature that provides some suggestions on any factors that influence preparedness in individuals that have been identified through the qualitative interview in Study 1. Hence a combination of theoretical frameworks remained the focus of initial exploration alongside qualitative data collection. The aim is to develop a model framework that can help assess preparedness for AI and CAIL.

For the purpose of this study Theory of Diffusion (Rogers et al., 2003, 2014; Zolait, 2020), psychology based study of affective attitudes (Shank et al., 2019), Technology Readiness Index (TRI) framework (Parasuraman, 2000; Parasuraman and Colby, 2015) were found partially useful to understand the key variables of interest namely innovativeness, attitudes, collaboration and concerns as predictors of readiness.

4.9.1.1 Change Readiness

Change readiness refers to the state or level of preparedness of individuals, teams, or organizations to effectively adapt and respond to changes. Readiness to change also refers to the state of being willing and open to participate in a specific process or to adopt a specific behaviour (DiClemente et al., 2004).

The Transtheoretical Model of Change (Norcross et al., 2011) is the leading paradigm for understanding readiness. The term "readiness for change" is commonly used in both conceptual and empirical research as a dependent variable. Some past studies on organizational change have shown that change readiness is dependent on self-efficacy, positive attitudes towards change, access to information and active participation (Oreg, 2006; Wanberg and Banas, 2000).

Technology readiness can be understood as a mindset or disposition towards technology. Some studies in the field of IT adoption acknowledge the notion of "unfreezing" from theory of social change (Lewin, 1948, 1947).

Technology readiness, which denotes an individual's inherent inclination to adopt and utilize novel technologies to achieve objectives in both personal and professional domains (Parasuraman, 2000) was conceived as a personal quality rather than a state but has proven to be a useful measurement instrument for individual’s technological readiness. Technology readiness can be likened to the readiness for change, as it reflects an individual's willingness to at least try using technology (Lin et al., 2007). Lin and his colleagues defined technology readiness as comprising four subdimensions: optimism, innovativeness, discomfort, and insecurity. Optimism entails a favourable perspective on technology as a whole, and the conviction that it provides individuals with greater authority, adaptability, and effectiveness. Innovativeness refers to the inclination to be at the forefront of technology and to be an influential figure in shaping opinions (Rogers, 2003). Discomfort is a state of feeling powerless and overwhelmed by unfamiliar technologies. Insecurity is a manifestation of a lack of trust in new technology and doubt over its functionality. Technology readiness is considered to have an impact on one's attitude towards the usage of a particular technology, similar to how perceived ease of use and perceived utility affect it. However, it is important to note that technology readiness is a characteristic, while the other two factors are temporary conditions.

Several theories exist that elucidate consumers' adoption of novel technologies and their inclination to utilize them. A brief enumeration of the theories is presented below.

Technology readiness (TR) pertains to individuals' inclination to adopt and utilize novel technologies to achieve objectives in both personal and professional domains (Parasuraman and Colby, 2001). Parasuraman and Colby (2001) categorized technology consumers into five divisions based on their technology readiness score and level of technology readiness. These segments are explorers, pioneers, sceptics, paranoids, and laggards. This is analogous to the S-shaped adoption curve proposed by Rogers (1995), which categorizes individuals into innovators, early adopters, early majority, late majority, and laggards. The process of spreading new ideas or products, known as the diffusion of innovation, is a widely studied phenomenon. The readiness of technology is crucial for the successful implementation of a company because it determines its market emphasis.

Task-technology Fit (TTF) focuses on the individual's influence (Goodhue and Thompson, 1995). Individual impact pertains to the enhancement of efficiency, effectiveness, and/or superior quality. Goodhue et al. (1995) posited that a strong alignment between the job and technology enhances the probability of usage and boosts performance impact. This alignment occurs when the technology closely matches the needs and desires of users. This paradigm is well-suited for examining the practical use of the technology, particularly for testing new technology and obtaining feedback. The task-technology fit is an effective measure for evaluating technology applications that have already been released in the marketplace, such as those found in the Google Play Store or Apple Store app (iTunes), among others.

The Theory of Reasoned Action (Fishbein and Ajzen, 1977) is a widely used theory that focuses on a key factor in determining an individual's behavioural intention based on their attitudes towards a particular behaviour. In their 1975 study, Fishbien and Ajzen provided definitions for key terms. They defined "attitude" as an individual's assessment or judgment of an object. They defined "belief" as the connection between an object and a specific quality. Lastly, they defined "behaviour" as the outcome or purpose resulting from these evaluations and connections. Attitudes are emotional and derived from a specific set of beliefs regarding the target of one's actions, such as the opinion that credit cards are convenient. Another component is an individual's subjective norms, which refers to their perception of their immediate community's attitude towards specific behaviours. For example, if someone's peers are using credit cards and they view it as a status symbol, this can influence their own behaviour.

Theory of Planned Behaviour, focuses on a single component that influences an individual's intention to engage in a certain behaviour: their attitudes towards that behaviour (Ajzen, 1991). The initial two criteria align with the Theory of Reasoned Action proposed by Fishbein and Ajzen in 1975. The third aspect, referred to as perceived control behaviour, encompasses the extent to which consumers believe their actions may be restricted.

The Decomposed Theory of Planned Behaviour (Decomposed TPB) comprises three primary determinants that influence the intention to engage in a behaviour and the actual adoption of that action (Taylor and Todd, 1995). These determinants are attitude, subjective norms, and perceived behaviour control.

The Theory of Planned Behaviour, proposed by Ajzen in 1991, and the Decomposed Theory of Planned Behaviour, developed by Taylor and Todd in 1995, are commonly employed in the context of existing items in the market. These theories incorporate the societal perspective, particularly through the consideration of subjective norms.

The Technology Acceptance Model (TAM)) is a modified version of the Theory of Reasoned Action that is specifically designed to analyse and predict consumers' acceptance of information systems or technologies (Davis, 1985).

Technology Acceptance Model (TAM) was used by the author to elucidate the behaviour of computer usage (Davis, 1989) with the aim to elucidate the fundamental factors that influence the acceptance of computers, hence explaining user behaviour across many types of end-user computing technologies and user groups. The fundamental TAM model incorporated and examined two distinct beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Perceived Usefulness is the subjective probability that a potential user believes that using a specific system, will enhance their actions. Perceived Ease of Use, on the other hand, refers to the extent to which a potential user anticipates that the target system will be effortless (Davis, 1989). One's perception of a system can be impacted by external variables in the Technology Acceptance Model (TAM).

Venkatesh and Davis (1996) developed the definitive version of the Technology Acceptance Model. They discovered that both perceived usefulness and perceived ease of use directly affect behavioural intention, rendering the attitude construct unnecessary. Venkatesh and Davis (2000) introduced the Technology Acceptance Model 2 (TAM 2). This study offered comprehensive explanations for the factors that users perceived as valuable in a particular system at three specific time points: before installation, one month after implementation, and three months after deployment. According to TAM2, users evaluate how well their main work goals align with the outcomes of using the system, and this evaluation influences their view of the system's usefulness (Venkatesh and Davis, 2000). The findings indicated that TAM 2 demonstrated strong performance in both voluntary and forced settings.

In 2008, Venkatesh and Bala merged TAM2 with the model of the determinants of perceived ease of use to create TAM3, an integrated model of technological adoption.

The TAM3 was constructed by incorporating four distinct categories: human differences, system characteristics, societal impact, and facilitating conditions. These categories serve as factors that influence the perception of utility and ease of use. The TAM3 research model incorporates the moderation of experiences on the relationships between perceived ease of use and perceived usefulness, computer anxiety and perceived ease of use, and perceived ease of use and behavioural intention. The TAM3 research model underwent testing in real-world environments where IT implementations were carried out.

Venkatesh, Morris, Davis, and Davis (2003) conducted a study based on earlier models and theories, resulting in the development of the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model includes four factors that predict users' behavioural intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. The performance expectancy in the UTAUT model is composed of five related constructs: perceived usefulness, extrinsic incentive, job-fit, relative advantage, and result expectancies. On the other hand, effort expectancy encompasses the concepts of perceived ease of use and complexity. In terms of the social setting, Venkatesh et al. (2003) conducted validation tests and determined that social influence did not have a substantial impact in voluntary contexts.

These theories have been widely used however do not allow for assessment of all the variables of interest pertaining to this dissertation. Hence for the purpose of this research a combination of theories that help this research has been identified and the same are enumerated below.

4.9.1.2 Theory of Diffusion

The concept of innovativeness, or personal innovativeness, originates from the field of innovation theory. Innovativeness can be defined as an individual's capacity to embrace and utilize new technology, products, services, (Rogers et al., 2003) or ideas

(Midgley and Dowling, 1978) ahead of others. Forward-thinking individuals have a reduced level of anxiety towards dangers, display a strong curiosity towards novel concepts, and possess a more favourable attitude towards embracing new technologies. In simpler terms, innovativeness refers to an individual's capacity to embrace risk and maintain a positive mindset towards novelty (Bommer and Jalajas, 1999). Innovative persons possess a strong inclination towards and are receptive to novel concepts, have the ability to handle situations with a high degree of uncertainty, and overall have a more favourable disposition towards novelty (Rogers et al., 2003). Research has found that innovativeness can greatly influence how people perceive risk in relation to new and developing technology advancements (Makki et al., 2016). Innovation has been utilized as a quantifiable factor in assessing an individual's readiness for technology, (Parasuraman, 2000; Parasuraman and Colby, 2015). The technological readiness index (TRI) incorporates innovativeness as a component to assess an individual's inclination to embrace and implement state-of-the-art technology in various facets of their everyday life, whether it be at home or in the workplace. Personal innovativeness is an inherent characteristic in individuals that enables them to engage in experimentation, learning, and discourse on novel technical advancements (Blut and Wang, 2020a) both in their personal lives and professional environments. Innovation is regarded as a catalyst that has a favourable impact on technical readiness, as well as optimism (Godoe and Johansen, 2012). Research has shown that creativity has a crucial role in shaping the perception of new technologies in terms of their utility and ease of use. The acceptability and utilization of technology depend on three crucial factors (Blut and Wang, 2020). The level of innovativeness also acts as a mediator in the correlation between perceived usefulness and technology usage. Specifically, this effect is more noticeable for persons who are more innovative. Further, the level of creativity impacts the technical inclinations of persons. Individuals with a greater propensity for invention often show a preference for hedonic technologies, which emphasize amusement, rather than utilitarian technologies, which highlight practical functions. Innovativeness is a dynamic attribute that is neither fixed or consistent, but instead varies and depends on certain conditions. It can also evolve gradually, as individuals acquire more information and encounter new technologies, or as their particular circumstances alter. Hence, it is imperative to assess and grasp the degree of novelty in relation to the particular technology and pertinent circumstances.

The theory of diffusion can elucidate the role of innovativeness in influencing parental readiness for the implementation of child AI literacy in primary classrooms. The diffusion of innovation theory examines the process by which new ideas and practices are spread among individuals within a social system (Zolait, 2020). This study investigates the process of adopting innovation and the various aspects that impact it. Within the realm of child AI literacy (CAIL), this theory can provide insights into the process by which parents develop an openness to the concept and subsequently embrace it for their children. The idea posits that elements such as exposure, awareness, experience, and knowledge have an influence on the process of adoption (Sampaio et al., 2012). By comprehending these variables, educators and policymakers can formulate tactics to foster AI literacy among children and tackle any anticipated hazards or ambiguities linked to the advancement (Sampaio et al., 2013). In addition, engaging in practical tasks and using narrative techniques can be highly effective approaches for youngsters to acquire knowledge about AI and its significance in daily existence (Rogers et al., 2003, 2014). The Theory of Diffusion has been extensively utilized and has demonstrated strong predictive capability in elucidating the acceptance and spread of innovations across several sectors. It offers a structure for comprehending the mechanisms and reasons behind the dissemination of innovations among a population. The idea posits a linear and uniform adoption process, disregarding the intricacies and diversities in individuals' adoption behaviours. It may not comprehensively encompass the various incentives, obstacles, and decision-making processes that individuals experience when adopting innovations. Additionally, the theory does not clearly take into account the impact of contextual elements, such as cultural, economic, and organizational factors, on the process of dissemination. These elements can have a substantial influence on the acceptance and spread of new ideas and may not be sufficiently considered by the theory. Moreover, this framework predominantly emphasizes the assimilation of novel ideas and may not offer a thorough comprehension of the lack of assimilation or the rationales behind individuals' decisions to refrain from adopting specific innovations. It might fail to consider significant observations regarding obstacles and opposition to acceptance.

4.9.1.3 Attitudes

Parental attitudes towards AI use in early childhood education are influenced by factors such as perceived risks and benefits, as well as the collaborative and communicative experiences of children from different socio-economic and cultural backgrounds. An individual's mindset can significantly influence the acceptance of new technologies or advancements, such as AI. To assess attitudes the affective attitude measure developed by Shank et al. (2019) and subsequently modified by Park and Woo

(2022) has proven to be extremely efficacious. Affective attitudes, which refer to an individual's emotional responses or feelings towards a certain object or concept, significantly impact the adoption of new innovative technologies (Park and Woo, 2022; Shank et al., 2019). These attitudes can significantly influence an individual's willingness to adopt and employ new technologies such as AI. A study found that the majority of persons exhibit various emotions, such as astonishment, wonder, happiness, disappointment, amusement, anxiety, and confusion, (Shank et al., 2019) when engaging with an AI that has consciousness. These emotional reactions occur during the process of experiencing the mind, as individuals navigate between the conflicting concepts of programmed technological devices and behaviours that mimic those of human minds. The findings suggest that people's emotional attitudes towards AI might be complex and varied, encompassing both positive and negative thoughts (Shank et al., 2019). Further, a link was found between extraversion and unpleasant feelings, as well as decreased functionality. Agreeableness had associations with both positive and negative emotions, and it revealed a favourable correlation with social interaction and effectiveness (Park & Woo, 2022). These findings suggest that emotional attitudes are influenced by both the technology itself and the individual's personality traits. Acquiring understanding of these factors may help enhance the creation of technologies and services that are more likely to be accepted and adopted by users and even an individual's preparedness for use of new technological developments such as AI.

4.9.1.4 Collaboration

There have been several studies on collaboration between parents and teachers on students’ education in the past three decades. And views have evolved on the importance of parents' role in their children's learning largely due to the adoption of comprehensive approach in education or the holistic approach in learning. This approach focuses on nurturing all aspects of a student's development, including cognitive, social, emotional, and spiritual components. Adopting a comprehensive approach in education necessitates redefining the roles of both teachers and parents. Research shows that parents' positive attitudes and actions towards their children's learning, schooling, and schools have a productive and positive impact. Research has clearly demonstrated that the position of parents has a good effect on adolescents' academic performance and overall learning (Epstein, 2018; Goodall and Montgomery, 2014; Hoover-Dempsey et al., 1992; Hoover-Dempsey and Sandler, 1995; Silinskas et al., 2015). Studies on parental engagement in education have primarily concentrated on the beneficial impact it has on students' academic performance, self-perception about accomplishment, and intrinsic motivation. Research on involvement in recent decades has primarily focused on influential frameworks that define it as parents' engagement in their children's schools or education, namely in the educational activities related to learning in school. A framework categorized parental involvement in their child's learning under three categories (Grolnick and Slowiaczek, 1994). This framework categorizes parents' involvement into behavioural, personal, and cognitive-intellectual aspects based on their participation in school activities, positive interactions with their children, and extended support at home to enhance their children's skills. Another model emphasizes the importance of relationships between parents and educators, outlining the various benefits of incorporating parents in schools for students, teachers, and parents themselves (Epstein, 2018). The two models mentioned focus on parental involvement from both a school-based and home-based standpoint. School-based involvement involves parents interacting with instructors and the school community, whereas home-based involvement includes helping with homework, providing study support, and discussing school matters with children. Research has demonstrated that the connection between academic achievements and parents' involvement in school activities is not as strong as the connection between academic achievements and parents' involvement in activities at home. Recent research has increasingly highlighted the need of successful communication between teachers and parents, shifting towards a more family-cantered approach and raising questions about the concept of parental engagement and its effectiveness. The term "involvement" should be eliminated and substituted, as recommended. Parental engagement has been increasingly prominent in studies on home-school relationships, particularly in the United States and the United Kingdom, revealing new insights on the topic. This is particularly true for studies that examine parental involvement comprehensively, aiming to explore not just the impact of parents on child's academic achievement, but also their influence on communication between teachers and parents, as well as parent-child interactions beyond academics (such as parenting styles and non-academic activities outside of school). Consistent viewpoints are present in educational policy texts from international organizations (Bollmann et al., 2021; Programme for International Student Assessment, 2012). Goodall and Montgomery (2014) developed a contemporary paradigm on parental participation by incorporating and expanding upon existing parental involvement techniques, drawing from various findings and prominent ideologies. Goodall and Montgomery's model focuses on the interaction between parents and their children, emphasizing their children's learning both academically and non-academically, both in and out of school. This model differs from earlier ones by not emphasizing the parents' relationship with schools or their children's schooling. Goodall and Montgomery's approach assumes that children's learning takes place in various contexts beyond the school environment, with the home environment, experiences, and other contexts influenced by parents playing a significant role in children's learning. This paradigm is depicted as a dynamic continuum consisting of three primary points, along which the parent-teacher duo can navigate during their exchanges about the child's learning. Goodall and Montgomery (2014) define parental engagement as involving a deeper commitment and sense of ownership in parenting actions, where parents are aware of their responsibility. According to this model, a genuine teacher-parent relationship involves open-mindedness, mutual learning, shared interest in each other's perspectives, and a sincere concern for the child's overall well-being beyond just academic success. Teachers recognize parents' expertise on their children and elevate their position. Both teachers' and parents' viewpoints are important and have equal influence on the children's learning. The framework provided enables the examination and understanding of significant relationships between parents and teachers about children's learning from a holistic viewpoint. Engagement, as opposed to involvement, denotes a wider and more global concept, along with a more proactive and authentic approach from parents. The term "children's learning" is used in this framework to emphasize that the learning process is not limited to the classroom or school environment but is essential for the holistic development of the student in various aspects of life such as cognitive, social, moral, emotional, and spiritual growth. Goodall (Goodall, 2016) introduces the term dialog to more accurately describe a two-way communication pattern in a partnership.

Parental collaboration in child’s learning has two aspects namely parent-child collaboration and parent-teacher collaboration.

4.9.1.4.1 Parent-teacher

Evidence from research shows that teachers believe family involvement is crucial for students' academic success. They acknowledge that parents play a positive role in enhancing learning outside of school, particularly by supporting homework. This type of parental involvement is highly valued.

Teachers' psychological and behavioural traits related to parental engagement have shown a substantial correlation with the actual level of parental involvement (Eccles, 2007; Hoover-Dempsey et al., 2005; Simpkins et al., 2015; Souto-Manning and Swick, 2006).

Enhancing communication between home and school and the quality of teacher-parent interactions, rather than the quantity of interactions, are key factors in building trust between teachers and parents (Adams et al., 2016; Adams and Christenson, 2000; Christenson and Reschly, 2010; Epstein, 2018; Hoover-Dempsey et al., 2002). It is crucial for each dialogue to make instructors and parents feel heard and valued, rather than maintaining frequent communication without genuine dedication and interest from both parties. Effective communication between parents and teachers, where parents feel listened to and their opinions valued, is critical for establishing trust and positive relationships. Parental participation increases when parents perceive that teachers involve them and appreciate their input (Epstein and Sanders, 2006; Hoover-Dempsey et al., 2005).

4.9.1.4.2 Parent-child collaboration

Research has extensively examined the impact of parents on their children's academic success (Eccles, 2007; Grolnick and Slowiaczek, 1994; Hoover-Dempsey and Sandler, 1995; Peixoto and Carvalho, 2009). Parents' financial level and educational background are recognized as indicators of students' academic performance, school adjustment, and parental engagement (Epstein, 2002; Hornby and Witte, 2010; Kim, 2009). Literature consistently shows that parents respond positively to their children's learning when teachers expect and encourage parental involvement. This is believed to help parents see their role as important through the perspective of teachers. In recent times, there has been a growing focus on studying the role and attitudes of parents in parental participation. The phenomenon can be partly attributed to the historical perspectives of schools and homes viewing each other as distinct entities with unique and complementary goals. In this view, children's education was seen as the responsibility of schools, while parents were solely responsible for their children's overall well-being and healthy growth. Recently, the integration of these two significant duties has led to a growing consideration of the holistic perspective on the importance of parents' attitudes and conduct. Current research indicates that parents who recognize the significance of their involvement in influencing their child's academic success are more likely to support the development of their child's interests, as opposed to parents who do not perceive their position as significant. Research has identified role assumptions that are partly associated with what modern expectancy-value theory defines as task-value (Eccles and Wigfield, 2002). Beliefs about the importance of a task play a crucial role in influencing one's decision-making, perseverance, and involvement in tasks. Eccles and Wigfield (2002) identified four elements of task-value: attainment value, intrinsic value, utility value, and expenses. Parental engagement components include the parent's personal value in contributing to their child's learning, their genuine enjoyment in doing so, the connection between contributing to their child's learning and their personal life goals, and the effort or negative experiences they associate with the process. Recent research indicates that parents' genuine interest and enthusiasm in their children's learning have long-lasting positive effects. Parents who engage in leisure reading with their young children and have informal discussions with their adolescent children on political or social topics are more likely to positively influence their children's life and academic achievements compared to parents who do not. Engaging in these practices with children from a young age can influence not only their language skills in the future but also their development of important cross-cutting competencies, like the ability to plan, establish goals, and effectively pursue their studies and personal projects. Collaborative efforts between parents, teachers, and children can create a stimulating environment for learning and enhance children's early literacy acquisition skills (Osabinyi and Ouko, 2023). Additionally, parents who engage in collaborative activities with their children, such as reading together, can contribute significantly to their children's learning and development (Dai et al., 2023). Further, parents who are willing to engage and believe that schools are open to facilitating their involvement are more likely to participate in AI literacy initiatives (Druga et al., 2022a). Therefore, fostering collaboration and communication between parents, teachers, and children is crucial for parental readiness and support for child AI literacy initiatives in primary schools. Collaboration has not yet been widely studied as a factor that can impact readiness of individual’s for adoption and use of new technology such as AI. And this study endeavours to assess if collaboration is a factor that predicts Parental readiness for AI and in particular introduction of CAIL in primary schools of UK.

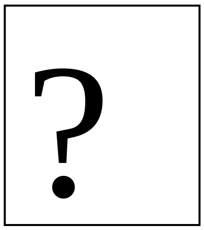
4.9.1.5 Concerns

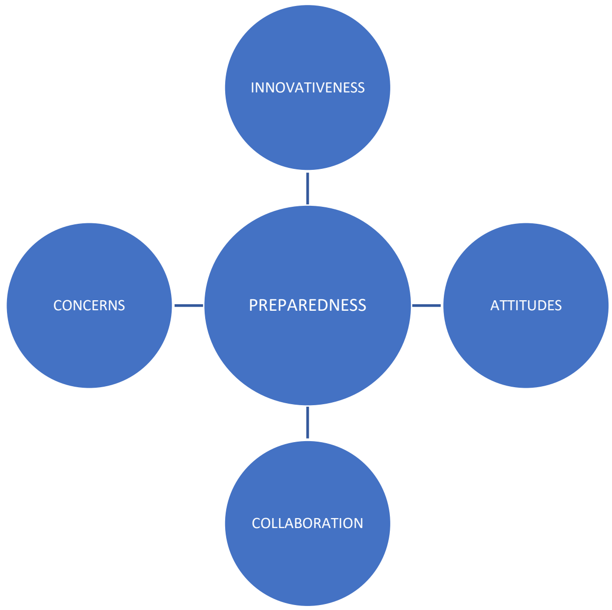
Parental concerns in the context of this study would entail personal insecurities to do with new technology such as AI, their worries pertaining to their child's exposure to technology such as AI. Parental concerns related to new technology, especially its impact on children, have been a topic of interest. In UK in the past few years there have been several news articles that have highlighted parental concerns pertaining to children's technology use. Another report based on UK wide surveys highlighted the challenges of homeschooling during Covid, stating that 40% families were not equipped with laptops, stationary and internet to facilitate children's remote learning (CPAG, 2020). A survey found that 43% of the 7000 surveyed European parents worried about how excessive engagement with and use of technological gadgets impacted their child's sleep quality, 38% worried about how using tablets and mobile phones affected their children's social skills and 32% were concerned about how excessive technology use was impacting the mental health of their children (BBC News, 2018) . Similar concerns among parents were also reported in The United States (Clark and Woolford, 2023) by a study conducted by University of Michigan Health.. However a study also found that parental concerns pertaining to increased screen time or other technology interactions with screens of their toddlers were not a detriment but beneficial for child's learning (Plowman et al., 2010). Another study studied both positive and negative effects of digital technology use in children and emphasized that excessive technology use could be problematic (Žulec et al., 2022). AI literacy initiatives in primary schools. Parents believe that new technologies, including AI, are beneficial for their children's learning process (D. Ng et al., 2022). However, they also have concerns about excessive screen time and the potential impact on their children's socialization skills (Voulgari et al., 2022). Understanding how AI systems work and developing critical thinking skills are seen as crucial for children to navigate the benefits and challenges of AI (Lin et al., 2020). Educators play a critical role in AI education and literacy by providing teacher training courses on AI and ML education (Kaltsidou et al., 2020). By employing pedagogical strategies such as digital story writing (DSW), educators can effectively foster students' AI literacy by improving language and technological abilities (Druga et al., 2019). Two dimensions of Technology Readiness Index (Parasuraman, 2000; Parasuraman and Colby, 2015) framework facilitate an understanding of inhibitors, that impede the adoption of new technology. These inhibitors are Insecurity and discomfort. Insecurity refers to a deficiency in trust and a sense of unease when using technology, sometimes stemming from a fear of making mistakes. Discomfort refers to the perception of being overwhelmed or dominated by technology (Blut and Wang, 2020). When contemplating the integration of AI instruction in schools, the TRI can function as an appropriate instrument to evaluate participants' concerns. The dimension of insecurity can be employed to assess the degree of confidence that participants place in AI technology, as well as their apprehensions around privacy and inaccuracies. The discomfort component can help determine if participants feel overwhelmed by the concept of AI training. In addition, the TRI facilitates the investigation of emergent concepts, such as the idea that technology can potentially have a dehumanizing effect. This holds particular importance when assessing concerns over the introduction of CAIL in primary schools (Parasuraman, 2000; Parasuraman and Colby, 2015).

4.9.2 Conclusion

Initial qualitative interview in Study 1 combined with literature review shows ample support for the variables generated for further study. Innovativeness, attitudes, collaboration and concerns were the identified variables of interest. These variables find evidence in research as factors influencing preparedness as has been shown in the previous section. In addition, there is some evidence that certain demographic factors also have some bearing on preparedness. However, no single theoretical framework encompasses all these variables thus making an argument for development of a model framework for testing (Figure 6)

Figure 6 - Constructed Theory: Predictors of preparedness model





However, in order to develop the model, the variables need to be tested rigorously. For this reason, hypotheses were designed for further testing which are as follows:

H1: *Innovativeness predicts preparedness for CAIL in parents*

H2: *Attitudes predict preparedness for CAIL in parents*

H3: *Collaboration predicts preparedness for CAIL in parents*

H4: *Concerns predict preparedness for CAIL in parents*

4.10 Summary

Unsystematic research of available literature shows us that AI technology whilst ubiquitous in nature still remains less understood by people which often leads to misconceptions and aversion to usage of this technology. AI Literacy is hence being viewed as an important bridge to set right both expectations and perceptions of what AI can and cannot do. AI education has largely remained an area of study within computer science courses at university level so far. But recent research has emphasized that AI education must be provided to all. This essentially means AI education/AI Literacy, is imperative for even those that do not have a technical educational background, given that AI is being predicted to remain at the heart of all future technological development. AI Literacy and its importance has been recognized by global entities as well as governments across the globe and some have also mandated that basic concepts of AI be taught to students in schools as well, in order to prepare the next generation to get a head start and thrive in an AI driven environment in the future. Whilst this may be true research in the field of AI Literacy has gained momentum only in the past three years and there is much more research required to fully comprehend what to teach, how to teach and with what tools to teach. A few breakthroughs in the form of frameworks have been developed and are being tested by various researchers globally. Collaborations between AI developers and teachers and governments are being suggested as the path forward to develop age-appropriate curriculums to teach basic concepts of AI at K-12 school levels. However very little is known about how parents, students and teacher will adopt CAIL. Studies have shown that parents play a key role in a child's learning experiences and it is thus important to understand how ready they are for the introduction of CAIL initiatives in primary schools for their children. Parental readiness for CAIL may be influenced by several factors to do with their own personality traits, and demographic characteristics.

The UK was the first country to introduce coding and programming courses in schools at K-12 levels in 2014 as part of digital literacy initiative and as such acknowledges the importance of AI literacy in schools. However, there is a dearth of studies that explore the various factors influencing readiness/preparedness of parents for such initiatives especially in the UK context.

Hence in order to understand the various factors that influence parental readiness for CAIL a single research question was formulated:

RQ: What are the various factors that influence parents' readiness for introduction of CAIL initiatives in primary schools in The UK?

Qualitative interview with an AI expert in combination with literature review helped identify some key variables of interest for further investigation. Hypotheses were designed to understand the role of each of these variables (innovativeness, attitudes, collaboration, concerns) in predicting parental preparedness for CAIL. In addition, there was a suggestion that demographic variables also play a part in preparedness of individuals. All these aspects will be investigated in Study 2 which utilizes a quantitative approach to test the hypotheses.

CHAPTER V:

STUDY 2: QUANTITATIVE APPROACH

5.1 Operationalization of Theoretical Constructs

This phase of dissertation, namely Study 2, exemplifies one of the results of an action research-oriented, mixed method approach. It should be noted that the data collection process involved gathering additional data that is not included in this study. This investigation is conducted at the individual level of analysis, using an instrument that consists of scales specifically designed for this level. Further, the selection of participants for this study was based on their alignment with the previous qualitative study and the specific objectives of the research. Since there is little research to understand the various factors that predict preparedness of parents for CAIL this study focused on the key variables generated from the themes of Study 1.

5.2 Research Purpose and Questions

A quantitative approach was adopted for this stage of research to test the following hypotheses:

Hypotheses

H1: Innovativeness predicts preparedness for CAIL in parents

H2: Attitudes predict preparedness for CAIL in parents

H3: Collaboration predicts preparedness for CAIL in parents

H4: Concerns predict preparedness for CAIL in parents

However, since this phase of research is also focused on confirmation as well as further exploration, demographic variables and their impact on parental preparedness for CAIL, as well as certain other aspects were also assessed in the data.

5.3 Research Design: Study 2

A quantitative approach was adopted for study 2. Quantitative research design is a robust and methodical strategy to gathering and examining numerical data (Bhandari, 2023). It has vital significance in multiple domains. Quantitative research differs from qualitative research in that it concentrates on numerical data to identify patterns, averages, and correlations between variables. Statistical models and mathematical approaches are employed to assess hypotheses and derive results. The quantitative method has numerous advantages. Firstly, it offers factual and confirmable information. Scientists have the ability to assess and measure phenomena, which enhances the reliability of the results and reduces the likelihood of bias.

When analysing participants' demographics, quantitative data enables us to objectively determine precise trends and behaviours.

Further, quantitative research enables the generalization of findings to broader populations. Through the utilization of suitable sampling techniques, researchers are able to make inferences that extend beyond the sample being studied.

Additionally, quantitative research has the advantage of being replicable. Establishing standardized data collection techniques and providing clear descriptions of abstract terms allows other researchers to replicate the study.

Replication improves the reliability of research findings and promotes scientific advancement.

Further, individuals involved in quantitative studies have the option to maintain their anonymity. Quantitative data collecting does not require identifying information, unlike qualitative research which often involves personal revelation.

The ability to remain anonymous fosters engagement and minimizes potential prejudices.

Quantitative research design offers a systematic and rigorous framework for comprehending intricate phenomena. The advantages of this approach are rooted in its impartiality, generalizability, and efficiency. Researchers enhance evidence-based decision-making in diverse fields by using quantitative methodologies.

Moreover, the utilization of quantitative research design significantly contributes to improving the efficacy of both sequential exploration and following sequential explanation research designs (Gogo and Musonda, 2022).

During the preliminary investigation stage, scientists aim to comprehend a phenomenon, detect regularities, and formulate theories. During this stage, qualitative methods are frequently used to extensively investigate the background, individual experiences, and emerging themes.

Quantitative research enhances its worth by offering a systematic framework for gathering and analysing data. Collecting quantitative data guarantees that there is uniformity and the capacity to make comparisons between different examples or contexts. Researchers have the option to employ standardized surveys, questionnaires, or assessments to accurately capture pertinent factors, or they can develop their own methods.

Moreover, the quantitative results obtained from exploratory studies have the potential to be extrapolated to broader groups. Qualitative insights provide detailed and precise information within a particular context, but quantitative facts enable us to deduce patterns that extend beyond the sample being researched.

Quantitative exploration ultimately aids in the identification of potential links and associations. During this phase, researchers have the ability to develop hypotheses by analysing numerical trends or correlations.

In the succeeding part of the research, which follows the exploration phase, the goal is to validate and provide explanations for the patterns that have been observed. Researchers go from providing descriptions to conducting explanatory analyses.

Quantitative research design remains valuable as it enables rigorous testing of hypotheses. Statistical techniques such as regression and ANOVA can be employed by researchers to analyse causal links and determine the importance of variables.

Through the process of quantification, researchers are able to ascertain the magnitude and orientation of correlations. This level of specificity improves our comprehension of the underlying causes of specific events.

Additionally quantitative models have the ability to forecast results by considering certain characteristics that have been identified. In this dissertation research, prediction models can be used to evaluate characteristics related to preparation.

Quantitative analysis offers p-values and confidence ranges, enabling us to assess the importance of discoveries. This provides information that is used to make decisions and formulate policy recommendations.

Thus, this research method has several advantages for this dissertation for both exploratory and explanatory purposes.

5.4 Population and Sample

In this study, for the quantitative phase we used convenience sampling to recruit participants for parents' survey. We chose this sampling method because it was the most practical and cost- effective way to reach a large number of potential participants in a short time. However, given that convenience sampling is susceptible to introducing biases in the data and compromise generalizability of study results, some additional steps were taken as a counter measure. Firstly, participant recruitment was done across multiple platforms instead of using a single venue or platform. Secondly a larger sample size was used to increase statistical power and precision of the study estimates. Finally, a strict criterion of inclusion and exclusion was used to ensure that the participants recruited fit the population appropriate for the study.

5.5 Participant Selection

A total sample size of 438 responded to the parents' survey. Of these post implementing inclusion exclusion criteria the total remaining sample size consisted of 403 individuals residing within the UK. Participants were parents or guardians of children in primary school, namely between the ages of 5 to 11. Participants with older or younger children were excluded from the sample. Further demographic characteristics for the description of the sample are presented in Table 8.

Table 8 - Factor loadings of Demographic characteristics of the sample

Demographic Variables		Percentage %
Gender	Male	34.7
	Female	65.0
Age	Under 18	0.2
	18-24	1.2
	25-34	30.3
	35-44	52.9
	45-54	12.7
	55-64	2.7
Relationship Status	Cohabiting with a significant other or in a domestic partnership	16.1
	Single, never married	10.4
	Married	69.2
	Separated	1.2
	Divorced	2.2
	Prefer not to say	0.2
Ethnicity	African	3.0
	Asian	15.1
	South American	1.7
	Chinese	1.2
	European	73.2
Income	Under £ 20,000	17.4
	Between £ 20,000 and £ 39,999	33.3
	Between £ 40,000 and £ 59,999	16.6

	Between £ 60,000 and £ 79,999	13.6
	Between £ 80,000 and £ 99,999	5.0
	£ 100,000 and above	13.2
Education	No / Low Education	6.5
	High School Education	28.3
	Partial College Education	15.4
	Vocational Education	3.0
	College Education	25.1
	Higher Education (Masters, PhD)	21.8
Employment Status	Disabled, not able to work	2.7
	Not employed, not looking for work	7.4
	Not employed, looking for work	5.7
	Employed, working part-time	15.6
	Employed, working full-time	63.8
	Business Owner / Self-employed	4.5
Child’s Grade Level	Primary Year 1 (5-6 years old)	21.3
	Primary Year 2 (6-7)	18.4
	Primary Year 3 (7-8)	13.6
	Primary Year 4 (8-9)	17.1
	Primary Year 5 (9-10)	12.4
	Primary Year 6 (10-11)	17.1

5.5.1 Missing values Analysis (Quantitative Survey)

In this study, missing data were carefully examined to assess the extent and patterns of missingness across the variables of interest and demographic characteristics. The percentage of missing values for each variable is presented in Table 9.

Table 9 - Counts and Percentages of Missing Values per Variable

		Missing	
Variables	N	Count	Percent
Innovativeness	403	0	.0
Attitude	403	0	.0
Collaboration	403	0	.0
Concerns	403	0	.0
Readiness	403	0	.0
Child’s Grade Level	403	0	.0
Gender	402	1	.2
Relationship Status	401	2	.5
Age	403	0	.0
Ethnicity	380	23	5.7
Income	399	4	1.0
Education	403	0	.0
Employment Status	402	1	.2
Child’s Readiness	395	8	2.0
CAIL as Tool	386	17	4.2
CAIL as Subject	390	13	3.2

The missing values in the dataset were examined to determine if they were missing completely at random (MCAR). Little's MCAR test was conducted on all variables, and the results indicated that the data were missing completely at random (χ^2 (5) = 4.03, p = .546). Missing scores on the interval scaled variables of innovativeness, attitudes, collaboration, concerns, and readiness were imputed using the Expectation Maximization algorithm to increase the statistical power of the analysis. All statistical analysis regarding missing values were performed according to the guidelines (Schafer and Graham, 2002).

5.6 Instrumentation

The measuring instruments of the variables of interest, namely, innovativeness related to AI technologies, attitudes towards AI, concerns towards AI, collaboration, and overall readiness for CAIL, were designed based on different references and adapted to fit the purpose of this study. The questionnaire was first circulated to 10 parents and two academicians specializing in AI education. The final survey was then designed using feedback and further reviewed by the two experts and post their validation the survey was opened for data collection. The survey was designed using the Survey Monkey website.

5.6.1 Innovativeness

Innovativeness or personal innovativeness emerges from innovation theory. One definition of innovativeness is an individual's ability to adopt new technologies, products and services (Rogers et al., 2003) or ideas (Midgley and Dowling, 1978) before others. Innovative individuals are less concerned about risks are curious about new things and more positively disposed to experiencing new technologies. In other words innovativeness is a trait that describes an individual's ability to take risk and also form positive attitude towards newness of things (Bommer and Jalajas, 1999). Innovative individuals have high acceptance for and are open to new ideas, can cope with high levels of uncertainty and generally have more positive attitude towards newness (Rogers et al., 2003). When it comes to new and emerging technological developments some studies have stated that innovativeness may have a significant negative impact on how risk is perceived (Makki et al., 2016). Innovativeness has been further used as a measurable aspect for an individual's technology readiness (Parasuraman, 2000; Parasuraman and Colby, 2015). The technology readiness index (TRI) uses innovativeness as one of the dimensions which measures the tendency of an individual to accept and adopt cutting-edge technology in all aspects of daily life be it at home or at work. Personal innovativeness is a trait in individuals that allows them to experiment, learn and talk about new technological developments (Blut and Wang, 2020a) at home and at work. Innovativeness positively influences technology use. Another aspect of the TR index is optimism, which is a general trust that technology and innovation have positive benefits.

For the purpose of this study, we have combined the two aspects of optimism and innovativeness to measure participants' predisposition towards AI technology and called it innovativeness regarding AI or Innovativeness. A scale was developed consisting of 6 items related to AI technologies such as *"I am generally among the first in my circle to acquire new AI technology as it comes out"* and *"Normally, I can use new AI products and services smoothly without help from others"*. The development of the scale was done using references from the TR index (Parasuraman, 2000; Parasuraman and Colby, 2015) questionnaire and modifying the same to make them relevant for the purpose of this study. Each item was rated on a 5-point Likert scale, from 1 ("*strongly disagree*") to 5 ("*strongly agree*"). The factor structure of the innovativeness scale was examined through Principal Component Analysis (PCA). The analysis revealed a single component (*EV* = 4.23), explaining a substantial proportion of variance (70.43%). All items loaded significantly onto this single component, suggesting a unidimensional structure of the innovativeness scale. Detailed presentation of the items and their component loadings is presented in Table 10. Regarding the internal consistency of the scale, the Cronbach's alpha was .92, indicating a very high reliability for the scale. To create the variable innovativeness the average response of each participant was calculated, therefore creating an interval scaled variable, in which high values indicate high levels of innovativeness pertaining AI technology.

5.6.2 Attitudes towards AI

Further to measure participants' attitudes towards AI a scale was developed consisting of 8 items pertaining to AI such as "*I am excited about the idea of introducing AI concepts to my students"* and "*The idea of AI's influence on teaching can make me fearful."* The development of the scale was based on (Park and Woo, 2022; Shank et al., 2019) questionnaire. Each item was rated on a 5-point Likert scale, from 1 ("*strongly disagree*") to 5 ("*strongly agree*"). Items that were negatively worded were reverse coded in a way that high values would suggest more positive attitudes towards AI. The factor structure for the scale was analysed with PCA, in which all items load into a single component (*EV* = 3.61) which explains 45.20% of variance (Table 10). Regarding the internal consistency of the scale, Cronbach's alpha was .82, suggesting a high reliability for the scale. To create that variable attitude the average response of each participant was calculated, therefore creating an interval scaled variable, in which high values indicate more positive attitudes towards AI technology.

5.6.3 Concerns pertaining to AI

Similarly to measure participants' concerns pertaining to AI and CAIL a scale was developed consisting of 9 items related to AI and CAIL such as "*I am concerned that my child's personal information shared with AI will be seen by other people"*, "*I worry that lack of well-trained teachers in some schools might affect the quality of AI education"* and *"I am concerned that AI education might be too complex for my child".* The scale was developed based on (Parasuraman, 2000; Parasuraman and Colby, 2015) questionnaire. Each item was rated on a 5-point Likert scale, from 1 (*"strongly disagree"*) to 5 (*"strongly agree"*). Principal component analysis was performed to investigate the structure of the scale. The results indicate that items load into a single component (EV = 5.69) and the percentage of variance explained 47.38% (Table 10). The reliability of the scale was very high with a Cronbach's alpha of .90. To create that variable concerns the average response of each participant was calculated, therefore creating an interval scaled variable, in which high values indicated higher concerns towards AI and CAIL.

5.6.4 Favourability towards Collaboration for CAIL

Further to measure how favourable participants were towards collaboration with other stakeholders such as students and parents in enabling CAIL a scale was developed consisting of 3 items such as *I am willing to collaborate with my child's teachers in teaching AI concepts* and *I am ready to engage with my child through activities at home* *that reinforce what is being taught about AI in school.* This scale was developed as an original scale to verify a previous study's outcome which exhibited that involvement of parents in a child's AI learning experience at home through games and activities enhances child's AI learning outside of school (Druga et al., 2022). Each item was rated on a 5-point Likert scale, from 1 ("*strongly disagree*") to 5 ("*strongly agree*"). From the PCA analysis it can be concluded that the scale is unidimensional, since all items load in a single factor (*EV* = 2.44), which explains 81.27% of the variance (Table 10). To create that variable collaboration the average response of each participant was calculated, therefore creating an interval scaled variable, in which high values indicate higher favourability towards collaboration for CAIL. Regarding the internal consistency of the scale, the Cronbach's alpha was .88.

5.6.5 Preparedness for CAIL

Further to measure participants' readiness for CAIL a scale was developed consisting of 7 items pertaining to AI such as "*I am comfortable with the idea of integrating AI into my child's learning"* and "*I feel confident in my ability to use AI tools and applications to teach my child"*. The development of the scale was based on (Parasuraman, 2000; Parasuraman and Colby, 2015) (Park and Woo, 2022; Shank et al., 2019) questionnaire. Each item was rated on a 5-point Likert scale, from 1 (*"strongly disagree"*) to 5 (*"strongly agree"*). Results of the PCA indicated that the scale is unidimensional with all items loading in a single component (*EV* = 4.68), which explains 58.34% of the variance (Table 10). Regarding the internal consistency of the scale, the Cronbach's alpha was .90, suggesting that the scale has a very high reliability. To create that variable readiness the average response of each participant was calculated, therefore creating an interval scaled variable, in which high values indicate more readiness for CAIL.

5 variables were developed in this study namely innovativeness, attitudes, concerns, collaboration and preparedness. In addition to these demographic variables such as gender, age, education levels, employment status, relationship status, ethnicity were also assessed to find correlations with the 5 variables. Further two stand-alone items were created to assess parents' preference on how CAIL must be implemented in schools. CAIL as tool refers to introducing CAIL as a tool to teach existing subjects in the curriculum such as English, math, science etc. CAIL as subject refers to introducing CAIL as an additional subject in the curriculum such as computer science, English, math etc. Another standalone item was created to assess parents' opinion on their own child's readiness for CAIL. These items will provide more information that may be beneficial for policymakers, curriculum designers and all stakeholders when introducing CAIL.

Table 10 - *Descriptive Statistics of the Scales and Summary of Principal Component Analysis Results*

Component	*M*	*SD*	*Eigenvalue*	*% of Variance Explained*	*Factor Loadings*
Innovativeness	3.49	.90	4.23	70.43	Item 1: .85 Item 2: .81

					Item 3: .87
					Item 4: .86
					Item 5: .78
					Item 6: .86
Attitudes	3.06	.70	3.62	45.20	Item 1: .73
					Item 2: .56
					Item 3: .76
					Item 4: .66
					Item 5: .74
					Item 6: .67
					Item 7: .68
					Item 8: .54
Collaboration	3.81	.84	2.44	81.27	Item 1: .92
					Item 2: .87
					Item 3: .91

Concerns	3.65	.67	5.69	47.38	Item 1: .57
					Item 2: .75
					Item 3: .78
					Item 4: .80
					Item 5: .75
					Item 6: .67
					Item 7: .60
					Item 8: .66
					Item 9: .60
Readiness	3.59	.77	4.66	58.34	Item 1: .59
					Item 2: .82
					Item 3: .80
					Item 4: .69
					Item 5: .82
					Item 6: .76

	Item 7: .77

5.7 Data Collection Procedures

Convenience sampling was used to collect responses for the quantitative survey. Data utilized in the study was collected using a survey form generated via Survey Monkey. An online AI survey was designed and was shared across parents' platforms for children studying in primary classes in the UK. The survey was left open from 4th of November 2023 until 12th December 2023. The platforms with which the survey link was shared include posts with survey link on relevant Facebook groups comprising of parents to primary class children in the UK, survey links sent to relevant WhatsApp groups comprising of parents of primary class children in the UK. Follow-up calls and messages were sent to group administrators to encourage parents to respond. Parents were compensated to participate in this study.

Participants were informed about the purpose of the survey and the study, at the beginning of the quantitative survey and also informed of their right to discontinue filling out the survey at any point before, during or after the survey was filled-out, thereby seeking informed consent from all participants. Confidentiality of any personal information was also assured at the beginning of the survey in the introduction section. The survey collected background data such as age-group of participants, education levels, gender, income, ethnicity, relationship status, employment status and job profile.

Additionally, data was collected through survey questionnaire on parents/guardians and their affinity towards technological innovations in AI (Innovativeness), attitudes towards AI, their opinion on collaboration with other stakeholders such as their children and teachers of primary class students to enhance child's AI learning experience, their concerns pertaining to AI and their preparedness to introduce CAIL in primary schools in the UK.

5.8 Statistical Analysis

First, descriptive statistics and Spearman correlations were computed among the variables of interest and demographic characteristics of the sample. Spearman correlations were chosen for this particular study because various variables are ordinally scaled and exhibit non-normal distributions. Upon investigation of significant correlations, further analytical decisions were made. Overall readiness for CAIL was consistently treated as the dependent variable in all subsequent analysis. When a significant correlation was detected between readiness and demographic characteristics, various statistical tests were employed to delve deeper into these relationships. This approach ensured a comprehensive exploration of the factors influencing readiness for CAIL, with a focus on both variables of interest (i.e., innovativeness, attitudes, collaboration and concerns) and relevant demographic characteristics. In addition to demographic questions, it was also investigated whether parents prefer introduction of CAIL as a separate additional subject (like math, science, English etc.) (CAIL as subject) or as a tool to teach existing subjects in classrooms (CAIL as tool). Further parents' opinion on the readiness of their child for CAIL was also checked.

In particular, a one-way ANOVA was computed to assess differences between various ethnic groups on their readiness levels for CAIL. A 2-way ANOVA was computed to examine the mean differences between parents' responses regarding their preference for introduction of CAIL as tool and CAIL as subject on their readiness levels. Next, a 2-way ANOVA was calculated to investigate mean differences of gender and income on parents' readiness for CAIL. Further, a 1-way ANOVA was computed to investigate differences in parents' readiness means related to their employment status and an independent samples t-test was calculated to examine differences in readiness according to their relationship status. Participants who reported to be single, divorced or separated were categorized as single parent household, whereas participants who reported to be married or cohabiting with a significant other or in a domestic partnership, were categorized as two parents/guardian households.

Finally, to predict the level of parents' readiness for CAIL a hierarchical multiple linear regression was computed with innovativeness with AI, attitudes towards AI, willingness to collaborate with other stakeholders (i.e. parents and children) and concerns regarding AI as predictors in block 1 and gender as a control variable in the second block.

Additionally simple percentages were calculated to assess parents' opinion on their child's readiness for CAIL. Quantitative data was computed using SPSS version 25.

5.9 Research Design Limitations

Quantitative study design as a stand-alone approach has some limitations such as reductionism, lack of depth, biases generated from sampling, measurement and researcher assumptions and lacks flexibility since it follows predefined protocols.

However, using this approach as part of sequential exploratory and sequential explanatory research design alleviates all these limitations and add a great deal of richness to the research. By integrating qualitative and quantitative methods in the main research design as is the case with this research, a balanced approach and rigorous in-depth findings are attainable.

5.10 Conclusion

This study utilised a mixed methods approach to initially explore the study topic and then further quantitatively assess the identified variables to understand how they impact preparedness for CAIL among UK parents of primary school going children. Target population comprised of parents with at least one child in primary class in the UK. Further participants needed to be residents of the UK to participate in the survey. Convenience sampling technique was used. Survey questionnaire was developed using appropriate scales and opened for participation for a month approximately. 438 participants responded to the survey. Post data cleaning and inclusion and exclusion criteria implementation 403 participants remained. Cronbach alpha for each of the scales was also computed and showed good consistency and scale reliability. Data was categorized and coded for further analysis. Missing value analysis was also conducted basis guidelines provided by Scahfer & Graham (2002). Appropriate techniques were then decided for further data analysis to test the hypotheses as also explore associations between dependent variable (preparedness) and other demographic variables. SPSS version 25 was used to compute the quantitative outcomes.

CHAPTER VI:

RESULTS: STUDY 2 QUANTITATIVE APPROACH

6.1 Hypotheses

H1: Innovativeness predicts preparedness for CAIL in parents

H2: Attitudes predict preparedness for CAIL in parents

H3: Collaboration predicts preparedness for CAIL in parents

H4: Concerns predict preparedness for CAIL in parents

6.2 Correlations

Spearman correlations are presented in Table 11. Results of the statistically significant correlations suggest that males are more in favour with CAIL as tool (r_s = -.12) and find their children more prepared for CAIL (r_s = -.12). Further, they have more positive attitudes towards AI (r_s = -.23), they more in favour of collaboration (r_s = -.11) and are overall more prepared for CAIL (r_s = -.13). Further, income was positively correlated with education (r_s = .31) and relationship status (r_s = .26), suggesting that participants with high income are more likely to have completed a higher level of education and be in a two parents or guardian households relationship status. Further, participants with higher incomes are more in favour of both CAIL as tool (r_s = .20) and subject (r_s = .14) and reported that their children were more prepared for CAIL (r_s = .26). Additionally, parents with high income have higher levels of innovativeness with AI (r_s = .40), they are more in favour of collaboration (r_s = .17), and they are overall more prepared for CAIL (r_s = .31). Regarding education, participants with higher level of education have higher levels of innovativeness (r_s = .19), are more in favour of collaboration (r_s = .14), have more concerns towards AI (r_s = .14) and are overall more prepared for CAIL (r_s = .14). Participants who are in a two parents or guardian households are more in favour of both CAIL as tool (r_s = .14) and subject (r_s = .11), believe their child is ready for CAIL (r_s = .13) have higher levels of innovativeness (r_s = .15) and are overall more prepared for CAIL (r_s = .17).

Table 11 – Spearman Correlations

Measures	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*
1. Gender											
2. Income	-.08										
3. Education	.01	**.31**									
4. Relationship	-.09	**.26**	.07								
5. CAIL as tool	**-.12**	**.20**	.08	**.14**							
6. CAIL as subject	-.07	**.14**	.10	**.11**	**.58**						
7.Child's Readiness	**-.12**	**.26**	.08	**.13**	**.52**	**.40**					
8. Innovativeness	-.10	**.40**	**.19**	**.15**	**.36**	**.26**	**.53**				
9. Attitudes	**-.23**	.00	.00	.03	**.50**	**.33**	**.43**	**.28**			
10. Collaboration	**-.11**	**.17**	**.14**	.08	**.48**	**.34**	**.52**	**.41**	**.41**		
11. Concerns	.08	.08	**.14**	.01	**-.22**	**-.15**	**-.10**	.04	**-.44**	**.13**	
12. Readiness	**-.13**	**.31**	**.14**	**.17**	**.58**	**.42**	**.73**	**.63**	**.51**	**.74**	.05

Notes. Significant correlations at α = .05 are in bold. Gender is coded as 1 = male, 2 = female; Relationship status was coded as 1 = single parent household, 0 = two parent/guardian households; CAIL as tool and CAIL as subject were coded as 1 = Yes, 0 = No.

Next, regarding participants in favour of CAIL as tool, the strong and positive correlations with CAIL as subject (r_s = .58), child's readiness (r_s = .52), innovativeness (r_s = .36), attitudes (r_s = .50), collaboration (r_s = .48) and readiness (r_s = .58) suggest that participants will be also in favour of CAIL as subject, will believe their children are more ready for CAIL, they will have higher levels of innovativeness, more positive attitudes towards AI, will be more in favour of collaboration and overall more prepared for CAIL. On the contrary, the negative correlation with concerns (r_s = -.22), indicates lower levels of concern. Similarly, participants in favour of CAIL as subject believe their child is ready for CAIL (r_s = .40), will exhibit high levels of innovativeness (r_s = .26), more positive attitudes (r_s = .33), will be more in favour of collaboration (r_s = .34), will have lower concerns regarding AI (r_s = -.15) and will be overall more prepared (r_s = .42).

Parents who believe their child is ready for CAIL will also have high levels of innovativeness (r_s = .53), more positive attitudes (r_s = .43), will be more in favour of collaboration (r_s = .52), will exhibit less concerns towards AI (r_s = -.10), and will be overall more prepared for CAIL (r_s = .73). Further, parents with high levels of innovativeness will also have more positive attitudes (r_s = .28), are more in favour of collaboration (r_s = .41) and will be overall more prepared for CAIL (r_s = .63). Parents with positive attitudes towards AI will be more in favour of collaboration (r_s = .41), will have less concerns towards AI (r_s = -.44) and are more prepared for CAIL (r_s = .51). Finally, parents in favour of collaboration will also exhibit high levels of concern (r_s = .13) and will be more prepared for CAIL (r_s = .74).

6.3 Ethnicity

To inspect potential mean differences on participants' readiness for CAIL basis their ethnicities a one-way ANOVA was computed. The main effect of ethnicity was found to be significant ($F(4, 375) = 3.25$, $p = .012$, $\eta^2_p = .03$), however after examining the post hoc follow up analysis using the Bonferroni adjustment the mean differences between the ethnic groups were not significant. The only marginally significant difference was observed between European and African ethnicity ($M_{diff} = .60$, $SE = .22$, $p = .065$), suggesting that participants with European ethnicity are less prepared than participants with African ethnicity. Descriptive statistics of each ethnic group are presented in Table 12.

Table 12 - Descriptive Statistics of Ethnicity on Readiness for CAIL

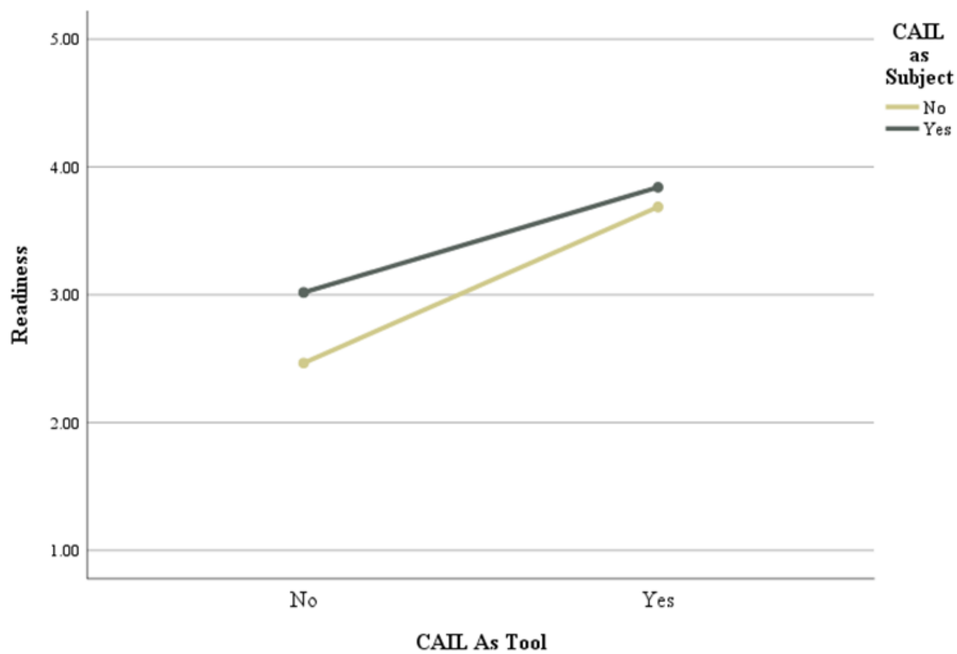
Ethnicity	M	SD	N
African	4.13	.66	12
Asian	3.75	.60	61
South American	3.98	.79	7
Chinese	3.64	.76	5
European	3.53	.77	295
Total	3.59	.75	380

6.4 CAIL as Tool and CAIL as Subject

A 2-way ANOVA was computed to examine the mean differences between parents' responses regarding CAIL as tool and CAIL as subject on their readiness levels. A significant main effect was detected between participants who were in favour of CAIL as subject and those who were not $F(1, 381) = 13.91$, $p < .001$, $\eta^2_p = .04$). In particular, participants in favour of CAIL as subject had a significantly higher mean in readiness (M= 3.43, SE = .06) in comparison to participants who reported against it (M= 3.08, SE = .08).

Similarly, a significant main effect was detected between participants in favour of CAIL as tool and those who were not ($F(1, 381) = 116.47$, $p < .001$, $\eta^2_p = .23$), suggesting higher readiness for those in favour (M = 3.76, SE = .07) in comparison to those against (M = 2.74, SE = .07). A significant interaction effect was also detected ($F(1, 381) = 4.43$, $p = .036$, $\eta^2_p = .01$) as presented in Figure 7.

Figure 7 - Interaction Effect between CAIL as Tool and CAIL as Subject on readiness



6.5 Gender and Income

To examine mean differences on readiness of parents in relation to their gender and income level a 2-way ANOVA was computed. Results indicate a significant main effect of gender (F(1, 386) = 2.64, p = .027, η^2_p = .01), with males (M = 3.79, SE = .07) having significantly higher mean in readiness in comparison to females (M = 3.58, SE = .06).

The main effect of income was also significant (F(5, 386) = 5.86, p < .001, η^2_p = .07), suggesting that participants with higher income are more likely to be prepared for CAIL in education in comparison to participants with low income, as presented in Table 13. From post hoc analysis with Bonferroni correction, it is suggested that participants earning less than £ 20,000 (M_{diff} = .77, SE = .13, p < .001), between £ 20,000 and £ 39,999 (M_{diff} = .62, SE = .12, p < .001), between £ 40,000 and £ 59,999 (M_{diff} = .43, SE = .13, p = .020), and between £ 60,000 and £ 79,999 (M_{diff} = .58, SE = .14, p = .001), differ statistically from participants earning £ 100,000 and above.

Table 13 - Descriptive Statistics of Income on Readiness

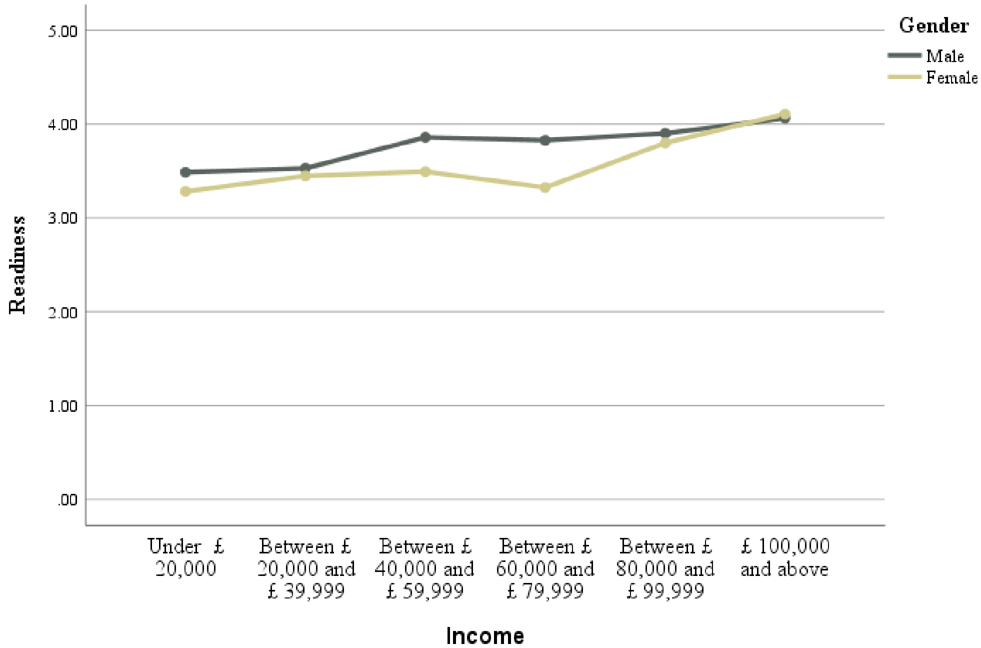
Income	M	SE
Under £ 20,000	3.38	.11
Between £ 20,000 and £ 39,999	3.49	.06
Between £ 40,000 and £ 59,999	3.68	.09
Between £ 60,000 and £ 79,999	3.58	.10
Between £ 80,000 and £ 99,999	3.85	.16
£ 100,000 and above	4.09	.11

Finally, regarding the interaction effect between gender and income, no significant effect was detected ($F(5, 386) = 1.05$, $p = .335$). The means and standard deviations of all levels of the independent variables on readiness alongside the interaction graph are presented below in Tables 14 and Figure 8.

Table 14 - Descriptive Statistics on Readiness per Gender and Income

Income	*Gender*	*M*	*SD*	*N*
Under £ 20,000	Male	3.42	.68	15
	Female	3.30	.64	64
Between £ 20,000 and £ 39,999	Male	3.51	.79	56
	Female	3.45	.80	92
Between £ 40,000 and £ 59,999	Male	3.81	.58	32
	Female	3.48	1.07	37
Between £ 60,000 and £ 79,999	Male	3.83	.46	20
	Female	3.32	.65	35
Between £ 80,000 and £ 99,999	Male	3.79	.51	12
	Female	3.70	.98	12
£ 100,000 and above	Male	4.01	.58	18
	Female	4.07	.37	38

Figure 8 - Interaction Effect between Gender and Income on Readiness



6.6 Employment Status

To examine mean differences between participants with different employment status on their readiness for CAIL a one-way ANOVA was calculated. Employment status has a significant effect on readiness ($F(5, 396) = 5.80$, $p < .001$, $\eta^2_p = .07$). From post hoc analysis with Bonferroni correction, a statistically significant mean difference was detected only between participants working part-time and participants working full-time ($M_{diff} = -.47$, $SE = .10$, $p < .001$). As presented in Table 15, participants in part-time employment were the least prepared for CAIL in comparison to participants in full-time employment, who were the most prepared.

Table 15 - Descriptive Statistics of Employment Status on Readiness

Employment Status	M	SD	N
Disabled, not able to work	3.37	.86	11
Not employed, not looking for work	3.42	.81	32
Not employed, looking for work	3.41	.60	26
Employed, working part-time	3.25	.83	72
Employed, working full-time	3.71	.71	275
Business Owner / Self-employed	3.28	.62	19
Total	3.57	.75	435

6.7 Relationship Status

An independent samples t-test was computed to compare the mean differences between participants in a single parent household and participants in two parent/guardian households on their readiness for CAIL. Results from the independent samples t-test revealed a significant mean difference between groups ($t(400) = -2.76$, $p = .006$), suggesting that single parent households were less prepared for CAIL ($M = 3.33$, $SD = .74$) in comparison to two parent/guardian households ($M = 3.63$, $SD = .76$).

6.8 Hypotheses testing: Innovativeness, Attitudes, Collaboration and Concerns

To predict the level of parents' readiness for CAIL a multiple linear regression was computed with innovativeness with AI, attitudes towards AI, willingness to collaborate other stakeholders (i.e. teachers and children) and concerns regarding AI as predictors and readiness as outcome variable.

A significant linear equation was found (F(4, 398) = 341,90, p < .001), with innovativeness, attitudes, collaboration and concerns explaining the 77.5% of the variance in readiness for CAIL. In particular, innovativeness can positively predict readiness for CAIL (*b* = .29, *SE* = .02, *p* <.001), suggesting that parents with high levels of innovativeness with AI are more likely to be also prepared for CAIL. Similarly, parents with more positive attitudes towards AI (*b* = .26, *SE* = .04, *p* <.001) and parents more willing to collaborate with other stakeholders (*b* = .48, *SE* = .03, *p* <.001) are also more likely to be prepared for CAIL. Finally, regarding concerns, the variable did not significantly predict readiness for CAIL (*b* = .05, *SE* = .03, *p* = .117). Regression coefficients are presented in Table 16.

Table 16 - Regression Coefficients

	Unstandardized Coefficients		*Standardized Coefficients*		
	b	*SE*	*Beta*	*t*	*p*
Intercept	-.17	.17		-1.19	.233
Innovativeness	.29	.02	.34	12.74	<.001
Attitude	.26	.04	.23	6.75	<.001
Collaboration	.48	.03	.52	16.62	<.001
Concerns	.05	.03	.05	1.57	.117

Viewing this alongside the hypotheses:

H1: Innovativeness predicts preparedness for CAIL in parents is supported

H2: Attitudes predict preparedness for CAIL in parents is supported

H3: Collaboration predicts preparedness for CAIL in parents is supported

H4: Concerns predict preparedness for CAIL in parents is not supported

6.9 Conclusion & Summary

This phase of dissertation research adopted quantitative approach to assess variables of interest (innovativeness, attitudes, collaboration, concerns) as predictors of parental preparedness (dependent variable) for CAIL. Appropriate scales were developed for each of the variables and an online survey was disseminated. A total of 438 participants filled-out the survey. Post implementing inclusion and exclusion criteria 403 participants remained. The analyses were then conducted on the responses of these participants. Multiple linear regression computed to predict the level of parents' readiness for CAIL found a significant linear equation, with innovativeness, attitudes, collaboration and concerns explaining the 77.5% of the variance in readiness for CAIL in our model. Innovativeness, attitudes and collaboration were good predictors of parental preparedness for CAIL while concerns did not predict preparedness significantly. Our Hypotheses 1 (Innovativeness predicts preparedness for CAIL in parents), H2 (Attitudes predict preparedness for CAIL in parents), H3 (Collaboration predicts preparedness for CAIL in parents) were supported in the model. However, H4 (Concerns predict preparedness for CAIL in parents) was not supported suggesting that while innovativeness, attitudes and collaboration are good predictors of preparedness for CAIL concerns do not predict preparedness.

Additionally, relations between demographic variables and variables of interest were also assessed and education, income, gender, relationship status and parental opinion on child readiness as well as how CAIL must be implemented (CAIL as tool or CAIL as subject) exhibited significant correlations with each other as well as some variables of interest. Females were found to be less innovative, have more negative attitudes, less willing to collaborate, had high concerns and were overall less prepared for CAIL than males. Also, participants with higher income, higher education, in a two-parent household were found to be more prepared than others. These findings will be further discussed in detail in the Discussion Chapter VIII of the dissertation.

CHAPTER VII:

STUDY 3: DEDUCTIVE EXPLANATION: RESEARCH DESIGN

7.1 Research design

For this phase of research, a deductive qualitative approach was used to explain findings of Study 2.

The deductive qualitative explanatory design is an exceptional framework for enhancing our comprehension of intricate occurrences, distinguishing itself from other designs. It integrates deductive reasoning with qualitative research. The process begins by establishing a theoretical framework or utilizing an existing theory (deduction), which is then supported or confirmed by the examination of empirical facts (explanation). Deductive qualitative research, in contrast to fully inductive methodologies, initiates with pre-established notions or hypotheses rather than deriving theory from facts.

Researchers commence their work by creating hypotheses or research questions. Qualitative data collecting typically involves methods such as interviews, focus groups, or content analysis. The qualitative findings are subsequently compared to the underlying hypotheses or theoretical conceptions.

This design facilitates researchers in testing and refining theoretical claims by utilizing current ideas as a starting point. Qualitative data offer a comprehensive understanding and insight into the intricacies and unanticipated trends. Sequential mixed methods research involves the use of deductive qualitative design to enhance and support quantitative findings. Qualitative research offers explanatory depth when quantitative data raise questions or uncover associations. Combining deductive qualitative ideas with quantitative data improves the accuracy of study conclusions.

It facilitates a more thorough comprehension of intricate occurrences. Deductive qualitative analysis is used to explain or provide context to the quantitative data that have been obtained. Qualitative data enhance the depth of statistical relationships.

Researchers have the ability to investigate the reasons behind the emergence of specific patterns or the ways in which contextual elements impact outcomes. The deductive qualitative explanatory design connects theory and empirical data, enhancing both sequential exploratory and sequential explanatory research. By incorporating qualitative inputs, researchers improve the accuracy and comprehensiveness of their findings.

7.2 Population and Sample

Participants were parents and guardians of at least one primary school going child and residing in the UK.

7.3 Participant Selection

Participants were identified during quantitative survey (Study 2) and were further requested to participate in an interview. Several parents were invited to participate in this phase of the study. Only two parents from the survey participated while three others agreed to participate basis an invite sent via WhatsApp text message. All participants were informed about the research and their informed consent was received. Three male parents and two female parents were interviewed. The age group of all parents was between 34 and 55. All parents possess high level of education with at least a bachelor's degree or higher. One male parent is a psychiatrist (P1), the other works in the banking sector (P5) and the third works in technology sector (P3). Both female parents belonged to the technology field (P2, P4). Females working in technology fields and belonging to high income, high education groups were a deliberate addition since we wanted to assess if preparedness increases in females if they possess higher education and income.

7.4 Data Collection Procedures and Instrument

Semi-structured interviews were conducted online with each of the participant between 2nd February and 5th February 2024. The questions were largely focused to seek responses to verify and further explain crucial findings from Study 2. Set of broad questions are presented in APPENDIX I. Each interview was approximately 20-30 minutes long. Transcription software Simon Says was used to transcribe the interviews. The transcriptions were cleaned only of stutters and fumbles that did not add any value. Informed consent was received from all participants prior to the interview.

7.5 Data Analysis

Thematic analysis was used to assess the interview data. Relevant quotes were culled out to explain various findings from Study 2. Names and all information that could compromise the identity of the participants was removed and codes were assigned to each participant to maintain confidentiality and anonymity upon participants' request.

7.6 Results

The following are the results from the qualitative interviews. Quotes have been kept longer and more detailed for understanding purposes here.

Innovativeness

The five parents (P1, P2, P3, P4, P5) showed varying levels of innovativeness with P1, P2, P3, P4 leaning more towards being adopters of AI technology while P5 being slow adopter and relatively less innovative. And even though most of them identified themselves as cautious adopters upon further description it was identified that some of them were in the moderate to high innovativeness categories while the others were highly technophobic. Most of them found it easy to use new technology including AI enabled tools and services without seeking help.

P1: "In this day and age, there are certain things that you are expected to know…in my field medical practitioners are expected to know and use technology more and more these days. So, if I don't know (how to use a new technology like AI) I would probably look, at YouTube or read out tutorials or try and understand it myself, at least make an attempt to understand it myself. I won't just crash and say, I can't do it. However, I am not a fan of technology so I will use it only if I need to."

P2: “No I’m definitely not technophobic. I think I am probably on the verge of being cautious at the same time being an early adopter in the sense that I use technology as long as it is safe and I am aware of the dos and don’ts of it I’m happy. I’m very much happy for my child to use technology as well as long as he is aware of the dos and don’ts of it.”

P3: “I work in the field of technology and internet security so I am definitely very aware of everything. However, when it comes to personal use and for family use, I apply caution when embracing any new technology. Having said that I am not averse to any new technology as such.”

P4: “I work in the field of technology so I am not averse to it at all. Cautious, yes. But I am not first one to adopt new technology. I do take my time to actually wait and watch and then if it is useful for me to use, I adopt it. So, if it is a helpful tool then I would be more inclined to adopt it.”

P5: “I don’t have much of a technology background…technology throws a lot at you. I know we need more and more technology but then I realize that it makes things more complicated in terms of the whole structure that we work with…AI is all around us at the moment, especially in the news. So, you know what it can do to people, jobs. So, though I would ideally want to be an early adopter, I am very cautious.”

Attitudes

In terms of attitudes towards AI P1, P2, P3, P4 showed positivity with P1 addressing his attitude as cautious optimism, while P5 held more negative attitudes towards AI.

P1: “My attitude towards AI is I would say cautious optimism. So, on the one hand, I have seen the benefits. And I mean, it's clear to see the benefits of AI in your everyday life. It just makes things easy and it sort of helps you achieve outcomes faster. But I'm aware that obviously there are pitfalls, people can get sucked into the negative aspects of AI.”

P2: “To be honest there is no hiding away. It is just the need of the hour and we have to adopt and embrace. As long as it is safe for everybody, for the community, that’s all that matters. So, I think it’s a welcome change.”

P3: “I am very positive towards AI technology. Everything is moving towards AI. All businesses and even in our daily life we interact with so many products that are using AI at the backend. So, it is the future we are already stepping into. It is always wise to tread carefully with everything new but it doesn’t mean that we do not go for it. As long as proper knowledge of how it can help and harm is there with you, you can use any new technology.”

P4: “So I understand that AI is going to grow massive in the coming years and as such am okay with it.”

P5: “I am not personally for AI. I won’t say I am all against it. It does have benefits but I think many of us are using AI only because we have no other choice because all products and services are now building on top of AI.”

Collaboration

On Collaboration P1, P2, P3, P4 agreed that it is important to collaborate with teachers as well as their children to be able to support learning of the children better at home. P5 however did not clearly respond to the question and seemed to not want to be involved with the learning process and wanted schools and government to take more active role in ensuring there is uniformity in how and what is being taught. P1 mentioned that for this collaboration to be effective parents who possess comparatively less knowledge of AI or how to teach their children at home about AI must receive adequate learning support from the schools. P1 also opined that both parents and teachers must be involved in curriculum design for CAIL. P2 not only saw the benefits of collaboration between teachers and children but also in the community with other parents and teachers who are experts in the AI field. Workshops for parents organized by schools where other parents with AI expertise come and speak with the parents with less knowledge according to P2 will be very useful in making collaborative efforts a success for children's AI learning.

P1: "Yes, parents and teachers should be made part of designing the course. There's a valid point for that…but there is also the need for the parents to be carried along because we are recognizing that in our generation or certainly my generation, this is not how we learnt. So, parents are new to this as well. But we need to facilitate our children when they are home. There's a lot of inputs that the parents have to give. So, parents need to be carried along, otherwise it's going to make the teacher's job frustrating. And this disconnect between home and school will also confuse the child...When it comes to facilitating things like homework, learning at home or learning outside the school, the parents have a role to facilitate that....Things like snippets of tutorials should be sent to the parents to say, okay, this is what needs to be done.... if you have technophobia as a parent does not mean that your children are not going to be exposed to AI, so they (schools) need to have some resources or whatever needs to be done to make things easier."

P2: "Collaborative approach with teachers will be definitely helpful, because I've been speaking to his teachers on multiple occasions for all other subjects. And basis that I have been working with them in terms of what support I can offer him at home, in addition to what they are doing in school. So, I think that regular dialogue and that communication between teachers and parents is super important going forward for AI education as well."

P2: "Yes there is definitely an opportunity there to explore and have that collaboration within the community. You see there is a lot of difference in what professions parents are in. So, if we can have some professionals who come from technology background speak with parents and teachers it will be very helpful. I work on the technology side with my company and very often we go out and do workshops at schools. And sometimes we also have parents present. So, I think this kind of collaboration will be very helpful for all parents to learn and to then support their children in learning about AI at home as well."

P3: "Yes, I think it is very important and not just between parents and children or parents and teachers but even peers and older siblings have some influence on how a kid develops interest. You know my brother he went into engineering and automatically as a younger brother I got interested in that and I am a software engineer now. Also, I feel how parents interact at home with children and sit with them to understand what's going on and help them when they need even with school work it helps the child learn faster."

P4: Yes, totally agree with it. It does make a difference when you are sitting with your child or reading, helping them out with the homework, or just having discussions… it just brings about that discipline and that interest in some of the subjects. And if parents help out with what children have learnt in school in the home environment it just rekindles their interest in the subject or topic that they may have lost interest in. So, it is a good idea for us to be involved with teachers to make sure children can be supported in the home environment to learn new concepts like AI."

P5: "Collaboration is okay but if you involve parents then 30 will say one thing and 25 will say something else. So, I don't't think it is a great approach. Government should formalize AI education and then schools should make sure the agreed curriculum is taught to the kids instead of every school and teacher doing their own thing."

Concerns

In terms of concerns, parents had varied concerns. P1 was concerned about the kind of content kids could access which could make them vulnerable to P2 worrying about excessive screen time, P3 worried about how data is stored and assessed for children long-term and lack of government level measures to control that as of now P4 was concerned about children's ability to develop social skills and P5 was concerned about AI still being in its evolutionary phase and using people as a testing ground to enhance and refine its (AI's) own knowledge.

P1: "My concerns are similar to that you would have with things like social media, where it's a tool for accessing information, understanding current trends but is also a tool that could be used to affect people who are vulnerable. So, managing of information access for children is my main concern. How do we judge how much and what information to share with these young children."

P2: "So the concern I have is probably the screen time overall, because after pandemic you know technology and screens became a part of life and kids were hopping from one screen to the other for all sorts of reasons. And education is also on screens...So there has to be a balance. And I feel that as long as we as parents are involved with what our children are doing this concern can be reduced to half. I think if you are not involved then that's where it worries you 100% because you don't know what they are doing. But if you are involved and at least you can see for yourself what they are doing, that gives you a little bit of peace of mind. Like in my boy's school they have introduced Chromebook quite at a young age. But the school gave us confidence that they have right software in place which will block kids from accidentally getting into unsafe environment online. There are hackers out there to get into kids' software because they are so vulnerable. And you want to keep an eye and make sure they have a safe environment when they are online. Forget about AI literacy for a minute, even if it's a sports activity or some event going on in school, if there is no adult or no teacher monitoring, then accidents will happen. So that applies for AI literacy as well. As long as there is right monitoring and governance around it, I think that's what is important as a parent I would say.”

P3: “So my concern is not just to do with today. My concern is security of information for my child even twenty years from now. You see AI identifies patterns. So, if you search say a holiday related query multiple times you automatically start receiving more information on the same in all your email, social media accounts etc. So, AI is identifying patterns at the backend. Which means it is storing information about you somewhere. Now when it comes to children it gets more serious. When they engage in any online activity starting at such an early age AI is collecting data on them from that age and imagine how well AI knows you by the time this child is say 20 years old. This kind of collection of data on individuals can be heavily misused and there have to be some measures to contain large corporates from doing that... It should not be like the cigarettes case where initially the corporates kept saying it is healthy to smoke and even pregnant women should smoke and then 20-30 years later research shows us it causes cancer and so many other problems. So, while I believe AI is a good technology, I am not going to say that we must ignore the pitfalls. And if it is going to be made part of education for minors all the more reason for us to ensure some policy is put in place before exposing them to it.”

P4: “AI can make things simpler; kids might stop thinking creatively like with calculators, you know once you started using them you forgot how to do simple calculations without them. So, overdependence on AI is a worry. Also, AI is faceless and as a parent it does worry me as to what I may be exposing my kid to. His social skills should not suffer in the process. So, face to face contact with teachers is very important. I don’t want AI to replace traditional form of teaching.”

P5: AI technology run products are in first generation and as of now they are all using us as data sources to refine AI's own knowledge. I am not very comfortable with being experimented on as a user. I use AI in day-to-day life only because the products and services I use have started using AI. It's not out of choice but because I have to. I am all for AI if they can first refine it and not use my data to teach the AI. So, these are my concerns with AI Literacy in schools as well. Plus, the children in primary are taught everything in a set format. With AI it will be different. There is no formalized course material available and then every school will do their own thing and I am not comfortable with that for my child. All children should receive equal and same education just like is true for all other subjects and I'm not sure any thought has been put into it so far."

Child readiness for CAIL

In terms of child readiness all except P5 felt that their own child and children in primary are generally ready for CAIL.

P1: "My younger one sees her brother using all sorts of technological apps. And I think having an older sibling plays a part in how much younger one learns. And I think like all children she is already aware of so many things and I am sure she is ready."

P2: "He's ready to be honest. Because of the overall nature of things now, they already understand much more than parents do. Kids at this age are open to learning new concepts. So, they would embrace anything quickly. Not just my son but I think overall, his friends and you can tell from the grasping capacities they have, right? So, I think they are probably ready."

P3: "Oh not just my child they are all ready. Kids are born into technology these days. It's not like our times anymore. So, they have incredible skills already and they learn very fast especially when it's something new and interesting and involves using a mobile or a computer. So, they are all more than ready. Only thing we need to focus on is what and how to teach them about it."

P4: "I think he is more than ready. I think kids of this generation, they are probably so exposed to technology, they really pick up much, much quicker than we do."

P5: “I don’t think children will have any understanding at this stage about anything to do with AI. And I don’t think primary is when AI should be taught.”

Parental Preparedness for CAIL

As regards parents’ own preparedness for CAIL All parents P1, P2, P3, P4, P5 exhibited readiness. P2 mentioned that irrespective of when CAIL initiatives are introduced schools and parents should start talking about it now so as to be better prepared. P4 expressed readiness provided introduction of CAIL did not compromise a child’s social skills like interacting with other people including teachers in this context. P5 too expressed preparedness despite personal reservation against CAIL for primary children, provided it is implemented in a formalized manner under government mandate with adequate measures put in place.

P1: “So I am optimistic and, in that sense, ready if it is going to benefit the children and, in the process, less technology aware parents. There's so much learning and there's so many ways artificial intelligence can make our learning easier, faster, quicker, outcomes better... but we need to head with a level of caution.”

P2: “Yes, I think I am ready as a parent and the only hand holding, I would need is how what type of support parents are expected to offer at home when it gets introduced and then educate myself accordingly to get up there. Because like I said it is coming in the near future so it would be good to start talking about it now so we can provide proper support to both children and teachers. It doesn’t matter when schools introduce it, we need to start talking about it now. It is the need of the hour and the earlier we start the better rather than waiting until it happens.”

P3: “I am obviously ready for this. I believe this change is necessary and important to make sure our kids are well acquainted with AI as by the time they step into the grown-up world everything will be AI enabled so yes just like computer education was a requirement knowledge of AI is going be a need to live in this world so yes, I am prepared for anything that helps my kid be future ready in that sense.”

P4: “I think if it's done in a controlled and planned manner, and it's not taking away the social aspect of in-person teaching and all that stuff, and if it's a balanced approach, then I would definitely give it a go.”

P5: “So firstly I'm not for AI Literacy to be introduced at primary level but if the government's approach is that we must have it I’m not completely against it. But I would want it to be done responsibly. And if the government comes up with a uniform approach for AI education, I will be okay.”

CAIL as tool or Subject

As regards parents’ opinion on whether CAIL should be introduced as a tool to teaching existing subject and CAIL to be introduced as a separate subject P1 felt it should be introduced first as a separate subject and then subsequently in combination with CAIL as tool to teach other existing subjects. P2 preferred the CAIL as tool option, P3 stated that both CAIL as tool and CAIL as subject must be introduced simultaneously. P5 felt that CAIL should only be introduced as a topic in a workshop for primary kids and not as a tool or subject.

P1: “Because this is new, I think it should be first of all introduced as a separate subject. Let everybody sort of get into it. And then eventually, make it phased sort of learning, probably mixed (both implementing CAIL as tool and CAIL as subject) and then it will just be embedded in the curriculum.

P2: “I have been involved with my son in his technology learning journey and we know that AI platform along with traditional way of learning can be used to teach math, English, science. So, I’m probably biased that the combination of the subject along with some platforming has helped. And I’m quite comfortable with that.”

P3: “Honestly, I am for both. I am not an educator but I do feel there is some benefit in introducing AI in children's life early on so whether we use it as a tool to support current curriculum or bring it in as a separate subject is not an issue for me. I would prefer both ways being used simultaneously.”

P5 : “I don't think it should be introduced in either form. If at all maybe they should introduce AI as a topic in a workshop. That's it. They have workshops about so many things in school so I think that is the only thing they should do for primary kids.”

When and what to teach under CAIL

In addition to the above parents were also asked the most appropriate age to introduce CAIL and what to teach. P1 mentioned ethics and morality of AI use must be taught and he also thought in his professional capacity as a psychiatrist that children between the age-group of 6-7 would be the most appropriate group. P2 also felt that age 7 was the most appropriate time to introduce CAIL, P4 agreed with introduction of CAIL in primary classes and P5 felt it should be introduced in secondary grades where children can choose their subjects.

P1: What should be taught: I don’t think it is morally right for something that is as impactful as artificial intelligence to be just taught as to how it can be used without understanding the ethics and the morality behind it. I think they need to walk line in line, hand in hand. I think it's only right that that should be done and passed across (to the children) from the start. So, it should be part of the introductory, you know in my idealistic mind I'm thinking if your start at age 6 to 7 and you start teaching these kids about AI then it (Ethics and Morality) should be part of the introductory course.

P2: I think seven plus is the right age. They can be independent at the same time they understand what the dos and don’ts are and they can be aware of what they are doing. I can only speak for myself. I will go with my own experience. I have a boy… I think until six the maturity level is still evolving. So, I think seven probably was the age where when I give him some instructions, he would understand and follow them…So one step at a time with maybe first introducing this to slightly older kids and then slowly you know go to the younger kids after testing its fit you know will definitely help. And when I say older, I mean within primary testing this with kids 7 years and older and then perhaps younger kids. So, a phase wise approach. As for what to teach like I said earlier I am okay with him learning how to use AI in different settings, different subjects. You know just like they organically learned about how to use computers and mobiles.

P3: I am not really sure but I feel children are already very tech savvy these days. Like we say they are born into technology so I think any age within primary classes should be okay. Maybe say around 7 or 8. But I am not an expert so I don’t really know. As for what to teach well again I am no teacher so I can’t be sure. But maybe start with basics first like we do for everything else.

P4: I think with the increasing use of AI in different fields of life, it does help them create that awareness early on and prepare them with the right set of tools, rather than leaving it on to them to actually pick it up. So, it does help in that sense. But it should be introduced gradually and, in an age,- appropriate manner. So maybe around 7- to 10-year-olds should be the target group. Start with basics I think like we teach alphabet before making words and sentences.

P5: It should be introduced in secondary classes as then children have a choice on whether they want to learn about it or not. You know they can choose from all the subjects and AI can be a choice not a compulsion. In primary kids can't choose their subjects so I why force them to learn something that they can anyways learn better later and by choice.

7.7 Conclusion & Summary

Study 3 focused on explaining the findings of Study 2. Deductive qualitative approach was used here. Five participants (3 males and 2 females) were invited to participate in semi-structured interviews. Participants belonged to high income groups and possessed high education levels and were in a two-parent household. Thematic analysis was used to assess data with a focus on themes pertaining to variables of the research. However other observations were also reported. Participants that exhibited higher levels of innovativeness, more positive attitudes, willingness to collaborate were also found to be more prepared for CAIL. Further these participants also thought their child was ready for introduction to CAIL. Female participants with high education and income and living in matrimony also exhibited high innovativeness, positive attitudes, willingness to collaborate and were more prepared. All participants expressed varied concerns (internet safety, loss of social skills and problem-solving skills, overdependence on technology, screen time and lack of policy and lack of formal uniform curriculum for CAIL) but these concerns did not impact their preparedness levels. Even P5 who was strongly opposed to the introduction of CAIL expressed readiness subject to proper policy and government mandated curriculum are put in place. This shows that concerns of parents do not influence their preparedness. Further all except P5 though that their child was ready for introduction to CAIL initiatives. As for the appropriate age for when the child should be introduced to CAIL all participants except P5 believed 7 to 8 years of age was appropriate. P5 opined that children should be provided a choice to learn or not learn which could be possible only in secondary classes. On what to teach within CAIL knowledge of ethics of AI and basics remained the common answer. Further participants also expressed their own willingness to learn about AI and suggested schools run tutorials or workshops where parents can learn from AI experts who could also be other parents working in AI fields. All these findings not only validate the findings from Study 2 but also provide some insights into how to collaborate, what to teach, when to teach etc. One exception was P5 who was highly educated and in high income group but held, less innovativeness, negative attitudes, less willingness to collaborate, high concerns believed no children in primary classes were ready for CAIL, did not agree with CAIL being introduced as a tool or subject and was overall not very prepared for CAIL unless it was implemented after rigorous policy and planning by the government of the UK in a centralised manner. These findings conclude our research and the subsequent Chapter VIII will discuss overall research findings from Study 1, Study 2 and Study 3.

CHAPTER VIII:

DISCUSSION

8.1 Discussion of Study 1, Study 2, & Study 3

This research investigated predictors of parental preparedness for introduction of CAIL in primary classes in UK schools using mixed methods combining Sequential exploratory and Sequential explanatory approach thread technique (one study informing the next). The research was conducted in three stages with Study 1 using qualitative thematic analysis approach. An AI expert was interviewed to answer the research question. Themes developed at this stage were further categorized under variables of interest. Innovativeness, attitudes, collaboration and concerns were the four key independent variables and the dependent variable was preparedness. And hypotheses were developed for further investigation (Study 2)

Study 2, tested the hypotheses and also explored other demographic variables and their association with preparedness (dependent variable). Quantitative survey was conducted with 438 parents of primary class children in the UK. Post implementing inclusion and exclusion criteria 403 participants remained. Appropriate scales were designed for each variable and data was analysed using SPSS version 25 and all scales showed consistency with high Cronbach values.

Findings showed that innovativeness, attitudes, collaboration proved to be good predictors of preparedness while concerns did not predict preparedness. Other studies have also shown that Innovativeness impacts technology readiness (Blut and Wang, 2020b). Further positive attitudes and their impact on an individual's readiness for use and adoption of new technology has also shown a positive association in other studies (Blut and Wang, 2020b; Geng et al., 2019; Kampa, 2023). These papers highlight the importance of positive attitudes in shaping technology readiness and adoption. Further collaboration between parents teachers and children has been proven to increase child's learning through home based family activities according to a recent research (Druga et al., 2022a). Another study showed that technology readiness plays a role in students' willingness to adopt AI, regardless of their concerns (Nouraldeen, 2023). This shows that our results are in line with previous findings pertaining to our key variables namely innovativeness, attitudes, collaboration and concerns and how they predict readiness.

The Model created in this dissertation explains 77.5% of the variance in readiness for CAIL and innovativeness, attitudes and collaboration positively predict preparedness. The model created to assess parental preparedness for CAIL is thus reasonably reliable.

As part of our research one essential variable that has shown high predictive value is collaboration. This as far as is known to the author has not been utilized as a factor in any technological readiness models or studies in the past. Parent-teacher and parent-child collaboration has been an essential part of enhancing learning experiences of children as research has shown. Thus, including this variable to assess parental preparedness for CAIL has been a vital addition to the model.

All key findings of Study 2 were further explained through Study 3 where semi-structured qualitative interviews were conducted with five parents who again fit the target population that has remained consistent for the entire research in each phase (parent of primary kid/s in the UK). The findings were largely in line with those in Study 2 outcomes.

Demographic factors were also assessed in Study2 and further verified and explained through Study 3.

8.2 Gender

Correlations matrix outcomes for gender showed several associations. The results of the statistically significant associations indicate that males exhibit a stronger preference for CAIL as a tool and perceive their children as being more prepared for CAIL. Moreover, individuals who possess a greater inclination towards collaboration have more favourable attitudes towards AI and are generally better equipped for the challenges posed by CAIL. Consequently, women exhibit lower levels of support for CAIL as a tool, perceive their children as less prepared for CAIL, hold fewer favourable attitudes about AI, are less inclined to collaborate with other stakeholders (such as children and teachers), and are generally less prepared for CAIL. Hence, we have found that there is a significant gap between males and females when it comes to AI preparedness. Women were found to be more sceptical compared to men towards AI and CAIL. It was found that male parents are more in favour of introducing CAIL as tool and believe that their children are more prepared for CAIL overall. They also possess more positive attitudes towards AI and are more in favour of collaboration and as such are more prepared for CAIL than female parents.

Past research also supports this finding. Previous studies have shown that women exhibit less capability and interest in using computers as compared to men (Hargittai and Shaw, 2015; Imhof et al., 2007; van Deursen et al., 2015). Several other studies also posit that technology acceptance is dependent on gender of the user and how the gender interacts with the characteristics of the technology such as ease of use of the technology (Venkatesh et al., 2003). The main reason for this is the perceived notion that technology use belongs predominantly in the male domain and not in the female domain (Morahan-Martin and Schumacher, 2007). Other studies have suggested that women exhibit lower self-confidence, lower computer self-efficacy and higher anxiety when it comes to computer usage (Busch, 1995; Jackson et al., 2010; Saleem et al., 2011). Within AI, there is evidence to suggest that women are generally more sceptical about AI than men. A survey (Pew Research Center, 2022) has also shown that men (54%) use more AI than women (35%) in work place, are more likely to allow their children to use generative AI (31%) than women (4%). In fact, majority of women stated that they would ban their children from using AI altogether. Another study found that mothers had a higher tendency to restrict internet usage of their children as compared to fathers (Barandiarán et al., 2019) which according to another study is due to mothers' low technology usage and limited perceptions about technology (Brito et al., 2017). A study in Chili also found that mothers had more involvement in children's school lives and were hence the main person in the family to implement mediation strategies when it came to technological access and use (Condeza et al., 2019) . Women are also highly sceptical of AI based programs' abilities to consistently make fair decisions. Similar results were also posited by another study which suggested that fathers were generally more tolerant to their child's internet use than mothers (Symons et al., 2017). Mothers' key role in child's upbringings in the household is also applicable to child's access and use of Internet.

The reasons for this scepticism are manifold. Firstly, women historically have been less preferred in technical and technological fields. There are less women in STEM fields than men. This initial entry barrier restricts a large majority of women from learning about new technologies and hence suffer from lack of awareness and knowledge of technology. This underrepresentation leads to increasing the gap between men and women when it comes to adoption of new technologies such as AI (Fung, 2019). This reservation against AI may also be causal in women being less ready to allow their children from learning about AI and consequently less prepared for introduction of CAIL initiatives in primary schools in the UK. Our research outcome pertaining to gender and AI is thus validated by past research. Given adequate literature support for women being less technologically inclined we decided to make some calculated assumptions that education and lack of knowledge and exposure to technology may have some bearing on this. Hence in Study 3 we invited two female participants both of whom are working in the technology field. Contrary to our findings in Study 2 these women were more innovative, had positive attitudes towards CAIL, were willing to collaborate, had concerns but were very prepared for CAIL. They belong to high income groups and are living in matrimony (two parent household). This suggests that education, access and exposure to technology can also help women attain higher innovativeness, more positive attitudes, increase their willingness to collaborate and become more prepared for new technologies or technology related initiatives such as CAIL in this case.

8.3 Income

Correlations matrix showed that there was a positive association between income and both education and relationship status. This implies that those with higher income are more inclined to have achieved a better level of education and be in a relationship and live in a two parents or guardian household. In addition, individuals with higher incomes exhibit a greater preference for both utilizing CAIL as a tool and CAIL as a subject. Further, they indicated that their children were more prepared for CAIL. In addition, parents with a higher income exhibit greater degrees of innovativeness in relation to AI. They also demonstrate a stronger inclination towards collaboration and possess a higher overall level of preparedness for CAIL. Other studies have also found that higher income is linked to a higher level of innovativeness and a greater propensity to adopt new technologies (Anca and Gheorghe, 2009; Jyoti and Supran, 2016).

8.4 Education

Correlations matrix also showed that participants with a higher level of education exhibit greater levels of innovativeness and are more inclined towards collaboration with other stakeholders such as children and teachers to ensure efficient implementation of CAIL. These participants exhibit greater concern regarding AI but are generally better prepared for the introduction of CAIL initiatives in primary schools. This finding is in line with other research which suggests that parents with high level of education use and adopt more internet communication technology (ICT) and new media technology than those with lower education (Condeza et al., 2019; Nikken and Opree, 2018). Further since parents with higher education and higher usage possess higher technology literacy they are more aware of the advantages and disadvantages of media technologies their children use and hence these parents tend to play a more active role in mediating what and how the child uses technology than those with lower education (Nikken and Opree, 2018). This was also the case in our Study 3 findings where all participants were highly educated and had concerns.

8.5 CAIL as tool

Correlations regarding participants who support the use of CAIL as a tool, showed that there are strong and positive correlations with CAIL as a subject, the readiness of the child, innovativeness, attitudes, collaboration, and the readiness of parents. This suggests that these participants are likely to also support CAIL as a subject, believe that their children are more prepared for CAIL, have higher levels of innovativeness, hold more positive attitudes towards AI, are more supportive of collaboration, and overall, more prepared for CAIL. In contrast, the negative connection with concerns suggests a decline in the levels of concern.

8.6 CAIL as subject

Likewise, supporters of CAIL as a subject assert that their child is ready for CAIL. Further these parents exhibit high levels of innovativeness, positive attitudes, willingness to collaborate, minimal concerns about AI and CAIL, and higher level of preparedness for CAIL. This was also seen in Study 3 where P1 opted for CAIL to be introduced as a separate subject. He expressed proactive learning about new technologies (exhibiting some aspects of innovativeness), was cautiously optimistic about AI and CAIL, had few concerns and was highly prepared for CAIL.

8.7 Child Readiness

Parents who perceive their child as prepared for CAIL will also possess elevated levels of innovativeness, harbour more favourable views towards collaboration, display fewer concerns around AI, and demonstrate overall greater readiness for CAIL. This holds true for all participants of study 3. P1, P2, P3 and P4 who opined that their child was ready for CAIL also exhibited positive traits (innovativeness, attitudes, collaboration) and were prepared for CAIL themselves. P5 did not however believe children in primary classes included his own were ready to learn about AI and his own levels of innovativeness, attitudes, willingness to collaborate were very low. P5 was least prepared for CAIL among the sample.

8.8 Correlations between key variables

Key variables also showed associations with each other. Parents that possess high degrees of innovativeness also exhibit more positive attitudes, are more inclined towards collaboration, and demonstrate more overall readiness for CAIL. Similarly, parents with positive attitudes were more willing to collaborate, had fewer concerns and were more ready for CAIL. In addition, parents that are willing to collaborate exhibit higher levels of concerns but despite that they also show more preparedness for CAIL.

8.9 Ethnic Differences on Level of Preparedness for CAIL

Outcomes in this study also suggested that African ethnicities (Black Caribbean, Black African) were more prepared for CAIL than the European category comprising of a large majority of White British, Scottish, Welsh, Irish and some American Whites. In this research only marginally, significant difference was found between African ethnic groups and European ethnicities prior to post hoc test. However it is important to mention this here since these outcomes have been evidenced in past studies that have shown that migrants from African and Caribbean ethnicities to western Europe have higher ambition and determination which may be caused by their desire to have a better life and better opportunities (Arpino and de Valk, 2018; Damelang et al., 2021). This may explain in part the higher level of preparedness for CAIL in Africans as compared to Whites in the UK. However future research focusing on ethnicities and their preparedness for CAIL may be necessary to further evaluate this aspect.

8.10 CAIL as tool and CAIL as subject

The study investigated parents' preference for CAIL, both as a subject and as a tool. The results indicated that parents who supported CAIL, either as a subject or a tool, had higher levels of readiness compared to those who did not support it. Further, a notable interaction effect was observed, indicating that the disparity in readiness levels between CAIL as subject preferences and CAIL as tool preferences was not consistent.

The interaction graph indicated that parents who supported both CAIL as a subject and tool exhibited the highest level of preparedness, whereas parents who opposed both CAIL as a subject and tool displayed the lowest level of readiness. The findings suggest that parents' perspectives on CAIL as both a subject and a tool play a significant role in determining their preparedness for CAIL. This was also seen with P5 in qualitative study 3 where the participant did not prefer either (CAIL as tool or CAIL as subject) and he was least prepared for CAIL among the participants.

8.11 Income and Gender

This study examined the impact of parental gender and income on their preparedness for introduction of CAIL in primary schools. The findings indicated that male parents and parents with a higher socioeconomic status had a greater propensity towards CAIL compared to female parents and parents with a lower socioeconomic status. Nevertheless, the findings also indicated that the impact of gender on readiness was not contingent upon the income level, and vice versa. This indicates that the disparity in preparedness between male and female parents was consistent across various income levels, while the disparity in preparedness between high- and low-income parents was consistent across different genders. Gender disparity has been observed in some studies that examine skills and use of technologies by males and females. While one study found a marginally significant difference between boys and girls with boys faring better in skills and use of communication technology than females (Qazi et al., 2022), the other study conducted during covid-pandemic detected that online learning outcomes are significantly impacted by gender, education level and individual’s personal traits and that female students, graduate students, and students with greater levels of dedication and curiosity exhibit superior performance in online learning (Yu, 2021).

Further income disparity was also identified as a factor in another study which found that income and education were positively correlated with information and communication technology adoption and use, which means that higher levels of wealth and education are linked to greater adoption and usage of information and communication technology (ICT) (Mubarak et al., 2020). The study also stated that poverty was causal increasing the digital divide consequently posing a great hindrance in low-income countries' access and use of ICT. However, the study also posited that education was a more significant factor influencing ICT use and adoption than income.

8.12 Employment Status

Here we saw that participants in part-time employment were the least prepared for CAIL in comparison to participants in full-time employment, who were found to be most prepared. The reason for the same could be that those working part-time have vocational education background and as such lack knowledge and access to training to effectively use new technologies (Felten et al., 2019), possess lower motivation affecting their attitudes and intention to use new technologies and may also suffer from challenges of lack of time and energy to use new technologies (Donati et al., 2021).

CHAPTER IX:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

9.1 Summary

This research endeavoured to develop a model that could help predict preparedness for CAIL among parents of primary class children in the UK. A sequential exploratory and sequential explanatory mixed methods design comprising of three studies (Study 1, Study 2, and Study 3) was adopted to investigate. Study 1 used a qualitative approach to answer the initial research question namely:

RQ: ***What are the various factors influencing parental preparedness for introduction of CAIL initiatives in Primary schools in the UK?***

An AI expert was interviewed to identify key themes that could help answer the research question. The themes were further categorised to form variables for further investigation. These variables are innovativeness, attitudes, collaboration and concerns. Hypotheses were developed for further testing using quantitative approach in Study 2.

H1: Innovativeness predicts preparedness for CAIL in parents is supported

H2: Attitudes predict preparedness for CAIL in parents is supported

H3: Collaboration predicts preparedness for CAIL in parents is supported

H4: Concerns predict preparedness for CAIL in parents is not supported

Quantitative computation showed that H1, H2, H3 were supported by our tests while H4 was not supported. This means innovativeness, attitudes and collaboration predict preparedness whereas concerns do not predict preparedness among parents. Simply put if a parent is innovative, has positive attitudes and is willing to collaborate with other stakeholders (children and teachers in this research) they will be more prepared for CAIL. Further exploration of quantitative data was also conducted to investigate associations between other demographic variables and the dependent variable preparedness. It was found that men were more prepared for CAIL than women, and had more positive attitudes towards CAIL than women. Additionally higher education and higher income had an impact on how prepared the participant was for CAIL. Meaning those with higher income and higher education were more prepared for CAIL than others.

The results of the statistically significant associations indicate that males exhibit a stronger preference for CAIL as a tool and perceive their children as being more prepared for CAIL. Moreover, individuals who possess a greater inclination towards collaboration have more favourable attitudes towards AI and are generally better equipped for the challenges posed by (CAIL). Consequently, women exhibit lower levels of support for CAIL as a tool, perceive their children as less prepared for CAIL, hold fewer favourable attitudes about AI, are less inclined to collaborate with other stakeholders (such as children and teachers), and are generally less prepared for CAIL.

Further, there was a positive association between income and both education and relationship status. This implies that those with higher income are more inclined to have achieved a better level of education and be in a relationship and live in a two parents or guardian household. In addition, individuals with higher incomes exhibit a greater preference for both utilizing CAIL as a tool and CAIL as a subject. Further, they indicated that their children were more prepared for CAIL. In addition, parents with a higher income exhibit greater degrees of innovativeness in relation to AI. They also demonstrate a stronger inclination towards collaboration and possess a higher overall level of preparedness for CAIL.

Participants with a higher degree of education exhibit greater levels of innovativeness and are more inclined towards collaboration with other stakeholders such as children and teachers to ensure efficient implementation of CAIL. These participants exhibit greater concern regarding AI but are generally better prepared for the introduction of CAIL initiatives in primary schools.

Participants residing in households with two parents or guardians have a greater favourability for both CAIL as a tool and CAIL as a subject, displaying elevated levels of innovativeness and more preparedness for CAIL.

Regarding participants who support the use of CAIL as a tool, there are strong and positive correlations with CAIL as a subject, the readiness of the child, innovativeness, attitudes, collaboration, and the readiness of parents. This suggests that these participants are likely to also support CAIL as a subject, believe that their children are more prepared for CAIL, have higher levels of innovativeness, hold more positive attitudes towards AI, are more supportive of collaboration, and overall be more prepared for CAIL. In contrast, the negative connection with concerns suggests a decline in the levels of concern

Likewise, supporters of CAIL as a subject assert that their child is ready for CAIL. Further these parents exhibit high levels of innovativeness, positive attitudes, willingness to collaborate, minimal concerns about AI, and higher level of preparedness for CAIL.

Parents who perceive their child as prepared for CAIL will also possess elevated levels of innovativeness, harbour more favourable views towards collaboration, display fewer concerns around AI, and demonstrate overall greater readiness for CAIL.

In addition, parents that possess high degrees of innovativeness will also exhibit more positive attitudes, be more inclined towards collaboration, and demonstrate more overall readiness for CAIL.

Parents who possess a positive attitude towards AI are more inclined to support collaboration, exhibit fewer concerns towards AI, and demonstrate more readiness for CAIL.

Parents who support collaboration have elevated levels of concerns but are also more prepared for CAIL.

This study has shown that there is a significant gap between males and females when it comes to AI. Women were found to be more sceptical compared to men towards AI and CAIL as compared to men.

Male parents have more positive attitudes towards CAIL, and also believe that their children are more prepared for CAIL than female parents. Further Male parents are also more in favour of introducing CAIL as a tool to teach existing subjects and also favour collaboration with teachers compared to female parents. Past research also supports this finding. Previous studies have shown that women exhibit less capability and interest in using computers as compared to men (Hargittai and Shaw, 2015; Imhof et al., 2007; van Deursen et al., 2015). Several other studies also posit that technology acceptance is dependent on gender of the user and how the gender interacts with the characteristics of the technology such as ease of use of the technology (Venkatesh et al., 2003) The main reason for this is the perceived notion that technology use belongs predominantly in the male domain and not in the female domain (Morahan-Martin and Schumacher, 2007). Other studies have suggested that women exhibit lower self-confidence, lower computer self-efficacy and higher anxiety when it comes to computer usage (Busch, 1995; Jackson et al., 2010; Saleem et al., 2011).Within AI, there is evidence to suggest that women are generally more sceptical about AI than men . A recent survey (Pew Research Center, 2022) has also shown that men (54%) use more AI than women (35%) in work place, are more likely to allow their children to use generative AI (31%) than women (4%). In fact, majority of women stated that they would ban their children from using AI altogether. Women are also highly sceptical of Ai based programs abilities to consistently make fair decisions.

The reasons for this scepticism are manifold. Firstly, women historically have been less preferred in technical and technological fields. There are less women in STEM fields than men. This initial entry barrier restricts a large majority of women from learning about new technologies and hence suffer from lack of awareness and knowledge of technology. This underrepresentation leads to increasing the gap between men and women when it comes to adoption of new technologies such as AI (Fung, 2019). This reservation against AI may also be causal in women being less ready to allow their children from learning about AI and consequently less prepared for introduction of CAIL initiatives in primary schools in the UK. Our research outcome pertaining to gender and AI is thus validated by past research.

This research also found that participants with higher income, higher education, two parent households exhibit more positivity towards AI than those with lower education levels, lower income and in single parent households.

Participants with higher income were also more predisposed to innovativeness, in favour of introducing CAIL as a tool to teach existing subjects as well as CAIL being introduced as a separately taught subject. This means high income participants were keen on introduction of CAIL in primary schools in any manner which shows that they were positively in favour of CAIL. High income participants were also found to be more in favour of collaborations with other stakeholders namely teachers and children.

Outcomes in this study also suggested that African ethnicities (Black Caribbean, Black African) were more prepared for CAIL than the European category comprising of a large majority of White British, Scottish, Welsh, Irish and some American Whites. In this study only marginally, significant difference was found between African ethnic groups and European ethnicities prior to post hoc test. However it is important to mention this here since these outcomes have been evidenced in past studies that have shown that migrants from African and Caribbean ethnicities to western Europe have higher ambition and determination which may be caused by their desire to have a better life and better opportunities (Arpino and de Valk, 2018; Damelang et al., 2021). This may explain in part the higher level of preparedness for CAIL in Africans as compared to Whites in The UK. However future research focusing on ethnicities and their preparedness for CAIL may be necessary to further evaluate this aspect.

The study investigated parents' preference for CAIL, both as a subject and as a tool. The results indicated that both components had significant main effects. This suggests that parents who supported CAIL, either as a subject or a tool, had higher levels of readiness compared to those who did not support it. Further, a notable interaction effect was observed, indicating that the disparity in readiness levels between CAIL as subject preferences and CAIL as tool preferences was not consistent. The interaction graph indicated that parents who supported both CAIL as a subject and tool exhibited the highest level of preparedness, whereas parents who opposed both CAIL as a subject and tool displayed the lowest level of readiness. The findings suggest that parents' perspectives on CAIL as both a subject and a tool play a significant role in determining their preparedness for CAIL.

The study examined the impact of parental gender and income on their preparedness for introduction of CAIL in primary schools. The findings indicated that male parents and parents with a higher socioeconomic status had a greater propensity towards CAIL compared to female parents and parents with a lower socioeconomic status. Nevertheless, the findings also indicated that the impact of gender on readiness was not contingent upon the income level, and vice versa. This indicates that the disparity in preparedness between male and female parents was consistent across various income levels, while the disparity in preparedness between high- and low-income parents was consistent across different genders. Gender disparity has been observed in some studies that examine skills and use of technologies by males and females. While one study found a marginally significant difference between boys and girls with boys faring better in skills and use of communication technology than females (Qazi et al., 2022), the other study conducted during covid-pandemic detected that online learning outcomes are significantly impacted by gender, education level and individual's personal traits and that female students, graduate students, and students with greater levels of dedication and curiosity exhibit superior performance in online learning. female students, graduate students, and students with higher conscientiousness and openness perform better in online learning (Yu, 2021).

Further income disparity was also identified as a factor in another study which found that income and education were positively correlated with information and communication technology adoption and use, which means that higher levels of wealth and education are linked to greater adoption and usage of ICT(Mubarak et al., 2020). The study also stated that poverty was causal increasing the digital divide consequently posing a great hindrance in low-income countries' access and use of ICT. However, the study also posited that education was a more significant factor influencing ICT use and adoption than income.

To examine mean differences between participants with different employment status on their readiness for CAIL a one-way ANOVA was calculated. Employment status has a significant effect on readiness. Participants in part-time employment were the least prepared for CAIL in comparison to participants in full-time employment, who were found to be most prepared. The reason for the same could be that those working part-time have vocational education background and as such lack knowledge and access to training to effectively use new technologies (Felten et al., 2019), possess lower motivation affecting their attitudes and intention to use new technologies and may also suffer from challenges of lack of time and energy to use new technologies (Donati et al., 2021).

In this study parents from dual-parent homes, on average, expressed a higher level of readiness for the implementation of CAIL programs in their child's primary school education compared to parents from single-parent households. This means that, parents from households with two parents or guardians felt more equipped for the implementation of CAIL initiatives in their child's primary school education compared to parents from single parent households. A previous study suggests that found that involvement of parents was an important factor that predicted how committed a child would be to online learning (Lawrence and Fakuade, 2021). Another study A study found that the parent-child relationship was directly correlated with adolescents' learning engagement. The study also found that the parent-child relationship also indirectly influenced the adolescents' motivation to learn as well as self-efficacy (Shao and Kang, 2022). These studies do not clearly suggest if parental relationship status has any bearing on a how prepared they are to accept CAIL or any form of technology learning for their children but do show a relationship between parent-child relationship and how parents can influence a child learning and self-efficacy levels.

Additionally, the scales developed for this study were found highly reliable (mention Cronbach) for all variables namely Innovativeness, attitudes, collaboration, concerns to explain preparedness for CAIL. This could be used as a model in future research to predict preparedness for AI initiatives in general and CAIL in specific. Collaboration has not been assessed widely within AI Literacy and hence addition of this variable in this study is of great importance. Parents that have exhibited high favourability to collaborate have also exhibited more preparedness for CAIL in the child's/children's primary schools.

The study reveals a significant gender gap in the adoption of Child AI Literacy (CAIL) as a tool and subject. Males have a stronger preference for CAIL as a tool and perceive their children as being more prepared for it. Individuals with higher incomes exhibit greater preferences for both CAIL as a tool and subject, and are generally better equipped for the challenges posed by CAIL.

Education is another factor that influences the willingness of participants to support CAIL as a tool. Those with a higher degree of education exhibit greater levels of innovativeness and are more inclined towards collaboration with other stakeholders, such as children and teachers. These participants also exhibit greater concern regarding AI but are generally better prepared for the introduction of CAIL initiatives in primary schools.

Relationship status is another factor that influences the willingness of participants to support CAIL as a tool and subject. Participants residing in households with two parents or guardians have a greater favourability for both CAIL as a tool and CAIL as a subject, displaying elevated levels of innovativeness and more preparedness for CAIL.

Child readiness is another factor that influences the willingness of parents to support CAIL as a subject. Supporters of CAIL as a subject assert that their child is ready for CAIL, and these parents exhibit high levels of innovativeness, positive attitudes, willingness to collaborate, minimal concerns about AI, and higher level of preparedness for CAIL.

The gender gap in AI adoption is further supported by past research, which has shown that women are generally more sceptic about AI than men. This scepticism may be due to the underrepresentation of women in technical and technological fields, which restricts a large majority of women from learning about new technologies and suffers from lack of awareness and knowledge of technology.

In conclusion, the study highlights the importance of understanding gender differences in the adoption of AI and CAIL in primary schools. By addressing these gender gaps, the development of effective CAIL initiatives can be made more accessible and effective for all stakeholders involved.

The study investigates the preparedness of parents for the introduction of Computer-Aided Learning (CAIL) in primary schools. It found that African ethnicities were more prepared for CAIL than European ethnicities, possibly due to their higher ambition and determination. Parents' preferences for CAIL as both a subject and tool were also significant, with those who supported both exhibiting the highest level of preparedness.

The impact of parental gender and income on their preparedness for CAIL was examined, with male parents and parents with higher socioeconomic status having a greater propensity towards CAIL compared to female parents and parents with lower socioeconomic status. However, the impact of gender on readiness was not contingent upon the income level, and vice versa. Income disparity was also identified as a factor in another study, which found that higher levels of wealth and education are linked to greater adoption and usage of ICT.

Employment status had a significant effect on readiness, with part-time employment participants being the least prepared for CAIL compared to full-time employment participants. This could be due to the lack of knowledge and access to training to effectively use new technologies, lower motivation, and challenges of lack of time and energy to use new technologies.

Relationship status showed that parents from dual-parent homes expressed a higher level of readiness for the implementation of CAIL programs in their child's primary school education compared to parents from single-parent households. This suggests that parents from households with two parents or guardians felt more equipped for the implementation of CAIL initiatives in their child's primary school education.

Innovativeness, attitudes, collaboration, and concerns were found to explain 77.5% of the variance in parents' readiness for the introduction of CAIL initiatives in their child's primary school learning. These findings suggest that innovativeness, positive attitudes towards AI, and willingness to collaborate with other stakeholders are all important factors in predicting parents' readiness for CAIL. However, concerns regarding AI did not significantly predict readiness for CAIL in this study.

The scales developed for this study were highly reliable (mentioned Cronbach) for all variables namely innovativeness, attitudes, collaboration, and concerns to explain preparedness for CAIL. This could be used as a model in future research to predict preparedness for AI initiatives in general and CAIL in specific.

9.2 Implications

Through this research the author has presented a model to predict preparedness which must be tested in other studies and also in other settings since the study has only focused on UK. Further collaboration a variable previously not used within any technological readiness models and theories was developed in this research. The author also developed an original 3 Item scale for collaboration which had high Cronbach value (suggesting scale consistency and reliability). It proved to be a key predictor of preparedness. This has implications for technological theories and models. Combining the constructed model in this research with other theoretical frameworks may help create a more evolved model to assess technological preparedness. As within the sphere of AI this model must be tested in other studies to assess its replicability.

Further this research also exhibits that mixed methods research design with Sequential exploration followed by sequential explanation is highly effective especially when researching an area that has limited understanding or is a novel area of research. Triangulation offered by this design helps verify findings making the results more reliable. In-depth insights attained from this research will prove valuable for other researchers.

Findings have also highlighted gender gaps in preparedness, innovativeness, attitudes and collaboration which have also been found in other literature. However, through qualitative assessment in Study 3 it was also found that education is the biggest barrier that hinders women from holding more positivity towards technological innovations, possess positive attitudes towards technologies, increase their willingness to collaborate, reduce their concerns and increase their preparedness.

This research has also found several other information such as how CAIL should be implemented, at what age must children be introduced to CAIL and what should be taught according to parents of primary children. These findings can help inform other stakeholders such as policy makers, AI literacy technology developers, researchers etc.

Further qualitative assessment of our quantitative findings has shown that with adequate measures put in place even parents that are strongly averse to AI usage and learning may also be prepared for CAIL introduction for their young children in UK. Given this policy makers and developers as other stakeholders can focus on developing educational products bearing in mind key concerns. Further policy makers must ensure that key concerns of parents in terms of formal curriculum, data protection and safety measures are put in place prior to introduction of CAIL for primary class children. Additional resources to educate parents about AI must be developed to enhance their understanding to positively predispose them towards CAIL. Additionally, parents have shown high willingness to collaborate with teachers to support their children’s learning. Schools should take cognizance and design activities and workshops where parents can be involved and also learn how to support their Childrens' AI learning to supplement what is taught in schools, at home.

This is the first study to assess the various variables that impact parents' readiness for CAIL. The scales developed and the variables studied have shown consistency implying that they are replicable in other studies as well. Collaboration is especially one variable developed and assessed in this study that hasn't been so far studied within AI literacy context within the UK and has been a key predictor of readiness. Overall using mixed methods with initial exploration to develop variables of interest and subsequent sequential explanatory approach has helped explain the depth of each variable which makes the findings of the study more robust.

Apart from this gender, education levels, income and relationship status have been identified as factors that may impact parental preparedness for CAIL. Female parents are less prepared for CAIL and the gender gap in education opportunities and work opportunities in technological disciplines and fields has led to this gap. Policy makers, schools and even developers need to pay special heed to this and ensure measures are taken to support them and provide them with adequate tools and knowledge to increase their AI awareness, minimize their concerns, alleviate their negative attitudes and increase their technology adoption, so as to ensure better preparedness among them for CAIL.

Education, income, relationship status are also factors that may impede preparedness of parents for CAIL. Free resources and continual knowledge and awareness initiatives to bring those with lower education, limited economic capability and in single parent households on par with those possessing higher education, higher income and in two-parent households.

9.3 Recommendations for Future Research

This study opens opportunities for further research within CAIL. Since collaboration has proven to be an important predictor of readiness among parents for CAIL, this aspect needs to be studied further in more detail to also understand the various factors that lead to willingness to collaborate. Collaboration is also a factor that must be tested among other stakeholders namely developers, teachers and children.

Further the model itself while dealing with CAIL and AI belongs in the larger change readiness universe of theories and must be tested to see its efficacy and fitment in other technological change readiness scenarios.

Additionally, all key variables assessed in this research namely innovativeness, attitudes, willingness to collaborate, concerns and preparedness can change over time basis several other factors. For example, innovativeness is a flexible factor and with adequate knowledge and training innovativeness levels in individuals can change. Hence a study with technophobic individuals where they are provided adequate learning, training and overall knowledge and then assessed on their level of innovativeness for CAIL will be useful.

Similarly, attitudes can also shift and a similar study can be conducted to understand how attitudes of individuals change post adequate knowledge and training support to help them understand AI can prove beneficial. This holds true for concerns and willingness to collaborate (participate, get involved) as well as preparedness as well. Hence a longitudinal assessment of how the levels of these variables (studied independently or in combination) change with external stimuli (technology literacy programs training, knowledge sharing, exposure to technology and encouragement to engage with technology) may provide some valuable insights.

Overall testing our findings with a larger sample may also be beneficial to see whether the results are generalizable beyond the UK in other countries as well.

Comparative studies assessing readiness levels of participants from other countries will also be a beneficial study.

Another thought that the author has is that introduction and implementation of CAIL is in some ways similar to technology implementation in large organisations. Change management is an essential part of all business transformation initiatives be it making the company more sustainable as is now happening in several parts of the world and especially in the European union or an Enterprise resource planning initiative (ERP Implementation). Employees are supported with extensive knowledge and training to be able to adopt changing ways of working in their jobs through change management. As part of this several motivated employees are identified and made into change agents to help motivate other employees.

Parents in implementation of CAIL can play the role of change agents (Hargis and Blechman, 1979; Johnson and Katz, 1973; Reisinger et al., 1976) especially because many of them see CAIL as an upskilling opportunity to make their children future ready. This is a big motivator that helps them surmount their own personal concerns and be prepared for it as has been seen in this research.

Author proposes that viewing CAIL implementation as a project and therein viewing parents as change agents may help not only educate children but in the process benefit parents as well and must be tried on a case study basis as a pilot project in certain schools or in a city of UK and further basis its efficacy on a larger scale countrywide. This twin pronged exercise may help alleviate fears and misconceptions pertaining to AI and also transform UK's technology adoption ability at the unit level.

9.4 Conclusion

This study has provided a suitable model to assess readiness for CAIL among parents. The same model may be a reliable model to use for future studies in similar context. Among the variables developed collaboration is a new variable that has so far not been included in other studies pertaining to AI literacy and must be tested in other settings and research scenarios. The scale for collaboration used in this research is an originally developed scale consisting of 3 items and has been found highly reliable and consistent. The study used a mixed methods design with initial exploration of the topic and subsequently followed by a sequential explanatory approach making the findings in-depth and robust. Innovativeness, attitudes, collaboration predict parental readiness for CAIL in a significant way, whereas concerns did not predict readiness significantly. Females were less positive about CAIL than male parents and it may be due to lack of education, exposure and opportunities to engage with AI among women. Income and education too showed disparity in readiness levels among participants. Further the research is first of its kind within the UK context. New scales and variables tested in this research can be replicated for future studies. Future research must also adhere to a longitudinal approach, in order to cull out how attitudes, innovativeness and concerns change when aspects like knowledge and training are imparted to parents. Further the author also proposes implementing a Change management model along with the model presented in this research to help parents become change agents in the process.

To conclude, AI literacy is an imperative for all especially for the younger generations to make them future ready to thrive in an AI-driven world. Parents play an important part in early childhood learning experiences of children and it is essential to involve them in any learning decisions that may impact the future of their children. However given the rapid progress within the AI domain many parents may feel less equipped to comprehend AI technologies. Training and informational workshops must also be designed specifically for parents in order for them to first equip themselves with AI knowledge so they can provide adequate learning support at home to their children in learning new concepts and information about AI. Further training and knowledge will also help alleviate misconceptions and concerns pertaining to AI in the minds of parents. On the part of the government a robust AI literacy policy must be designed keeping in mind all stakeholders and their views. AI Literacy policy must also entail a special focus on teaching young kids about AI. Child internet safety and other ethical implications are important to parents and if appropriate measures are put in place parents that feel reticent towards AI may also develop positive attitudes towards CAIL being introduced. This will also help parents ability to adopt AI in their lives. Parental preparedness hence is very important for CAIL implementation and efficacy. Collaborative efforts between all stakeholders will thus go a long way in making the children of today responsible, ethical and knowledgeable citizens of the AI powered world tomorrow. We just need to prepare parents to become change agents!

APPENDIX A

INTERVIEW QUESTIONS: STUDY 1

Q1. Hi, could you tell me a little bit about yourself. Your name, your profession, education as well as family?

Q2. How important do you think AI education is for everyone today?

Q3. Some countries are introducing AI literacy in schools for children in primary classes. What is your opinion on the same?

Q4. How do you feel as a parent of a young child about this?

Q5. What according to you are the factors that impact a parent's readiness for CAIL initiatives in the UK?

Q6. How should CAIl be introduced in primary classes in schools? Should it be made part of the existing curriculum to support learning of existing subjects? Or should it be introduced as a separate subject just like English, maths etc? Or would an approach of using both ways be better?

Q7. Family environment is crucial in child's early years to enhance learning abilities according o research. DO you agree with it?

Q.8 Do you think parents should collaborate with both children and teachers to ensure benefits of CAIL when the initiative is introduced?

Q9. Has there been any information from the government or Education department to parents regarding when and if CAIl initiatives will be introduced in primary schools?

Q.10 Would you support introduction of CAIL for your child?

APPENDIX B

SURVEY COVER LETTER-STUDY 2

This survey is meant for parents in the UK and will help contribute important insights towards a research thesis for the above-mentioned study title. While it is desired that you fill out all the information, you are not obliged to participate in this survey and may decide not to participate. All the information you provide will be kept confidential by the researcher to safeguard your privacy. The entire questionnaire will take approximately 10–11 minutes to fill out.

Participation and eligibility criteria:

If you are a parent or guardian of a child or children studying in primary school within the UK, you qualify for participation in this study.

APPENDIX C

SURVEY QUESTIONS STUDY 2

Demographic and qualifier:

What is your child's grade level in school?

What is your gender identity?

Which of the following best describes your current relationship status?

Married

Widowed

Divorced

Separated

Cohabiting with a significant other or in a domestic partnership

Single, never married

Prefer not to answer

Which age-group do you belong to?

Which ethnic/race group best describes you?

What is your annual income?

Which city do you live in within the United Kingdom?

What is the highest level of education you have completed?

Which of the following categories best describes your employment status?

Likert Scale: Strongly agree, Agree, Neither agree nor disagree, Disagree and Strongly disagree. This scale was used for all questions below unless specified otherwise

Innovativeness

I am generally among the first in my circle to acquire new AI technology as it comes out.

Normally, I can use new AI products and services smoothly without help from others.

I keep up with the latest AI technological developments in my field.

I like the challenge of learning to work with AI-enabled tools and applications (e.g., ChatGPT, Bing, etc.).

I feel I have fewer problems than others with making AI technology work for me.

Other people come to me for advice on new AI technologies.

Attitudes

I am excited about the idea of introducing AI concepts to my child.

I sometimes feel disappointed when considering the changes AI could bring to my child's learning.

I am happy when considering the changes AI may bring in my child's learning.

The idea of AI's influence on my child's learning can make me fearful.

The thought of the AI's influence on the future of my child's learning surprises me in a positive way.

It would be amusing to see how primary-class children respond to AI teaching practices.

I feel uneasy when thinking about how AI can change the process of learning for young children.

AI's potential impact on my child's learning often leaves me confused.

Collaboration

I am willing to collaborate with my child's teachers in teaching AI concepts.

I believe that parent-teacher collaboration is essential for effective AI education.

I am ready to engage with my child through activities at home that reinforce what is being taught about AI in school.

Concerns

I am concerned that AI education might be too complex for my child.

I worry that my child might spend too much time on screens if they learn about AI.

I worry that AI education might lead to an over-reliance on technology in my child's life.

I worry about the ethical implications (e.g., privacy) of teaching AI to my child.

I am concerned about the disparity in the quality of AI education between different types of schools (e.g., private schools, grammar schools, state schools, etc.).

I worry that schools with better facilities might provide a superior AI education compared to other schools.

I am concerned that children from minority communities and lower economic strata might not have equal access to quality AI education.

I worry that lack of well-trained teachers in some schools might affect the quality of AI education.

I worry that teaching with AI will significantly increase my child's workload.

Readiness

My child's school has the necessary technological resources (e.g., reliable internet connection, computers etc.) to teach with AI.

I understand the importance of teaching AI when teaching primary students.

I am comfortable with the idea of integrating AI into my child's learning.

My home has the necessary technological resources (e.g., a reliable internet connection, computers, etc.) to teach with AI.

I feel confident in my ability to use AI tools and applications to teach my child.

My child's school's administration supports the integration of AI literacy into the curriculum.

I am interested in receiving training to incorporate AI concepts in my child's learning.

CAIL as a tool

I would support the integration of AI education in my child's school curriculum.

Yes

No

CAIL as subject

I would support the integration of AI education as a separate subject in my child's school curriculum.

Yes

No

APPENDIX D

EMAIL INVITE FOR SURVEY: STUDY 2

Subject: Invitation to Participate in a Survey on AI Education in Primary Schools

I hope this email finds you well. My name is Malini Nair, a journalist and doctoral student conducting a study on the introduction of Artificial Intelligence (AI) education in primary schools across the UK. I am studying for my doctorate at Swiss School of Business & Management (SSBM) and I am Dutch of Indian origin.

The purpose of this study is to assess the attitudes, preparedness, and concerns of parents towards this significant educational shift.

I am writing to kindly request your assistance in distributing the attached survey to the parents within your circle of influence. The survey is designed to be completed in approximately 10-11 minutes and all responses will be kept strictly confidential.

The insights gathered from this survey will not only contribute to my doctoral thesis but also inform UK policy writers. The contributions from parents a will go a long way in designing an appropriate strategy, policy, and curriculum for young children. This is a unique opportunity for you to influence the future of AI education in the UK.

The results of the study will be shared with you should you so desire post participation in the survey. I would also like to inform you that this invite to participate is not mandatory and you may choose to not participate. If you do choose to participate, you are still not obliged to answer all questions and may decide to stop or exit the survey at any time.

I understand that your time, is valuable, and I greatly appreciate your consideration of this request. If you have any questions or require further information, please do not hesitate to contact me via phone or email.

Here is the link for the survey:

https://www.surveymonkey.co.uk/r/ZTVQK8H

Thank you in advance for your support in this important research.

Best regards,

Malini Nair

Journalist and Doctoral Student

Phone: +31613684628

Parents Survey

https://www.surveymonkey.co.uk/r/ZR7LDKN

APPENDIX E

WHATSAPP INVITE FOR SURVEY: STUDY 2

📣 Calling all parents of primary school children in the UK! 🇬🇧

We need your help for a doctoral research study titled "Assessing Attitudes, Concerns, and Preparedness of Parents Towards Introduction of Artificial Intelligence Literacy in UK Schools for Primary Class Children".

Your insights will be invaluable in helping us understand how ready we are as a society to introduce AI education to our young ones. The results of this study will be shared with policymakers in the UK and will contribute to designing an appropriate strategy for this important educational initiative. It is not compulsory for you to participate and even if you decide to participate you may exit at any point without filling-out the full survey. Having said that you participation will be highly appreciated!!

Rest assured; all information collected from the survey will be kept confidential. 🤐 The survey will take around 10-11 minutes to complete. You can access it at https://www.survey…

APPENDIX F

SOCIAL MEDIA GROUPS' POST FOR SURVEY: STUDY 2

Calling all parents of primary school children in the UK! GB

We need your help for a doctoral research study titled "Assessing Attitudes, Concerns, and Preparedness of Parents Towards Introduction of Artificial Intelligence Literacy in UK Schools for Primary Class Children". Your insights will be invaluable in helping us understand how ready we are as a society to introduce AI education to our young ones. The results of this study will be shared with policymakers in the UK and will contribute to designing an appropriate strategy for this important educational initiative.

Rest assured; all information collected from the survey will be kept confidential. 🤐 It is not mandatory for you to participate but would be highly appreciated if you did. And you may decide to exit the survey at any point in time should you so desire.

The survey will take around 10-11 minutes to complete. You can access it at https://www.surveymonkey.co.uk/r/ZR7LDKN

Thank you in advance for your time and contribution to this important research! 🙏

APPENDIX G

INTERVIEW INFORMATION SHEET STUDY 1 AND STUDY 3

Participant Information Sheet

Research project title: EXPLORING ATTITUDES, READINESS AND CONCERNS OF PARENTS TOWARDS INTRODUCTION OF CHILD AI LITERACY (CAIL) AT PRIMARY SCHOOL LEVEL IN THE UNITED KINGDOM

Research investigator: Ms. Malini Nair

Research Participants name:

Purpose of the Study:

This research is being conducted to assess the attitudes, readiness and concerns of Parents towards introduction of child Artificial Intelligence Literacy at Primary levels in schools in The United Kingdom. I am inviting you to participate in this research project about your personal views on the topic. The purpose of this research project is to understand how parents view introduction of AI literacy in schools for young children studying in primary education.

What will be the Procedure:

You will participate in an interview lasting approximately 30 minutes to 45 minutes. You will be asked questions about your views on introduction of AI education in schools, your views on Artificial Intelligence (AI) and how ready you feel you are to accept introduction of AI education in schools for young children, your concerns if any towards AI and children's exposure to it as a taught topic/subject in schools.

Sample interview questions for parents include:

How do you feel about the integration of AI literacy at the primary school level?

What are your expectations for your child's AI education?

Studies have shown that family environment helps children learn new concepts.

Would you as a parent like to be more involved in Child Artificial Intelligence Literacy (CAIL) initiatives that may require parental involvement outside of school?

Do you have any concerns about AI education for your child?

Conditions:

You must be at least 18 years old or above and a resident of The United Kingdom. You must be a teacher, teaching in a school in The United Kingdom and or a parent of school going children.

Potential Risks and Discomforts to you:

There are no obvious physical, legal or economic risks associated with participating in this study. You do not have to answer any questions you do not wish to answer. Your participation is voluntary and you are free to discontinue your participation at any time.

Potential Benefits to you:

Participation in this study does not guarantee any beneficial results to you directly. As a result of participating you may help contribute towards drawing a holistic picture on attitudes, readiness as well as concerns of parents and teachers towards AI education being incorporated in schools at primary levels for young children to learn about the basic concepts of AI, which can in turn help develop better teaching strategies, affect educational policy changes and also help researchers and educationists design suitable age appropriate AI curriculum for children in primary level classes.

Confidentiality:

Your privacy will be protected to the maximum extent allowable by law. All personal identification information gathered will be coded so as to ensure your privacy and only coded names or identification method will be used for research. No personally identifiable information will be reported in any research product. Moreover, only trained research staff will have access to your responses. Within these restrictions, results of this study will be made available to you upon request post completion.

As indicated above, this research project involves making audio recordings of interviews with you. Transcribed segments from the audio recordings may be used in published forms (e.g., journal articles and book chapters). In the case of publication, pseudonyms will be used. The audio recordings, forms, and other documents created or collected as part of this study will be stored in a secure location in the researchers' offices or on the researchers password-protected computers and will be destroyed within ten years of the initiation of the study.

Compensation:

Since this research is being self-funded the researcher is unable to offer any compensation other than gratitude for your participation.

You have the Right to Withdraw:

Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalized or lose any benefits to which you otherwise qualify. The data you provided before you stopped participating however will be processed in this research; no new data will be collected or used.

If you decide to stop taking part in the study, if you have questions, concerns, or complaints, or if you need to report an injury related to the research, please contact the primary investigator:

Malini Nair-Rai (Primary researcher)

Address: Swiss School of Business and Management School Geneva

Geneva Business Center

Avenue des Morgines 12

1213 Genève

Switzerland

Email: malinirai@gmail.com

Mobile Telephone: +31 6 13684628

Alternatively, you may contact the Supervisor on this Research study:

Dr. Minja Bolesnikov

Address: Swiss School of Business and Management School Geneva

Geneva Business Center

Avenue des Morgines 12

1213 Genève

Switzerland

Email: minja@ssbm.com

Institute Telephone: +41 (022) 508-7796

APPENDIX H

STUDY 1 AND STUDY 3 INTERVIEW CONSENT FORM

Research project title: EXPLORING ATTITUDES, READINESS AND CONCERNS OF TEACHERS, AND PARENTS TOWARDS INTRODUCTION OF CHILD AI LITERACY (CAIL) AT PRIMARY SCHOOL LEVEL IN THE UNITED KINGDOM: A CROSS-SECTIONAL EXPLORATORY STUDY

Research investigator: Ms. Malini Nair-Rai

Research Participants name:

The interview will take 30 minutes to 1 hour. We don't anticipate that there are any risks associated with your participation, but you have the right to stop the interview or withdraw from the research at any time.

Thank you for agreeing to be interviewed as part of the above research project. Ethical procedures for academic research require that interviewees explicitly agree to being interviewed and how the information contained in their interview will be used. This consent form is necessary for us to ensure that you understand the purpose of your involvement and that you agree to the conditions of your participation. Would you therefore read the accompanying **information sheet** and then sign this form to certify that you approve the following:

- the interview will be recorded and a transcript will be produced
- you will be sent the transcript and given the opportunity to correct any factual errors
- the transcript of the interview will be analysed by (name of the researcher) as research investigator

- access to the interview transcript will be limited to (name of the researcher) and academic colleagues and researchers with whom he might collaborate as part of the research process
- any summary interview content, or direct quotations from the interview, that are made available through academic publication or other academic outlets will be anonymized so that you cannot be identified, and care will be taken to ensure that other information in the interview that could identify yourself is not revealed
- the actual recording will be (kept or destroyed state what will happen)
- any variation of the conditions above will only occur with your further explicit approval

I also understand that my words may be quoted directly. With regards to being quoted, please initial next to any of the statements that you agree with:

	I wish to review the notes, transcripts, or other data collected during the research pertaining to my participation.
	I agree to be quoted directly.
	I agree to be quoted directly if my name is not published and a made-up name (pseudonym) is used.
	I agree that the researchers may publish documents that contain quotations by me.

All or part of the content of your interview may be used;

- In academic papers, policy papers or news articles

- On our website and in other media that we may produce such as spoken presentations
- On other feedback events
- In an archive of the project as noted above

By signing this form I agree that;

1. I am voluntarily taking part in this project. I understand that I don't have to take part, and I can stop the interview at any time;
2. The transcribed interview or extracts from it may be used as described above;
3. I have read the Information sheet;
4. I don't expect to receive any benefit or payment for my participation;
5. I can request a copy of the transcript of my interview and may make edits I feel necessary to ensure the effectiveness of any agreement made about confidentiality;
6. I have been able to ask any questions I might have, and I understand that I am free to contact the researcher with any questions I may have in the future.

Printed Name

Participants Signature — Date

Researchers Signature — Date

Contact Information

This research has been reviewed and approved by the Edinburgh University Research Ethics Board. If you have any further questions or concerns about this study, please contact:

Malini Nair

Full address:

Swiss School of Business and Management School Geneva

Geneva Business Center

Avenue des Morgines 12

1213 Genève

Switzerland

Tel: +31613684628

E-mail: malinirai@gmail.com

You can also contact the primary researcher’s supervisor:

Dr. Minja Bolesnikov

Full address:

Swiss School of Business and Management School Geneva

Geneva Business Center

Avenue des Morgines 12

1213 Genève

Switzerland

Tel: +41 (022) 508-7796

E-mail: minja@ssbm.com

What if I have concerns about this research?

If you are worried about this research, or if you are concerned about how it is being conducted, you can contact SSBM by email at contact@ssbm.ch.

APPENDIX I

INTERVIEW QUESTIONS: STUDY 3

Q 1. Hello could you introduce yourself and tell me a little bit about yourself. You age, profession, educational qualifications and your family please?

Q2. When it comes to technology how would you define yourself and early adopter, cautious adopter or technology averse?

Q3. Do you finding AI technology use very difficult or easy?

Q4What is your opinion on AI literacy for children in primary classes?

Q5. As a parent how would you define yourself? Are you involved in your child’s learning process?

Q.6 How important do you think it is for parents and teachers to collaborate to help children learn better especially when it comes to new topics such as AI?

Q.7 Are there any specific things about AI that are worrisome to you?

Q8. What could be done to reduce these concerns r?

Q. 9 How prepared do you feel for the introduction of CAIl initiatives for your child in primary class?

Q. 10 According to you what should be taught about AI to young kids in primary classes?

Q. 11 Which age group do you think is most appropriate to start AI learning?

Q.12 How prepared do you think you child is to learn about AI?

Q. 13 Do you think CAIL should be introduced to kids as a tool to teach existing curriculum subjects or as a separate subject altogether?

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