Media Technologies and Artificial Intelligence in Education: Essential for the Future or Unwelcome Innovation?

A look at general attitudes towards media technologies and artificial intelligence in education, and the framework for innovation adaptation

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ABSTRACT

Since the role of education is of indescribable importance in societies, it is essential that education stays up to date with its time. As of recent decades, media technologies (MT) have been increasingly important in society and implemented in education, and now artificial intelligence (AI) is rapidly developing and also seems poised to be majorly implemented in education. This study explores the positives and negatives of both MT and AI in education, tries to assess general attitudes towards the implementation of MT and AI in education, and tries to unravel key predictors that influence these attitudes. Based on adaptation innovation frameworks such as the diffusion of innovation theory, the technological acceptance model and the unified theory of acceptance of use of technology, certain predictors are implemented in this research. The associations that perceived usefulness, perceived ease of use, experience, mobile self-efficacy, age and Schwartz' human values have with attitude towards both MT and AI in education are researched. A self-administered online questionnaire was carried out to test these predictors (N=165), with predominantly positive results. The overall attitude towards MT and AI in education seemed neutral, however younger age groups were predominantly positive towards both MT and AI, where older age groups were predominantly negative towards both MT and AI. All predictors that were hypothesised to have associations with attitude towards MT and AI, were at least partially significant. As single predictors, perceived usefulness, perceived ease of use, experience, mobile self-efficacy, age and Schwartz' human values all had strong significant associations with both attitude towards MT and AI in education. In a wider model with all predictors implemented, perceived usefulness and age were seen as the strongest predictors for attitude, with perceived ease of use and conservatism also both having significant associations with both attitude towards MT as AI in education. Further research on both the attitudes towards MT and AI in education, as on the advancement of adaptation innovation frameworks is desirable, as it seems unavoidable that MT and AI are (going to become) essential in societies. Because of this, refined and future-proof frameworks to help with innovation adaptation could help with the implementation of MT and AI, and future innovations.

<u>KEYWORDS:</u> *Media technologies, artificial intelligence, education, innovation adaptation frameworks*

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1) Introduction

Education is, as Nelson Mandela famously put it, 'the most powerful weapon which you can use to change the world. (Nelson, 1990)' A quote like this does not counter much resistance, as an education system has, in every society, an incredibly important societal function, and is of indescribable importance. The benefits of education are easily measurable, as there are countless of direct links between education and for example improved risk perception (Torani, Majd, Maroufi, Dowlati & Sheikhi, 2019), improved health (Kemp & Montez, 2020) and empowerment (Singh, 2016). However, to write off education as a handful of beneficial consequences would be doing it short, as education entails much more than this on both an individual and societal level. Education is the foundation for the rest of your life, prepares you to individually and responsibly be a part of society, and functions as a medium for personal, social, political, economic and cultural development (Bhardwaj, 2016). Because of this essential role education has in our society, it is incredibly important that an education system progresses along with its time and keeps preparing the youth for the world awaiting them. However, in the past (few) decade(s), this has not always necessarily been the case. Over recent years, education in countries that historically have performed well in the education sector, has been slipping in overall quality, attainment and participation (Inspectie van het onderwijs, 2018; Busteed, 2020; Weale, 2020). Technology, and especially media technologies, have been so rapidly developing over the last decades, that education systems are accused of not being able to keeping up with their developments (Reams, 2017; Tsuboya-Newell, 2019). This is concerning considering teachers, even back in 2013, almost unanimously claimed that media technologies have massively impacted education (Purcell, Buchanan & Friedrich, 2013). Education systems, which should prepare new generations for the world ahead of them, are thus now in danger of preparing new generations for a time which has already past, and it is essential that they keep up with their time to successfully keep fulfilling its societal role.

Two of the most important technological developments which have brought a plethora of possible positives and negatives to education systems are media technologies and artificial intelligence. Media technologies (MT) have become so ubiquitous in daily life that they are practically unavoidable, especially amongst younger age groups (Anderson & Jiang, 2018). MT, which are defined as 'any hardware, software or tool that is used to compose, create, produce, deliver and manage media', refer in the context of this study only to hardware, so for example laptops, tablets, mobile phones and other comparable hardware. Over the last few decades, these media technologies have been increasingly used in education, through for example laptops and tablets, for which usage has soared (Truong, 2020). Artificial intelligence (AI), a relatively newer concept, is now also taking the world by storm, making its way in various essential sectors such as healthcare (Panch, Mattie & Celi, 2019), entertainment (Sweichowski & Slezak, 2018), and more. Artificial intelligence, which is defined as the ability of a computer to do tasks that are usually done by humans, in this context strictly refers to software, that is run on the hardware that are MT. Famous everyday examples of AI software, or software that utilizes AI, are is for example Google, Uber and Facebook (Faggella, 2020). However, now there are innovative ways being found to also integrate AI into various education systems. This increasing implementation of MT and AI into education provides both opportunities and problems for education systems. Further MT and AI integration into education systems could personalize learning more, and learning to work with these media technologies and AI could prepare the youth for a future where these technologies seem unavoidable. Additionally, that media technologies in education and their usage are on the up, is apparent. The EdTech market, which is the market for educational technologies, for example media technologies, has a market size value of 76.4 billion as of 2019, and is expected to grow by 18 percent annually for a market size of 285.2 billion in 227, the exponential growth partially explained by the current covid-19 pandemic (Paykamina, 2021). While the market of AI in education is currently worth only a fraction of this, at 1 billon, it is expected to grow much more exponentially at 45% a year (Dukaninovska, 2020). Both MT and AI are poised to have a massive impact in many sectors of society, but possibly education is one of the sectors where it will have most influence.

However, despite the positives both media technologies and AI can bring to education, and despite how necessary it might be for education to fulfill its societal function, not everyone is very happy about these developments. Numerous calls to action have been made to ban certain media technologies, for example laptops, tablets and phones, from classrooms (Lieberman, 2017; Kurz, 2019; Truong, 2020; Criddle, 2021). Additionally, while artificial intelligence is not yet integrated to such a degree that media technologies are, people are scared about the possible integration of AI in education, and even AI in general (Ghafourifar, 2017; Pega, 2020). But it goes further than that, with a sizeable portion of a recent survey even claiming they thought that AI would bring about the end of the human race (Bucholz, 2019). What is interesting that most of these critiques and fears come from older generations, parents teachers, generally the groups who use MT and AI less, but also have the less knowledge about both MT and AI and are less competent in using them, compared to younger generations and students. This digital skills and knowledge gap, which research shows is only getting wider (Udeze & Oko, 2013; Milano, 2019), could be harmful to the integration of MT and AI in various sector, but also towards other future innovations. We have seen this in the past, for example with the integration of computers into our daily life. While computers are now pretty widely seen as incredibly important in our lives and in society (Villalta, 2019), its integration was met with resistance from predominantly older age groups, who still have a more negative attitude towards them (Broady, Chan & Caputi, 2010; Lee, Czaja, Mozley, Sharit, Boot, Charness & Rogers, 2019). It is evident that not everyone is on board with the revolution that MT and AI possibly are bringing to education, and it'd be both interesting and relevant to unravel the reasons and motivators for this.

It is both scientifically as societally highly relevant to assess the attitudes people have towards media technologies and AI in education, and what the reasons behind these attitudes are. Scientifically, there is a lack of research thus far in attitudes towards AI and what the reasons behind these attitudes are, considering it is still a relatively new phenomenon, and research on it is still somewhat scarce. Research on the acceptation of MT is a lot more common, yet research on the usage of MT in general education, and what people think about this, is surprisingly scarce. Furthermore, it is scientifically relevant to research the several interrelating reasons for attitudes towards innovations/technologies. This is the case because while current frameworks on innovation adaptation do exist, they are arguably, and especially in the light of the covid-19 pandemic, outdated and/or obsolete (van den Heuvel, 2020; Al-Emran & Granic, 2021). The societal relevance is also quite sizeable, as there are three components as to why its societally important to research this phenomenon. Firstly, as education has an immensely important societal function, it is important that, as mentioned before, it stays up to date and prepares the youth for the future ahead. Considering that AI in the US alone already has cost 60 million jobs (Kelly, 2020), is projected to cost 85 million jobs by 2025, but also projected to create 97 million new jobs (Shalamanov, 2021), it is highly important that the new generation are able to deal with this technology in able to participate in society, what essentially the role is of education. Secondly, it is societally relevant to assess the attitudes towards MT and AI considering that MT are now a ubiquitous presence in life, and AI is poised to have a massive impact in societies too. Therefore, assessing attitudes towards these technologies to see if specific action, for example regarding acceptation or education, needs to be taken regarding these technologies is highly relevant. Lastly, it is societally relevant to extend the existing frameworks on innovation adaptation, or establish a new framework for adaptation innovation which is future-proof. Considering humanity, and their technology, is developing rapidly, a framework to easily assess the key factors in innovation adaptation would help in adapting future innovations and assessing where possible problems lie for these innovations. For example, if gender or age proves to be highly significant in adapting innovation, a country with a high populations of certain age groups would have to deal different with implementing these innovations than others, considering the resistance it might bring. All things considered, the scientific and societal relevance for assessing attitudes towards MT and AI in education is apparent, which brings to the following RQ with the subsequent sub questions.

RQ 1: To what extent do people look positively towards the implementation of media technologies and artificial intelligence into education ?

SQ 1: What direct technology-related factors are associated with attitudes towards media technologies and artificial intelligence in education?

SQ 2: What socio-demographic factors are associated with attitudes towards media technologies and artificial intelligence in education?

SQ 3: What factors are the most important predictors for attitudes towards media technologies and artificial intelligence in education?

2) Theoretical Framework

2.1) Media Technologies in Education

Media technologies (MT) have, over the course of history, become increasingly significant in education, to the point where they are now essential. MT are defined as 'any hardware, software or tool that is used to compose, create, produce, deliver and manage media' (Spacey, 2019), and include 'traditional' technologies such as VHS, cassette players, televisions and projectors. However, for this research, the focus is solely on electronic and digital media technologies, which is hardware that depends on electricity and uses screens, so this excludes most of the aforementioned traditional MT. While electronic MT were absent in classrooms until the beginning of the 20th century (Domine, 2009), these types of traditional technologies were steadily introduced into education during the 20th century, and have since been replaced by newer and, arguably, better media technologies. These technologies, dubbed new media technologies, are defined as technologies that use digital computer technology for distribution and exhibition (Manovich, 2002). The distinction between new media and new media technologies must be made, as there are papers and research that use the terms interchangeably. New media, also often referred to as web 2.0, refers to the development of the internet into a fully interactive platform of applications and content. New media technologies then, are the technologies used to access these applications and content. To illustrate, an online blog is a form of new media, as it is a user-generated form of content accessible on the internet. A media technology then, is for example the laptop or phone you use to access that content, so the term media technologies strictly refers to hardware. Over the last 2 decades, since the uprising of new media and new media technologies, we have seen these technologies implemented rapidly into education. The usage of MT such as tablet, laptops and smartphones has skyrocketed across all levels of education (Cavanagh, 2015; Hassler, Major & Hennesy, 2016). Furthermore, during 2020 and 2021, education has essentially become solely dependent on MT such as videocall technology, for example the application Zoom. This is the case because the Covid-19 pandemic, in many countries, prevented students from physically attending classes. MT have become a core element which are highly embedded in all levels of education (Westera, 2015), and the expectations are that this trend of growing importance will continue (Walsh, 2020; Hughes, 2021).

The reason why MT have grown to be so important in education, is because there is a general consensus that they aid with education. This is not a new insight, as research from back in the 1980s, 1990s, and even before that , already established that MT have a positive effect on education. However, an effort must be made in clearly distinguishing two types of learning that MT enable (Reeves, 1998). The first type of learning is learning from media, through for example instructional media, integrated learning systems or other explanatory material (Seels, Berry, Fillerton & Horn, 1996; Reeves, 1998; Holden & Westfall, 2007) . You can think of for example how a teacher can spend an hour trying to explain what a bee or any other animal looks like, but a video of a minute will do a more effective job at doing the exact same thing. While older research, through predominantly Richard Clark (1983; 1994; 2001), argued that there were no learning benefits to be gained from any specific medium, and even that MT would never influence learning, countless research and the current situation where MT are highly embedded in education has proven those assumptions wrong. The second type of learning, originated by Robert Kozma (1991), is learning with media. This is described as a complementary learning process where MT provide for example 'cognitive tools and constructivist learning environments' (Reeves, 1998, p.4). Kozma argued that certain strengths of a media technology, combined with methods or applications that take advantage of these strengths, 'interact with and influence the ways learners represent and process information' (Kozma, 1991, p.179), and that because of this, learning is enhanced. Further research has since indicated that different MT can indeed be implemented in various way to facilitate and enhance the learning experience (Reeves, 1998; Singhal, Bagga, Goyal & Saxena, 2012; Ibáñez, Di Serio, Villarán & Kloos, 2014). What this means, is that for example the usage of tablets in a mathematics class can directly lead to increased engagement, increased accuracy and a deeper understanding of mathematical concepts (Murphy, 2016; Schacter & Jo, 2017), because the strengths of tablets help address problems of disinterest, inaccuracy and misunderstanding, which are otherwise commonly seen in mathematics classes. Countless further research with a wide variety in MT and level of education exists to back up the general consensus regarding MT and education, which is that MT can enhance education by allowing students to learn both from as with MT.

However, the possible ineffectiveness or harmfulness of MT in education are also widely researched and discussed. Some have even claimed that MT have 'extensively plagued education' (Khoshnnevisan, 2019, p.85). One of the biggest complaints about MT in education is that they are a distracting factor, a claim backed up by an extensive amount of research showing for example laptops, tablets and mobile phones to be a distraction in classes (Jackson, 2012; Goundar, 2014; Taneja, Fiore & Fischer, 2015; Aaron & Lipton, 2018). While the argument could be made that distraction in class is ever-present and has always been a problem (Kemp, 2008), various research over the last decade shows that MT have been increasing the amount of distraction in education (Douglas, Angel & Bethany, 2012; Spitzer, 2014), and a recent survey shows that over half of students in class are continuously distracted by MT, despite the fact that they think MT in the classroom are unavoidable (Hazelrigg, 2019). Because of the distracting function MT have, calls to action have been made over the years to ban (certain) MT from education (Yamamoto, 2007; Rockmore, 2014; Reed, 2016; Selwyn and Aagaard, 2021), with France even banning mobile phones at certain levels of education because of this back in 2018 (Hess, 2019). While it is debatable whether this is the right solution to the problem, it is apparent that distraction is a consequential problem of the implementation of MT in education.

The other major problem this research will touch upon is the combination of limited effectiveness and our current overreliance on MT in education. As mentioned before, Richard Clark strongly argued that MT would not have a specific effect on learning (1983). While there is some research arguing for the limited effectiveness of MT, such as a study which found that physical note-taking is actually more effective than digital note-taking (Mueller & Oppenheimer, 2014), the research on both positive and negative effects of MT on education rebuke Clark's statement regarding complete ineffectiveness. However, Clark (1983) also states that pedagogy and the role of the instructor in education (should) outweigh the importance of MT used, as he claims that MT are 'mere vehicles that deliver instruction but do not influence student achievement any more than the truck that delivers our groceries causes changes in our nutrition," (Clark, 1983, p. 445). Van Lier furthermore emphasized the supporting role MT should have, stating that MT 'should not be cast as an alternative to classroom teaching, or as replacing the teacher, but as a tool that facilitates meaningful and challenging classroom work' (Van Lier, 2003, p.2). Considering MT as supportive towards the main pedagogic goal of education is extremely relevant nowadays, considering that the current central role MT have gotten is, according to research, leading to a dehumanization of the educational environments and a distortion of social interactions (Alhumaid, 2019). This trend of the centralisation of MT in and dehumanization of education, has never been more apparent than through the Covid-19 pandemic, wherein most education is held through MT. Both students (Rimer,

2020) as teachers (Cheung, 2021), have had mixed responses to this new learning environment. However, almost two thirds of students felt that education is physical classrooms was better (Chakraborty, Mittal, Gupta, Yadav & Arora, 2020), and many students and teachers named technical problems (Wong, 2021a), a lack of social interaction with both fellow students as teachers (Wong, 2021b) and a lack of support and guidance (Schwartz, 2020) as major problems that plague online education. The unarguable core and essential position MT now have in education is evidently causing problems for both students as teachers, and the role of MT when physical classes become possible again might need to be rediscussed.

All things considered, trends show that MT have over time become increasingly important in all levels of education, and have now claimed an essential role. This has been possible due to the fact that MT evidently aid in the learning process, allowing students to learn both from as with MT. Despite this, MT are also a distracting factor, and our current overreliance on MT combined with the ideal assisting role MT should have, has also led to several problems in education today. Despite the problems however, the general consensus is still that MT are helpful in education. Because of this, this thesis hypothesises as follows:

<u>H1: People are predominantly positive about the implementation of media technology in education</u>

2.2) Artificial Intelligence in Education

Artificial intelligence is a rapidly growing and spreading technology in all types of sectors, and it is expected to have a big influence on education in the coming years. Artificial intelligence, better known as AI, is 'the simulation of human intelligence processes by machines' (Tucci, 2020), meaning that it makes it possible for machines, including digital devices and man-made technology, to learn from experience and adjust to new inputs to perform human-like tasks. Early development dates back to the 1950s, when Alan Turing published the work 'Computing Machinery and Intelligence', first introducing the concept of artificial intelligence (Yampolskiy, 2013). Since then, it has developed immensely to what it is now, and in today's world it is already a helpful tool in for example healthcare, for example through being able to 'suggest courses of medication based on real-time biomarkers' (Panesar, 2019, p.18). While AI has thus far not been implemented into education as much as in other sectors, like for example transportation or the aforementioned healthcare (Sekar, 2018), AI in education was already a market worth 1 Billion USD in 2019, and is expected to grow annually by 45% (Dukadinovska, 2020). It must be noted that AI in education is already used more than people might expect, for example on things such as data collection on attendance and assignments (Luckin, Holmes, Griffiths & Forcier, 2016). Despite this quick growth and current usage, which shows the demand, there is also doubt amongst people whether this rapid development of AI is a good thing. Notable people, such as Stephen Hawking and Elon Musk, warned about the dangers of this rapid development and even think that AI could replace humans altogether (Gall, 2018; Marr, 2018). A recent global survey by Pega (2020) amongst consumers furthermore showed this fear of the rapid development, with almost a quarter of respondents indicating they fear the enslavement of humanity as the result of the rapid development of AI. While there is evidently hesitance regarding the development of AI, it is apparent that its development and implementation in different sectors is proceeding rapidly, with education likely dealing with major implementation in the foreseeable future.

The implementation of AI in education is beneficial, as its strengths aid both students in learning as teachers in teaching. The biggest advantages to AI are, arguably, its reduction in human errors, its precision and its efficiency (Kumar, 2019), and all three of these traits make AI useful in aiding education. Perhaps the biggest positive about AI in education would be the efficiency created. For teachers, who a study showed spend 50 hours a week working (Bryant, Heitz, Sanghvi, & Wagle, 2020), AI could assist in reducing their time spent on non-teaching tasks such as administrative work and marking tests, which a survey showed teacher spend a significant amount of time on (Southworth, 2019). For students, AI could focus on identifying 'what a student does and doesn't know through diagnostic testing and then developing personalized curricula based on each student's specific needs' (Kulkarni, 2019). An efficient personalized curriculum tailored to students' needs, could be an answer to the relative ineffectiveness of the traditional standardized approach to education (Rouhiainen, 2019). The effectiveness of AI is evident, as for example a study showed that the educational language application Duolingo, which relies on AI to identify what a user does and does not know, is more effective in language learning than a full university semester language course (Vesselinov & Grego, 2012). The effectiveness and precision of AI go hand in hand, as the precision of the aforementioned system where student's needs are tailored would increase the efficiency of learning. Precision education requires 'accurate predictions of academic performance based on early observations of the learning process' (Tempelaar, Rienties & Nguyen, 2021, p. 109), something which AI can and already does provide (Buckingham & Luckin, 2019). Lastly, this precise and effective scenario in which AI identifies students' strengths and needs could also address the much criticised issue with standardized testing. Standardized testing has been criticized heavily as they are supposed to determine whether the students control the material they are supposed to learn, but the standardizes testing eliminates certain subjects such as arts and social studies (Delgado, 2018), because it ignored different needs different students have and because it undermines actual teaching as both teachers and students predominantly care about scores for accountability reasons (William, 2010; Aydeniz & Southerland, 2012; Shelton & Brooks, 2019). With a precise and effective curriculum for students, the focus would be readjusted to making sure students acquire necessary information and skills (Kulkarni, 2019). All things considered, AI could be a useful enhancer in education to make students learn more effectively and focus more on their strengths and weaknesses

However, the implementation of AI in education also brings some notable negatives, and just as with media technologies, the biggest negatives arise when we over rely on AI. The biggest negatives to AI are, arguably, that they do not possess social intelligence and common sense reasoning (Piletic, 2018). As these inherently human traits are (yet) impossible for AI to mimic, people fear that an implementation of AI in education will lead to a dehumanization of education. The dehumanization of education as a consequence of (media) technology has long been a talking point (Nissenbaum & Walker, 1998), and throughout the last two decades arguments have been made that this has been constantly happening (Haslam, 2006; Alhumaid, 2019). The argument could also be made that AI would only make education more of a human environment, as AI would automate the most repetitive and physical tasks in education today. This would then lead to a situation where uniquely human skills, such as for example empathy, sense-making and creativity will be developed more (Uria-Recio, 2019). These types of skills are, besides the dehumanization of education, another notable problem to some regarding AI implementation into education. While AI has showed to be of aid in learning material such as (sign) language (Vesselinov & Grego, 2012; Paudyal, Lee, Kamzin, Soudki, Banerjee & Gupta, 2019) and mathematics (Gadanidis, 2017), AI does possess certain essential 21st century skills, which are, often indirectly, taught in education nowadays. These skills, also called the 4 C's, are (1) critical thinking, (2) creativity, (3) collaboration and (4) communication, which are all deemed important skills, yet they are unique to humans (Germaine, Richard, Koeller, Schuert-Irastorza, 2016). Just like with media technologies, AI could be important as an aid in education, but considering the important pedagogic function of education, it is not advisable to over rely on it as it is in no way a replacement of human teaching.

In short, AI has developed massively over the last few decades, and especially in the last few years. It is, at the moment, being implemented predominantly in sectors that require a high amount of precision and efficiency, but it is also expected to have a big influence on education in the upcoming years or decades. The efficiency and precision that AI bring could aid in educating students more personally and effectively, and how it could automate certain processes leading to a reduced workload for teachers, are sizeable positives. However, as AI is not a replacement for teaching, society should be aware for an over reliance on AI, as it misses certain essential skills unique to humans. Considering the positives AI does have, however, this research hypothesises as follows:

H2: People are predominantly positive about the implementation of artificial intelligence in education

2.3 Innovation and Media technology adoption Frameworks

Because the implementation of new media technologies in education is a complex matter concerning both innovation and technology adaptation, on both a societal as a personal scale, elements from multiple frameworks regarding innovation/technology adaptation have been adopted in this thesis. The first framework from which elements have been adopted is the diffusion of innovations theory (Rogers, 2003). The theory, which was originated by Everett Rogers in 1962 (Rogers, 1962), seeks to explain the societal adoption process of innovations through a five stage-process. These stages are knowledge/awareness (1), persuasion (2), decision (3), implementation (4) and confirmation/continuation (5) (Rogers, 2003). Rogers actually uses the words innovation and technology as synonyms, as most diffusion research involves technological innovations (Sahin, 2006). Furthermore, the theory is described as most appropriate for investigating adoption of innovation in education and educational environments (Parisot, 1995; Medlin, 2001). The second framework from which elements have been adopted is the technology acceptance model (TAM). The model, which was originally proposed in 1986 by Davis (Davis, 1986), but ultimately finalized in 1996 (Venkatesh & Davis, 1996), is a widely used model to understand and predict how technology will be accepted and adopted. The model provides two predictors of attitude towards technology, namely perceived usefulness and perceived ease of use (Venkatesh & Davis, 1996). Both of these predictors are influenced by what are called external factors, such as age, gender and experience. However, those two predictors are, in the TAM, the essential predictors. The third and final framework incorporated into this thesis is the unified theory of acceptance and use of technology (UTAUT). The theory and model, devised by Venkatesh et al. in 2003, is in essence a extended and unified version of eight previous models of innovation adaptation, including the TAM (Venkatesh, Morris, Davis & Davis, 2003). The model shares the two main predictors of attitude towards innovation that the TAM also has, but adds a third predictor for attitude, namely social influence, which is considered only an external factor in the TAM. A fourth predictor which directly predicts usage of technology is also included in the UTAUT, but since this thesis focuses on attitude towards new media technologies, this is not as relevant. Venkatesh et al. (2003) found that while any of the eight previous models they extended upon could only explain for between 17 and 53 percent of the variance within attitude towards new technologies, the UTAUT could explain for 70 percent of this variance, meaning it is a more extensive and complete framework in comparison to the TAM.

While all three theories and models provide useful elements which are used in this thesis and have a lot of commonalities, all three theories and models also have significant differences and shortcomings which is why not just one theory was drawn upon. First of all, all three theories agree on the fact that an increase in positive attitude towards an innovation or technology leads to an increase in usage (Venkatesh & Davis, 1996; Venkatesh et al., 2003; Rogers, 2003). Through backwards reasoning, this would mean that the attitude towards media technologies would be more positive than towards AI, considering media technologies are implemented more in education, and more of an ubiquitous presence in everyday life. Furthermore, all three theories agree on two types of barriers or predictors of technology acceptance, whether they are called first and second order barriers, or internal and external predictors, or something else. In all three theories, there are barriers/predictors directly related to the technology, and more indirect, often social, barriers/predictors more related to the person itself and several socio-demographic factors. Lastly, the theories agree on a lot of these predictors/barriers, which will be expanded upon in the upcoming sections. However, all three theories also deal with criticism and notable differences between them. The diffusion of innovation, theory, while widely implemented and seen as a standard for analysing a society's response to new innovations/technology has been criticised for overlooking the importance of social factors and how all predictors of innovation acceptance are interrelated (Lyytinen & Damsgaard, 2001; Lundblad, 2003). The TAM is also a widely used model to predict technology acceptance on a more personal level, and is praised for being an easily applicable model with an comprehensive amount of variables (Lim, 2018). However, its simplicity is also its main criticism, with several claims that it hold little practical value. It is argued that a model so simple can not be expected to explain such a complex social phenomenon and the model is criticised for being able to explain less variance in attitude, compared to for example the UTAUT (Venkatesh et al., 2003; Bagozzi, 2007; Benbasat & Barki, 2007; Chuttur, 2009). Also, similar to the diffusion of innovation theory, the neglect of the social context and socio-demographic factors in the TAM is also criticised (Bagozzi, 2007). Lastly, we have the UTAUT, which is in essence a more extensive version of the TAM and other models, and is lauded for explaining more variance in attitude and usage of technology, and incorporating the social context, and socio-demographic factors, as one of the main predictors in attitude towards new technology. However, this model is criticised because it is too extensive, leading to what some claim a chaotic model (Bagozzi, 2007), and it is impractical to apply generally because of the many interdepending variables in the model (Van Raaij and Schepers, 2008, Li, 2020). Because of this, the main role social context and the correlating socio-demographic variables it has in attitude towards new technology are adapted, but most other variables are emitted from this research.

In this research, elements from three prominent theories on innovation/technology adaptation are implemented in order to try and establish the most important predictors for attitude towards media technologies and AI in education. From the diffusion of innovation theory, the central role of experience in predicting attitude is implemented, and its general societal outlook on innovation adaptation. From the TAM, the simplicity of the model along with its two main predictors are implemented. Lastly, from the UTAUT, the important role of social context along with several socio-demographic factors as a main predictor rather than an external variable is implemented, in order to see how important the social context on its own is. While the three theories differ on significant points, major predictor for attitude towards new innovations/technologies are common, and also the reasoning that more experience with a technology leads to a more positive attitude. Because of this, and the fact that media technologies are more ubiquitous and have been used longer than AI, this thesis hypothesises as follows:

<u>H3: People are more positive about the implementation of media technologies in education, than they are about the implementation of AI in education.</u>

2.4 <u>Technology-related predictors for attitude</u>

While there are a lot of interconnected variables that come up in the aforementioned theories, perceived usefulness is consistently one of the main predictors of attitude towards new (media) technology. Perceived usefulness or performance expectancy is defined in the extended UTAUT as the perceived 'degree to which using a technology will provide benefits to consumers in performing certain activities' (Venkatesh, Thong & Xu, 2012, p.159). Perceived usefulness or performance expectancy is, according to both the TAM and the UTAUT, influenced by many external variables, which include image of the innovation/technology, its relevancy to one's job, the demonstrability of results and experience with the innovation/technology (Venkatesh & Davis, 1996; Venkatesh et al., 2003; Venkatesh, Thong & Xu, 2012). This predictor has, according to the UTAUT, been consistently the strongest predictor of attitude towards new technologies (Venkatesh et al., 2003). The effect of perceived usefulness on attitude towards a certain (media) technology has been widely explored and tested, for example regarding the attitude towards laptops (Moses, Wong, Bakar, Mahmud, 2013), e-books (Letchumanan & Muniandy, 2013), online shopping (Ramayah & Ignatius, 2005), and even educational technology (Hart & Laher, 2015). Because of the wide theoretical support and empirical evidence, it is expected that perceived usefulness has a positive correlation with attitude towards both media technologies and AI in education.

The relation between perceived ease of use or effort expectancy and a positive attitude towards technology is also established both through theory as empirical evidence. Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort' (Davis, 1993, p. 320). Similar to perceived usefulness, perceived ease of use is also influenced by many external factors. Age and gender are presumed to have a sizeable influence on it, but what perhaps is more important are the grouped external variables of 'usability'. Under these variables of usability fall perspicuity, which is the extent to which a technology is clearly expressed and presented, and dependability, which is the extent to which a technology is dependable (Mlekus, Bentler, Paruzel, Kato-Beiderwieden & Maier, 2020). Much like perceived usefulness, perceived ease of use is also supported by both theories and empirical evidence, for example researching its effect on attitude towards 3G (Suki & Suki, 2011), mobile banking (Raza, Umer & Shah, 2017), and once again educational technology (Joo, Park & Lim, 2018). Because of this, it is expected that perceived usefulness too, has a positive correlation with attitude towards both media technologies and AI in education.

The last directly related predictor for attitude towards media technologies and AI in education is experience, meaning the amount of interaction one has had with media technologies and AI during their education. While this was initially seen as an external predictor, only indirectly influencing attitude towards innovation, the revised UTAUT does include experience and habit as direct predictors for attitude (Venkatesh, Thong & Xu, 2012), but the definition of both are for this topic slightly outdated, and a mix of the two is better suited for this research. Experience in the revised UTAUT is defined as 'the passage of time from the initial use of a technology by an individual' (Venkatesh, Thong & Xu, 2012, p.161). However, according to this, older adults, who have been exposed to media technologies for longer than younger adults have, would have more experience with this than younger adults. Data showing media technology usage and competence however shows that younger adults are more competent with media technologies and also use them a lot more (Smith & Anderson, 2018). Habit then, is explained as both prior behaviour (Kim and Malhotra, 2005), but also as 'the extent to which an individual believes the behaviour to be automatic (Venkatesh, Thong & Xu, 2012, p. 161). While predominantly the prior behaviour is relevant to this study, the perceived automatic behaviour is not applicable since most adults are not anymore in their respective education system, thus restricting media usage in this field from becoming a habit. Experience then, in this research, is seen as the amount of meaningful experience one has had with a certain media technology. Previous research has shown that increases in experience lead to for example better attitudes towards personal computers (Thompson, Higgins and Howell, 1994), is a big influence on direct attitudes and behaviour (Haselhuhn, Pope, Schweitzer & Fishman, 2012), and more specifically on attitudes towards media technologies (Mlekus et al., 2020). Because of this, this research hypothesizes that direct experience with media technologies and AI during one's education leads to a better attitude towards media technologies and AI in education.

This chapter discussed three predictors, directly related to one's relationship with MT and AI in education, that are expected to influence the attitudes towards MT and AI in education. Perceived usefulness, perceived ease of use and direct experience all have theoretical and empirical evidence showing that an increase of any of these predictors, likely leads to an increase in positive attitudes towards MT and AI in education. Hence, this research hypothesizes as follows:

<u>H4: People with higher perceived usefulness of MT and AI in education, have a more positive attitude towards MT and AI in education.</u>

<u>H5: People with higher perceived ease of use of MT and AI in education, have a more positive attitude towards MT and AI in education.</u>

<u>H6: People with more direct experience with MT and AI in education, have a more positive attitude towards MT and AI in education.</u>

2.5 Socio-demographic and indirect predictors

Besides the predictors directly related to MT and AI in education, there are several other sociodemographic and indirect predictors, amongst which age is a prominent and important one. In the TAM and the UTAUT, age is seen as an external predictor, which moderates the effect of the direct predictors mentioned in the previous chapter (Davis, 1993, Venkatesh et al., 2003). However, based on previous research and present data, this research hypothesises that age is also a direct predictor of attitudes towards MT and AI in education. Both media technology usage as competence are significantly lower amongst older adults, and that older adults need a lot more training to become competent with media technologies (Broady, Chan & Caputi, 2010; Kim & Choudhury, 2020). In the theories adapted in this thesis, a lower usage is the result of a worse attitude towards those technologies, so it being a fact older adults use less MT, this would have to be the result of a worse attitude towards those technologies. But the influence of age goes further than just usage and competences with media technologies and AI. Research shows that as we get older, we grow more conservative (Tilley, 2015), we become less open to change (Schwaba, Luhmann, Denissen, Chung &

Bleidorn, 2018), become more set in our ways and less open to new experiences (Mühlig-Versen, Bowen & Staudinger, 2012). Because of this data and research, it is expected that age is a negative predictor of attitudes towards MT and AI in education.

Besides age, one's personality and accompanying values are also hypothesized as predictors for one's attitude towards MT and AI in education. While it is difficult to quantify and recognize global values, especially in intercultural research, theory does exist which identifies universal values, recognised throughout all major cultures. The theory of basic human values, which is develop by Shalom Schwartz in 1992, identifies 10 distinct motivational values, grouped in four higher order groups (Schwartz, 1992), out of which two are relevant to this research. The theory, which was further refined in 2012 (Schwartz, 2012; Schwartz, Cieciuch, Vecchione, Davidov, Fischer, Beierlein, Ramos, Verkasalo, Lönnqvist, Demirutku, Dirilen-Gumis & Konty, 2012), has been widely used in cross-cultural research (Berry, Poortinga, Pandey, Segall & Kâğıtçıbaşı, 1997) and the ten universal values are recognised throughout all major cultures (Schwartz, 2012). Two of the four higher-order groups which are relevant for innovation adoption are openness to change and conservation. Openness to change, which contains the values of self-direction and stimulation, 'emphasizes the readiness for new ideas, actions, and experiences. (Schwartz et al., 2012, p. 668)'. This directly contradicts the higher order group of conversion, which emphasizes self-restriction, order and avoiding change (Schwartz et al., 2012). Schwartz' human values, and especially openness to change and conservation, have been widely used to explain adopting innovation (Isomursu, Ervasti, Kinnula & Isomursu, 2011; Barbarossa, De Pelsmacker & Moons, 2017). Because of this, it is expected that openness to change and conservation, as described in Schwartz' theory, both influence one's attitude towards MT and AI in education.

The last indirect predictor which is hypothesized to influence attitudes towards MT and AI in education, is mobile self-efficacy. Mobile self-efficacy, a term which stems from Bandura's research on self-efficacy (Bandura, 1977; Bandura, 2010), is the amount to which an individual believes in his/her capabilities to effectively use mobile devices (Keith, Babb, Furner & Abdullat, 2011), for example MT such as laptops, phones and tablets. There is numerous existing research that shows that people who have a higher amount of self-efficacy, are more positive towards (using) for example mobile learning (Yang, 2012; Yorganci, 2017), but also for teacher's usage of technological devices in classes (Kwon, Ottenbreit-Leftwich, Tari, Khlaif, Zhu, Nadir & Gok, 2019). Because of the existing research, it is expected that mobile self-efficacy too effects one's attitude towards MT and AI in education.

This chapter covered three major predictors, seen as indirect or external predictors in the frameworks that were adapted in this research, but which this research hypothesises to be direct predictors of one's attitude towards the usage of MT and AI in education. The three predictors of age, values, and mobile self-efficacy are , based on existing research, all predicted to influence attitudes towards MT and AI in education, and there this research hypothesises as follows:

H7: People of higher age have a less positive attitude towards MT and AI in education.

H8: People with a higher reported score for openness to change, have a more positive attitude towards MT and AI in education.

H9: People with a higher reported score for conservatism have a less positive attitude towards MT and AI in education.

H10: People with more mobile self-efficacy have a more positive attitude towards MT and AI in education.

3) Thesis methodology

3.1) Choice of method

For this research, a quantitative approach using self-administered online questionnaires was carried out. Quantitative methods were best suited for this research, as one of the two main goals was to quantify opinions about media technologies and AI in education, and generalize them to a certain degree. The other main goal of this research was to test the influence of certain predictors on the attitude towards media technologies and AI in education, based on hypothesises coming forth out of theoretical and empirical support. Both of these main goals fit can only be achieved through obtaining a large number of data, thus explaining the choice for quantitative methods.

Online self-administered questionnaires were chosen as the means to get this large amount of data, because they are 'a very useful tool that allow large populations to be assessed with relative ease' (Jones, Baxter & Khanduja, 2013). Furthermore, they are easy to conduct, and can be quickly distributed with global reach, which in the context of the current pandemic, is a big advantage (Andrade, 2020). There are also downsides to the choice for this method, as for example the increased difficulty to generalise outcomes (Andrade, 2020), and the increased difficulty in engaging respondents for a longer amount of time (Guin, Baker, Mechling & Ruyle, 2012). However, with a careful sampling process opted to select a generalizable sample, and through keeping the online survey at a low completion time, these disadvantages were not seen as significant problems in this research. The online self-administered questionnaire implemented in this research asks about people's general opinions on both MT and AI in education, their experience and perceived competence with MT and AI (in education), and people's motivational domains through Schwartz' human values. This research acknowledges there might be some age bias regarding one's opinion of MT and AI in education, considering it would have been impossible for most older age groups to have experience with those technologies in education. Because of this, these age groups might have found it harder to relate as to how useful and easy to use MT and AI are in education, and it might also capture their general attitude towards MT and AI and not necessarily their attitude towards MT and AI in education.

3.2) <u>Research Unit</u>

The research units in this research are adults in the Netherlands, the United Kingdom, Ireland, the United States, Canada and Australia. These 6 countries are chosen not only because they are, to a certain degree, comparable on an economic and cultural level (Nijman, Muller & de Blij, 2016), but also because their education systems and the relation those have with media technology and AI are relevant. While there are many differences between the education systems of the specified countries, they are in their basics and essence comparable if we look at quality. While there is no absolute way to quantify which countries have the best education systems, in various research over the last few years, all 6 specified countries consistently score highly, with all countries except Ireland even ranking in the top 10 on a regular basis (Ireland, 2020). Furthermore, all countries can, arguably, be considered frontrunners on the acceptance and usage of both media technology and AI in their education system. The countries specified all use educational media technologies to a relative high extent (Hamidi, Ghorbandordinejad, Rezaee & Jafari, 2011; Trucano, 2014), EdTech companies predominantly originate in these countries (IPRAN, 2020), and these countries also rank quite highly on the 'AI readiness index', which is an index based on how ready governments are to implement AI into various sectors (IDRC, 2020).

A conscious decision was made to not include other countries which are comparable on a cultural and economic level and are also frontrunners on media technologies and AI in education. Countries such as Germany, Norway, Denmark and more all have similar quality education systems to the ones from the countries in the research unit, yet were not included in the research unit. The main reason for this is in order to be able to offer all respondents a survey in their own domestic language. This is the case because the usage of the English language in cross-national research obscures national differences (Harzing, 2005), but also because the average person from non-english countries should not be assumed to speak English, despite that in a lot of these countries the English proficiency is rather high (Clark, 2019).

3.3) <u>Sampling</u>

The sampling for this research existed out of two separate stages. The first sampling stage entailed nonprobability sampling through chain/snowball sampling, while the second stage took place through the crowdsourcing platform Prolific. The first stage produced about a 125 respondents, which happened through volunteers who sent it through to family and friends. Initially, a group of between 40-50 people were reached out to, mostly coming from the Netherlands, Australia, the United Kingdom and Canada, but also people coming from both the United states and Ireland. This sample consists out of friends, (ex-)colleagues and acquaintances, from current or former (international) work, travel and study of the researcher. The order of reaching out to this group of respondents was based on nationality, making sure to have a sample from every country as large as possible before sampling respondents from other countries, to keep the amount of respondents from different countries comprehensible. This initial group of the first sampling stage then distributed it further amongst their friends and families. These respondents, of which there were approximately 80, was more diverse, ranging more in age groups and education level. Reaching out to this the first stage of the sampling stage took approximately 9 days, between the 17th of May and the 26th of May. By implementing this strategy for the first stage of sampling, the costs of the study were limited and a large sample of predominantly younger respondents was collected. While this kind of nonprobability sampling is not ideal for the representativeness and generalizability of the sample, as the initial volunteers are mostly highly educated, this approach was necessary to ensure a large international sample without high costs. The first part of the sample consisted out of predominantly younger people, and most respondents came out of the Netherlands, Australia, the United Kingdom and Canada.

The second stage of the sampling, which occurred through Prolific, produced approximately 40 people, selected through selection criteria. Prolific is a crowdsourcing platform, through which people can sign up to fill in questionnaires, for which they get a small monetary compensation per questionnaire filled in. Prolific enables high quality data collection from a big diverse population. Target participants can be targeted accurately through selecting certain selection criteria for respondents. This part of the sampling process, and the accompanying selection criteria, had the purpose of making the sample more representative regarding predominantly age, but also nationality. The first part of the sampling produced an insufficient amount of respondents in the highest age category, and also from Irish and American nationality. Because of this, the second part of the sampling and its selection criteria were used to create a more coherent, representative and generalizable sample. There are some methodological issues with selecting predominantly older people through a crowdsourcing platform. The biggest issue with this is that respondents who fill in the survey through prolific, must be familiar with this website, the internet and have to be able to use media technologies to be able to participate. Therefore, a decent amount of new media technologies competence must be acknowledged, and considering that this thesis hypothesises that competency with media technology results in a more positive attitude towards media technologies and AI in education, the issue of representativeness for older respondents occurs. While this is a shortcoming that this research acknowledges, there was no alternative feasible strategy to generate respondents from all age groups, thus this research accepts this negative and pays attention to it in discussing the results.

3.4) <u>Operationalisation</u>

3.4.1) <u>Schwartz' human values</u>

Measuring universal human motivational domains has traditionally been difficult, considering the high amount of differences between cultures nationally, but also within nations. The theory of Schwartz' human values has brought this back to 7 main motivational domains recognized across all cultures. To measure Schwartz' human values, two separate types of scales already exist. The first one of these, is the Schwartz' values survey (SVS), where respondents have to attach a score to all the human values, given to them in the survey, which there are 30 of (Schwartz, 1992; Schwartz, 2006). However, this type of scale has been criticized as it is too explicit, too incomprehensible and too long, leading to a bad response rate (Lindeman & Verkasala, 2005). The alternative to this, and from which this research takes elements, is the portrait values questionnaire (PVQ). The PVQ was created to reduce the complexity of the scale, making it easier for people to fill in, and not directly ask for one's values but implicitly ask for them (Knoppen & Saris, 2009; Schwartz, 2012). While originally intended for children, the PVQ 'works equally well with adults in representative national samples. (Schwartz, 2012, p.11)'. An 8-item scale on a 7 point Likert scale (1 = strongly disagree, 7 = strongly agree) was created to measure openness to change, and an 8-item scale on a 7 point Likert scale (1 = strongly disagree, 7 = strongly agree)was created to measure conservatism. For openness to change, 8 items from the PVQ as seen in the European social survey (ESS), (Knoppen & Saris, 2009; Bilksy, Janik & Schwartz, 2011), were adopted, coming from the subscales of self-direction and stimulation. Statements in this scale included statements such as 'I am always looking for new things to try' and 'It is important to me to see life as an adventure'. The Cronbach's alpha for this scale measure openness to change reported at .858. For conservatism, 8 items from the same PVQ as seen in the ESS were adopted, coming from the subcategories of security, conformity and tradition. Statements in this scale included statements such as ‘I believe people should be satisfied with what they have’ and ‘I find it important that the established order is protected’. The cronbach’s alpha for this scale measuring conservatism reported at .872.

3.4.2) <u>Experience</u>

While there are some scales to measure parts of one’s experience with predominantly MT, such as for example the spatial presence experience scale (SPES) (Hartmann, Wirth, Schramm, Klimmt, Vorderer, Gysbers, Böcking, Ravaja, Laarni, Saari, Gouveia & Sacau, 2015), a conscious decision was construct a scale as simple as possible, simply asking respondents to which degree they have used the three most well-known and widely implemented examples of MT and AI in education. A three-item scale was developed for this research, asking respondents for their experience with certain technologies/applications during their time in education on a 5 point Likert scale (1 = never, 5 = most of the time). For MT, the three technologies that were chosen were laptops, tablets and interactive whiteboards. While there is no official data on what is used most in education, research and articles often mention laptops and tablets as main media technologies and reports show their usage is going up (Truong, 2020). The interactive whiteboard was chosen instead of for example a mobile phone, because mobile phones might be too familiar to the other two, and interactive whiteboards, either through original display or through a beamer, are widely used in education (Chade, 2021). The Cronbach’s alpha for this scale reported at .833. For measuring experience with AI, it was important to pick three application of AI that would be easily understandable for everyone, considering data shows a lot of people actually do not know what AI exactly is (Mozilla, 2019; Pega, 2020). The three applications that were picked were learning applications such as Duolingo, automatic grading systems and online custom quizzes and tests based on strengths and weaknesses, as these are, while still relatively new, some of the more used application of AI in education (Marr, 2018; Fagella, 2019; Gupta, 2020). The Cronbach’s alpha for measuring experience with AI during one’s education reported at .879.

3.4.3) <u>Mobile self-efficacy</u>

At the point of writing, no widely used and validated scale exists to measure mobile self-efficacy. For this research, a scale was constructed to measure one’s amount of mobile self-efficacy. A six-item scale was constructed, based on Bandura’s research on self-efficacy, and other research on the effects of mobile self-efficacy and new media literacy (Bandura, 1986; Ozturk, Bilighan, Nusair & Okumus, 2016; Koc & Barut, 2016; Nikou & Economides, 2017; Chao, 2019). The scale, which focuses on one’s belief in themselves to meaningfully and effectively interact with media technologies, draws from the new media literacy scale too. It does this because mobile media technologies nowadays are a ubiquitous element in everyday life (Sigerson & Cheng, 2018), and it is therefore important to test whether someone believes (s)he can effectively and meaningfully use mobile media technologies rather than just use them. The scale, which respondents answered on a 5 point Likert scale (1 = strongly disagree, 5 = strongly agree), asked questions such as whether the respondent was proficient in creating accounts/profiles on websites/applications and whether they were proficient in finding the online information they want or require. Furthermore, because people, and then especially the lowest performers, overestimate their own digital literacy skills (Mahmood, 2016), the question are phrased as simple as possible, in a manner that it does not seem condescending or bad if someone were to fill in a negative answer. For example, the scale asked whether the respondents stays up to date with changes in the media, and whether the respondent would sometimes find it difficult to find the online information they want. The Cronbach's alpha for the scale reported at .879.

3.4.4) Perceived usefulness and perceived ease of use

As perceived usefulness (PU) and perceived ease of use (PEOU) are the two main predictors for behavioural attitude in both the TAM as the UTAUT, both predictors have been measured often in previous research and a scale can be constructed from these previous researches. A scale for both PU and PEOU for both MT and AI was developed, however the differences between scales for MT and AI were solely semantic. A six-item scale was constructed, on a 5 point Likert scale (1 = strongly disagree, 5 = strongly agree) to measure one's PU and PEOU for both MT and AI in education. The scales, which were mostly adopted from the frameworks embedded into this research and previous research related to the effect of PU and PEOU (Venkatesh et al,2003; Cimperman, Brenčič & Trkman, 2016; Šumak & Sorgo, 2016; Hogue & Sorwar, 2017; Khalilzadeh, Ozturk & Bilighan, 2017), but was slightly adjusted to fit the topics of this research more clearly and effectively. The Cronbach's alpha for the scale that measured the PU of MT was .939, where this was .919 for the scale that measured PU of AI. The scales that measure PEOU for MT and AI, had an Cronbach's alpha of .870 and .816 respectively.

3.4.5) Attitude towards media technologies and AI

Considering that the attitude towards MT and AI is the most essential part of this research, it was vital that a reliable and trustworthy scale was implemented to measure one's attitude towards MT and AI in education. While scales measuring attitudes towards (media) technologies have historically been quite sparse, despite attitude being seen as a major factor in innovation adaptation (Edison & Geissler, 2003), there is one major scale which is widely used in research, namely the media and technology usage and attitudes scale (MTUAS) (Rosen, Whaling, Carrier, Cheeever & Rokkum, 2013). The MTUAS, which consists out of 60 items divided into 15 subscales, has 4 subscales for attitude towards media (technologies). From these subscales for attitude,6 items were taken, slightly adjusted and implemented into this research on a 7-point Likert scale (1=Strongly disagree, 7 = Strongly agree). The items were slightly adjusted to fit the topic of this research, and play into the biggest positives and negatives about both MT and AI in education. For example, two of the items correlated with a negative attitude in the MTUAS attitudes subscales mention topics such as isolation and wasting time. Considering the biggest criticism towards MT and AI in education are that they are too distracting and dehumanize education, the items are slightly adjusted to fit this exact topic to make more sense. The Cronbach's alpha for attitude towards MT reported at .844, and the Cronbach's alpha for attitude towards AI reported at .904.

3.5) <u>Survey design</u>

Some conscious considerations were made in order to make the survey valid, methodologically solid, and in order to have a high finish rate on the survey. Firstly, the survey starts with explaining the context of the research, a small description of what it is about without actually giving away what the underlying goal of the research is. This is done, as when context is created early and effectively, 'the less likely people will be to dismiss the questionnaire before they even start responding' (Thayer-Hart, Dykema, Elver, Schaeffer & Stevenson, 2010). Context is repeatedly established in the survey, especially at the parts before questions specifically about MT and AI in education. The difference between MT and AI is established clearly and through examples which are as common as possible, considering that a high amount of people do not exactly know what AI is (Mozilla, 2019; Pega, 2020). Attention was also given to the order of the questions. The survey starts, as almost all surveys, with the socio-demographic factors, but after this the first scale that is brought up is the one for Schwartz' human values. This is done on purpose, because surveys should unfold in a logical order, preferably starting with easy to answer, engaging questions that respondents will be interested in (Pew Research Center, 2021; Qualtrics, 2021). Questions about one's personality are easy to answer, and people like answering questions about their personality (Dahl, 2017). Leading from this, the other predictors come first, followed by ultimately the questions about MT and AI in education, considering these take the most thought, and are therefore arguably the hardest. In order to avoid that respondents figured out the pattern of scales, knowing which answers related to high values and which to low values, reverse coding was applied for at least one, but mostly for two or three items per scale. This is done as it increases validity of the scales and it negates response style bias (Álvarez, Pedrosa, Lozano, Cuteo, Izquierdo & Fernandez, 2018). The questionnaire was carried out between the 17th of May and the 28th of May. The questionnaire had a response rate of about

70%, after most people did not finish the questionnaire at either the questions about MT and AI, or right at the beginning.

3.6) Tools, reliability and validity

For constructing the questionnaire, the platform Qualtrics was used, who suggest certain adjustments in order to maximize response and engagement. To supplement the sample and make it more representative, the crowd-sourcing platform prolific was used, where respondents receive a small amount of payment for a valid response. To analyse the gathered data, the program SPSS was used. The descriptive, such as the means and standard deviations, of all scales were reported.

The reliability of the different scales was assessed and reported through the Cronbach's alpha. The content validity of these scales is established through using the Likert scale verified, and through mostly implementing (elements of) scales from previous research and literature. The validity of the respondents was assessed carefully, and about 25 responses were deleted, because they showed clear signs of response style bias or completed the questionnaire in a time that was deemed unrealistic. Considering that respondents through prolific have an economic incentive to fill in the survey, these respondents were assessed most carefully before administering them to the date. No attention was given to the responses, but when for example a respondent of 65+ year old, or any age for that matter, completed the survey in under two minutes and responded the highest or lowest answer for every question, the data was deemed invalid and deleted.

4) Results

4.1 Descriptive statistics

4.1.1) Sample descriptives

This research administered 174 complete and valid responses. From these 174 respondents, 9 originated from countries other than the countries that were specified in the research unit, and therefore these 9 respondents were excluded from the analyses, leaving 165 respondents available for analyses (N=165). Gender was evenly distributed, with 83 of the respondents were male (50.3%), 81 were female (49.1%), and 1 being Non-binary (0.6%). The age group of 18-24 was represented most with 61 respondents (37%), there were 31 respondents aged 25-39 (18.8%), 35 between 40-64 (21.2%), and 38 aged 65 and above (23%). The nationality of respondents was also quite evenly distributed, with 36 being Dutch (21.8%), 28 being American (17%), 26 being Canadian (15.8%), and 25 from each Australia, Ireland and the UK (15.2% each). Lastly, when looking at the highest education completed, most respondents finished high school with 54 respondents (32.7%), followed by 46 who completed a bachelor of science (27.9%), and 35 who completed a practical education or community college (21.2%). There were 12 respondents who had completed a master degree (7.3%), 9 with a bachelor of applied science (5.5%), 8 who finished no education (4.8%) and 1 who finished a doctorate (0.6%).

4.1.2) <u>Scale descriptives</u>

The descriptive statistics for some of the measures scales resulted in somewhat surprising results. The scale used to measure openness to change had a mean of 4.33, with a standard deviation of 1.20. The average score for conservatism was 4.61 with a standard deviation of 1.26. Mobile self-efficacy was quite high at a mean of 3.60, with a standard deviation of 1.38. The reported experience with MT and AI were both quite low, with a mean of 2.37 for MT with a standard deviation of 1.38, and a mean of 1.85 with a standard deviation of .95. This shows that not a lot of people have experience with AI in education, and that the results for experience with MT in education are quite mixed, considering the rather high standard deviation. The minimums and maximums, and the other descriptive statistics, for all scales are found in table 1.

This research hypothesised that people would be predominantly positive towards both MT and AI in education, based off of the proven positive influences it can bring to education. However, the descriptive results for attitude towards MT and AI in education may have been the most surprising of all scales. The mean for attitude towards MT in education laid at 4.15, with a standard deviation of 1.28. Considering 4 corresponds a neutral score, and this thesis hypothesised that people would be predominantly positive towards MT, H1 is rejected. The mean for attitude towards AI in education reported somewhat lower, at 3.76 with a standard deviation of 1.55. This shows that the respondents were slightly more negative towards AI in education than they were towards MT in education, and also slightly negative in their view towards AI in education overall. As this thesis hypothesised that people would be predominantly positive towards AI, H2 is also rejected. This research however also hypothesised that people would be more positive towards MT in education than they would be towards AI in education, given to which extent they are both implemented in various education systems at the moment. The mean for attitudes towards MT in education was higher than the mean for attitudes towards AI in education, and the standard deviation lower. Besides this, a paired t-test was conducted to test whether the difference in attitude towards MT and AI was significant. The test proved significant ($t(130)=7{,}19$, $p<.001$), and therefore H3 is accepted.

	Minimum	Maximum	Mean	Std. Deviation
Openness to change	2.00	6.63	4.33	1.20
Conservatism	1.88	6.75	4.61	1.26
Mobile self-efficacy	1.00	5.00	3.60	1.38
MT experience	1.00	5.00	2.37	1.38
AI experience	1.00	4.67	1.85	.95
MT attitude	1.67	6.33	4.15	1.28
AI attitude	1.33	6.5	3.76	1.55

Table 1: Characteristics of used scales

In the next few sections, different analyses are conducted to test the significance of the hypothesised predictors, but also to test the strength of the predictors and to find out the key influences on attitudes. How this is done, is by first going through all predictors singularly, testing if the predictors are associated with attitude towards MT and AI on their own (section 4.2, 4.3, 4.4 and 4.5). After this, predictors are grouped together to see which predictors are key in influencing attitude, and if perhaps predictors that are significant on their own are no longer significant when grouped with others (section 4.6).

4.2) Effect of perceived usefulness and ease of use on attitude

Based on the various frameworks and theories embedded into this research, the hypotheses were made that perceived usefulness (PU) and perceived ease of use (PEOU) would have a positive associations with one's attitude towards MT and AI in education. To test this, two simple linear regressions were run. One with attitude towards MT as the dependent variable, and perceived usefulness of MT as the independent variable. The other with attitude towards AI as the dependent variable, and perceived usefulness AI separately as the independent variable. For both attitude towards MT as AI, the normality of errors and the constant error variance in the two different analyses was mostly held (except for a few deviations at the tails of the distribution for attitude towards MT), and in both analyses the constant error variance (homoscedasticity) was not violated. For attitude towards MT in education, the effect of PU proved significant ($F(1,163)=753,07$, $p<.001$). The adjusted R^2 reported at .821, and the standardized coefficients reported at .907, with a significance of $p<.001$. This means that the increase of PU lead to an significant and strong increase ($b^*=.907$) of attitude towards MT in this sample. For the effect of PU on attitude towards AI, a similar significant association was found ($F(1,163)=739,08$, $p<.001$). The adjusted R^2 reported at .818, and the standardized coefficients laid at a significant .905, $p<.001$. This means that the increase of PU also lead to a strong and significant increase (b^*=.905) of attitude towards AI in education. Because PU was a strong and significant predictor for both attitudes towards MT and AI in education, and a large amount in the variance could be explained by PU, H4 is supported.

For the effect of PEOU on attitude towards MT and AI in education, once again two simple linear regressions were run. One with attitude towards MT as the dependent variable, and PEOU of MT as the independent variable. The other with attitude towards AI as the dependent variable, and PEOU of AI as the independent variable. Homoscedasticity was established for both models, however the normality of errors was not held for attitude towards AI, with some deviations, mostly at the middle of the distribution, violating the normality. Because of this, the coefficient estimates are possibly biased and the results for attitude towards AI are somewhat tentative. The effect of PEOU proved significant on both attitude towards MT (F(1,163)=438,79, p<.001) as on attitude towards AI (F(1,163)=264,82, p <.001). The adjusted R^2 for attitude towards MT was .727, where this was .617 for attitude towards AI. For both attitude towards MT (b^*=.854) as attitude towards AI (b^*=.787), PEOU was a strong and significant predictor, however for attitude towards AI the results are somewhat tentative. Because of the strong and significant effect, H5 is, tentatively, supported.

While no specific hypotheses existed regarding the strengths of certain predictors, this research did aim to find out the key predictors and influences in predicting attitude towards innovations. To test the strengths of PU and PEOU combined on attitude towards both MT and AI, two multiple regression analysis were run. The first with attitude towards MT as the dependent variable, and PU and PEOU of MT as the independent variables. The second with attitude towards AI as the dependent variable, and PU and PEOU of AI as the independent variables. For attitude towards MT, the model with both PU and PEOU proved significant (F(2,162)=453,85,p<.001). The adjusted R^2 laid at .847, meaning that this model including both PU and PEOU as independent variables explained more variance in the data for attitude towards than the models including PU and PEOU separately did, albeit only slightly more than the variance that was explained by PU of MT on its own (R^2 =.821). In this model, PU of MT was still strongly and positive associated with attitude towards MT (b^*=.648, p<.001), but PEOU of MT was now moderately and positively associated with attitude towards MT (b^*=.305, p<.001), where this was strongly and positively associated when analysed as a single predictor (b^*=.854). This means that for attitude towards MT, PU seems a significantly stronger predictor than PEOU is. For attitude towards AI, the model including both PU and PEOU of AI as independent variables also proved significant (F(2,162)=435,69, p<.001). The adjusted R^2 reported at .841, which is once again higher than the variance explained by either PU or PEOU of AI as single predictors. In this model, PU of AI once again was strongly and positively associated with attitude towards AI (b^*=.726, p<.001), but PEOU of AI was now only weakly positively associated with attitude towards AI (*b**=.237, *p*<.001). This means that for attitude towards AI, PU is once again a stronger predictor than PEOU, despite both of these predictor being strongly and positively associated with both attitude towards MT as AI as single predictors.

4.3 Effect of mobile self-efficacy and experience

This research hypothesised that mobile self-efficacy would have a positive association with attitude towards MT and AI in education. To test this, simple linear regressions were run with mobile self-efficacy as the independent variable, and attitude towards MT and AI in education as the dependent variable. Homoskedasticity was established in both cases, however the normality of errors was not held for attitude towards MT, with deviations especially in the middle, leading to possibly biased and tentative results, probably as the consequence of outliers. While there were some deviations at the tails for attitude towards AI, the normality of errors was mostly held here. The effect of mobile self-efficacy proved significant on both attitude towards MT in education ($F(1,163)=108{,}99$, $p<.001$) as on attitude towards AI in education ($F(1,163)=118{,}02$, p<.001). The variance for attitude towards AI was explained slightly more (R^2 of .416) than the variance for attitude towards MT (R^2 of .397) by the effect of mobile self-efficacy, but mobile self-efficacy proved a significant, strong influence of both attitude towards MT (*b**=.633) as attitude towards AI (*b**=.648), with the notion that the results for attitude towards MT are somewhat tentative. Because of these clear and decisive results, H10 is tentatively supported.

Furthermore, this research also hypothesised that direct experience with MT and AI in education would also influence one's attitude towards MT and AI in education. Simple linear regression were run with attitudes towards MT and AI as the dependent variables, and experience with MT and AI in education as independent variables. Homoskedasticity was established and the normality of errors was not violated in either case. Once again, the effect of experience proved significant on both attitude towards MT ($F(1,163)=260{,}54$, $p<.001$) as on attitude towards AI ($F(1,163)=166{,}32$, $p<.001$) in education. For attitudes towards MT, the adjusted R^2 was .613, where this was .502 for attitudes towards AI in education. Experience had a strong and significant positive effect on attitude towards MT (*b**=.784), and also a strong and significant positive effect on attitude towards AI (*b**=.711), therefore H6 is supported.

4.4 Effect of age on attitude

This research hypothesized that there would be a significant difference in terms of attitudes towards MT and AI in education when it comes to different age groups, namely that older people would be more negative towards both. To test this, ANOVAs were run to compare the means of attitude towards both topic, a separate ANOVA for each DV, between the different age groups. The difference between age groups overall was highly significant (F(3)=123,31, p<.001), and when looking at Scheffe's test, almost every mean difference between the different age groups was significant. The difference between 18-24 year olds (M=5.12, S.D= .689) and 25-39 year olds (M=4.98, S.D=.698) was too small to be significant (p=.867), but the difference between 18-24 year olds and both 40-64 year olds (p<.001) as 65+ year olds (p<.001) was highly significant , as was the difference between 25-39 year olds and both these age groups (p<.001 for both). The difference between 40-64 year olds (M=3.34, S.D=.948) and 65+ year olds (M=2.65, S.D=.457) was also significant (p=.001). The drop-off in attitude towards AI as age increases is both significant and interesting, as especially between the age groups of 25-39, where the average is still predominantly positive about MT in education, and 40-64 year olds, where this has shifted to a predominantly negative view, this is especially apparent. Furthermore, the standard deviation for the age group of 65+ is the lowest, meaning they are without too many outliers considerably negative about MT in education.

Age groups	*Mean for MT Attitude*	*$M_{difference}$ with 18-24*	*$M_{difference}$ with 25-39*	*$M_{difference}$ with 40-64*	*$M_{difference}$ with 65+*
18-24 year	5.12	N/A	.134 (*p*=.867)	1.779 (*p<.001*)	2.464 (*p<.001*)
25-39	4.98	-.134 (*p*=.867)	N/A	1.646 (*p<.001*)	2.33 (*p<.001*)
40-64	3.34	-1.779 (*p<.001*)	-1.646 (*p<.001*)	N/A	.685 (*p=.001*)
65+	2.65	-2.464 (*p<.001*)	-2.33 (*p<.001*)	-.685 (*p*=.001)	N/A

Table 2: Mean and mean differences of attitude towards MT in education for age groups

When looking at the ANOVA regarding the mean differences for age groups for attitude towards AI in education, the overall results prove just as significant (F(3)=119,69, p<.001). The most positive group towards AI in education is once again 18-24 year olds (M=5, S.D=.976), followed by 24-39 year olds (M=4.63, S.D=.872), followed by 40-64 year olds (M=2.71, S.D=.927), followed by lastly 65+ year olds (M=2.02, S.D=.58). When looking at scheffe's test, once again the only difference between groups that is insignificant is between 18-24 year olds and 25-39 year olds (p=.294). Besides this, all other differences between groups are significant. What is noticeable about the attitudes towards AI between the different age groups is that the attitude for every age group is lower than their same age group's attitude towards MT in education, but that the differences get bigger as the age gets older. For 18-24 year olds, the mean difference is .12, where this is .35 for 25-39 year olds, .62 for 40-64 year olds and .63 for 65+ year olds. However, considering the strong differences in attitudes, and also the significant and strong differences between even close age groups, H7 is strongly supported.

Age groups	*Mean for AI Attitude*	*$M_{difference}$ with 18-24*	*$M_{difference}$ with 25-39*	*$M_{difference}$ with 40-64*	*$M_{difference}$ with 65+*
18-24 year	5	N/A	.371 (p=.294)	2.29 ($p<.001$)	2.982 ($p<.001$)
25-39	4.63	-.371 (p=.294)	N/A	1.646 ($p<.001$)	2.33 ($p<.001$)
40-64	2.71	-2.29 ($p<.001$)	-1.646 ($p<.001$)	N/A	.692 ($p=.011$)
65+	2.02	-2.982 ($p<.001$)	-2.33 ($p<.001$)	-.692 (p=.011)	N/A

Table 3: Mean and mean differences of attitude towards AI in education for age groups

4.5 effect of Schwartz' human values

This research hypothesised that both Schwartz' human universal values of openness to change and conservatism would affect both one's attitude towards MT and AI in education. To test this, a simple linear regression was run with openness to change as the independent variable, and attitude towards MT and AI as the dependent variable. In both cases, homoscedasticity was established and the constant error variance was not violated (despite some minor deviations in the middle for both). For attitude towards MT in education, openness to change proved a significant factor (F(1,163)=279,70, p<.001), having an adjusted R^2 of .63, and being a strong, positive effect (b^*=.795, p<.001). For attitude towards AI, openness to change also proved to be a significant factor (F(1,163)=234,02, p<.001), having a adjusted R^2 of .59, and also being a strong and positive effect (b^*=.768, p<.001). Considering openness to change has a strong positive effect on both attitude towards MT as AI in education, H8 is supported.

` A simple linear regression was run to test whether conservatism was a significant predictor for attitude towards MT and AI in education. Conservatism was the independent variable and attitude towards MT and AI in education once again as the dependent variable. For both cases, homoskedasticity was once again established, and the normal error variance was mostly held, despite some small deviation at the tail for attitude towards MT, and some small deviation at the middle for attitude towards AI. Conservatism too, was a significant factor for both attitude towards MT ($F(1,163)=188,55$, $p<.001$) as attitude towards AI ($F(1,163)=244,36$, $p<.001$). For attitude towards MT in education, conservatism explained 53.3% of the variance in the date ($R^2=.533$), where this was 59.7% for attitude towards AI ($R^2=.597$). Conservatism proved to be, for both attitude towards MT in education ($b^*=-.732$, $p<.001$) as attitude towards AI in education ($b^*=-.775$, $p<.001$), a strong negative, significant, effect. Because of this clear data, H9 is supported.

4.6 Strength of predictors

Considering all hypothesised predictors proved significant in affecting attitude towards MT and AI, additional tests were run to check which predictors were the strongest and explained for most variance in the data. To test the strongest predictor for attitudes towards MT in education, a multiple regression analysis was conducted with all continuous variables, being openness to change, conservatism, mobile self-efficacy, experience, PU and PEOU as independent variables and attitude towards MT as the dependent variable. The effect of all predictors overall was significant ($F(6,158)=171,87$, $p<.001$), and this model explained more variance in the data than any single predictor when run in analysis ($R^2=.862$, where the highest for a single predictor was $R^2=.821$ for PU). This model also explained more of the variance in the data than the model containing only PU and PEOU of MT as independent variables ($R^2=.847$) However, when looking at the individual effect of the predictors in this overall model, only 3 predictors still proved significant. PU still had a moderate positive effect ($b^*=.573$, $p<.001$), PEOU was still a weak positive effect ($b^*=.235$, $p<.001$), and conservatism was still a weak negative effect ($b^*=-.121$, $p=.026$). The effect of openness to change, mobile self-efficacy and experience proved non-significant in this model, and PU proved to be the strongest predictor for attitude towards MT, which is also was on its own when run as a simple linear regression. The comparison of the strengths of the predictors, between being used as a single predictor versus in this wider model, can be found in table 4. Different multiple regression analyses were run with combinations of the variables in order to try and find a model that would explain more variance in the data, but no other model explained more variance in the data than the model containing all these predictors. The loss of significance for some of the predictors that were associated with attitude towards MT on their own might lead to think they are not significant at all. However, considering that all predictors had significant and strong associations with attitude towards

MT as single predictors, and the fact that the deletion of these certain predictors in the bigger model did not lead to more variance explained in the data, no hypothesises are adjusted.

Independent variables	*Variance explained as single predictor*	*Variance explained in the wider model*	*Variance explained difference between single and wider model*	*b* as single predictor*	*b* as predictor in wider model*	*b* difference between single and wider model*
PU of MT	.821	.862	.041	.907, *p<.001*	.573, *p*<.001	.334
PEOU of MT	.727	.862	.135	.854, *p<.001*	.235, *p*<.001	.619
Mobile self-efficacy	.397	.862	.465	.633, *p*<.001	.074, *p*=.065	.559
MT experience	.613	.862	.249	.784, *p*<.001	.076, *p*=.193	.708
Openness to change	.630	.862	.232	.795, *p*<.001	-.062, *p*=.316	.857
Conservatism	.533	.867	.329	-.732, *p*<.001	-.121, *p*=.026	.611

Table 4: Variance explained and effect of independent variables on attitude towards MT as single predictors compared to the wider model

The same multiple regression analysis was run for attitude towards AI in education, now with attitude towards AI as the dependent variable and the same predictors (except PU, PEOU and experience of/with MT switched for PU, PEOU and experience of/witch AI) as independent variables. Once again, the results overall proved significant (*F*(6,158)=177,58, p<.001) and the variance explained for this model was once again higher than any single linear regression (R^2=.866 compared to R^2=.821 for PU). Precisely similar to attitude towards MT, the same three predictors proved significant in this wider model. The strongest was once again PU (*b**=.548, p<.001), followed by PEOU (*b**=.220, *p*<.001) and lastly conservatism (*b**=-.197, p<.001). Mobile self-efficacy was still weakly significant (*b**=.074, *p*=.061), but experience and openness to change proved to be non-significant. PU of AI had a moderate positive association with attitude towards AI, while PEOU of AI had a weak positive association with attitude towards AI, and conservatism had a weak negative association with attitude towards AI. Once again, PU proved to be the strongest predictor, albeit slightly less strong than it was for MT. The comparison of the strengths of the predictors, between being used as a single predictor versus in this wider model, can be found in table 5.

Independent variables	*Variance explained as single predictor*	*Variance explained in the wider model*	*Variance explained difference between single and wider model*	*b* as single predictor*	*b* as predictor in wider model*	*b* difference between single and wider model*
PU of AI	.818	.866	.048	.905, *p<.001*	.548, *p*<.001	.357
PEOU of AI	.617	.866	.249	.787, *p<.001*	.220, *p*<.001	.567
Mobile self-efficacy	.416	.866	.450	.648, *p*<.001	.074, *p*=.061	.574
AI experience	.502	.866	.364	.711, *p*<.001	.070, *p*=.123	.641
Openness to change	.590	.866	.276	.768, *p*<.001	-.062, *p*=.253	.830
Conservatism	.597	.866	.269	-.775, *p*<.001	-.197, *p*=.026	.578

Table 4: Variance explained and effect of independent variables on attitude towards AI as single predictors compared to the wider model

While PU seemed to be the strongest of the continuous variable, the most important predictor for attitude towards MT and AI, and also for the other predictors in this research, is possibly age. Chapter 4.4 already showcased how age was of high significance for someone's attitude towards MT and AI, but age had an effect on literally all predictors too. The effect of age was significant for openness to change (F(3,161)=110,75, p<.001), conservatism (F(3,161)=79,19, p<.001), mobile self-efficacy (F(3,161)=39,43, p<.001), experience with MT (F(3,161)=164,96, p<.001), experience with AI (F(3,161)=117,32, p<.001), PU of MT (F(3,161)=136,94, p<.001), PU of AI (F(3,161)=130,21, p<.001), PEOU of MT (F(3,161)=92,65, p<.001) and PEOU of AI (F(3,161)=45,08, p<.001). There is a consistent significant drop-off in means between 25-39 year olds and 40-64 year olds, and the mean differences between 18-24 year olds and 65+ year olds are high in every category. When compared to 65+ year olds, 18-24 year olds have higher means for every predictor, most noticeably experience with MT ($M_{difference}$ of 2.58 over a scale of 5, p<.001), PU of MT ($M_{difference}$ of 2.27 over a scale of 5, p<.001) and openness to change ($M_{difference}$ of 2.35 over a scale of 7, p<.001). Only for conservatism do 65+ year olds score (significantly) higher compared to 18-24 year olds

$M_{difference}$ of 2.07 over a scale of 7, $p<.001$), but considering conservatism was a negative effect on attitude towards MT and AI in education, this follows the trend seen in this research. The effect of age is seen throughout the entire research, and might be the most important predictor for attitude towards MT and AI overall.

5) Conclusion

5.1 Summary of findings

This research tried to answer the overall question of to what extent people are positive about the integration of media technologies (MT) and artificial intelligence (AI) into education, what elements would be in predicting this attitude and what the most important factors in predicting these attitudes would be, in order to establish an extended framework on innovation adaptation and the encompassing challenges that brings. This research hypothesised, based on a balanced overview of the positives and negatives that MT and AI bring to education, that people would be predominantly positive towards both MT and AI in education. Tests proved that people overall were neither very positive nor negative towards MT and AI in education, although the standard deviation for both attitudes were quite high. Younger people were predominantly positive towards both MT and AI in education, but older adults proved to be quite negative towards both. This research furthermore hypothesises, based on the diffusion of innovation theory, that people would be more positive towards MT in education than they would be towards AI in education, considering MT are already integrated into education to a considerable amount, where AI is not yet. Respondents were slightly more positive about MT in education than they were about AI in education, however the difference was not monumental.

This research also hypothesised, based on the technology acceptance model (TAM) the unified theory of technology acceptance and usage (UTAUT), and previous related research, that a higher amount perceived usefulness (PU) and perceived ease of use (PEOU) would both lead to a more positive attitude towards both MT and AI in education. Perceived usefulness had a significant, strong and positive association with both attitude towards MT as attitude towards AI, meaning that a higher amount of perceived usefulness lead to a more positive attitude towards MT and AI in education. Perceived ease of use also had significant, strong, positive association with both attitude towards MT and AI in education. The association between perceived ease of use and attitude towards AI in education was tentative, as the constant error variance was not held. However, the strong, positive association and the high explained amount of variance in the model lead to the assumption that the result is still valid.

This research furthermore hypothesised that the amount of mobile self-efficacy one has, and the amount of experience one has had with MT and AI in education respectively, would also have a positive association with attitude towards MT and AI in education, based on previous research, and experience being an external factor in the TAM and UTAUT. Mobile self-efficacy proved to have a strong, positive, significant association with both attitude towards MT and AI in education, meaning that an increase in mobile self-efficacy would lead to a more positive attitude towards MT and AI in education. The association mobile self-efficacy had with attitude towards AI in education was slightly higher than the association it had with attitude towards MT in education, but it was not far apart. Experience with MT and AI in education also proved a significant factor in explaining attitude towards both MT as AI. Experience once again had a strong and positive association with both attitude towards MT and AI, meaning an increase in experience lead to a more positive attitude towards MT and AI in education. The association between experience and attitude towards MT was higher, but the overall amount of experience with AI amongst the respondents was a lot lower.

This research also hypothesised that amongst demographic factors, age would be an important factor in attitude towards MT and AI in education, based on previous research, the fact that older adults have less experience and competence with MT and are more conservative. Age proved to be a highly significant factor in explaining attitude towards MT and AI, as there was a sizeable drop off in attitude between the age groups of 25-39 and 40-64. Also, the differences in attitude between the youngest age group (18-24) and the oldest age group (65+) was surprisingly high for both attitude towards MT and AI, leading to believe that age is a very important factor in attitude towards new technologies and innovations. Age was not only a factor in attitudes towards MT and AI however, as age influenced nearly all other predictors as well. As age increased, conservatism increased, openness to change decreased, experience decreased, mobile self-efficacy decreased, PU decreased and PEOU decreased, meaning that age influenced all significant predictors for attitude towards MT and AI.

Ultimately, this thesis hypothesised that two of Schwartz' human values, namely openness to change and conservatism, would affect one's attitude towards MT and AI in education, considering the relation between both openness to change and conservatism, and innovation adaptation has been discovered in previous research. The association that openness to change had with both attitude towards MT and AI was significant. The association was strong and positive, meaning that more openness to change led to a more positive attitude towards MT and AI in education. The association that conservatism had with both attitudes towards MT and AI in education also significant. However, conservatism had a strong negative association, meaning that the more conservative a person was, the more negative that person's attitude was towards MT and AI in education.

Lastly, while no hypothesis was specifically made for this, some extra tests were run to test which predictor proved the most influential, considering nearly all predictors which were hypothesised to, actually had a strong association with both attitude towards MT and AI. When run in a bigger model, results were slightly different. For attitude towards MT, PU was still the strongest predictor, followed by PEOU and after that conservatism. Experience, mobile self-efficacy and openness to change proved an insignificant association with attitude towards MT in education, in the wider model. The significant predictors in the wider model however were moderate and weak compared to strong when they were measured separately, however they did account for more variance in the data than any predictor did on its own for attitude towards AI in education, the same model was run, and the same predictors proved significant and insignificant as in the model with attitude towards MT. The strongest predictor in the model for attitude towards AI was once again PU, followed by PEOU and lastly conservatism. Experience, mobile self-efficacy and openness to change were once again non-significant. The significant predictors in the wider model for attitude towards AI also changed from strong to moderate and weak associations however, yet once again the predictors combined accounted for more variance in the data than any one of the predictors measured separately. While the insignificance of some predictors in the wider model could lead to believe that they are overall insignificant, and that the hypothesis for these predictors should be adjusted, these predictors were still significant on their own, and including them in the wider model did lead to a higher amount in variance explained. This means that while they are not they key predictors, they still have associations with attitude. All the independent variables are interrelated, and while the wider model might make it look like some of them become insignificant, they still do have an effect, but the strength of the key predictors that were discovered might masque this. Therefore, the hypothesises related to these predictors that were accepted, remain accepted.

5.2 Theoretical implications

A number of findings from this research can be put in a wider theoretical perspective. The overall answer to the main question in this research, namely to what extent people would be positive towards the integration of MT and AI in education, was that people overall are somewhat neutral towards it, so neither very positive or negative. However, this is where the data might mislead us, as when looking at different age groups, none of the groups are neutral towards either MT or AI.

Because older groups are predominantly negative towards MT and AI, and younger groups predominantly positive, the overall score somewhat evens out in the middle, leading to believe the overall population is neutral, but this would not be exactly correct. So what would be theoretically interesting is to figure out why older adults are more negatively opinionated towards MT and AI in education, besides the effects found in this research. What is interesting is that the positives about MT and AI in education are very factual and objective, for example the increased efficiency and accuracy that both MT and AI bring to education (Murphy, 2016; Schacter & Jo, 2017; Kuma, 2019; Southworth, 2019), yet older groups still perceived both as not very useful. The negatives that surround MT and AI in education are all more subjective and personal, such as the distracting factor they bring and the possible dehumanization of education (Haslam, 2006; Alhumaid, 2019), yet younger groups agreed with this more than that older groups agreed with MT and AI being effective and accurate. The reasoning behind these polarizing views should be explored further, perhaps with qualitative research to fully try and grasp exactly why younger groups think positively about this, and why older groups do not.

The strong association both perceived usefulness and perceived ease of use had with both attitudes towards MT and AI was hypothesised, and possibly should be internalised in attitudes themselves. PU being the strongest predictor, both as a single predictor as the most influential one in the wider model, backs up what the UTAUT already stated, namely that PU is the most consistently heavy influencer of attitude (Venkatesh et al., 2003). The same goes for PEOU, which was the second strongest predictor both on its own as in the model. However, to truly advance a present and future-proof framework of innovation adaptation, it might prove fruitful to invest other important factors/predictors for attitude, considering it is arguable that PU and PEOU are part of one's attitude. Since attitude is defined as the beliefs, perceptions and emotions someone has about a thing/person/object/etc., it is arguable that to what extent someone thinks an innovation is useful and easy to use, is already part of their overall attitude towards that innovation. Following that logic, it is arguable, not that it is useless to investigate PU and PEOU, but that other factors which might be more easily traceable and influenceable are looked for, in order to help adaptation innovation and establish a more comprehensible framework. In any case, attention given to PU and PEOU in order to promote innovation adaptation is clear, considering that the group that was the most negative and had the least amount of PU and PEOU, is the group that has the least experience, competence, and digital literacy skills related to MT and AI. Furthermore, older people are overall less knowledgeable about MT and AI, and fairly often do not know what it is (Mozilla, 2019; Pega, 2020), where young people are now growing up around it and get this knowledge in early on in their life (Axente, 2018; Hao, 2019) .Education and training in dealing with these topics should be favourable to the whole of society, as previous research does show that this works, and it seems unavoidable that MT and AI are losing their place in our society anytime soon.

Lastly, the influence age had in this research can not be dismissed, and should be further explored theoretically or taken action upon in real life. This research not only showed that age is an important factor in attitudes towards MT and AI in education, but also a factor in conservatism, openness to change, mobile self-efficacy, experience, where previous research has already shown age to be a factor in digital literacy and new media competence. Age might be the most important factor in a innovation adaptation framework, while current frameworks solely see it as an external factor. There are already examples out there where age has shown to be a negative factor in taking action or adapting innovation. Take for example the problem of climate change, which is arguably the result of human action, despite the general scientific consensus that it is. Older generations believe less in climate change (Reinhart, 2018), they are less concerned about it (Ballew, et al., 2019), they believe it will not affect them as much (Haq, Brown, & Hards, 2010) and they are less willing to take action against it (Pew Research Center, 2020), despite claims that it is these generations that are most to blame for climate change, as they have for example emitted the most carbon emissions (Nagourney, 2013; Loria, 2018). This trend of older generations that are somewhat negative about things they perhaps do not entirely understand, both seen in this research, many other research and the climate change example, is worrying considering that not only the average age in the world is increasing (Ritchie & Roser, 2019), but that most politicians and political leaders, especially those in the G20, are relatively old, often significantly older than the average age of the population (The Learning Network, 2020; Asrar, 2021). If a wider comprehensive model for innovation adaptation is to be devised, age might be the single most important factor in this model, and it would likely take education and experience, or a bigger influence of younger generations, to minimise the effect age has on the adaptation of innovation.

5.3 Limitations and future research

This research had some considerable limitations, which keep a part of the findings from being as generally applicable and generalizable as they could have been, and as the goal was. Firstly, due to the costs and time constraints, and also due to the exceptional circumstances regarding the covid-19 pandemic, the sample was not as representative as it could have been. Non-probability snowball sampling, as was the case in the first stage of the sampling for this research, is not ideal, considering that the respondents will be somewhat close to the researcher, meaning they are often coming from the same sphere of education, culture and preferences. The second stage of the sampling also could have been subjected to some improvements. Due to the personal influence on the first stage of the sampling, predominantly younger people and certain nationalities were represented more than others, meaning that the second stage of the sampling existed more to add to an otherwise unrepresentative sample. However, considering age was a big factor in this research, having older respondents who are probably more competent with MT than the average of that age, considering they would have had to be proficient in navigating an account and website where surveys need to be filled in, might have skewed this part of the sample to more experienced MT users, and therefore more positive about MT and AI. Perhaps the effect of age would have been bigger if older respondents were garnered naturally as opposed to paid respondents. Another issue this research has is the problem of causality. While never explicitly stated in this research, it is implicit that most predictors have a causal relationship with attitude towards MT and AI, meaning that if for example openness to change would increase, then an increase in attitude towards MT and AI would follow. While the hypothesises were guided by research and existing models, it is possible the hypothesises would go in the opposite direction and still have an effect. For example, someone's lower amount of mobile self-efficacy and experience with MT and AI might be explained by one's attitude towards MT and AI being low, thus feeling no need to use it. Lastly, this research is hindered possibly by its oversimplification of predictors. While purposefully done to establish some key predictors for attitude towards MT and AI, and in extension for a framework for innovation adaptation, in practice it probably is not as simple. In reality, a lot of these predictors are interrelated, moderate each other and all have effect on each other and ultimately attitude. While PU and age seemed the biggest predictors in this research, they might be moderated by, or moderate themselves, other predictors who then could be seen as the most important. While simplicity should be key, reality often is not that simple, and pointing to a few predictors in what is in essence a highly complicated societal process might be underestimating a lot of other predictors.

More research on this topic and its predictors is highly desirable. While some predictors, such as PU and PEOU, are already firmly established as predictors for attitude in previous research, research on less researched predictors and perhaps predominantly easily checkable socio-demographic factors would further a comprehensible model for innovation adaptation on both a personal level as a societal level. Ideally, research should continue for, for example, the UTAUT, in identifying more complex latent predictors, as to fully understand which predictors all influence attitude and if possible also see which predictors moderate which. However, research and development of a easily comprehensible model is also desirable, mostly with easily checkable socio-demographic factors as to quickly be able to assess a country's/city's/region's willingness for innovation adaptation. A model like this would make it possible for decision/policy makers to quickly assess where energy and resources need to go in accepting innovation. If for example a country then has a high median age, more energy and resources could be allocated towards schooling and education of the public in order to make sure everyone is informed, experienced and competent with the innovation, thus easing the adaptation process and preventing a situation now where predominantly older people call for, for example, MT to be banned from classrooms. Lastly, considering that AI was influenced easier by certain predictors, further research on knowledge and attitude seems desirable. It would be fruitful to research how knowledge first of all can be increased quickly and efficiently, and also what predictors and how much attitude are affected by knowledge. Innovation is inherent to mankind, and understanding how we deal with is as not only an individual but as a society is extremely relevant, and should be of high importance.

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Appendix A: Survey

Master Thesis - Attitudes towards Media technology/AI

Start of Block: Introduction

Q1 Welcome, my name is Timo, and thank you for taking the time to participate in this master thesis survey.

Over the last few decades, media technologies such as laptops and tablets have become increasingly important in education. Additionally, Artificial Intelligence, in for example learning applications, is also starting to become very important in education. This survey aims to discover attitudes towards the usage of media technologies and Artifical Intelligence in education, and what the reasons for these attitudes could be.

The survey consists out of three stages. In the first stage questions are asked about your media usage and personality. The second stage asks about your opinion of media technology usage in education. The Third stage asks the same questions as the second, but now about your opinion on AI usage in education.

Your responses are completely anonymous and will be held confidentially. They will not be shared with any third party. Your participiation is voluntary and you may stop the survey at any point if you do not wish to continue. The survey should take no longer than 5 to 6 minutes. Thank you for your participation.

If you have any questions, please send them to 447060tl@student.eur.nl

Q2 By clicking 'I agree', you indicate that you take this survey voluntarily and that you are 18 years or older.

o I agree (1)

End of Block: Introduction

Start of Block: Control variables/Indirect predictors

Q3 What is your gender?

o Male (1)

o Female (2)

o Non-binary / third gender (3)

o Prefer not to say (4)

Q4 What is your age?

o 18-24 years old (1)

o 25-39 years old (2)

o 40-64 years old (3)

o 65 years or older (4)

Q5 What is your nationality?

____

Q6 What is the highest education that you have completed?

o None (1)

o High school (2)

o Practical education/Community college (6)

o Bachelor of applied Science (7)

o Bachelor of Science (3)

o Master (4)

o Doctorate (5)

End of Block: Control variables/Indirect predictors

Start of Block: Schwarz Human Values

Q17 Please indicate to what extent you agree with the following statements

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I like to do things in my own original way (1)	o	o	o	o	o	o	o
I like to be free to plan and choose activities for myself (2)	o	o	o	o	o	o	o
I like to be curious and to try and understand all sorts of things (3)	o	o	o	o	o	o	o
I do not like to rely on myself (4)	o	o	o	o	o	o	o
I am always looking for new things to try (5)	o	o	o	o	o	o	o
I do not like taking risks (6)	o	o	o	o	o	o	o

I like surprises (7) o o o o o
o o

It is important to me to see life as an adventure (8) o o o
o o o o

Q18 Please indicate to what extent you agree with the following statements

Strongly disagree (1) Disagree (2) Somewhat disagree (3) Neither agree nor disagree (4)
Somewhat agree (5) Agree (6) Strongly agree (7)

I tend to avoid things that might endanger my safety (1) o o o
o o o o

I believe that people should follow rules at all times, even when no one is watching (2) o
o o o o o o

I never try to disturb or irritate others (3) o o o o
o o o

I believe people should be satisfied with what they have (4) o o o
o o o o

I like drawing attention to myself (5) o o o o
o o o

I believe it is important to follow the customs I have learned (6) o o
o o o o o

I tend to do things even if people say they are wrong (7) o o o
o o o o

I find it important that the established order is protected (8) o o o
o o o o

End of Block: Schwarz Human Values

Start of Block: New media literacy/Mobile self-efficacy & Experience

Q11 Please indicate to what extent you agree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I stay up to date with changes in the media (1)	o	o	o	o	o
I can determine when media content has commercial messages in them (2)	o	o	o	o	o
I sometimes find it difficult finding the online information I want (3)	o	o	o	o	o
I can distinguish facts and opinions in media content (4)	o	o	o	o	o
I sometimes find it hard to create user profiles/accounts on new websites (5)	o	o	o	o	o
I can use laptops/tablets/phones to create media content quite well (6)	o	o	o	o	o
I am good at sharing digital media contents and messages on the internet (7)	o	o	o	o	o

Q14 Please indicate how much the following technologies were used (by students or teachers) during your education, for educational purposes

	Never (1)	A small amount (2)	Sometimes (3)	A lot (4)	Most of the time (5)
Laptops (1)	o	o	o	o	o
Tablets (2)	o	o	o	o	o
Digital whiteboards (3)	o	o	o	o	o
Learning apps (such as duolingo) (4)	o	o	o	o	o
Automatic grading systems (5)	o	o	o	o	o
Personal online quizzes or tests (6)	o	o	o	o	o

End of Block: New media literacy/Mobile self-efficacy & Experience

Start of Block: All MT related questions (Perceived usefulness/ease of use & Attitude)

Q8 The following sets of questions are about new media technologies in education.

You might be wondering what the difference between media technologies and AI in education is. The main difference is that media technologies are hardware, so for example laptops, tablets or phones, while AI is certain software run on those media technologies. Certain software that reacts to your input, just as how Siri or Google reacts to your input.

Some examples of new media technologies that are used in education are laptops, tablets, phones, digital whiteboards and other technologies of that kind.

Q12 Indicate to what extent you agree with the following statements

Strongly disagree (1) Somewhat disagree (2) Neither agree nor disagree (3) Somewhat agree (4) Strongly agree (5)

Media technologies in education make students accomplish tasks quicker (1) o o o o o

Media technologies in education increase productivity (2) o o o o o

Media technologies in education are not effective (3) o o o o o

Media technologies in education help out teachers (4) o o o o o

Media technologies in education make it easier to do work (5) o o o o o

Media technologies in education are useful (6) o o o o o

Q13 Please indicate to what extent you agree with the following statements

Strongly disagree (1) Somewhat disagree (2) Neither agree nor disagree (3) Somewhat agree (4) Strongly agree (5)

I think it is easy to learn how to use media technologies (1) o o o o o

I think teachers find it easy to teach using media technologies (2) o o o o o

I think students find it more difficult to learn using media technologies (3) o o o o o

It is hard to become skillfull in using media technologies (4) o o o o o

It is hard to understand how media technologies work (5) o o o o o

Media technologies in education are easy to use (6) o o o o o

Q7 Please indicate to which extent you agree with the following statements

Strongly disagree (1) Disagree (2) Somewhat disagree (3) Neither agree nor disagree (4) Somewhat agree (5) Agree (6) Strongly agree (7)

Media technologies provide solutions to many problems in education (1) o o o o o o o

Media technologies in education are too distracting (2) o o o o o o o

It is important that media technologies are used in education (3) o o o o o o o

Media technologies in education make students accomplish more (4) o o o o o o o

Media technologies dehumanize education (5) o o o o
o o o

The positives of media technologies in education outweigh the negatives (6) o o
o o o o o

End of Block: All MT related questions (Perceived usefulness/ease of use & Attitude)

Start of Block: All AI related questions (Perceived usefulness/ease of use & Attitude)

Q10 The following questions are about the usage of artifical intelligence (or AI in short) in education.

Some examples of how artifical intelligence is used in education, are learning apps that adapt based on your strenghts and weaknesses, automatic grading, personalized curriculums for students, and data analytics to identify the needs of students.

The following questions are mostly similar to the ones you just filled in. However, these questions are on a new topic, so please do not worry you are repeating yourself.

You might be wondering what the difference between media technologies and AI in education is. The main difference is that media technologies are hardware, so for example laptops, tablets or phones, while AI is certain software run on those media technologies. Certain software that reacts to your input, just as how Siri or Google reacts to your input.

Q15 Indicate to what extent you agree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
AI in education makes students accomplish tasks quicker (1)	o	o	o	o	o
AI in education increases productivity (2)	o	o	o	o	o
AI in education is not effective (3)	o	o	o	o	o
AI in education helps out teachers (4)	o	o	o	o	o
AI in education makes it easier for students to do work (5)	o	o	o	o	o
AI in education is useful (6)	o	o	o	o	o

Q19 Please indicate to what extent you agree with the following statements

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)

I think it is easy to learn how to deal with AI (1) o o o
o o

I think teachers find it easy to teach using AI (2) o o o
o o

I think students find it more difficult to learn using AI (3) o o o
o o

It is hard to become skillfull in dealing with AI in education (4) o o o
o o

It is hard to understand how AI work (5) o o o o
o

AI in education is easy to use (6) o o o o
o

Q9 Please indicate to which extent you agree with the following statements

Strongly disagree (1) Disagree (2) Somewhat disagree (3) Neither agree nor disagree (4)
Somewhat agree (5) Agree (6) Strongly agree (7)

AI provides solutions to many problems in education (1) o o o
o o o o

AI in education is too distracting (2) o o o o
o o o

It is important that AI is used in education (3) o o o o
o o o

AI in education helps students to accomplish more (4) o o o
o o o o

AI dehumanizes education (5) o o o o o
o o

The positives of AI in education outweigh the negatives (6) o o o
o o o o

End of Block: All AI related questions (Perceived usefulness/ease of use & Attitude)