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MASTER THESIS

Technophobia Related Factors in Lithuanian Middle School Teacher Educational Technology Acceptance	**Su technofobija susiję veiksniai Lietuvos vidurinių klasių mokytojų edukacijos technologijos įsisavinime**
English	*Lithuanian*

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Summary

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This study explored the determinants influencing Lithuanian middle school teachers' intentions to adopt educational technology. It focused on understanding how factors like computer anxiety, perceived usefulness, ease of use, social influence, and facilitating conditions affect teachers' readiness to integrate technology into their teaching practices.

The primary aim was to identify and analyze the factors that influence the intention of Lithuanian middle school teachers to use educational technology. The study aimed to apply the Behavioral Reasoning Theory (BRT) to understand these influences better and provide insights for improving technology adoption in the educational sector.

The research employed a quantitative approach, utilizing a structured questionnaire to collect data from middle school teachers across Lithuania. Statistical methods like correlation analysis and structural equation modeling were used to analyze the data.

The study revealed that reasoned action elements (perceived usefulness and ease of use) significantly predicted the intention to use educational technology. Computer anxiety, while present, did not significantly correlate with demographic factors. Situational context elements, such as social influence and facilitating conditions, positively influenced technology adoption intentions.

The findings underscore the importance of reasoned action in driving technology adoption among teachers. The lack of demographic influence on computer anxiety suggests a broader, more universal issue that transcends age or experience. The study emphasizes the need for policy and administrative strategies focusing on enhancing the perceived benefits and ease of use of educational technology.

Santrauka

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Šis tyrimas nagrinėjo veiksnius, įtakojančius Lietuvos vidurinių mokyklų mokytojų ketinimus įdiegti švietimo technologijas. Tyrimo tikslas buvo suprasti, kaip kompiuterio baimė, suvokiamas naudingumas, patogumas naudoti, socialinis poveikis ir palankios sąlygos veikia mokytojų pasirengimą integruoti technologijas į jų mokymo praktikas.

Pagrindinis tyrimo tikslas buvo nustatyti ir analizuoti veiksnius, kurie veikia Lietuvos vidurinių mokyklų mokytojų ketinimus naudoti švietimo technologijas. Tyrimo uždavinys buvo taikyti elgesio pagrindimo teoriją (BRT), kad geriau suprastume šias įtakas ir pateiktume įžvalgas, kaip pagerinti technologijų įsisavinimą švietimo sektoriuje.

Tyrimas buvo atliktas naudojant kiekybinį metodą, struktūruotą anketą, skirtą duomenų rinkimui iš Lietuvos vidurinių mokyklų mokytojų. Duomenų analizei buvo naudojami statistiniai metodai, pvz., koreliacijos analizė ir struktūrinės lygtys.

Tyrimas parodė, kad pagrįsto veiksmo elementai (suvokiamas naudingumas ir patogumas naudoti) reikšmingai prognozuoja ketinimą naudoti švietimo technologijas. Kompiuterio baimė, nors ir buvo, nežymiai koreliavo su demografiniais veiksniais. Situacinio konteksto elementai, tokie kaip socialinis poveikis ir palankios sąlygos, teigiamai įtakojo technologijų įsisavinimo ketinimus.

Išvados pabrėžia pagrįsto veiksmo svarbą skatinant technologijų įsisavinimą tarp mokytojų. Demografinių veiksnių įtakos kompiuterio baimės nebuvimas rodo platesnę, universalesnę problemą, kuri peržengia amžiaus ar patirties ribas. Tyrimas pabrėžia politikos ir administravimo strategijų, orientuotų į suvokiamo naudingumo ir patogumo naudoti švietimo technologijose didinimą, poreikį.

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Introduction

The adoption of new educational technologies by teachers has been an area of interest for researchers for decades. However, the emergence of the COVID-19 pandemic in 2020 led to an unprecedented rapid shift to online and hybrid learning models, accelerating the need for teachers to adopt new technologies. This dramatic change brought to the forefront factors that can inhibit or facilitate technology adoption, including the critical role of technophobia.

Technophobia refers to the fear, anxiety, and aversion towards technology that leads to avoidance and reluctance to engage with it (Brosnan, 1998). While technophobia has long been studied in relation to computer anxiety, the construct has evolved to encompass anxiety and negative attitudes towards technology more broadly, especially as new advanced technologies like artificial intelligence proliferate. Technophobia can be a major barrier to technology acceptance and integration (Gerli et al., 2022), with higher levels associated with lower usage rates (Brosnan, 1998). However, research on tech adoption inhibitors like technophobia in education is limited, especially following recent tech proliferation spurred by COVID-19 school closures. Understanding key factors that contribute to technophobia can inform strategies to facilitate adoption.

There are indications that technophobia may be quite prevalent among teachers. For example, Wilson et al. (2022) developed the Abbreviated Technology Anxiety Scale (ATAS) to measure anxiety towards use of technology in general. They found that preservice teachers reported moderate levels of technology anxiety, suggesting it could hinder integration of technology in classrooms. Similarly, Makumane & Mpungose (2022) found evidence of discomfort, intimidation and resistance to educational technologies among teachers forced to rapidly adopt technologies during COVID-19 shutdowns. Even prior to the pandemic, Celik & Yesilyurt (2013) suggested that negative attitudes were a key factor inhibiting computer use by teachers.

Understanding the factors contributing to technophobia has been an important research focus. Lack of technical skills and knowledge is commonly cited, as teachers with less experience and competence with technology tend to report higher computer anxiety (Chien, 2008). Demographic factors also play a role, with females frequently reporting higher technology anxiety than males (Brosnan, 1998; Bao et al., 2013). Age differences exist as well, with younger teachers typically more comfortable with technology compared to late career teachers (Manyeredzi & Mpofu, 2022). Personality traits like neuroticism also correlate with technology anxiety tendencies (Korukonda, 2005).

Beyond inherent individual differences, the environmental context also contributes to technophobia among teachers. For example, limited access to technology resources, unreliable infrastructure like networks, lack of technical support, and inadequate training leave teachers underprepared to use new educational technologies, elevating anxiety and resistance (Hart, 2023). Heavy workload expectations and lack of dedicated time to learn new technology skills also increase teacher technology anxiety (Watty et al., 2016).

While technophobia has presented a persistent barrier to technology adoption, the dramatic shift to online learning spurred by the COVID-19 pandemic brought this issue to the forefront. School closures forced teachers to rapidly transition to online teaching, often without proper training and support. This forced adoption increased stress, anxiety, and resistance (Makumane & Mpungose, 2022; Gabiadini, 2023). The sudden reliance on videoconferencing, lecture capture, learning management systems, and other educational technologies led to technostress emerging from the pressures of significantly increased technology usage (Gabiadini, 2023).

However, the pandemic also increased focus on support systems to reduce technostress and facilitate adoption. For example, Ray (2021) outlined adaptations like use of both synchronous and asynchronous components to accommodate students facing challenges in the transition to remote learning. Gradual technology exposure along with modeling, encouragement, and cooperative learning can help teachers overcome computer anxiety as well (Brosnan, 1998). Ongoing professional development and training customized to teacher technology skill levels is critical (Bonczek et al., 2018). As teachers gain more computer experience, confidence and adoption rates tend to improve (Chien, 2008).

While technophobia has centered around computer anxiety in the past, new technologies like artificial intelligence (AI) are creating new dimensions of anxiety. AI anxiety refers to fear or apprehension towards AI technology leading to avoidance, distinguishable from traditional computer anxiety due to factors like AI's autonomy, lack of transparency, and potential to replace human roles (Johnson & Verdicchio, 2017).

Understanding this emerging issue is key as AI technologies become more prominent in education.

Perceived usefulness and perceived ease of use have been validated consistently as key determinants of technology acceptance and usage intentions in seminal models like the Technology Acceptance Model (TAM) (Venkatesh & Davis 2000). When teachers believe that a technology will enhance their instructional activities and is easy to use, they are much more likely to accept and integrate it into their practice.

Additionally, social influence from peers and management has been shown to encourage technology adoption by instilling positive subjective norms (Watty et al. 2016). Facilitating conditions like availability of support and resources also directly enable usage by making it easier to integrate technology (Venkatesh et al. 2003).

This study will collect survey data from approximately 100 current middle school teachers in Lithuania to measure their computer anxiety levels, perceived usefulness and ease of use of educational technologies, social influence perceptions, and facilitating conditions availabilities. Adoption intentions will also be measured as the key outcome variable. Behavioral reasoning theory (Westaby 2005) will provide the framework for analyzing the relationships between these factors influencing adoption intentions.

Structural equation modeling will be used to test the predictive model and hypothesized relationships between the constructs. Confirming these relationships can help identify evidence-based interventions to reduce technophobia barriers and facilitate greater technology adoption among teachers to enrich instruction and student learning.

The COVID-19 pandemic necessitated major urgent shifts in educational technology adoption. However, even in post-pandemic times, new advances like AI will continue elevating technology use. Research on inhibiting factors like technophobia remains highly relevant. This thesis aims to explore predictive relationships that can inform strategies to smooth adoption of emerging educational technologies.

Problem: there is a lack of understanding of the factors contributing to techno-phobia and computer anxiety that inhibit Lithuanian middle school teachers from accepting and adopting new classroom technologies.

Goal: to develop and validate a predictive model of technology acceptance that incorporates computer anxiety, technophobia, and other relevant variables in order to identify evidence based interventions to support Lithuanian middle school teachers in integrating emerging education technologies.

Significance: this study can identify evidence-based interventions to alleviate technophobia barriers inhibiting Lithuanian teachers from integrating new classroom technologies. The results can guide strategies to smooth adoption of emerging education technologies in the post-pandemic period possibly outside of Lithuania as well.

Tasks:

1. Conduct a literature review synthesizing prior research on technophobia, computer anxiety, and technology acceptance models.
2. Develop a conceptual research model grounded in behavioral reasoning theory hypothesizing relationships between computer anxiety, perceived usefulness, perceived ease of use, social influence, facilitating conditions, and technology adoption intentions.
3. Collect survey data from a sample of Lithuanian middle school teachers to measure computer anxiety, technology acceptance, and associated variables.
4. Validate the hypothesized predictive model using structural equation modeling on the collected dataset.
5. Analyze the results to identify significant predictors of technology adoption intentions and formulate evidence-based recommendations for alleviating technophobia barriers.
6. Discuss theoretical and practical implications, acknowledge limitations, and suggest directions for future research.

Definition of Terms

1. Technophobia – Anxiety, fear, and aversion towards technology leading to avoidance and reluctance to engage with it.

2. Computer anxiety – Anxiety experienced by users when interacting with computer technology.
3. Technology acceptance – Users' willingness and intentions to utilize new technologies.

Organization of the Thesis

This thesis is organized into three chapters and conclusion. Chapter 1 reviews relevant literature. Chapter 2 outlines the research methodology. Chapter 3 presents the results and analysis. Thesis wraps up with a discussion and conclusion.

1. Literature Review

1.1. Technophobia

Technophobia refers to an individual's fear, anxiety, and aversion towards technology (Gerli et al., 2022). It involves active resistance and avoidance of technology use due to negative attitudes and emotions associated with technology interaction. Technophobia has been defined as "a resistance to talking about computers or even thinking about computers; fear or anxiety towards computers; hostile or aggressive thoughts about computers" (Brosnan, 1998). According to Wang and Wang (2019), technophobia could be a personality trait related to external locus of control and low self-efficacy that causes avoidance of technology.

Technophobia exists on a spectrum, ranging from mild dislike of technology to severe avoidance and inability to use technology (Gerli et al., 2022). It shares similarities with computer anxiety, which has been defined as "fear of impending interaction with a computer that is disproportionate to the actual threat presented by the computer" (Chien, 2008). However, technophobia is focused on a broader range of digital technologies beyond just computers. It stems from fear of the unknown aspects of rapidly evolving technologies and fears of negative prior experiences when using technology (Gerli et al., 2022). Insufficient technology skills and lack of trust are key causes of technophobia, which then leads to technology avoidance behaviors (Sugandini, 2022).

Technophobia has cognitive, behavioral, and emotional components (Heinssen et al., 1987). Cognitively, it involves negative thoughts, self-preoccupation, and lack of confidence when using technology. Behaviorally, it leads to avoidance, reluctance, and inability to use technology properly. Emotionally, it encompasses feelings of anxiety, stress, hostility, and fear associated with technology. Physiological anxiety symptoms like sweaty palms, racing heartbeat, and dizziness can also occur with technophobia (Heinssen et al., 1987).

Demographic factors like gender, age, personality, and cognitive styles relate to technophobia tendencies. Research suggests women may be more prone to technophobia than men (Brosnan, 1998; Bao et al., 2013; Gerli et al., 2022). However, these gender differences could also stem from differential access to technology, stereotypes, and social influences rather than innate differences (Brosnan, 1998). Regarding age, some studies found younger users had lower technophobia, while others suggested older adults were less anxious than younger ones (Chien, 2008). Personality factors like neuroticism, introversion, and thinking vs. feeling cognitive styles were associated with higher technophobia (Chien, 2008; Celik & Yesilyurt, 2013).

Computer experience and skills significantly impact technophobia. Users with more experience, knowledge, and skills around technology tend to have lower anxiety and more confidence (Chien, 2008). However, some research suggests simply repeated exposure does not reduce anxiety if it is unsuccessful or forced (Hauser et al., 2012). Positive mastery experiences where users successfully accomplish tasks appear most effective for building self-efficacy and reducing technophobia over time (Bandura, 1982).

Technophobia can negatively impact acceptance and use of technology in various contexts like education, management, and healthcare. Teachers and students with high technology anxiety are less likely to adopt new educational technologies (Celik & Yesilyurt, 2013; Schlebusch, 2018). In business, managers with technophobia resist new systems and rely on subordinates, preventing efficiency gains (Brosnan, 1998).

However, some users initially resistant to technology adoption later incorporate it successfully into work processes (Brosnan, 1998). This suggests resistance can provide useful feedback to improve training, change management, and system design. Consulting technophobic end users and understanding their perspectives is key for successful implementation. With careful change management and inclusive design, technologies have potential to facilitate human understanding rather than undermine it (Brosnan, 1998).

Reducing user technophobia should be an explicit goal when introducing new technologies into schools, workplaces, and society. Potential interventions include training programs to increase competency and confidence, providing encouragement and peer modeling, starting exposure therapy from simple non-threatening steps, avoiding pressure, and framing technology as an aid not replacement (Bandura, 1982; Brosnan, 1998; Chien, 2008).

Adjusting how technology is portrayed can also combat technophobia. Emphasizing enjoyment and empathy rather than technical skill requirements has shown promise (Brosnan, 1998). Highlighting prosocial applications more than efficiency gains may also reduce anxiety. Actively teaching the principles behind technologies rather than just operations can build understanding and self-efficacy (Wang & Wang, 2022).

Understanding user perspectives through technophobia measurement tools allows segmenting audiences and targeting interventions towards higher anxiety groups (Gerli et al., 2022; Wang & Wang, 2019). Focusing change management, training, and messaging on addressing specific technophobia dimensions gives the best chance of successful adoption. With persistence and the right strategies, even initially resistant users can potentially transition to champions of new technology.

Humanity's relationship with evolving technology brings inherent tensions. But designing inclusive systems and empowering users with knowledge and agency can allow us to harness technology for human progress. Research insights on technophobia provide signposts to guide us on this journey. By illuminating barriers like anxiety, skills gaps, and negative attitudes, we gain awareness of pitfalls to avoid. And measuring technophobia shines a light on areas needing focus to realize technology's promise while avoiding its perils.

1.2. Computer Anxiety

As digital technologies like computers, smartphones, and artificial intelligence continue proliferating across education, workplaces, and society, it becomes increasingly imperative to promote broad inclusion and participation with these tools. However, successful adoption requires overcoming psychological barriers that inhibit engagement with technology. One such barrier is technophobia - the fear, hostility, and anxiety some individuals experience towards technology, leading to avoidance and ineffective use. Technophobia has cognitive, emotional, and behavioral components that combine to generate an aversion towards interacting with technology. In this chapter, I explore the roots and impacts of technophobia as a phenomenon in order to derive insights for alleviating this adoption barrier. By reviewing seminal research on individuals' technology anxiety, we gain perspectives to inform design of inclusive systems that empower users of all skill levels to harness the promise of digital innovation.

Computer anxiety refers to the fear, apprehension, and negative emotional reactions that some individuals experience towards computers and computer-based technologies (Heinssen et al., 1987). It is considered a type of state and trait anxiety that manifests specifically in situations involving computer use, and can inhibit performance, technology adoption, and overall functioning with digital technologies (Beckers et al., 2007). Computer anxiety is an important concept to study, as educational institutions and workplaces continue increasing utilization of computer-based technologies. Understanding the factors contributing to computer anxiety can help inform strategies to reduce it, enabling broader participation and more effective use of digital tools.

In this chapter, I will provide an overview of computer anxiety, including how it has been defined, the factors that contribute to it, its impacts, and potential ways to alleviate it. I will draw on seminal theoretical foundations and empirical research to characterize the concept of computer anxiety and highlight important considerations for research and practice.

Defining Computer Anxiety

Computer anxiety has been defined as the fear, apprehension, and negative affective reactions experienced by some individuals when it comes to using computers or considering computer use (Heinssen et al., 1987). It involves emotional responses like tension, intimidation, hostility, and concerns over embarrassment or damage when interacting with computer-based technologies (Heinssen et al., 1987). These negative reactions can lead to avoidance behavior, where individuals actively stay away from computer use opportunities due to their anxiety. As computers and digital technologies have proliferated across educational, workplace, and personal settings, computer anxiety has emerged as a salient factor potentially contributing to ineffective or non-use of these technologies.

Early research characterized computer anxiety as a type of state anxiety that arises in situations that involve computer use (Heinssen et al., 1987). This state anxiety manifests from pre-existing trait anxiety factors that predispose individuals to experience anxiety in situations with particular stimulus characteristics, like social evaluation, physical danger, or ambiguity (Heinssen et al., 1987). When individual traits like social evaluation anxiety combine with situational threats introduced by computer use like looking incompetent or risk of damaging expensive equipment, state computer anxiety emerges in response (Beckers et al., 2007).

Later research suggested computer anxiety also has stable trait-like components instead of just being a transient state phenomenon (Beckers et al., 2007). Trait computer anxiety develops over time through repeated experiences, leading technophobic individuals to feel computer anxiety consistently across situations involving technology use. Beckers et al. (2007) provided empirical evidence using repeated measurements that computer anxiety relates more strongly to general trait anxiety than temporary state anxiety influenced by the immediate presence of computers. This supports conceptualizing computer anxiety as having trait-like stability in predisposed individuals instead of only arising temporarily in specific contexts.

Overall, computer anxiety appears to be a specific form of anxiety encompassing both state and trait components, that manifests in situations involving use of computer-based technologies. The next sections will discuss the factors contributing to computer anxiety and its impacts on performance and technology adoption.

Factors Contributing to Computer Anxiety

There are several factors that have been found to contribute to increased computer anxiety levels based on prior studies. These include individual differences, prior experience, computer attitudes, and social/cognitive influences.

Certain individual differences like demographic factors and cognitive styles have been linked to higher computer anxiety. For demographic factors, some studies have found that women tend to report higher computer anxiety than men (Heinssen et al., 1987). However, there are potential gender biases underlying access to technology that could contribute to this difference. Younger students also tend to have lower computer anxiety than older adult learners, though findings on age differences have been mixed (Chien, 2008). Additionally, individuals with social or artistic vocational interests exhibit higher computer anxiety compared to investigative or conventional interests (Chien, 2008). Overall, these findings suggest women, older adults, and people with certain vocational inclinations may be more predisposed to computer anxiety. But contradictory findings on age and the potential role of gender bias necessitate further research.

Regarding cognitive factors, individuals with a field-dependent cognitive style emphasizing social reference and diffuse thinking have been found to experience higher computer anxiety compared to field-independent thinkers with more analytical and compartmentalized cognitive patterns (Brosnan, 1998). Those with lower self-efficacy regarding computer use also exhibit higher computer anxiety (Heinssen et al., 1987). Together, these results suggest cognitive and social cognitive traits can play a role in predisposing certain individuals to computer anxiety.

Limited experience with computer technologies has been consistently linked to higher computer anxiety across studies (Heinssen et al., 1987). Specifically, individuals with less direct hands-on experience using computers tend to have higher computer anxiety (Chien, 2008). This relationship persists even after statistical controls, supporting a causal effect of limited experience contributing to computer anxiety. Relatedly, individuals from lower socioeconomic backgrounds have been found to have higher computer anxiety, likely due to reduced access to technologies providing computer experience (Chien, 2008). Overall, these findings strongly indicate that lack of direct prior experience with computer use contributes to higher computer anxiety levels.

Negative attitudes about computers, including perceptions of computers as intimidating or threatening, have been linked to higher computer anxiety (Heinssen et al., 1987). Individuals exhibiting computer anxiety view computers as imposing machines that control the user. They also tend to have lower mechanical self-efficacy and interests (Heinssen et al., 1987). Hostile, antagonistic attitudes towards computer technologies appear closely tied to the experience of computer anxiety.

Computer anxiety also stems from social evaluation concerns and cognitive thought patterns according to some research. Individuals with computer anxiety report fears over looking incompetent or damaging expensive equipment when using computers, suggesting social evaluation threats contribute (Beckers et al., 2007). The computer experience may trigger negative thought patterns like rumination and self-preoccupation instead of task-focus that exacerbate anxiety (Heinssen et al., 1987). These social cognitive mechanisms represent additional factors potentially contributing to computer anxiety emergence beyond individual differences, inexperience, and attitudes.

In summary, the factors contributing to computer anxiety encompass individual differences in demographics like age and gender as well as cognitive styles, prior experience levels, computer-related attitudes, and social cognitive patterns. These elements likely interact to predispose certain individuals to experience computer anxiety. The following section discusses the impacts of computer anxiety.

Computer Anxiety Rating Scale (CARS)

Research has demonstrated that computer anxiety can exert substantial negative impacts on task performance, technology adoption, and overall functioning for the individuals experiencing it. These impacts underscore the importance of studying and alleviating computer anxiety.

High computer anxiety has consistently been linked to poorer task performance with technologies. In early studies, individuals with elevated computer anxiety took longer to complete assigned computer tasks demonstrating performance inefficiencies (Heinssen et al., 1987). Computer anxiety has also been associated with negative computer-related thoughts and preoccupation during task engagement, demonstrating impaired focus on the task (Heinssen et al., 1987). Overall, these findings indicate computer anxiety can substantially undermine effective and efficient performance when using computer-based technologies.

Beyond performance, computer anxiety has also been shown to inhibit adoption and use of new technologies. Individuals experiencing computer anxiety actively avoid and limit their use of computer technologies due to their anxiety (Brosnan, 1998). Repeated exposure alone does not appear to reduce computer anxiety, and may even exacerbate it for some individuals. Interventions targeting beliefs and emotions beyond skills training seem necessary to alleviate computer anxiety (Brosnan, 1998). These results demonstrate how computer anxiety constitutes a major psychological barrier inhibiting adoption and acceptance of emerging digital technologies.

In general education, computer anxiety appears to hinder acquisition of necessary technical skills for academic success, negatively impacting learning outcomes (Chien, 2008). In the workplace, computer anxiety reduces productivity with technologies and avoidance of computer-based tasks (Chien, 2008). As computers and digital tools continue proliferating across life domains, computer anxiety is increasingly problematic and constitutes a salient barrier to effective functioning and adoption.

To effectively measure computer anxiety levels, Heinssen et al. (1987) developed the Computer Anxiety Rating Scale (CARS). The CARS has been empirically validated as a reliable and valid self-report instrument for assessing computer anxiety, demonstrating high internal consistency and correlations with other computer anxiety measures (Heinssen et al., 1987). It captures multiple facets of computer anxiety including self-efficacy, attitudes, physiological arousal, negative thoughts, and performance expectations (Heinssen et al., 1987; Beckers et al., 2007). The CARS has been used successfully across diverse contexts to quantify computer anxiety levels and predict negative outcomes like poor task performance and technology avoidance (Heinssen et al., 1987).

Alleviating Computer Anxiety

Given the substantial negative impacts of computer anxiety, developing strategies to reduce it represents an important priority. Researchers have proposed several approaches for alleviating computer anxiety centered on changing attitudes, increasing experience, and adjusting training methods.

Since negative attitudes about computers contribute to computer anxiety, interventions aimed at changing maladaptive computer-related attitudes have been proposed (Chien, 2008). Techniques like cognitive restructuring, anxiety management, and perceived control enhancement could foster positive attitudinal shifts regarding technology to reduce computer anxiety stemming from antagonistic attitudes. Overall, addressing the cognitive-affective roots of computer anxiety through psychological interventions represents a promising direction.

Another consistent finding is that increased direct hands-on experience with computers reduces computer anxiety (Chien, 2008). This aligns with theories highlighting the importance of enactive mastery for building self-efficacy. Providing repeated successful experiences using computers under non-threatening conditions gives opportunities for desensitization and skill development. Though some find anxiety persists even after experience, carefully structured exposure therapies leveraging modeling, encouragement, cooperation, and considering user traits can successfully alleviate computer anxiety (Brosnan, 1998).

For institutionalized technology training initiatives like in schools, several recommendations have emerged to structure programs optimally to avoid inducing or exacerbating computer anxiety. Training should utilize cooperative learning instead of isolating learners, leverage same-gender instructor role models, and focus on confidence building through technology exploration instead of skills mastery (Brosnan, 1998). Adjusting training approaches to accommodate user psychology represents a systems-level approach to reduce computer anxiety barriers to participation.

In summary, a combination of guided experience programs to reduce unfamiliarity, attitudinal interventions targeting maladaptive thoughts, and training systems designed considering user psychology appear most promising for alleviating computer anxiety. A holistic approach spanning technological, psychological, and social factors is warranted given computer anxiety's multidimensional nature and complex origins. Furthermore, organizations should assess computer anxiety levels using appropriate measurement tools and be mindful of the barriers it poses during technology adoption initiatives.

Overall, computer anxiety constitutes a salient psychological barrier inhibiting effective use and adoption of increasingly pervasive computer-based technologies across life domains. A nuanced understanding of this phenomenon can inform initiatives to alleviate it through multidimensional change strategies spanning technological, individual, and systemic levels. With care, Computer anxiety can be converted to computer enthusiasm. As digital technologies continue proliferating, ensuring broad participation and enabling individuals to capitalize on technological advances remains an important goal requiring consideration of inclusivity barriers like computer anxiety.

1.3. Technology Acceptance Models (TAMs)

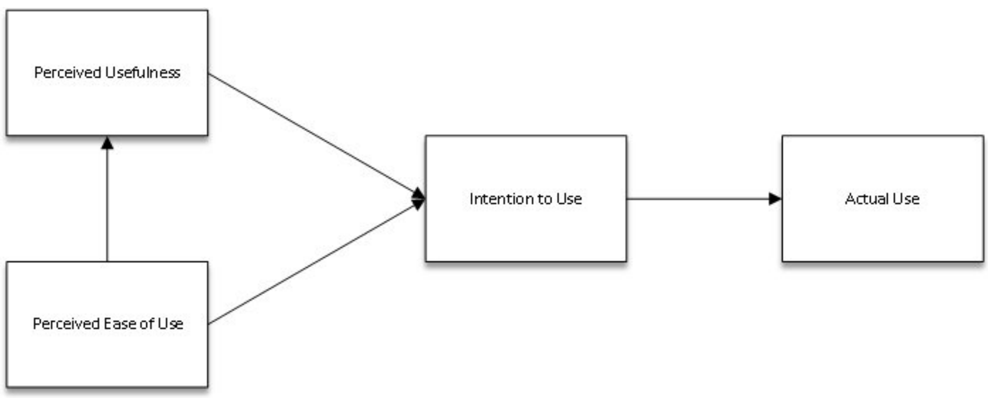

Figure 1. Technology Acceptance Model

Technology acceptance models (TAMs) have been developed and validated over decades of research to explain and predict user adoption and usage behavior towards technologies (Venkatesh and Davis 2000). These models identify key determinants that influence user intentions to use a technology and actual usage behavior. By measuring user perceptions on these determinants, organizations can predict and improve adoption of new technologies.

The foundation for many technology acceptance models is the theory of reasoned action (TRA), proposed by Fishbein and Ajzen in 1975 (Venkatesh et al. 2003). TRA posits that behavioral intention depends on attitude toward the behavior and subjective norms. Attitude is determined by beliefs about the consequences of the behavior. Subjective norm is determined by perceived social pressure (Venkatesh and Davis 2000). These belief structures influence intention, which in turn shapes actual behavior.

Building on TRA, Davis (1989) developed the technology acceptance model (TAM) to explain computer usage behavior. TAM adapted TRA specifically to model users' motivational responses to computing technology (Venkatesh and Davis 2000). It posited that perceived usefulness and perceived ease of use determine attitude toward using a technology, which then influences behavioral intention to use the technology and actual usage behavior.

Perceived usefulness is defined as the extent to which a user believes using the technology will improve their performance. Perceived ease of use refers to the degree to which the user expects the technology to be free of effort (Venkatesh and Davis 2000). TAM hypothesizes that perceived usefulness is influenced by perceived ease of use, as a technology that is easier to use is likely to be perceived as more useful.

TAM found that perceived usefulness was a major determinant of people's intentions to use computers, explaining up to 40% of the variance in usage intentions across empirical studies (Venkatesh and Davis 2000). Perceived ease of use was found to be a significant secondary determinant. Subsequent revisions of TAM have incorporated additional external variables to better understand technology acceptance and use (Gabiadini 2023).

One prominent extension of TAM is TAM 2 developed by Venkatesh and Davis (2000). TAM 2 explains the determinants of perceived usefulness and incorporates subjective norm as an additional predictor of intention under certain conditions.

TAM 2 posits that perceived usefulness depends on several cognitive instrumental processes (Venkatesh and Davis 2000). Job relevance refers to the degree to which the technology is applicable to the user's job. Output quality considers how well the system performs tasks. Result demonstrability refers to the perceived tangibility of the results.

Perceived ease of use retains its direct influence on perceived usefulness. TAM 2 also incorporates social influence processes like subjective norm, which can directly influence perceived usefulness through internalization and intentions through compliance.

Additionally, TAM 2 explores temporal dynamics in the model (Venkatesh and Davis 2000). The effect of subjective norm on intention is expected to attenuate over time with sustained usage. In contrast, cognitive determinants of perceived usefulness remain stable with sustained usage. TAM 2 has been empirically validated in longitudinal studies across multiple organizations, explaining 40-60% of the variance in usage intentions (Venkatesh and Davis 2000).

Further extending TAM, the unified theory of acceptance and use of technology (UTAUT) synthesized TAM elements with seven other technology adoption models (Venkatesh et al. 2003). UTAUT identified four key constructs that influence behavioral intention to use a technology:

1. **Performance expectancy**: The degree to which the user believes using the technology will benefit them in performing certain activities. Similar to perceived usefulness.
2. **Effort expectancy**: The anticipated ease of use of the system. Similar to perceived ease of use.
3. **Social influence**: The user's perception of how people important to them view their use of the technology.
4. **Facilitating conditions**: The availability of infrastructure and support to remove barriers to usage.

Unlike TAM, UTAUT found that attitudes did not significantly influence intentions after accounting for these four constructs. It also determined that facilitating conditions directly influenced technology use rather than just behavioral intentions.

Furthermore, UTAUT identified key moderating factors that impacted the relationships in the model: gender, age, voluntariness, and experience. For instance, the effect of social influence on intention is stronger for women, particularly older women in mandatory settings using a technology initially. The effect of effort expectancy on intention is also stronger for women, especially older women with limited experience with the technology.

In longitudinal studies, UTAUT explained up to 77% of the variance in usage intentions and over 50% of the variance in actual technology usage, outperforming TAM and other models (Venkatesh et al. 2003). This underscores its value in understanding technology adoption behavior.

While TAM and UTAUT provide robust baseline models, recent research has focused on adapting them to new technologies and contexts. For instance, mobile banking adoption has been studied by incorporating factors like mobility, reachability, compatibility and personalization (Shaikh and Karjaluoto 2015). Trust has been incorporated when studying adoption of electronic tax filing (Wang 2003).

Researchers have also expanded TAM and UTAUT to study acceptance of specific systems like Learning Management Systems (Fathema et al. 2015) or augmented reality (Yilmaz 2016). This often involves adapting model constructs or integrating additional constructs relevant to the technology.

TAM and UTAUT have also been applied and validated across different countries and cultures (Im et al. 2011; Tarhini et al. 2016). Analysis shows the models exhibit broad robustness and applicability across Western and Asian countries with appropriate modifications based on cultural dimensions like individualism/collectivism (Srite and Karahanna 2006).

Overall, TAM and UTAUT provide versatile frameworks to study technology adoption across diverse systems, user populations, and cultural settings (Venkatesh and Zhang 2010). As new technologies emerge, these models can be fruitfully adapted by incorporating relevant determinants and boundary conditions specific to the innovation and context. The strong predictive ability of TAM and UTAUT underscores their continued relevance for understanding user acceptance.

Application in Education

In education, TAM and its extensions have been widely used to study adoption of e-learning systems, learning management systems, mobile learning, and other educational technologies by both instructors and students (Raman et al. 2014; Šumak et al. 2011).

For instance, TAM elements like perceived usefulness, perceived ease of use and subjective norm were found to positively influence students' intentions to adopt mobile learning in Jordanian universities (Faqih 2022). The effect of subjective norm was stronger for female students compared to male students.

Other studies adapting TAM to educational contexts have incorporated additional factors like computer anxiety, self-efficacy, compatibility with pedagogical beliefs, technophobia, and attitude as relevant determinants (Pillai and Sivathanu 2018; Sugandini 2022). Training, social influence, and facilitating conditions helped overcome effort expectancy barriers.

Qualitative methods like interviews are often used to identify acceptance determinants specific to educational technologies before developing survey instruments based on TAM models (Watty et al. 2016). Statistical techniques like structural equation modeling help validate model fit.

By leveraging TAM frameworks, technology adoption studies in education can systematically identify key perceived benefits, external variables, and barriers that teachers and students associate with specific technologies. The predictive power of TAM can be harnessed to forecast usage intentions and actual adoption behavior when implementing new systems. Change management initiatives can then focus on addressing identified inhibitors and promoting facilitators to support successful adoption.

In conclusion, technology acceptance models provide a rich theoretical foundation to explore and explain user adoption of emerging technologies across diverse domains, including education. TAM and UTAUT offer versatile frameworks that can be adapted via relevant modifications and inclusion of external factors specific to the technology and context. The continued application of TAM models promises deeper insights into user perceptions and data-driven strategies to promote technology assimilation. As innovation accelerates, technology acceptance models will remain integral to bridging human and technical systems.

1.4. Behavioral Reasoning Theory

Behavioral Reasoning Theory (BRT) offers a comprehensive framework for understanding and predicting technology adoption intentions and usage behaviors. Proposed by Westaby (2005), BRT determines the linkage between beliefs, reasons, global motives, intentions, and actual behavior.

BRT has its origins in reasoned action theories like the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM). It integrates elements of these models with the Reasons Theory and the Theory of Explanation-Based Decision Making (TEDM). According to Reasons Theory, individuals assess the credibility of beliefs by finding reasons for and against them. TEDM states that explanations or reasons strongly influence global motives like attitudes, subjective norms, and perceived control. BRT captures this role of context-specific reasons in determining motives and intentions (Westaby, 2005).

The key constructs in BRT are beliefs, reasons, global motives, intentions, and behavior. Beliefs refer to the information individuals have about a behavior, while reasons are the subjective explanations individuals generate to justify performing or not performing the behavior. Reasons serve as the link between beliefs and global motives like attitude, social norms, and perceived control over behavior. Intentions capture the motivational factors influencing behavior, while behavior refers to the observable actions related to technology adoption and use (Westaby, 2005).

BRT suggests two broad categories of reasons exist – reasons for and reasons against. Reasons for capture the perceived benefits and facilitating factors related to adoption, while reasons against encompass the risks, barriers, and costs. Reasons provide a richer explanation of behavioral intentions than beliefs, as they are contextual and tap different motivational orientations. BRT states that reasons can directly influence intentions, beyond just through global motives. After behavior occurs, reasons are also used to rationalize or justify the behavior (Westaby, 2005).

Relationship to Technology Acceptance Models

Several existing technology adoption models like TAM, TPB, and UTAUT can be integrated within the BRT framework. These models already incorporate constructs like perceived usefulness, perceived ease of use, social norms, and facilitating conditions that can be readily mapped to the reasons and global motives components of BRT. For instance, perceived usefulness in TAM would act as a reason for adopting technology that shapes the global motive of attitude toward use. Effort expectancy in UTAUT would be a reason against adoption that impacts the perceived control over behavior. BRT provides the broader theoretical architecture to incorporate elements of these models and examine their interrelationships in determining usage intentions and behaviors (Venkatesh et al., 2003; Westaby, 2005).

The Computer Anxiety Rating Scale (CARS) developed by Heinssen et al. (1987) is a validated instrument for assessing computer anxiety as a type of trait anxiety that can act as a global motive in the BRT model. CARS measures computer anxiety on factors like computer literacy, efficacy, affect, arousal, and beliefs. Research shows computer anxiety is related to other motivational constructs like self-efficacy, attitudes, experience, and performance. Computer anxiety acts as a barrier to technology adoption and integration. BRT offers a framework to understand the relationships between computer anxiety, contextual reasons for and against adoption, intentions, and actual usage behavior (Heinssen et al., 1987).

Bringing together elements of TAM, UTAUT, and CARS, an integrated BRT model can be developed. Global motives like computer anxiety are determined by stable traits as well as beliefs formed from available information. Contextual reasons for and against adoption bridge global motives and intentions. Reasons for include perceived usefulness and perceived ease of use, while reasons against encompass effort expectancy and social influences. Intentions predict actual usage behavior. This model helps explain and predict adoption by capturing computer anxiety as a motivational barrier, while also mapping facilitators like usefulness and ease of use as reasoned actions encouraging adoption.

In conclusion, Behavioral Reasoning Theory integrates key elements of technology adoption models like TAM and UTAUT with the rich motivation-based explanation provided by Reasons Theory. BRT expands on these models by highlighting the pivotal role of context-specific reasons in determining usage intentions and behavior. It also elucidates the relationships between stable motivational traits like computer anxiety and contextual reasons that directly shape adoption decisions. By offering a broad framework founded on human motivations, BRT holds substantial promise for comprehensively explaining and predicting user acceptance of new educational technologies.

1.5. Factors Influencing Educational Technology Adoption

With foundational understanding of relevant concepts like technophobia, computer anxiety, and established technology acceptance models covered in previous chapters, we now transition to discussing application of this knowledge to the focal context of this thesis - educational technology adoption by middle school teachers. While concepts like technophobia and computer anxiety represent personal dispositional factors, and models like TAM and UTAUT provide understanding of cognitive factors driving acceptance, research also indicates the importance of social and organizational contextual factors in influencing technology adoption in schools (Dincher & Wagner, 2021).

A key tenet of Behavioral Reasoning Theory is that situational context helps shape intentions and behavior above and beyond an individual's global motives and reasoned action. The educational setting represents a distinct organizational environment with unique structural and social dynamics that research indicates can significantly impact teachers' acceptance and usage of instructional technologies (Mubarak, 2023). Gaining deeper understanding of this situational context is important for informing strategies to support successful integration of educational technologies in practice.

Situational context factors

One important situational factor repeatedly found to affect educational technology adoption is access to the required infrastructure, hardware, software, and connectivity needed to effectively utilize new tools (Hart, 2023). Lack of computers, limited software availability, insufficient bandwidth, and technical support deficiencies commonly hinder integration in schools (Mubarak, 2023). Ertmer (1999) suggested addressing resource barriers before targeting teacher beliefs and attitudes, as access facilitates forming direct experience that impacts acceptance. Sufficient infrastructure is a prerequisite, but alone does not determine usage (Dincher & Wagner, 2021). Still, limited access can prevent adoption regardless of motivations.

In addition to resource access, heavy teacher workloads and time limitations are consistently identified as barriers to technology integration (Watty et al., 2016; Hart 2023). Demands to cover content standards leave minimal time to learn new technologies. Insufficient prep periods prevent the curriculum redesign required for integration (Hew & Brush, 2007). University technology adoption studies found dedicated project time and workload models accommodating innovation facilitate adoption (Watty et al. 2016). This likely applies to teacher adoption as well. Availability of time to learn, implement, and institutionalize new practices is a key factor influencing integration.

Leadership support and vision have been identified as pivotal to facilitating educational technology integration (Anderson & Dexter, 2005). Principals prioritizing technology in improvement plans, dedicating resources, and modeling usage positively influence teacher adoption (Hart, 2023; Mubarak, 2023). A shared institutional vision for technology role can unify efforts (Watty et al., 2016). Top-down leadership provides infrastructure, professional development, ongoing support and incentive structures enabling innovation. Studies suggest lack of policy guidance at administrative levels negatively impacts integration (Makumane & Mpungose, 2022). Strategic institutional policies and committed leadership facilitate adoption.

One of the most critical elements enabling successful integration of instructional technology is teacher training (Mubarak, 2023; Hart, 2023). Despite increasing student tech-savvy skills, many teachers remain unfamiliar with emerging technologies (Watty et al., 2016). Even basic computer skills can be lacking, as is pedagogical knowledge for integration (Makumane & Mpungose, 2022). Ongoing professional development builds capacity and confidence for usage. Training tailored to teacher needs, experience levels, and specific technologies best supports adoption (Mubarak, 2023). Demonstrations of student-centered applications also facilitate positive attitudes. Pedagogical modeling helps teachers redesign instructional methods around new tools. Addressing knowledge gaps empowers usage.

Studies indicate teacher technology adoption is influenced by social norms and collegial usage (Watty et al., 2016; Hart, 2023). Diffusion of innovations theory highlights peer modeling and communication channels in facilitating integration (Straub, 2009). Faculty champions drive bottom-up experimentation (Watty et al., 2016). New users often seek informal peer support on new technologies. Normalizing usage through professional learning communities enables sustained integration organizationally. Peer coaching provides non-threatening assistance. Positive administrator encouragement also exerts social influence (Faqih, 2022). Faculty collaboration on integration decisions fosters buy-in (Watty et al., 2016). Social dynamics shape acceptance.

Teacher attitudes, tech anxiety, and computer self-efficacy are significant adoption factors (Mubarak, 2023; Wilson et al., 2022). Negative attitudes contribute to resistance while positive attitudes facilitate integration (Makumane & Mpungose, 2022). Computer anxiety manifests in avoidance behaviors that prevent adoption regardless of availability (Chien, 2008). Positive prior experiences develop favorable attitudes and self-efficacy. Enhancing computer self-efficacy through mastery experiences reduces anxiety. Fostering favorable outcome expectations bolsters perceived usefulness. User-centered design addressing novice needs aids perceived ease of use (Davis, 1989). Emphasizing intrinsic over extrinsic motivations facilitates acceptance (Wang et al., 2022). Reducing technophobia and cultivating confidence supports usage.

Lastly, while starting usage is important, continued and increasingly sophisticated classroom integration sustains benefits of educational technologies (Straub, 2009). Teachers may adopt tools but discontinue usage if expectations aren't met. Factors like reliability, relevance, required effort and distraction concerns affect sustained usage (Hart, 2023). Ongoing technical support facilitates persistence (Mubarak, 2023). Continuous training helps teachers expand usage. Evolving tech capabilities requires keeping skills current. Sustained leadership prioritization enables institutionalization.Usage behavior involves not just adoption, but integration for continuous improvement.

In summary, key contextual factors influencing teacher adoption include resource access, workload models, leadership vision, professional development, social influences, individual attitudes and self-efficacy, and sustaining usage over time. Understanding and addressing situational barriers through organizational policies enables individual factors to flourish. A supportive environment empowers teachers to innovate instruction leveraging new technologies' affordances. This will lay the foundation for an empirical study quantifying the influence of reasoned action and contextual elements on teachers' intentions to use classroom technologies.

1.6. Impact of COVID-19 of Educational Technology Adoption

The COVID-19 pandemic that began in early 2020 brought unprecedented changes to education systems around the world. As schools rapidly transitioned to online and hybrid learning models, educators were suddenly forced to adopt educational technologies at scale (Hart, 2023; Gabiadini, 2023). While educational institutions were already adopting learning technologies prior to the pandemic, the rate of adoption accelerated exponentially due to the crisis (Dincher & Wagner, 2021). This massive disruption provides important insights into factors influencing technology acceptance and integration among educators.

Several studies have examined how the pandemic affected educational technology adoption and usage by teachers. Gabiadini (2023) surveyed university instructors in Italy following emergency transitions to online teaching due to COVID-19 lockdowns. The results showed that the intensity of digital technology use for teaching during the pandemic significantly increased technostress among instructors. This technostress, in turn, negatively impacted their perceptions of the ease of use of these technologies, which then lowered their intentions to continue using them. The findings suggest that the abrupt imposition of remote teaching modalities without proper training or transition time contributed to technology resistance among faculty.

Dincher and Wagner (2021) analyzed determinants of German school teachers' willingness to use web-based educational technologies for distance teaching during COVID-19 school closures. They found that higher levels of technical affinity and perceived effectiveness of digital distance learning were significant predictors of technology usage. However, factors like teacher age, risk preferences, and school digital infrastructure had no significant predictive relationship with usage. Most importantly, less than half of the teachers in the study reported using educational technologies daily prior to the pandemic. This highlights the decisive role of teacher usage in technology adoption, beyond mere provision of infrastructure and resources.

In the United States, Wilson et al. (2022) developed a measure of technology anxiety among pre-service teachers during the pandemic transition to online learning. The technology anxiety scale showed high reliability and validity, negatively correlating with technology attitudes, self-efficacy and usage frequency. The prevalence of technology anxiety reflects barriers educators faced in rapidly shifting to remote teaching modalities. The researchers argue that understanding and addressing technology anxiety is key to successful integration of learning technologies.

Makumane and Mpungose (2022) examined perceptions of South African and Lesotho teachers and students regarding emergency remote teaching during COVID-19. Their findings revealed resistance and negative attitudes towards educational technologies among teachers, largely due to lack of preparation and training. Students also displayed technophobia and motivational issues with forced usage of devices for formal learning, preferring face-to-face modes. Unequal access to resources due to socioeconomic factors also exacerbated digital divides. The study highlights the challenges posed by abrupt imposition of technology without addressing preparatory factors like training, motivation, access, and infrastructure.

Several common themes emerge from these studies on the impact of the pandemic on educational technology adoption.

The lack of training during emergency transitions left many educators unprepared to effectively leverage learning technologies (Makumane & Mpungose, 2022). Investing in teacher training on integrating technology into pedagogy is essential for adoption success (Hart, 2023). Pre-pandemic studies already emphasized this need for technology-related professional development (Watty et al., 2016). The sudden shift online amplified these existing training gaps.

While infrastructure alone does not determine usage (Dincher & Wagner, 2021), lack of access to reliable technology resources severely constrained adoption during the pandemic (Makumane & Mpungose, 2022). Teachers need access to equipment when they need it (Rose Burnett Bonczek et al. 2018), which was challenging with the abrupt shift online. Resolving resource barriers like electricity, connectivity, and digital divides is critical during technology transitions (Hart, 2023).

Individual teacher attitudes play a powerful role in technology integration (Hart, 2023). Studies on pandemic transitions revealed technophobia, motivational issues, and discomfort towards educational technologies among teachers (Makumane & Mpungose, 2022). Addressing intrinsic barriers like computer anxiety requires focusing on influencing teacher beliefs and perceptions regarding learning technologies (Celik & Yesilyurt, 2013).

The Technology Acceptance Model highlights how perceived usefulness and ease of use determine integration (Hart, 2023). Teachers who saw technologies as useful for student learning and teaching strategies were more likely to adopt them (Dincher & Wagner, 2021). Perceptions of complexity negatively impacted acceptance intentions (Gabiadini, 2023). Ensuring technologies align with teaching values and enhance efficiency is key (Venkatesh & Davis 2000).

Adoption decisions occur in a social context impacting attitudes (Hart, 2023). Teacher interactions provide support and role modeling that facilitates technology usage (Rose Burnett Bonczek et al. 2018). Leveraging social dynamics by encouraging innovators and addressing group resistance is important for acceptance (Watty et al., 2016).

The COVID-19 pandemic environment provides a unique natural experiment to study technology adoption under immense behavioral pressure. The crisis forced schools into a technology adoption scenario more abrupt and challenging than typical planned organizational change. While educational institutions were already attempting to incrementally integrate learning technologies prior to the pandemic, the overnight shift online induced immense technological disruption and uncertainty. This jarring transition amplified many existing behavioral barriers like technophobia, lack of intrinsic motivation, gaps in skills and infrastructure, and negative attitudes. Addressing these impediments requires moving beyond merely providing equipment to focusing on influencing educator perceptions and beliefs through training, peer support, change management, and participatory technology implementation. Although the post-pandemic return to physical classrooms has relieved some of the immediate technology burden, the lasting impact on education makes it imperative that findings on technology acceptance from this period inform strategies for achieving sustained digital transformation. With careful assessment of the lessons learned during this technology shock, educational leaders can cultivate enabling conditions for technology-enabled teaching and learning that uplifts educators rather than disempowers them.

1.7. Gaps in the Literature

The adoption and integration of educational technologies in school contexts remains an important area of study, with implications for improving student learning, teacher effectiveness, and access to high-quality education. However, as the preceding review of literature has demonstrated, significant gaps remain in understanding the factors influencing technology acceptance and integration among teachers and educational institutions. Not even mentioning the lack of similar research done among Lithuanian educators.

One overarching gap is the lack of focus on middle school contexts specifically. Much of the existing research has focused on higher education, K-12 environments broadly, or isolated grade levels like high school or elementary school (Gabiadini, 2023; Makumane &

Mpungose, 2022; Mubarak, 2023). However, the middle school learning environment, with adolescent learners navigating key developmental changes and increasingly specialized subject content, represents a distinct context requiring targeted investigation. Not even mentioning the context of Lithuania – no similar research has been conducted here. Factors influencing technology adoption may manifest differently with middle school populations compared to other student age groups. More research focusing squarely on middle school teacher and learner populations is needed.

Additionally, there remains fragmentation across the literature examining technology adoption determinants. For instance, technophobia and computer anxiety research has largely developed independently from technology acceptance models like TAM, TPB, and UTAUT (Gerli et al., 2022; Schlebusch, 2018; Venkatesh et al., 2003). Meanwhile, studies on factors influencing teacher adoption of educational technologies rely on constructs from both technology anxiety and acceptance research but without necessarily integrating findings (Dincher & Wagner, 2021; Hart, 2023). Integrative frameworks like Behavioral Reasoning Theory (BRT) offer potential to consolidate insights across these streams of research but require further development and dedicated testing in educational contexts (Pillai & Sivathanu, 2018; Sahu et al., 2020).

Within educational technology adoption research, there is fragmentation concerning target technologies studied. Some research has focused narrowly on adoption of specific innovations like mobile learning, learning management systems, or multimedia (Faqih, 2022; Makumane & Mpungose, 2022). However, educational technologies constitute an evolving domain. Findings on adoption of specific technologies may not generalize across the domain. There is a need for research which measures acceptance of educational technologies broadly or develops instruments with adaptable items, rather than being restricted to singular applications (Wilson et al., 2022).

Most technology adoption studies, whether in workplace or educational settings, rely on behavioral intention rather than actual usage as the key dependent variable (Gerli et al., 2022; Kelly et al., 2023; Schlebusch, 2018). However, numerous studies have found gaps between intention and actual adoption behavior. Relying solely on intention measures provides an incomplete picture of acceptance and integration (Dincher & Wagner, 2021; Hart, 2023). More research measuring actual usage of educational technologies by teachers is required, through logs, direct observation or other means.

Additionally, there is a need to expand the outcome variables studied beyond adoption and usage alone. For instance, how does technology acceptance influence student learning outcomes, teacher performance, job satisfaction, and other downstream impacts (Watty et al., 2016)? Does technology anxiety among teachers negatively affect student motivation and engagement when technologies are integrated into instruction (Makumane & Mpungose, 2022)? Linking technology adoption to performance, attitudinal, and behavioral outcomes would provide a more complete understanding.

Many studies examining technology anxiety and acceptance employ cross-sectional rather than longitudinal designs (Gerli et al., 2022; Wilson et al., 2022). However, technology adoption occurs as a temporal process, with acceptance determinants changing over time as experience increases (Venkatesh et al., 2003; 2012). More longitudinal studies tracking how relationships between key variables evolve over time would enhance internal validity. Especially needed are longitudinal studies on interventions designed to reduce technology anxiety or enhance acceptance among teachers (Mubarak, 2023; Schlebusch, 2018).

There is also a need for more experimental studies to make causal inferences regarding effects of interventions or contextual changes on acceptance. For instance, studies manipulating facilitating conditions like training or technical support and measuring impacts on acceptance can clarify their causal role (Faqih, 2022; Gabiadini, 2023). Field or randomized experiments on different behavior change techniques to address technology anxiety would also make important contributions (Wang et al., 2022).

Additionally, more research is needed covering diverse geographical contexts and cultures. Most technology adoption studies focus on Western contexts (Sugandini, 2022; Wang et al., 2019). However, acceptance determinants likely vary cross-culturally based on factors like uncertainty avoidance, masculinity/femininity, collectivism, and power distance (Bao et al., 2013; Dincher & Wagner, 2021). Comparative research on how technology anxiety manifests and interventions fare across cultures would provide valuable insights for global education initiatives.

Another gap is the lack of research at levels beyond the individual. Technology acceptance models focus predominantly on individual determinants (Venkatesh et al., 2003).

However, organizational, institutional, and national factors likely shape acceptance as well (Ajzen, 2020; Hart, 2023). Multilevel studies incorporating system-level variables are needed to provide a more complete explanation. Especially pertinent in educational contexts are studies crossing levels, for instance examining how school leadership and organizational technology climate shape individual teacher acceptance (Dincher & Wagner, 2021; Makumane & Mpungose, 2022).

There is also a need to expand technology acceptance models to cover evolving technologies like artificial intelligence, virtual reality, and social robotics whose unique characteristics may introduce new determinants (Kelly et al., 2023; Nazaretsky et al., 2021). AI anxiety research represents early efforts to study acceptance of increasingly autonomous technologies, but applications in educational contexts remain minimal (Wang et al., 2019). Studies focused on AI and emerging technologies would enable updated models accounting for their distinctive features.

Additionally, further research on resistance warrants attention. Acceptance models focus predominantly on drivers of adoption rather than resistance. However, psychological reactance and technology avoidance merit equal focus, particularly among mandated users (Faqih, 2022; Venkatesh et al., 2003). Integrating insights from dedicated resistance models could provide a balanced perspective (Cenfetelli, 2004; Laumer & Eckhardt, 2012; Nazaretsky et al., 2021).

Finally, there is a need to consolidate models and findings into updated integrative theories of technology adoption tailored for educational contexts (Celik & Yesilyurt, 2013; Hart, 2023; Sugandini, 2022). Frameworks like UTAUT have synthesized existing models but require ongoing extension, validation and contextual adaptation. Developing integrative, education-specific theoretical models synthesizing anxiety, acceptance and resistance research could provide parsimonious explanations to guide interventions and policy aimed at technology integration in schools.

In conclusion, this review has highlighted critical gaps in the literature related to technophobia, computer anxiety, technology acceptance models, behavioral reasoning theory, factors influencing educational technology adoption, and the impact of COVID-19. Addressing these research gaps through dedicated studies employing longitudinal, experimental, multi-level, and cross-cultural designs can significantly advance understanding of technology integration in educational institutions. Developing updated integrative theoretical models tailored for educational contexts is particularly imperative to inform policies and practices that successfully leverage the promise of emerging technologies to transform teaching and learning.

2. Research Methodology

This study will utilize a quantitative cross-sectional survey design. A cross-sectional design is appropriate as the goal is to examine the relationships between the variables like computer anxiety, perceived usefulness, and intention to use educational technologies at a specific point in time rather than changes over time (Sekaran & Bougie, 2016). The key independent variables will be measured using established scales for computer anxiety (CARS), perceived usefulness and perceived ease of use (TAM), social influence and facilitating conditions (UTAUT). The dependent variable will be intention to use educational technologies.

A survey method will be used for data collection as it allows efficient collection of quantitative data from a sample to make inferences about the population (Fowler, 2014). Online surveys provide advantages like convenience, cost savings, access to geographically dispersed samples, and automated data entry (Wright, 2005). However, coverage error is a limitation if the sample is not fully representative of the target population.

The target population will be middle school teachers currently teaching grades 5-8 in Lithuania. There are approximately 27,000 teachers in Lithuania (OSP [1], 2023). A sample size of 200 teachers will be targeted for this study. With a population size of 27,000, a sample size of 200, and a 95% confidence level, the margin of error is approximately 6.81% (Israel, 2013). While a larger sample size would yield a lower margin of error, a sample of 200 middle school teachers in Lithuania will provide valuable insights into the research questions for the purposes of this master's thesis.

Convenience sampling will be used by contacting online teacher forums, schools, and teachers associations to recruit respondents. Though not fully random, this provides a reasonably efficient method to obtain the needed sample size. Demographic questions on age, gender, teaching experience, and grade levels taught will also be included. Data will be screened to check if key demographics like age, gender, and years of experience are adequately represented compared to the overall Lithuanian teacher population.

A structured questionnaire (available in English under Annex A or in Lithuanian under Annex B of this thesis) will be developed incorporating validated scales to measure each construct in the research model. All items will use 5-point Likert scale response formats.

Computer anxiety will be measured using the Computer Anxiety Rating Scale (CARS) developed by Heinssen et al. (1987). CARS includes 19 items across factors like computer literacy, efficacy, affect, arousal, and beliefs. It has demonstrated high reliability and validity in measuring computer anxiety levels (Heinssen et al., 1987). We will focus on 5 key items.

Perceived usefulness and perceived ease of use will be measured using scales from Davis (1989) that have been widely validated in technology acceptance research. Social influence and facilitating conditions will be measured using scales from Venkatesh et al. (2003). Intention to use educational technologies will be measured by 3 items adapted from Venkatesh et al. (2003).

Data will be collected using an online survey platform Typeform. A token financial incentive will be offered in the form of a raffle for 100 Euro worth gift certificate for survey completion to further boost response rates. Survey will optionally record personally identifiable information only for the purpose of the raffle. No IP addresses will be collected and data will be kept secure on encrypted cloud services to protect confidentiality.

The collected survey data will be downloaded from the online survey platform and analyzed using IBM SPSS v29.0.1.0 software. First, data cleaning will be conducted to identify any incomplete or invalid responses and make decisions on whether to include those cases in the analysis. Descriptive analysis will be performed to check for outliers and examine measures of central tendency and variability in key study variables. Reliability analysis will be conducted for each scale used.

Next, assumptions for conducting correlations, regressions, and structural equation modeling will be checked. Multiple linear regression analysis will test predictor relationships for perceived usefulness and intention to use educational technology.

Finally, structural equation modeling (SEM) using IBM SPSS software will be used to test the overall hypothesized model and relationships simultaneously. SEM allows testing complex relationships between latent constructs indicated by their measurement items (Kline, 2016). Path coefficients will determine strength of predictive relationships between constructs.

If model fit is inadequate, modification indices can guide re-specification of the model. Testing the hypothesized structural model using SEM provides a robust multivariate analysis

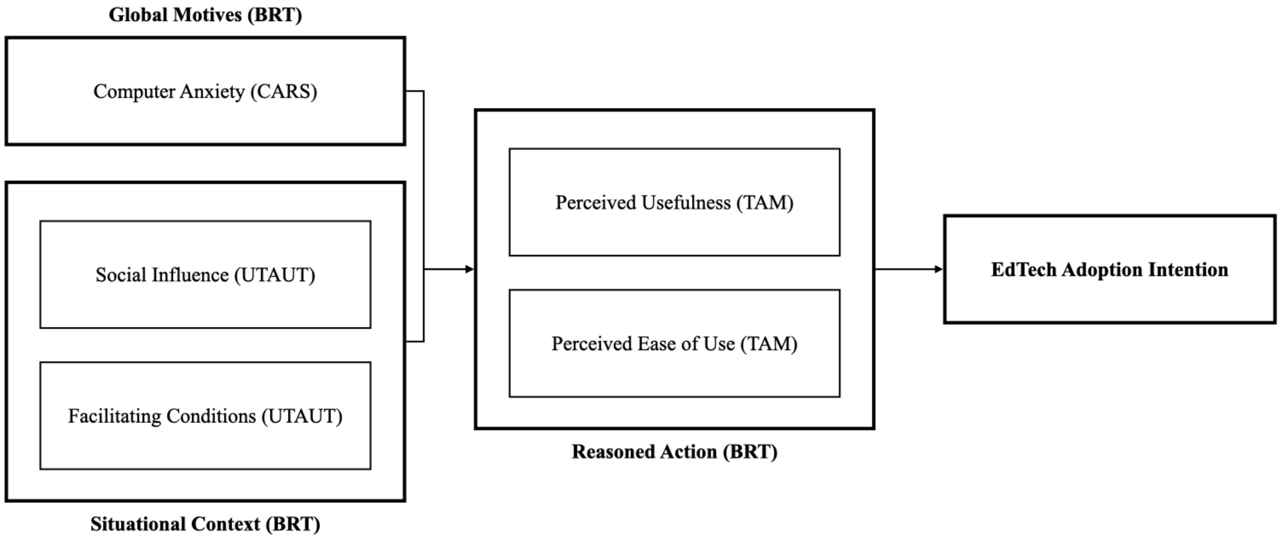

Figure 2. BRT Research Model

method for survey data to validate the predictive relationships specified in the theoretical research framework.

Based on the literature review, the following research model is proposed to examine factors influencing educational technology adoption intentions among middle school teachers. This model integrates elements of the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and the Computer Anxiety Rating Scale (CARS) within the broad framework of Behavioral Reasoning Theory (BRT).

As outlined in the literature review, BRT suggests that global motives, belief composites, reasoned action and situational context shape behavioral intentions, which then influence actual behavior (Westaby, 2005). Drawing on this framework, the model incorporates computer anxiety as a negative global motive, perceived usefulness and perceived ease of use from TAM as positive reasoned actions, and social influence and facilitating conditions from UTAUT as key situational factors. Educational technology adoption intention is the key dependent variable.

Based on the research model, the following hypotheses are proposed:

H1: Computer anxiety as global motive will negatively predict educational technology adoption intention. Higher computer anxiety, encompassing negative emotions like fear and stress associated with technology use, will decrease teachers' intentions to adopt new classroom technologies. This hypothesis is supported by prior research establishing computer anxiety as a significant barrier to technology adoption across contexts (Brosnan 1998; Makumane & Mpungose 2022).

H2: Reasoned action as perceived usefulness & ease of use will positively predict educational technology adoption intention. When teachers believe that using a particular technology will enhance their instructional activities and effectiveness, they will be more inclined to adopt it. The role of perceived usefulness as a key driver of adoption intentions is well-established in TAM research (Venkatesh & Davis 2000). When teachers believe that a new technology will be free of effort and easy to apply in practice, their intentions to adopt it will increase. Perceived ease of use has been validated as pivotal adoption factor in educational settings (Faqih 2022).

H3: Situational context as social influence and facilitating conditions will positively predict educational technology adoption intention. When teachers perceive that important referents like peers or administrators endorse use of a technology, they will be more likely to intend to adopt it themselves. Social influence supports adoption across contexts including education (Venkatesh et al. 2003; Faqih 2022). The availability of infrastructure, resources, training, and support to enable use of classroom technologies will directly improve teacher's intentions to adopt them. Facilitating conditions make integration practically achievable (Venkatesh et al. 2003).

H4: Reasoned action is the key predictor for intention to use technology among teachers.

H5: Situational context and computer anxiety are key predictors for reasoned action.

Here are the definition of constructs:

1. **Computer Anxiety**: Negative affective reactions associated with using computer-based technologies, including apprehension, stress, and avoidance tendencies (Heinssen et al. 1987).
2. **Perceived Usefulness**: The degree to which a teacher believes that use of a particular technology can enhance their instructional activities and effectiveness (Venkatesh & Davis 2000).

3. **Perceived Ease of Use**: The degree to which a teacher expects use of a particular technology to be relatively free of physical or mental effort (Venkatesh & Davis 2000).
4. **Social Influence**: Teacher's perception of how important institutional and peer referents view their use of a particular technology (Venkatesh et al. 2003).
5. **Facilitating Conditions**: Availability of technological infrastructure, training programs, and administrative support to remove barriers associated with educational technology usage (Venkatesh et al. 2003).
6. **Adoption Intention**: A teacher's self-reported motivation and plans to begin utilizing a particular educational technology in their classroom practice (Faqih 2022).

This chapter has outlined the theoretical research framework guiding the study, encompassing relevant constructs from technology acceptance and anxiety literature situated within the broad explanatory architecture of Behavioral Reasoning Theory. The model and hypotheses provide a foundation for the empirical methodology to quantitatively assess the relationships between key factors influencing educational technology adoption intentions among Lithuanian middle school teachers.

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3. Research Results

The survey conducted for this research, available in Lithuanian in Annex B and in its English translation in Annex A, reached an audience through online teacher forums, schools, and teacher associations. To enhance participation, responses were incentivized with a 100 Euro raffle. This approach led to 235 initial attempts, with 159 completing the survey successfully, resulting in a 67.65% completion rate. The average response time was 4 minutes and 55 seconds. However, two outliers who took an average of 67 minutes and 22 seconds each to complete the survey were excluded, leading us to analyze data from 157 respondents.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	141	89.8	89.8	89.8
	Male	16	10.2	10.2	100.0
	Total	157	100.0	100.0	

Table 1. Distribution by gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than or 30 years	20	12.7	12.7	12.7
	31-40 years	27	17.2	17.2	29.9
	41-50 years	44	28.0	28.0	58.0
	51-60 years	51	32.5	32.5	90.4
	More than 60 years	15	9.6	9.6	100.0
	Total	157	100.0	100.0	

Table 2. Distribution by age

3.1. Sample Characteristics

The survey's gender demographics, with 90% female respondents, reflect a potential skew. Yet, this mirrors the broader composition of the Lithuanian teaching profession, where male teachers account for only 11.7% according to 2022-2023 statistics (OSP [2], 2023). Therefore, our sample is a fair representation of the gender imbalance prevalent in the Lithuanian teacher population.

The survey revealed a notable overrepresentation in certain age groups compared to the general population of Lithuanian teachers in 2022-2023 (OSP [2], 2023). Specifically, teachers aged 30 years or younger comprised 12.7% of our respondents, while only 3.6% of

Lithuanian teachers fall into this age bracket. Similarly, for the age groups of 31-40 years and 41-50 years, our survey recorded higher percentages (17.2% and 28%, respectively) compared to 10.7% and 25.3% in the general teacher population. On the other hand, there was underrepresentation in the older age groups: those aged 51-60 years represented 32.5% in our survey, lower than the 37.5% in the broader teacher demographic, and the above 60 years group accounted for 9.6% in our sample, compared to 22.9% overall. This disparity suggests that our survey data may be skewed towards younger teachers.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than or 5 years	23	14.6	14.6	14.6
	6-10 years	24	15.3	15.3	29.9
	11-15 years	14	8.9	8.9	38.9
	16-20 years	25	15.9	15.9	54.8
	More than 20 years	71	45.2	45.2	100.0
	Total	157	100.0	100.0	

Table 3. Distribution by relevant teaching experience

Regarding teaching experience, over 45% of our respondents have at least 20 years of experience in middle-school teaching, and more than 40% are experienced educators. The remaining 15% are newer teachers. This suggests that our survey is informed by a wealth of professional experience, offering valuable insights into middle-school education practices and challenges.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	112	71.3	71.3	71.3
	No	45	28.7	28.7	100.0
	Total	157	100.0	100.0	

Table 4. Educators teaching Arts & Humanities

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	42	26.8	26.8	26.8
	No	115	73.2	73.2	100.0
	Total	157	100.0	100.0	

Table 5. Educators teaching STEM

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	17	10.8	10.8	10.8
	No	140	89.2	89.2	100.0
	Total	157	100.0	100.0	

Table 6. Educators teaching other subjects

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	14	8.9	8.9	8.9
	No	143	91.1	91.1	100.0
	Total	157	100.0	100.0	

Table 7. Multidisciplinary educators

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	83	52.9	52.9	52.9
	No	74	47.1	47.1	100.0
	Total	157	100.0	100.0	

Table 8. 5th grade teachers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	114	72.6	72.6	72.6
	No	43	27.4	27.4	100.0
	Total	157	100.0	100.0	

Table 9. 6th grade teachers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	98	62.4	62.4	62.4
	No	59	37.6	37.6	100.0
	Total	157	100.0	100.0	

Table 10. 7th grade teachers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	116	73.9	73.9	73.9
	No	41	26.1	26.1	100.0
	Total	157	100.0	100.0	

Table 11. 8th grade teachers

Subject specialization among our respondents also shows a skew. A significant 71% specialize in Arts & Humanities, compared to 27% in STEM and 11% in other subjects. When these figures are compared to the 2022-2023 Lithuanian teacher statistics (OSP [2], 2023), notable differences emerge. In the broader teacher population, 53.5% focus on Arts & Humanities, 29.1% on STEM subjects, and 17.4% on other subjects. Our survey, therefore, has a higher concentration of Arts & Humanities teachers, potentially impacting the perspectives and challenges highlighted in our findings.

Grade-level teaching distribution in our survey reveals that a significant majority teach 8th grade (74%) and 6th grade (73%), followed by 7th grade (62%). The relatively lower representation of 5th-grade teachers could highlight differences in teaching experiences, curriculum, or educational concerns at the start of middle school.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	102	65.0	65.0	65.0
	No	55	35.0	35.0	100.0
	Total	157	100.0	100.0	

Table 12. Share of Class mentors / Class teachers

Finally, 65% of respondents being class mentors or class teachers indicates a close relationship with their students, suggesting that our survey might provide deeper insights into student-teacher dynamics and classroom management strategies.

To sum up, survey data reveals a sample predominantly consisting of female, younger, and experienced middle school teachers, with a strong representation in Arts & Humanities and STEM. These characteristics suggest that the survey results are informed by a diverse yet experienced group of educators, providing a comprehensive, even if tad bit skewed, view of the current educational landscape in Lithuania.

3.2. Reliability and Validity Analysis

Respondents of the survey were presented with six distinct blocks of questions, each representing a specific component which was subsequently evaluated for reliability and validity.

Cronbach's Alpha	N of Items
.710	5

Table 13. Computer Anxiety component reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Computers make me feel uncomfortable	5.61	6.523	.430	.679
I get a sinking feeling when trying to use a computer	5.49	6.585	.378	.705
Computers make me feel uneasy and confused	5.76	7.005	.630	.625
Learning computer skills is a waste of time	5.61	6.098	.487	.656
Computers are intimidating to me	5.64	6.784	.504	.650

Table 14. Computer Anxiety component item-total statistics

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Computer Anxiety	.304	157	<.001	.701	157	<.001

a. Lilliefors Significance Correction

Table 15. Computer Anxiety component test of normality

Cronbach's Alpha	N of Items
.855	4

Table 16. Perceived Usefulness component reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Using educational technology enhances my teaching effectiveness	12.94	4.836	.659	.848
Using educational technology improves my productivity as a teacher	12.81	5.527	.728	.805
Using educational technology makes it easier for me to accomplish instructional objectives	12.84	5.250	.791	.777
Overall, I find educational technology useful for teaching	12.52	6.123	.663	.834

Table 17. Perceived Usefulness component item-total statistics

Computer Anxiety (Heinssen et al. 1987)

Cronbach's Alpha for Computer Anxiety component is above 0.7 and removing any of the questions wouldn't raise it higher. We are keeping all the original responses to create discrete Computer Anxiety component.

Kolmogorov-Smirnov test of normality reveals that Computer Anxiety component is statistically significant and we can proceed.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Usefulness	.183	157	<.001	.848	157	<.001

a. Lilliefors Significance Correction

Table 18. Perceived Usefulness component test of normality

Perceived Usefulness (Venkatesh & Davis 2000)

Cronbach's Alpha for Perceived Usefulness component is way above 0.8 and removing any of the questions wouldn't raise it higher. We are keeping all the original responses to create discrete Perceived Usefulness component.

Kolmogorov-Smirnov test of normality reveals that Perceived Usefulness component is statistically significant and we can proceed.

Cronbach's Alpha	N of Items
.919	4

Table 19. Perceived Ease of Use component reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Learning how to use educational technology is easy for me	11.05	8.049	.831	.890
It is easy for me to become skillful at using educational technology	11.05	7.779	.886	.872
I find it easy to get educational technology to do what I want it to do	11.29	7.478	.823	.893
Overall, I find educational technology easy to use	11.34	8.135	.728	.925

Table 20. Perceived Ease of Use component item-total statistics

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Ease of Use	.173	157	<.001	.910	157	<.001

a. Lilliefors Significance Correction

Table 21. Perceived Ease of Use component test of normality

Perceived Ease of Use (Venkatesh & Davis 2000)

Cronbach's Alpha for Perceived Ease of Use component is way above 0.91 but removing the question "Overall, I find educational technology easy to use" would raise it higher to 0.925. We keep 3 of the original responses to create discrete Perceived Ease of Use component.

Kolmogorov-Smirnov test of normality reveals that Perceived Ease of Use component is statistically significant and we can proceed.

Cronbach's Alpha	N of Items
.482	3

Table 22. Social Influence component reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
My school administration encourages me to use educational technology	7.57	2.439	.175	.631
My colleagues think that I should use educational technology	8.00	2.346	.317	.354
In general, my colleagues have supported the use of educational technology	7.68	2.413	.459	.159

Table 23. Social Influence component item-total statistics

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Social Influence	.163	157	<.001	.920	157	<.001

a. Lilliefors Significance Correction

Table 24. Social Influence component test of normality

Social Influence (Venkatesh et al. 2003)

Cronbach's Alpha for Social Influence component is below 0.6 but removing the question "My school administration encourages me to use educational technology" would raise it higher to an acceptable level of 0.631. We keep 2 of the original responses to create discrete Social Influence component.

Kolmogorov-Smirnov test of normality reveals that Social Influence component is statistically significant and we can proceed.

Cronbach's Alpha	N of Items
.745	3

Table 25. Facilitating Conditions component reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I have the necessary resources to use educational technology	7.59	4.193	.475	.786
Educational technology is compatible with teaching practices I am familiar with	7.61	3.753	.726	.476
Assistance is available if I have difficulties using educational technology	7.32	4.616	.540	.699

Table 26. Facilitating Conditions component item-total statistics

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Facilitating Conditions	.204	157	<.001	.902	157	<.001

a. Lilliefors Significance Correction

Table 27. Facilitating Conditions component test of normality

Facilitating Conditions (Venkatesh et al. 2003)

Cronbach's Alpha for Facilitating Conditions component is way above 0.74 but removing the question "I have the necessary resources to use educational technology" would raise it higher to 0.768. We keep 2 of the original responses to create discrete Facilitating Conditions component.

Kolmogorov-Smirnov test of normality reveals that Facilitating Conditions component is statistically significant and we can proceed.

Cronbach's Alpha	N of Items
.795	3

Table 28. EdTech Adoption Intention component reliability

Educational Technology Adoption Intention (Faqih 2022)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I intend to continue using educational technology in the future	8.54	2.225	.608	.751
I will always try to use educational technology in my teaching	8.75	1.922	.709	.641
I plan to increase my use of educational technology over time	8.85	2.143	.600	.761

Table 29. EdTech Adoption Intention component item-total statistics

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Intention to Use	.175	157	<.001	.802	157	<.001

a. Lilliefors Significance Correction

Table 30. Adoption Intention component test of normality

Cronbach's Alpha for EdTech Adoption Intention component is way above 0.79 and removing any of the questions wouldn't raise it higher. We are keeping all the original responses to create discrete Adoption Intention component.

Kolmogorov-Smirnov test of normality reveals that Adoption Intention component is statistically significant and we can proceed.

Combining Components

Cronbach's Alpha	N of Items
.659	2

Table 31. Situational Context component reliability

Cronbach's Alpha	N of Items
.666	2

Table 32. Reasoned Action component reliability

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Situational Context	.129	157	<.001	.957	157	<.001

a. Lilliefors Significance Correction

Table 33. Situational Context component test of normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Reasoned Action	.123	157	<.001	.919	157	<.001

a. Lilliefors Significance Correction

Table 34. Reasoned Action component test of normality

As mentioned before, this research will leverage the BRT Research Model (Figure 1), combining certain components into new composites. Our model will integrate Perceived Usefulness and Perceived Ease of Use components from TAM into Reasoned Action component. Additionally, Social Influence and Facilitating Conditions components from UTAUT will be integrated into Situational Context component. Adoption Intention will remain the key dependent variable, while Computer Anxiety (CARS) will be treated as a Global Motives component in the context of BRT Research Model. Accordingly, the new Reasoned Action and Situational Context components have to be checked for reliability and normality.

Cronbach's Alpha for Situational Context and Reasoned Action components are in acceptable range – 0.66 and 0.67 accordingly. Kolmogorov-Smirnov tests of normality reveal that Situational Context and Reasoned Action components are statistically significant. We can accept them to have discrete BRT Research Model components.

3.3. Descriptive Statistics

	N	Mean	Std. Deviation
Computer Anxiety	157	1.4051	.62015
Perceived Usefulness	157	4.2596	.75897
Perceived Ease of Use	157	3.7792	.95075
Social Influence	157	3.7866	.78079
Facilitating Conditions	157	3.7930	1.02383
Intention to Use	157	4.3546	.68944
Valid N (listwise)	157		

Table 35. Means across all respondents

Across all categories, the survey indicates that, on average, educators experience relatively low Computer Anxiety, scoring near the mid-range between 1 and 2 on a 5-point Likert scale. Their Perceived Usefulness of educational technology is notably high, averaging just above 4 on the same scale. Similarly, Perceived Ease of Use, Social Influence, and Facilitating Conditions are closely aligned, each nearing a score of 4. Notably, the Intention to Use technology shows the highest rating, approaching the midpoint between 4 and 5 on the 5-point Likert scale.

	N	Mean	Std. Deviation
Computer Anxiety	141	1.4270	.62984
Perceived Usefulness	141	4.2713	.71806
Perceived Ease of Use	141	3.7470	.93766
Social Influence	141	3.8227	.76096
Facilitating Conditions	141	3.7943	1.00901
Intention to Use	141	4.3546	.65491
Valid N (listwise)	141		

Table 36. Means across women

	N	Mean	Std. Deviation
Computer Anxiety	16	1.2125	.50316
Perceived Usefulness	16	4.1563	1.07964
Perceived Ease of Use	16	4.0625	1.04859
Social Influence	16	3.4688	.90312
Facilitating Conditions	16	3.7813	1.18278
Intention to Use	16	4.3542	.96968
Valid N (listwise)	16		

Table 37. Means across men

	N	Mean	Std. Deviation
Computer Anxiety	23	1.3652	.53819
Perceived Usefulness	23	4.4891	.63728
Perceived Ease of Use	23	3.7391	.84660
Social Influence	23	3.8478	.80389
Facilitating Conditions	23	4.2174	.61839
Intention to Use	23	4.5362	.50989
Valid N (listwise)	23		

Table 38. Means across ages 30 or less

	N	Mean	Std. Deviation
Computer Anxiety	24	1.1833	.35345
Perceived Usefulness	24	4.3854	.60334
Perceived Ease of Use	24	4.0556	.52628
Social Influence	24	3.8750	.51605
Facilitating Conditions	24	3.2917	.98815
Intention to Use	24	4.3333	.51075
Valid N (listwise)	24		

Table 39. Means across ages 31-40

	N	Mean	Std. Deviation
Computer Anxiety	14	1.5571	.86355
Perceived Usefulness	14	4.1429	1.18368
Perceived Ease of Use	14	3.7619	1.32967
Social Influence	14	3.5357	1.00889
Facilitating Conditions	14	3.8571	1.27745
Intention to Use	14	4.2619	1.04741
Valid N (listwise)	14		

Table 40. Means across ages 41-50

	N	Mean	Std. Deviation
Computer Anxiety	25	1.5040	.62748
Perceived Usefulness	25	4.2100	.67577
Perceived Ease of Use	25	3.7200	.98451
Social Influence	25	3.6800	.85245
Facilitating Conditions	25	3.7600	1.05198
Intention to Use	25	4.4000	.49065
Valid N (listwise)	25		

Table 41. Means across ages 51-60

	N	Mean	Std. Deviation
Computer Anxiety	71	1.4282	.65229
Perceived Usefulness	71	4.1831	.76644
Perceived Ease of Use	71	3.7230	1.00315
Social Influence	71	3.8239	.77965
Facilitating Conditions	71	3.8239	1.03198
Intention to Use	71	4.3052	.76790
Valid N (listwise)	71		

Table 42. Means across ages 60 or more

When analyzing the responses of women and men separately, the data reveals very similar scores in their Intention to Use, with both groups averaging 4.4 on a 5-point Likert scale. Likewise, attitudes towards Facilitating Conditions are identical for both, at 3.8.

However, slight differences emerge in areas such as Computer Anxiety, where women score 1.4 compared to 1.2 for men, and Perceived Usefulness, with women at 4.3 and men at 4.2. The most notable disparities are observed in Perceived Ease of Use, with women scoring 3.8 and men scoring higher at 4.1, and in Social Influence, where women's score is 3.8 compared to men's 3.5.

Analyzing the survey results by age groups, we find interesting patterns across various categories:

- Computer Anxiety remains low across all ages, with those under 30 and over 60 scoring 1.4, slightly higher for ages 41-50 and 51-60 at 1.6 and 1.5 respectively, and lowest for ages 31-40 at 1.2.
- Perceived Usefulness is consistently high across all age groups, with the youngest (under 30) rating it the highest at 4.5, and a slight dip for ages 41-50 at 4.1.
- Perceived Ease of Use is generally high, with the 31-40 age group finding it easiest (4.1), and other age groups hovering around 3.7-3.8.
- Social Influence scores quite uniform, with those under 40 rating it slightly higher at 3.9, and a minor dip for the 41-50 age group at 3.5.
- While those under 30 rate Facilitating Conditions highest at 4.2, there's a *notable drop for ages 31-40* at 3.3, with other age groups scoring around 3.8-3.9.
- Across all ages, the Intention to Use technology is high, peaking at 4.5 for those under 30 and remaining above 4.3 for other age groups.

	N	Mean	Std. Deviation
Computer Anxiety	112	1.4000	.63587
Perceived Usefulness	112	4.2455	.72206
Perceived Ease of Use	112	3.7589	.90953
Social Influence	112	3.8259	.78760
Facilitating Conditions	112	3.7946	1.02569
Intention to Use	112	4.3542	.63480
Valid N (listwise)	112		

Table 43. Means across Arts & Humanities educators

	N	Mean	Std. Deviation
Computer Anxiety	42	1.4524	.69149
Perceived Usefulness	42	4.3869	.75547
Perceived Ease of Use	42	3.9444	1.02520
Social Influence	42	3.7143	.73371
Facilitating Conditions	42	3.8929	1.01534
Intention to Use	42	4.4841	.64687
Valid N (listwise)	42		

Table 44. Means across STEM educators

	N	Mean	Std. Deviation
Computer Anxiety	14	1.8429	.99593
Perceived Usefulness	14	4.1964	.72177
Perceived Ease of Use	14	3.6667	1.16941
Social Influence	14	3.7500	.82625
Facilitating Conditions	14	3.7143	1.20439
Intention to Use	14	4.4762	.59505
Valid N (listwise)	14		

Table 45. Means across multidisciplinary educators

	N	Mean	Std. Deviation
Computer Anxiety	17	1.6824	.77801
Perceived Usefulness	17	3.9853	.91630
Perceived Ease of Use	17	3.4118	1.13364
Social Influence	17	3.6765	.88284
Facilitating Conditions	17	3.4706	1.15204
Intention to Use	17	4.1373	.98643
Valid N (listwise)	17		

Table 46. Means across educators of other subjects

Looking at insights based on subject specializations reveal some unique perspectives:

- Computer Anxiety is relatively low across all disciplines, with Arts & Humanities and STEM teachers reporting similar levels (1.4 and 1.5, respectively), but slightly higher among multidisciplinary (1.8) and other subject teachers (1.7).
- Perceived Usefulness is high across the board, with STEM teachers rating it slightly higher (4.4) compared to Arts & Humanities (4.3), multidisciplinary (4.2), and other subjects (4.0).
- Perceived Ease of Use is generally good, with STEM educators finding it easiest (4.0), followed by Arts & Humanities (3.8), multidisciplinary (3.7), and other subjects scoring the lowest (3.4).
- Social Influence is fairly consistent among all groups, with Arts & Humanities and multidisciplinary teachers both at 3.8, and STEM and other subject teachers close behind at 3.7.
- Facilitating Conditions is slightly varied, with STEM educators feeling the most supported (3.9), followed by Arts & Humanities (3.8), multidisciplinary (3.7), and teachers of other subjects (3.5).
- Intention to Use is strong across all specializations, particularly among STEM and multidisciplinary teachers (both at 4.5), with Arts & Humanities at 4.4 and other subjects at 4.2.

	N	Mean	Std. Deviation
Computer Anxiety	102	1.3686	.58682
Perceived Usefulness	102	4.2255	.82467
Perceived Ease of Use	102	3.8039	1.00751
Social Influence	102	3.7745	.84028
Facilitating Conditions	102	3.7892	1.10453
Intention to Use	102	4.3170	.75835
Valid N (listwise)	102		

Table 47. Means across class mentors

	N	Mean	Std. Deviation
Computer Anxiety	55	1.4727	.67808
Perceived Usefulness	55	4.3227	.62114
Perceived Ease of Use	55	3.7333	.84230
Social Influence	55	3.8091	.66312
Facilitating Conditions	55	3.8000	.86388
Intention to Use	55	4.4242	.53846
Valid N (listwise)	55		

Table 48. Means across non-class mentors

Looking at differences between class mentors or class teachers, and teachers who don't have a class to supervise, there's almost no difference:

- Computer Anxiety is slightly higher among non-class mentors at 1.5 compared to class mentors at 1.4, indicating a marginal difference in comfort with technology.

- But with Perceived Usefulness both non-class mentors and class mentors share a similar positive attitude towards the usefulness of educational technology, both scoring 4.3.
- With Perceived Ease of Use class mentors have a slight advantage, rating it at 3.8, marginally higher than the 3.7 from non-class mentors.
- With Social Influence and Facilitating Conditions both groups show near-identical perceptions, with scores of 3.8 in both categories, indicating a uniform understanding of the social environment and available support.
- Intention to Use is very close, with class mentors slightly lower at 4.3 compared to 4.4 for non-class mentors, suggesting similar levels of willingness to use educational technology.

			Computer Anxiety	Gender
Spearman's rho	Computer Anxiety	Correlation Coefficient	1.000	-.147
		Sig. (2-tailed)	.	.066
		N	157	157
	Gender	Correlation Coefficient	-.147	1.000
		Sig. (2-tailed)	.066	.
		N	157	157

Table 49. Correlation between Gender and Computer Anxiety

			Age group	Computer Anxiety
Spearman's rho	Age group	Correlation Coefficient	1.000	.146
		Sig. (2-tailed)	.	.068
		N	157	157
	Computer Anxiety	Correlation Coefficient	.146	1.000
		Sig. (2-tailed)	.068	.
		N	157	157

Table 50. Correlation between Age and Computer Anxiety

Overall, educators exhibit low Computer Anxiety and high Intentions to Use educational technology. While both men and women show similar attitudes towards technology's usefulness and intention to use it, slight gender differences emerge in ease of use and social influence. Age-wise, younger educators are more enthusiastic about technology, with slight variations across different age groups in all categories. When dissecting by subject specialization, STEM and Arts & Humanities teachers show similar attitudes, with slight variations among those teaching multiple disciplines or other subjects. Finally, the comparison between class mentors and non-class mentors reveals marginal differences, underscoring a generally uniform perception and acceptance of educational technology across different roles.

			Computer Anxiety	Experience group
Spearman's rho	Computer Anxiety	Correlation Coefficient	1.000	.081
		Sig. (2-tailed)	.	.316
		N	157	157
	Experience group	Correlation Coefficient	.081	1.000
		Sig. (2-tailed)	.316	.
		N	157	157

Table 51. Correlation between Years of Teaching Experience and Computer Anxiety

3.4. Correlation Analysis

Bivariate correlation between Demographics & Computer Anxiety as Global Motive

It is worth mentioning that none of the important demographic factors seem to be in a statistically significant relationships with Computer Anxiety. Neither gender (R=-0.147, p=0.07), age (R=0.146, p=0.07), and years of experience teaching (R=0.081, p=0.3) seem to be predictive of Computer Anxiety. Accordingly, we can dismiss that demographics have much to do with Global Motives (represented as Computer Anxiety) as they pertain to our BRT Research Model.

		Computer Anxiety	Intention to Use
Computer Anxiety	Pearson Correlation	1	-.348**
	Sig. (2-tailed)		<.001
	N	157	157
Intention to Use	Pearson Correlation	-.348**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 52. Correlation between Computer Anxiety and Intention to Use EdTech

		Intention to Use	Facilitating Conditions
Intention to Use	Pearson Correlation	1	.551**
	Sig. (2-tailed)		<.001
	N	157	157
Facilitating Conditions	Pearson Correlation	.551**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 53. Correlation between Facilitating Conditions and Intention to Use EdTech

		Intention to Use	Social Influence
Intention to Use	Pearson Correlation	1	.395**
	Sig. (2-tailed)		<.001
	N	157	157
Social Influence	Pearson Correlation	.395**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 54. Correlation between Social Influence and Intention to Use EdTech

		Intention to Use	Perceived Usefulness
Intention to Use	Pearson Correlation	1	.673**
	Sig. (2-tailed)		<.001
	N	157	157
Perceived Usefulness	Pearson Correlation	.673**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 55. Correlation between Perceived Usefulness and Intention to Use EdTech

		Intention to Use	Perceived Ease of Use
Intention to Use	Pearson Correlation	1	.515**
	Sig. (2-tailed)		<.001
	N	157	157
Perceived Ease of Use	Pearson Correlation	.515**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 56. Correlation between Perceived Ease of Use and Intention to Use EdTech

		Intention to Use	Situational Context
Intention to Use	Pearson Correlation	1	.555**
	Sig. (2-tailed)		<.001
	N	157	157
Situational Context	Pearson Correlation	.555**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 57. Correlation between Situational Context and Intention to Use EdTech

		Intention to Use	Reasoned Action
Intention to Use	Pearson Correlation	1	.672**
	Sig. (2-tailed)		<.001
	N	157	157
Reasoned Action	Pearson Correlation	.672**	1
	Sig. (2-tailed)	<.001	
	N	157	157

**. Correlation is significant at the 0.01 level (2-tailed).

Table 58. Correlation between Reasoned Action and Intention to Use EdTech

Bivariate correlation between BRT elements & Intention to Use

However, Computer Anxiety as a Global Motive in our BRT Research Model definitely has a statistically significant negative relationship with Intention to Use (R=-0.348, p<-0.001).

Facilitating Conditions (R=0.551, p<-0.001) and Social Influence (R=0.395, p<-0.001) as Situational Context elements in our BRT Research Model definitely have statistically significant positive relationships with Intention to Use.

Similarly, Perceived Usefulness (R=0.673, p<-0.001) and Perceived Ease of Use (R=0.515, p<-0.001) as Reasoned Action elements in our BRT Research Model definitely have a statistically significant positive relationships with Intention to Use.

Accordingly, once we measure the relationship between Situational Context (R=0.555, p<-0.001) and Reasoned Action (R=0.672, p<-0.001) with Intention to Use, we see statistically significant positive relationships. In other words, all core constructs in our BRT Research Model have strong and statistically significant correlation with Intention to Use educational technology among Lithuanian middle school teachers. However, Reasoned Action seems to have the strongest and statistically significant 1-tail relationship with Intention to Use (R=0.672, Steiger Z=1.775, p=0.038).

3.5. Structural Equation Modeling Analysis

Intention to Use as dependent variable

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Intention to Use	.175	157	<.001	.802	157	<.001

a. Lilliefors Significance Correction

Table 59. Intention to Use as dependent variable normal distribution check

Only two predictors have impact on Intention to Use. $R^2=0.513$, $F(3)=53.8$ $p<0.001$. Reasoned Action ($t=7.347$, $p<0.001$) has bigger impact on Intention to Use than Situational Context ($t=3.919$, $p<0.001$). Computer Anxiety had no direct impact on Intention to Use.

			Statistic	Std. Error
Intention to Use	Mean		4.3546	.05502
	95% Confidence Interval for Mean	Lower Bound	4.2459	
		Upper Bound	4.4633	
	5% Trimmed Mean		4.4317	
	Median		4.3333	
	Variance		.475	
	Std. Deviation		.68944	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.00	
	Skewness		-1.953	.194
	Kurtosis		6.432	.385

Table 60. Intention to Use normality statistics

	Mean	Std. Deviation	N
Intention to Use	4.3546	.68944	157
Computer Anxiety	1.4051	.62015	157
Situational Context	3.7898	.78625	157
Reasoned Action	4.0194	.74486	157

Table 61. Survey mean statistics

		Intention to Use	Computer Anxiety	Situational Context	Reasoned Action
Pearson Correlation	Intention to Use	1.000	-.348	.555	.672
	Computer Anxiety	-.348	1.000	-.314	-.356
	Situational Context	.555	-.314	1.000	.527
	Reasoned Action	.672	-.356	.527	1.000
Sig. (1-tailed)	Intention to Use	.	<.001	<.001	<.001
	Computer Anxiety	.000	.	.000	.000
	Situational Context	.000	.000	.	.000
	Reasoned Action	.000	.000	.000	.
N	Intention to Use	157	157	157	157
	Computer Anxiety	157	157	157	157
	Situational Context	157	157	157	157
	Reasoned Action	157	157	157	157

Table 62. BRT Research Model Correlations

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.717[a]	.513	.504	.48561

a. Predictors: (Constant), Reasoned Action, Computer Anxiety, Situational Context

b. Dependent Variable: Intention to Use

Table 63. BRT Research Model summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38.072	3	12.691	53.816	<.001[b]
	Residual	36.080	153	.236		
	Total	74.151	156			

a. Dependent Variable: Intention to Use

b. Predictors: (Constant), Reasoned Action, Computer Anxiety, Situational Context

Table 64. ANOVA analysis of BRT Research Model

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.748	.300		5.822	<.001		
	Computer Anxiety	-.097	.068	-.087	-1.421	.157	.851	1.175
	Situational Context	.231	.059	.263	3.919	<.001	.704	1.421
	Reasoned Action	.464	.063	.502	7.347	<.001	.682	1.466

a. Dependent Variable: Intention to Use

Table 65. Coefficients of BRT Research Model

Case Number	Std. Residual	Intention to Use	Predicted Value	Residual
3	-3.529	1.00	2.7137	-1.71371
45	3.753	5.00	3.1774	1.82256
125	3.018	4.33	2.8676	1.46572

a. Dependent Variable: Intention to Use

Table 66. Casewise diagnostics of BRT Research Model

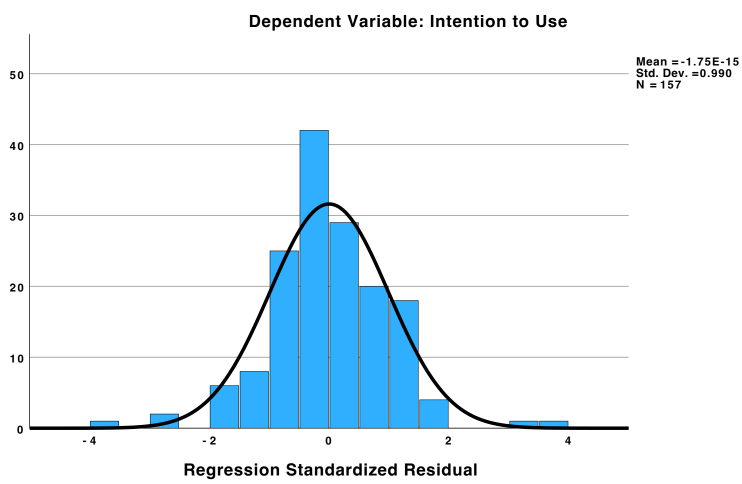

Figure 3. Histogram of BRT Research Model

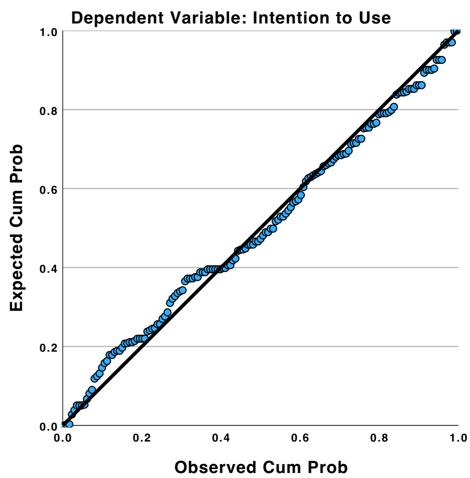

Figure 4. P-P Plot

Reasoned Action as dependent variable

Two predictors have impact on Reasoned Action. R^2=0.318, F(2)=35.9 p<0.001. Situational Context (t=7.347, p<0.001) has bigger impact on Reasoned Action than Computer Anxiety (t=-3.012, p=0.003). Both, however, have an impact thus validating the BRT Research Model.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Reasoned Action	.123	157	<.001	.919	157	<.001

a. Lilliefors Significance Correction

Table 67. Reasoned Action as dependent variable normal distribution check

			Statistic	Std. Error
Reasoned Action	Mean		4.0194	.05945
	95% Confidence Interval for Mean	Lower Bound	3.9020	
		Upper Bound	4.1368	
	5% Trimmed Mean		4.0752	
	Median		4.1250	
	Variance		.555	
	Std. Deviation		.74486	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		.96	
	Skewness		-1.077	.194
	Kurtosis		2.274	.385

Table 68. Reasoned Action normality statistics

Reasoned Action	4.0194	.74486	157
Computer Anxiety	1.4051	.62015	157
Situational Context	3.7898	.78625	157

Table 69. Survey mean statistics

		Reasoned Action	Computer Anxiety	Situational Context
Pearson Correlation	Reasoned Action	1.000	-.356	.527
	Computer Anxiety	-.356	1.000	-.314
	Situational Context	.527	-.314	1.000
Sig. (1-tailed)	Reasoned Action	.	<.001	<.001
	Computer Anxiety	.000	.	.000
	Situational Context	.000	.000	.
N	Reasoned Action	157	157	157
	Computer Anxiety	157	157	157
	Situational Context	157	157	157

Table 70. BRT Research Model Correlations

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.564[a]	.318	.309	.61908

a. Predictors: (Constant), Situational Context, Computer Anxiety

b. Dependent Variable: Reasoned Action

Table 71. BRT Research Model summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.528	2	13.764	35.913	<.001[b]
	Residual	59.022	154	.383		
	Total	86.550	156			

a. Dependent Variable: Reasoned Action

b. Predictors: (Constant), Situational Context, Computer Anxiety

Table 72. ANOVA analysis of BRT Research Model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.721	.314		8.673	<.001		
	Computer Anxiety	-.254	.084	-.211	-3.012	.003	.901	1.109
	Situational Context	.437	.066	.461	6.575	<.001	.901	1.109

Table 73. Coefficients of BRT Research Model

Case Number	Std. Residual	Reasoned Action	Predicted Value	Residual
110	-3.076	1.00	2.9041	-1.90410
125	-3.528	1.38	3.5590	-2.18398

a. Dependent Variable: Reasoned Action

Table 74. Casewise diagnostics of BRT Research Model

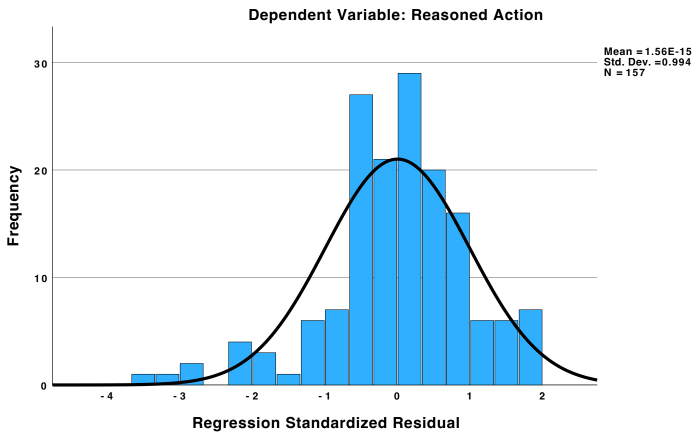

Figure 5. Histogram of BRT Research Model

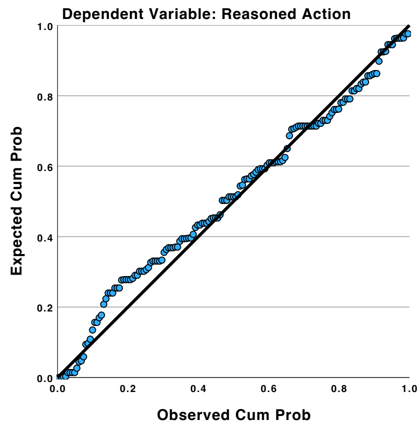

Figure 6. P-P Plot

3.6. Hypothesis Testing

H1: Computer anxiety as global motive will negatively predict educational technology adoption intention: it was assumed that prior research establishing computer anxiety as a significant barrier to technology adoption across contexts (Brosnan 1998; Makumane & Mpungose 2022) is correct in the context of Lithuanian middle school teachers. Computer

Anxiety as a Global Motive in our BRT Research Model definitely has a statistically significant negative relationship with Intention to Use ($R=-0.348$, $p<-0.001$).

H2: Reasoned action as perceived usefulness & ease of use will positively predict educational technology adoption intention: Research claims that perceived usefulness and ease of use are key drivers of technology adoption intentions (Venkatesh & Davis 2000; Faqih 2022), and we assumed this will be correct in the context of Lithuanian middle school teachers. Perceived Usefulness ($R=0.673$, $p<-0.001$) and Perceived Ease of Use ($R=0.515$, $p<-0.001$) as Reasoned Action elements in our BRT Research Model definitely have a statistically significant positive relationships with Intention to Use.

H3: Situational context as social influence and facilitating conditions will positively predict educational technology adoption intention: We believed that we will confirm prior research that teachers are likely to intend to adopt technology if important referents like peers or administrators endorse use of a technology and make infrastructure, resources, training, and support to enable use of classroom technologies available to teachers (Venkatesh et al. 2003; Faqih 2022). Facilitating Conditions ($R=0.551$, $p<-0.001$) and Social Influence ($R=0.395$, $p<-0.001$) as Situational Context elements in our BRT Research Model definitely have statistically significant positive relationships with Intention to Use.

H4: Reasoned action is the key predictor for intention to use technology among teachers.

Reasoned Action seems to have the strongest and statistically significant 1-tail relationship with Intention to Use ($R=0.672$, Steiger $Z=1.775$, $p=0.038$). More so, Reasoned Action ($t=7.347$, $p<0.001$) has bigger impact on Intention to Use than Situational Context ($t=3.919$, $p<0.001$); Computer Anxiety had no direct impact on Intention to Use.

H5: Situational context and computer anxiety are key predictors for reasoned action

Situational Context ($t=7.347$, $p<0.001$) has bigger impact on Reasoned Action than Computer Anxiety ($t=-3.012$, $p=0.003$). Both, however, have a statistically significant impact on Reasoned Action thus validating the BRT Research Model.

Conclusions & Recommendations

Study examined factors influencing technology use intentions among Lithuanian middle school teachers. Behavioral Reasoning Theory (BRT) was used to assess factors like perceived usefulness and ease of use.

Findings:

- Perceived usefulness & ease of use significantly predict technology adoption intention.
- Demographic factors don't significantly correlate with computer anxiety.
- Situational context elements (social influence, facilitating conditions) positively impact technology adoption intentions.
- Research aligns with BRT, emphasizing reasoned action in technology adoption.
- Environmental and peer support are as crucial as perceived technology attributes for adoption.

Implications for educational policymakers and administrators:

- Focus on perceived benefits and ease of use of technology.
- Foster a supportive environment and provide resources for technology adoption.

Study limitations:

- Regional focus on Lithuania and specific demographic limits generalizability.
- Self-reported measures may introduce response biases.

Recommendations for future research:

- Broaden demographics and geographical areas for generalizability.
- Explore other educational levels and conduct longitudinal studies.
- Investigate individual psychological factors and external environmental influences.

Conclusion: Reasoned action and situational context are key in shaping teachers' intentions for technology adoption in education.

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Annex A: Questionnaire in English

Raffle Questions

1. What is your name?
2. What is your e-mail address?

Demographic Questions

1. What is your age?
    - ○ Less than or 30 years old
    - ○ 31-40 years old
    - ○ 41-50 years old
    - ○ 51-60 years old
    - ○ Over 60 years old
2. What is your gender?
    - ○ Male
    - ○ Female
    - ○ Non-binary
3. What subjects do you currently teach? (Check all that apply)
    - ☐ Lithuanian language & literature
    - ☐ Foreign language & literature
    - ☐ Mathematics
    - ☐ Natural sciences & biology
    - ☐ Technology & informatics
    - ☐ History & geography
    - ☐ Physical education
    - ☐ Arts
    - ☐ Other (can be specified)
4. Are you a class teacher/tutor?
    - ○ Yes
    - ○ No
5. How many years of experience do you have as a middle school teacher?
    - ○ 0-5 years

- 6-10 years
- 11-15 years
- 16-20 years
- Over 20 years

6. What grade levels do you currently teach? (Check all that apply)
   - 5th grade
   - 6th grade
   - 7th grade
   - 8th grade

Computer Anxiety

(Measured using Computer Anxiety Rating Scale - CARS - by Heinssen et al., 1987)

Please rate how strongly you agree or disagree with the following statements regarding your feelings about computers and technology (from 1 to 5):

1. Computers make me feel uncomfortable.
2. I get a sinking feeling when trying to use a computer.
3. Computers make me feel uneasy and confused.
4. Learning computer skills is a waste of time.
5. Computers are intimidating to me.

Perceived Usefulness

(Adapted from Davis 1989)

Please rate your level of agreement with the following statements regarding educational technologies (from 1 to 5):

1. Using educational technology enhances my teaching effectiveness.
2. Using educational technology improves my productivity as a teacher.
3. Using educational technology makes it easier for me to accomplish instructional objectives.
4. Overall, I find educational technology useful for teaching.

Perceived Ease of Use

(Adapted from Davis 1989)

Please rate your level of agreement with the following statements about educational technologies (from 1 to 5):

1. Learning how to use educational technology is easy for me.
2. It is easy for me to become skillful at using educational technology.
3. I find it easy to get educational technology to do what I want it to do.
4. Overall, I find educational technology easy to use.

Social Influence

(Adapted from Venkatesh et al. 2003)

Please rate your level of agreement with the following statements (from 1 to 5):

1. My school administration encourages me to use educational technology.
2. My colleagues think that I should use educational technology.
3. In general, my colleagues have supported the use of educational technology.

Facilitating Conditions

(Adapted from Venkatesh et al. 2003)

Please rate your level of agreement with the following statements (from 1 to 5):

1. I have the necessary resources to use educational technology.
2. Educational technology is compatible with teaching practices I am familiar with.
3. Assistance is available if I have difficulties using educational technology.

Intention to Use Educational Technology

(Adapted from Venkatesh et al. 2003)

Please rate your level of agreement with the following statements (from 1 to 5):

1. I intend to continue using educational technology in the future.
2. I will always try to use educational technology in my teaching.
3. I plan to increase my use of educational technology over time.

Annex B: Questionnaire in Lithuanian

Konkurso klausimai

1. Kuo Jūs vardu?
2. Koks jūsų el. pašto adresas?

Demografiniai klausimai

1. Kiek Jums metų?
   - ○ Mažiau nei arba 30
   - ○ 31-40 metų
   - ○ 41-50 metų
   - ○ 51-60 metų
   - ○ Virš 60 metų
2. Kokia Jūsų lytis?
   - ○ Moteris
   - ○ Vyras
   - ○ Nebinarinė lytis
3. Kokius dalykus mokote? (Pažymėkite visus tinkamus variantus)
   - □ Lietuvių kalba ir literatūra
   - □ Užsienio kalba ir literatūra
   - □ Matematika
   - □ Gamtos mokslas ir biologija
   - □ Technologijos ir informatika
   - □ Istorija ir geografija
   - □ Kūno kultūra
   - □ Menai
   - □ Kita (can be specified)
4. Ar esate klasės auklėtoja(s)/mentorė/mentorius?
   - ○ Taip
   - ○ Ne
5. Kiek metų jau mokote 5-8 klases?
   - ○ 0-5 metus

- 6-10 metų
- 11-15 metų
- 16-20 metų
- Daugiau nei 20 metų

6. Kurių klasių mokinius šiuo metu mokote? (Pažymėkite visus tinkamus variantus)
   - ▢ 5 klasė
   - ▢ 6 klasė
   - ▢ 7 klasė
   - ▢ 8 klasė

Įvertinkite, kaip stipriai sutinkate ar nesutinkate su šiuo teiginiu (nuo 1 iki 5):

1. Naudodamasi(s) kompiuterine įranga jaučiuosi nepatogiai.
2. Kai naudojuosi kompiuterine įranga, jaučiuosi lyg grimzčiau gilyn.
3. Naudojimasis kompiuterine įranga mane verčia jaustis sumišus ir nejaukiai.
4. Mokymasis naudotis kompiuterine įranga yra laiko švaistymas.
5. Kompiuterinė įranga mane baugina.
6. Kai naudoju technologinius sprendimus, mano mokymo efektyvumas pagerėja.
7. Kai naudoju technologinius sprendimus, mano pačios/paties produktyvumas pagerėja.
8. Kai naudoju technologinius sprendimus, man yra lengviau pasiekti mokymo tikslus.
9. Manau, kad technologiniai sprendimai švietime apskritai yra naudingi.
10. Man yra lengva išmokti naudotis švietimui skirtais technologiniais sprendimais.
11. Man yra lengva įgusti naudotis švietimui skirtais technologiniais sprendimais.
12. Man yra lengva pasiekti, kad švietimui skirti technologiniai sprendimai veiktų taip, kaip aš noriu.
13. Manau, kad švietimui skirtais technologiniai sprendimais apskritai yra lengva naudotis.
14. Mano mokyklos administracija skatina mokytojus naudoti švietimui skirtais technologiniais sprendimais.
15. Mano kolegos mano, kad turėčiau naudoti švietimui skirtus technologinius sprendimusy.
16. Mano kolegos apskritai palaiko technologinių sprendimų naudojimą švietime.

17. Aš turiu visus man reikalingus išteklius, kad galėčiau naudoti švietimui skirtus technologinius sprendimus.
18. Švietimui skirti technologiniai sprendimai yra suderinami su mokymo praktikomis, su kuriomis esu susipažinusi ar susipažinęs.
19. Jei susidurčiau su sunkumais naudojantis švietimui skirtais technologiniais sprendimais, žinau, kur gauti pagalbą.
20. Esu tikra(s), kad ir toliau naudosiu švietimui skirtus technologinius sprendimus.
21. Savo mokyme nuolat stengiuosi naudoti švietimui skirtus technologinius sprendimus.
22. Ateityje ketinu švietimui skirtus sprendimus naudoti daugiau.