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ORIGINAL RESEARCH

Redefining, Reconfiguring, and Extending the UTAUT-2: A Case Study in the Context of the Use of ICT by Kindergarten Teachers

Emmanuel Fokides[1] · **Eleni Giagiakou**[1]

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Abstract
The Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) is a widely applied framework for understanding technology adoption behaviors. Despite its broad applicability, limitations in its conceptualization exist, such as the static treatment of constructs, lack of focus on interaction effects, and insufficient explanatory power in certain cases. The study addressed these limitations by incorporating teachers' self-efficacy in using ICT tools, redefining behavioral intention, introducing ICT certification levels as a control variable, and by reconfiguring the relationships of the framework's constructs. The revised model was tested with 312 Greek kindergarten teachers using Partial Least Squares Structural Equation Modeling. Direct effects were found on behavioral intention to use or continue using CT tools and applications for perceived social influence, performance expectancy, hedonic motivation, and habit, while a host of other direct and indirect effects emerged, highlighting the interconnected construct relationships. Overall, the model demonstrated significant in- and out-of-sample predictive/explanatory power. These findings offer critical insights for optimizing UTAUT-2.

Keywords ICT · Kindergarten teachers · Self-efficacy · UTAUT-2 · PLS-SEM

1 Introduction

The integration of technology into various domains has revolutionized practices previously bound by traditional methods, including education. Understanding the factors that drive the adoption of technology is essential for enhancing its implementation. Towards this end, several models have been developed. The Unified Theory of Acceptance and Use of Technology

✉ Emmanuel Fokides
fokides@aegean.gr

Eleni Giagiakou
elgiagiakou@gmail.com

[1] Department of Primary Education, University of the Aegean, 1 Dimokratias st., 85132 Rhodes, Greece

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2 (UTAUT-2) framework (Venkatesh et al., 2012) is one of the most impactful ones, because of its adaptability to different sectors (e.g., Akyar et al., 2024; Chu et al., 2022; García de Blanes Sebastián et al., 2022). By drawing insights from several theories, it retains key constructs from its predecessor which address the cognitive and environmental factors, while its added constructs reflect the importance of intrinsic drivers such as enjoyment, economic considerations, and habitual behaviors in shaping technology usage intentions (Venkatesh et al., 2012). Additionally, the inclusion of moderating factors (i.e., age, sex, and experience), signify the importance of demographic variations in technology usage behaviors.

While the model's contributions are significant, a closer examination of its structure and definition of certain constructs reveals limitation. For example, the dynamic interplay between core constructs is neglected. Moreover, the standard definition of behavioral intention and experience can be refined. Addressing these limitations calls for a revised model. Yet, to the best of the authors' knowledge, a significant re-configuration of the UTAU-2 model has not been previously attempted. Indeed, although some studies proposed a limited set of interactions between core components (e.g., Herrero & San Martín, 2017), the vast majority of them have utilized the model in its original form or made minor adjustments by adding or removing constructs to align with specific research objectives.

Educational settings present unique opportunities for evaluating technology adoption using UTAUT-2. While higher education contexts have been the focal point of existing research (e.g., Acosta-Enriquez et al., 2024; Rudhumbu, 2022), limited attention has been given to K-12 education (Kittinger & Law, 2024). Kindergarten teachers offer an interesting case for analysis. Despite the proven advantages of integrating ICT at this educational level, such as improved creativity, enhanced motivation, and tailored learning experiences for young learners (Akyar et al., 2024; Fokides & Klaoudatou, 2025), pre-school educators encounter significant barriers, including lack of technical training and institutional support, which may hamper the effective use of ICT in classrooms (Alotaibi, 2023; Kerckaert et al., 2015).

In response to these challenges and gaps, the study at hand presents the results from the testing of an extensively revised UTAUT-2 model, having as a target group Greek kindergarten teachers. Teachers' self-efficacy in using ICT tools was introduced as a construct, behavioral intention was redefined, and ICT certification levels were included as a control variable. Furthermore, new relationships among the framework's constructs were established to account for their interactions. By doing so, the study seeks to provide a better understanding of educators' behavioral intentions toward using ICT tools. In a broader sense, the study seeks to offer a novel perspective to the academic discourse surrounding users' behavioral intentions toward technology adoption. The rationale for the development of the modified UTAUT-2 version, the method that was followed, the data analysis, as well as the subsequent discussion of the results, are presented in the forthcoming sections.

2 The UTAUT-2 Framework

Utaut-2, as its predecessor UTAUT, was developed through a synthesis of key theoretical models, including the Technology Acceptance Model, Innovation Diffusion Theory, and the Theory of Planned Behavior. Additionally, it is rooted in constructs derived from theoretical models, such as the Theory of Reasoned Action, Social Cognitive Theory, and Motivational

Model (Huang & Chuang, 2017; Venkatesh et al., 2012; Yuliani et al., 2024), highlighting its inclusive approach to explaining technology use. UTAUT-2 retains the constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions found in UTAUT. The constructs of hedonic motivation, price value, and habit were added to account for the role that enjoyment, economic considerations, and habitual usage play in influencing user intentions and behaviors when adopting a technology (Venkatesh et al., 2012) (Fig. 1).

In detail, the UTAUT-2 model incorporates the following factors:

- Perceived facilitating conditions involve users' views about the resources and support

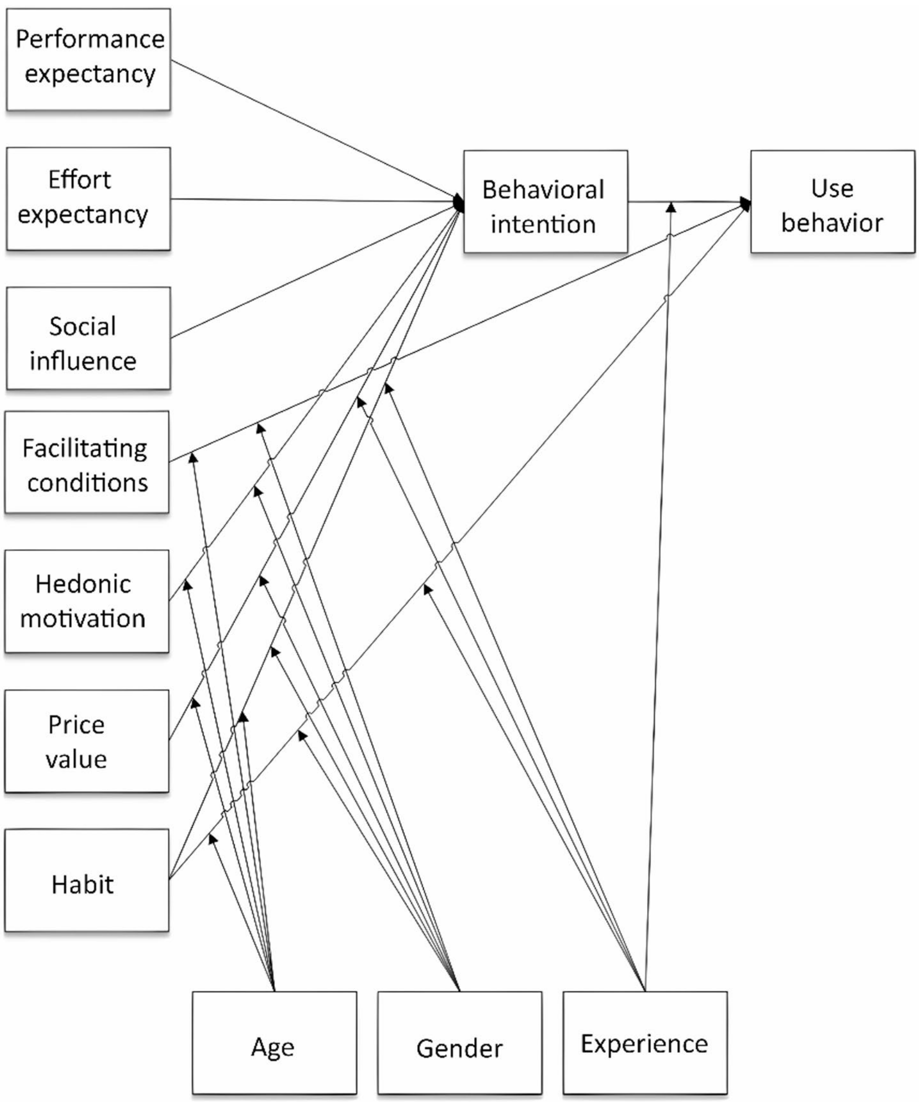

Fig. 1 The UTAUT-2 as suggested by Venkatesh et al. (2012). *Note*. The arrows from age, gender, and experience represent moderating effects

available to effectively use a technology; this, significantly affects the likelihood of adopting the given technology or its actual use (e.g., Mustafa et al., 2022; Neves et al., 2025; Palau-Saumell et al., 2019). However, non-significant effects were found in certain cases (e.g., Kim et al., 2024; Zuiderwijk et al., 2015), particularly when performance expectancy was considered a contributing factor in the analysis (Dwivedi et al., 2019). Furthermore, their effect on behavioral intention becomes non-significant in later stages of adoption (Marikyan & Papagiannidis, 2023). Interestingly, there are instances in which they exercised a negative influence (Chu et al., 2022).

- Perceived social influence refers to the degree to which individuals believe that important people in their lives suggest they should use a specific technology and can lead to changes in users' beliefs and intentions. For example, this construct has been shown to significantly affect the adoption of mobile phones (Nikolopoulou et al., 2020) or mHealth services (Palas et al., 2022). Yet, there are studies that found no such impact (e.g., Alalwan et al., 2017), implying that demographic and contextual variabilities can affect its influence. Indeed, it was found that gender affected the sensitivity to social influence (Wong et al., 2020). Moreover, social influence mediated the effects of behavioral intention on the use of wireless technology (Abdunool et al., 2024), indicating that the way individuals perceive social endorsements can affect their actual behavior. Social influence also indirectly impacted behavioral intention through performance expectancy, as suggested by Guetz and Bidmon (2022).
- Effort expectancy refers to the ease of use associated with a given technology. The effect of this construct on behavioral intention is controversial. There is research in which it was found to be significant (e.g., Beh et al., 2021; Huang, 2023). Yet, its effect on behavioral intention was found to be non-significant in quite a lot of cases, rendering it the weakest factor (Tamilmani et al., 2021). Some suggested that it becomes a non-significant factor after extended usage of technology or when the ICT tools do not demand any effort to operate them (Marikyan & Papagiannidis, 2023). It has effects on other factors as well, such as performance expectancy (Camilleri, 2024; Chu et al., 2022); a higher effort expectancy can lead to increased performance expectancy, suggesting that when users find a system easy to use, they are more likely to perceive it as beneficial. A significant association between hedonic motivation and effort expectancy was also found (Tamilmani et al., 2019).
- Performance expectancy refers to the degree to which an individual believes that using a particular technology will enhance their job performance or satisfaction. According to Davis (1989), perceived usefulness, which aligns closely with performance expectancy, is a significant predictor of behavioral intention in technology adoption scenarios (Gimpel et al., 2020; Neves et al., 2025) and correlates with increased likelihood of technology acceptance (Huang, 2023). In some cases, it was among the most significant factors influencing technology adoption (Nikolopoulou et al., 2021; Phibbs & Rahman, 2022; Vidal-Silva et al., 2024), as well as the trust in ICT systems (Choudhury & Shamszare, 2024). It also mediated the effects of social influence (Guetz & Bidmon, 2022) and the effects of locus of control (Ahadzadeh et al., 2021) on behavioral intention.
- Hedonic motivation refers to the intrinsic enjoyment and pleasure associated with technology use, contrasting with the utilitarian aspect of performance expectancy (Venkatesh et al., 2012). It serves as a predictor of behavioral intentions across various contexts including education (e.g., Marikyan & Papagiannidis, 2023; Narayan & Naidu,

2024; Nikolopoulou et al., 2021; Plohl & Babič, 2024). Individuals who experience higher levels of enjoyment from technology are more likely to express a willingness to adopt and continue using it (Venkatesh et al., 2012). Furthermore, the combined effect on behavioral intention of hedonic motivation and other constructs within the UTAUT2 model, suggest that enjoyable experiences can lead to habitual technology use and foster long-term engagement (Marikyan & Papagiannidis, 2023; Narayan & Naidu, 2024; Plohl & Babič, 2024; Sadiq et al., 2025; Schomakers et al., 2022; Tamilmani et al., 2019b). However, its effects can be moderated by demographic variables such as age and sex, and prior experience (Venkatesh et al., 2012).

- Habit is defined as the extent to which past behaviors influence current technology usage. It has been shown to significantly impact both intention and actual usage of technologies (Hagger et al., 2023; Tamilmani et al., 2019; Zheng et al., 2025). It has been shown that habit and continuance intention interact and reinforce each other's impact (Söllner et al., 2024). This suggests that as individuals develop habits around certain behaviors, their intentions to engage in those behaviors become more consistent and automatic. In educational settings, the effectiveness of ICT integration is often hindered by challenges such as insufficient training, lack of technical skills and inadequate support (Alotaibi, 2023; Kerckaert et al., 2015), which can affect the habitual use of digital tools.
- Price value refers to the perceived trade-off between the benefits of using a technology and its cost. This construct reflects users' assessment of whether the benefits outweigh the financial implications (Venkatesh et al., 2012).
- The above factors influence one's behavioral intention to use a given technology, which ultimately leads to the use of this technology.
- Moreover, age, sex, and experience (defined as the duration of an individual's engagement with a particular technological system) were included as moderating variables. Both sex and age play critical roles in shaping individuals' intentions to adopt new technologies. For example, older adults often exhibit distinct behavioral intentions compared to younger users, reflecting a heightened sensitivity to factors like social influence and facilitating conditions (Yap et al., 2022). Indeed, support is of importance among older users who may have troubles in using technology (Venkatesh et al., 2012). Age also moderated the effects of hedonic motivation, social influence, and effort expectancy on behavioral intention (Chang et al., 2019). Findings also suggested that men and women may exhibit different behaviors and attitudes toward technology adoption. For example, sex moderated the effects on constructs such as performance expectancy (Chang et al., 2019; Terblanche & Kidd, 2022), hedonic motivation (Venkatesh et al., 2012), and social influence (Chang et al., 2019; Wang et al., 2009). As for the effects of experience, individuals with prior experience tend to exhibit heightened confidence and trust in technology, which can enhance their intention to adopt ICT tools (Schomakers et al., 2022). Experience also moderated the effects on behavioral intention of key constructs such as effort expectancy, social influence, habit, and facilitating conditions (Chang et al., 2019; Marikyan & Papagiannidis, 2023).

Overall, UTAUT2's application across various domains, including e-learning, mobile commerce, and healthcare, highlight its versatility and significance in technology adoption studies (e.g., Akyar et al., 2024; Chu et al., 2022; García de Blanes Sebastián et al., 2022). Yet, despite its widespread application and empirical support, UTAUT-2 has faced criticism. For example, the inclusion of too many factors renders it unnecessarily complex compared to other more parsimonious models (Van Raaij & Schepers, 2008). Others suggested that the inclusion of moderating effects "artificially" increases its predictive power (Li, 2020). A rather significant limitation of UTAUT-2 is that the majority of the studies have focused on the core constructs to predict behavioral intentions without adequately addressing the interplay of the variables. For example, a meta-analysis covering 60 UTAUT-2 studies reported that none of the moderator relationships qualified for inclusion in meta-analysis due to a sheer lack of empirical examinations of these interactions and the "complexity paradox" they introduce (Tamilmani et al., 2021). This scarcity suggests that researchers overwhelmingly focus on direct paths and ignore the interplay that could reveal contingent or synergistic effects.

In the context of education, numerous studies have applied it to evaluate the factors that affect technology adoption in diverse educational environments. Constructs such as habit, performance expectancy, hedonic motivation, and social influence, significantly shape behavioral intentions and actual usage of technological tools for learning (e.g., Ain et al., 2016; Narayan & Naidu, 2024; Sergeeva et al., 2025). Researchers have also begun to utilize modified UTAUT-2 models to assess emerging innovations, such as artificial intelligence (e.g., Acosta-Enriquez et al., 2024; Grassini et al., 2024; Sergeeva et al., 2025). Moreover, the UTAUT-2 framework has been adapted to include additional dimensions (Kittinger & Law, 2024), which further illuminated the complexities of technology acceptance in varied educational contexts.

Despite its widespread application, it is mostly used in higher education contexts (e.g., Acosta-Enriquez et al., 2024; Rudhumbu, 2022). On the other hand, there is a limited body of research utilizing UTAUT-2 in K-12 education to examine teachers' views. Therefore, a gap exists, necessitating further exploration to better understand the unique dynamics of technology adoption among educators. For example, in a recent systematic literature review, only 14 relevant peer-reviewed studies were found and analyzed (Kittinger & Law, 2024). Nevertheless, according to this review, performance expectancy was found to be the most common factor influencing behavioral intention, followed by social influence and effort expectancy, although this factor quite frequently was found not to have a significant impact.

3 Self-Efficacy, Teachers' Self-Efficacy, and Their Self-Efficacy in the Use of ICT Tools and Applications

Bandura (1986) defined self-efficacy as an individual's belief in their capabilities to perform necessary behaviors to achieve desired outcomes, asserting its strong influence on cognitive processes, motivation, persistence, emotional states, and performance. Fundamentally, self-efficacy is the confidence individuals have in their ability to accomplish tasks (Shukri et al., 2023). Importantly, self-efficacy is not a fixed trait but varies according to specific contexts or tasks. Teacher self-efficacy (TSE), as described by Tschannen-Moran et al. (1998), refers to teachers' beliefs in their ability to manage and promote learning. High TSE correlates with greater teaching commitment and improved student engagement and achievement (Thommen et al., 2022). Teachers with strong self-efficacy experience less job stress and greater satisfaction, manage classroom challenges more effectively, and are more open to innovative teaching strategies (Barni et al., 2019; Lazarides & Warner, 2020).

Research demonstrated that factors such as positive attitudes, adequate preparation, and hands-on experiences enhance TSE, indicating that it is developed through both mastery and observation (Gordon et al., 2024; Narayanan et al., 2023). Teachers' intrinsic motivation and positive mindset significantly reinforce self-efficacy and perseverance (Mehmood, 2019). Additionally, a supportive school environment, strong professional relationships, and empowering leadership further enhance TSE (Gálvez et al., 2018; Lin et al., 2022). Access to resources, development programs, and mentoring opportunities are also essential; teachers in resource-rich environments consistently report higher self-efficacy (Makeleni et al., 2023; Menno et al., 2024).

Teachers' self-efficacy in the use of ICT refers to educators' beliefs in their capabilities to effectively integrate digital tools into their teaching practices. High levels of ICT self-efficacy are crucial for the instructional practices of teachers (Clipa et al., 2023). There seems to be a direct correlation between teachers' self-efficacy and their attitudes toward ICT usage in the classroom or their intention to use ICT in their teaching (Fokides & Kapetangiorgi, 2022; Peng et al., 2024). Moreover, self-efficacy directly influences educators' perceptions of technology, particularly in terms of perceived usefulness and ease of use. For instance, studies have shown that educators with higher self-efficacy are more likely to perceive technology as useful and easy to use, which in turn strengthens their behavioral intention to adopt it (Fearnley & Amora, 2020; Kapoor & Sohi, 2024; Yang & Lou, 2024). This direct influence is consistent across various educational technologies, including Learning Management Systems, e-learning platforms, and AI-based tools (Fearnley & Amora, 2020; Songkram & Osuwan, 2022; Tekin, 2024). Self-efficacy often acts as a mediator in the technology acceptance process. For example, it mediated the relationship between outcome expectancy and motivation for technology integration (Perkmen, 2024), and between perceived ease of use and behavioral intention (Yang & Lou, 2024). This mediating role highlights the importance of self-efficacy in shaping educators' attitudes and behaviors toward technology adoption.

Yet, there are cases where no significant correlation exists (Hickson, 2016; Motshegwe & Batane, 2015). This indicates that self-efficacy alone may not determine teachers' ability or intention to integrate ICT in their classrooms. Computer competencies, computer access, and frequency of computer use were significant predictors of teachers' self-efficacy in ICT (Ikhlas & Dela Rosa, 2023). Similarly, another study found that teachers' perceived ease of use and usefulness of ICT were significant predictors of their self-efficacy (Wu et al., 2020).

Moreover, demographic variables such as age and gender have shown varying effects on self-efficacy levels. Younger teachers often demonstrate higher ICT self-efficacy (Baytar et al., 2023; Wang et al., 2024), suggesting that age plays a significant role in shaping teachers' confidence in using technology. However, it is important to note that there are instances in which age did not play a role (Wu et al., 2020). While some studies have found no significant differences in ICT self-efficacy between male and female teachers (Ghazali et al., 2024; Wang et al., 2024), others have reported that male teachers tend to exhibit higher levels of self-efficacy (Clipa et al., 2023; Kölemen, 2023; Wu et al., 2020).

The above suggest that self-efficacy may be more influenced by contextual factors and personal experiences rather than demographic characteristics alone. In fact, positive attitudes toward technology were strongly associated with higher levels of self-efficacy (Clipa et al., 2023; Proedrou et al., 2023). Contextual factors, such as school environment, ICT infrastructure, ICT training and mentoring programs, and institutional support, also play a significant role in shaping teachers' self-efficacy in ICT (Ikhlas & Dela Rosa, 2023; Wu et al., 2020).

4 Reforming the UTAUT-2 Model

Although the UTAUT-2 model provided the theoretical foundation for several studies throughout the years and in several contexts, there is room for improvement. Probably the most critical limitation in the original UTAUT-2 framework emerges upon closer scrutiny of how its constructs are treated. As illustrated in Fig. 1, all, aside from "behavioral intention" and "use behavior," are modeled as exogenous variables, which restricts the analysis of interactions between them. However, it is reasonable to assume that such interactions do exist. For instance, it is logical to assume that effort expectancy affects performance expectancy, while perceived facilitating conditions play a role in shaping effort expectancy. Furthermore, indirect effects were overlooked and must be considered, as they have the potential to amplify or diminish the impact of a given factor. This static treatment calls for the reconfiguration of the model to more effectively distinguish between exogenous and various levels of endogenous variables, enabling an exploration of their dynamic interplay.

There are other issues with the original model that need to be tackled. The first is related to the conceptualization of the "behavioral intention" construct. A closer look at the questionnaire items the authors employed to measure it, reveals that it is more framed as the intention to *continue* using a system rather than the *initial* intention to adopt it. For example, the items "BI1. I intend to continue using mobile Internet in the future" and "BI3. I plan to continue to use mobile Internet frequently" (Venkatesh et al., 2012, p. 178), clearly suggest that responders already use the Internet and these items try to examine their intentions to continue doing so. Consequently, to align with the original conceptualization of this factor and to account for educators who, for various reasons, have not yet utilized ICT tools but intend to do so (or lack such intention), the "behavioral intention" construct was redefined as the "behavioral intention to use or continue using ICT tools and applications for teaching" (Beh. int.). This adjustment, on the one hand ensured alignment with the operational definition implied in the original framework and, on the other, strengthens the construct's applicability and inclusivity.

Also, the original UTAUT-2 includes a control variable termed "experience," which measures, in months, the length of an individual's interaction with a specific technology (Venkatesh et al., 2012). However, the duration of engagement with a technological tool does not equate to either actual proficiency or the perception of proficiency in its use. For instance, an individual who engages with an ICT tool rarely or sporadically over a span of several months is likely to exhibit a lower level of experience compared to someone who uses the same tool intensively over a shorter timeframe. To rectify this issue, this variable was replaced with "ICT certification levels" (ICT cert.). In many countries, educators can participate in in-service training programs focused on the application of ICT tools and applications in educational settings. For example, in Greece there are three rounds/levels of such training. Each requires hundreds of hours of commitment, followed by examinations to certify successful completion. Consequently, the certification levels obtained through this process can serve as reliable metrics for assessing teachers' actual proficiency and expertise in utilizing ICT tools and applications.

What is more, as elaborated in the section "Self-efficacy, teachers' self-efficacy, and their self-efficacy in the use of ICT tools and applications," this concept is instrumental for understanding user intentions, attitudes, and behaviors. Also, it is related to almost all UTAU-2's constructs. Recognizing that, it was decided to introduce it to the model as "self-efficacy in the use of ICT tools and applications for teaching" (ICT cert.). This ensured a better evaluation of a user's overall views, feelings, and attitudes.

Taking together the above, the UTAUT-2 model was restructured as follows:

- The constructs of "perceived facilitating conditions" (Fac. cond.) and "perceived social influence" (Soc. inf.) were treated as exogenous variables, affecting all the other factors in the model. That is because perceived facilitating conditions encapsulate individuals' perceptions of their work environment, in which, in most cases, have very little control over it. Therefore, it is exogenous in nature. Perceived social influence reflects how the opinions of others sway an individual's perspective on specific issues. As with Fac. cond., this factor is exogenous, as it encompasses stimuli originating from external influences.
- SE ICT was treated as a first order endogenous variable, affected by the exogenous factors and affecting the constructs labeled "effort expectancy" (Eff. exp.), "performance expectancy" (Perf. exp.), "hedonic motivation" (Hed. mot.), "habit" (Habit), and Beh. int. One might view SE ICT as a byproduct of other factors, such as ease of use (Eff. exp.) and usefulness of ICT (Perf. exp.), as others suggested (Wu et al., 2020). However, Bandura (1986), who originally conceptualized it, argued that it influences cognitive processes, levels of persistence, motivation, emotional states, and performance outcomes. Indeed, to effectively execute a task, it is reasonable to assume that one must possess confidence in their abilities, while repeated successful execution of the task subsequently becomes a habit. Consequently, it is an antecedent of most factors present in the UTAUT-2 model.
- Eff. exp. was conceptualized as a second-order endogenous construct, influenced by exogenous factors and SE ICT, theorizing that external variables can shape individuals' perceptions regarding the ease of use of an ICT tool, while individuals who are confident in their ability to use the given ICT tool are more likely to perceive it as easier to use. On the other hand, Eff. exp. can be considered as a factor influencing Perf. exp., Hed. mot., Habit, and Beh. int. That is because it can be assumed that when a tool or system is perceived as being easy to use, this results in being perceived as more useful and more enjoyable at its use, leading to continuous use and intention to continue using it.
- Similarly, Perf. exp. was treated as a third-order endogenous factor, shaped by the preceding constructs while influencing Hed. mot., Habit, and Beh. int. It has to be noted that while there is research suggesting that Hed. mot. impacts Perf. exp. (Tamilmani et al., 2019), this study suggests the reverse relationship given that, as previously mentioned, Perf. exp. was defined as the degree to which an individual believes that using a particular technology will enhance their performance or satisfaction.
- Hed. mot. was positioned as a fourth-order endogenous factor, affecting both Habit and Beh. int. The rationale for placing Hed. mot. as a predictor of the above factors is that the enjoyment derived from the use of an ICT tool can foster frequent engagement with it (thus, becoming a habit) and further reinforces users' intention to continue engaging with it.

- Habit, in turn, was conceived as a fifth-order endogenous factor that influences Beh. int.
- Beh. int. was designated as the primary dependent variable in the study, being impacted by all the preceding constructs.
- Sex and age, already present in the UTAUT-2 model, together with ICT cert. (which replaced Experience), were treated as control variables.
- The constructs labeled "price value" and "use behavior," though relevant in certain cases, were deemed irrelevant to the study's context and were excluded.

The conceptual framework for this revised UTAUT-2 model is presented in Fig. 2.

5 Method

5.1 Research Hypotheses

On the basis of the proposed model, the following research hypotheses (RHs) were examined:

- RH1a–f. Fac. cond. affect (a) SE ICT, (b) Eff. exp., (c) Perf. exp., (d) Hed. mot., (e) Habit, and (f) Beh. int.
- RH2a–f. Soc. inf. affects (a) SE ICT, (b) Eff. exp., (c) Perf. exp., (d) Hed. mot., (e) Habit, and (f) Beh. int.

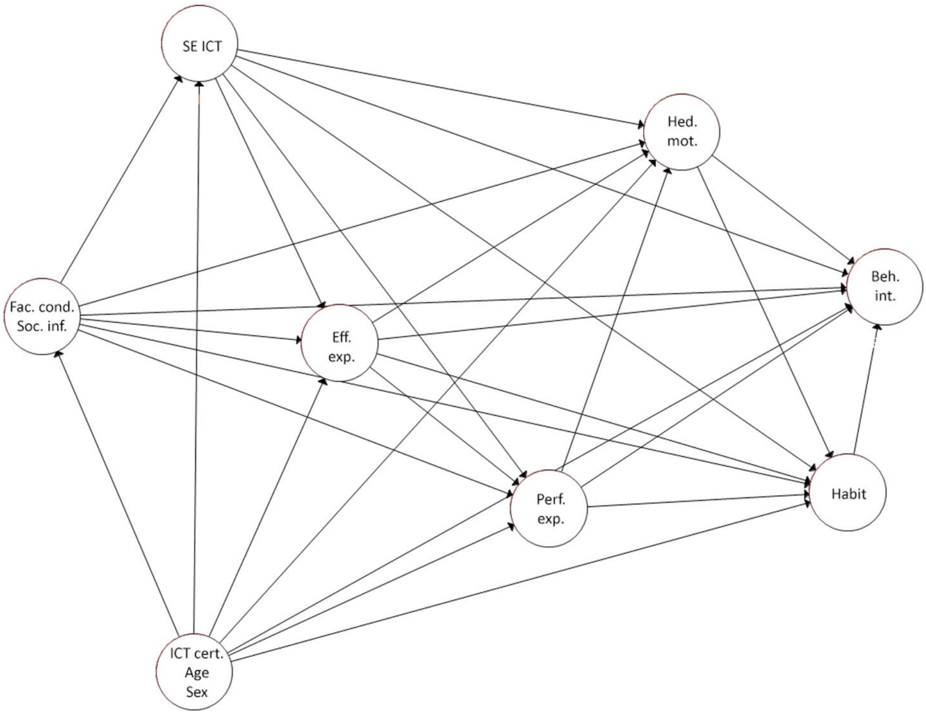

Fig. 2 The study's suggested model. *Note*. For the reduction of the number of arrows, some factors were grouped

- RH3a–e. SE ICT affects (a) Eff. exp., (b) Perf. exp., (c) Hed. mot., (d) Habit, and (e) Beh. int.
- RH4a–d. Eff. exp. affects (a) Perf. exp., (b) Hed. mot., (c) Habit, and (d) Beh. int.
- RH5a–c. Perf. exp. affects (a) Hed. mot., (b) Habit, and (c) Beh. int.
- RH6a–b. Hed. mot. affects (a) Habit and (b) Beh. int.
- RH7. Habit affects Beh. int.
- RH8a–h. Age affects (a) Fac. cond., (b) Soc. inf., (c) SE ICT, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.
- RH9a–h. Sex affects (a) Fac. cond., (b) Soc. inf., (c) SE ICT, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.
- RH10a–h. ICT cert. affects (a) Fac. cond., (b) Soc. inf., (c) SE ICT, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.
- RH11. The model will demonstrate sufficient in- and out-of-sample predictive/explanatory power.

5.2 Participants and Procedure

As mentioned in the "Introduction," the target group for this study was Greek kindergarten teachers. Several reasons led to this decision, besides the gap in research having this population as a target group (Kittinger & Law, 2024), as elaborated in a preceding section. The integration of ICT in kindergarten education offers numerous advantages that enhance learning experiences and outcomes of young children. For example, research indicated that the incorporation of ICT in kindergarten classrooms significantly enhances children's motivation to learn and creativity (Akyar et al., 2024; Fokides & Klaoudatou, 2025). Another advantage of ICT in kindergarten is its ability to tailor educational experiences to meet individual developmental needs (Fokides, & Klaoudatou, 2025). While, in general, preschool educators have positive attitudes towards ICT integration in their classes (Akyar et al., 2024), they face a range of challenges. Many struggle due to a lack of technical skills and insufficient training opportunities (Alotaibi, 2023). Moreover, the challenges extend to limited access to necessary ICT resources and inadequate support, which collectively impede the effective incorporation of technology in the classroom (Kerckaert et al., 2015).

Determining the appropriate sample size requires the evaluation of multiple factors, such as the number of items in the data collection instruments, the research context, the statistical method utilized for analyzing the data, and the complexity of the employed model (Brown, 2015). Given that Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected as the statistical method for data analysis, as will be detailed in a later section, a widely cited guideline for sample size determination is the "10 times rule." According to this rule, the minimum sample size should be ten times the highest number of arrowheads directed toward any latent variable in the PLS-SEM path model (Barclay et al., 1995). Based on the RHs, the maximum number of arrowheads pointing toward a single latent variable was identified as ten, requiring a minimum sample size of 100 participants. To refine this estimation and ensure precision, a power analysis was conducted using G*Power software (Faul et al., 2007). For a medium effect size ($f^2 = 0.15$), a power level of 0.95 (which exceeds the conventional benchmark of 0.80), a significance level of 0.05, and 10 predictors, the recommended sample size was calculated to be 172 participants.

To recruit participants, an open invitation to any kindergarten teacher interested in participating was disseminated through relevant Facebook groups and other social media platforms frequently used by teachers. A total of 312 participants were recruited, well above the recommended sample size. Participation in the study was voluntary, with no specific prerequisites required for involvement. Detailed demographic information about the participants is presented in the "Results" section. Approval for the study was granted by the Ethics and Research Committee of the Department of Primary Education, University of the Aegean. Participants were informed that participation was anonymous, no personal data were collected or stored, and that consent to participate was deemed to have been given by submitting the questionnaire (described in section "Instrument"), which was administered online using Google Forms.

5.3 Instrument

To collect data addressing the research hypotheses, a questionnaire was employed. The questionnaire items were derived from two sources. First, the seminal work of Venkatesh et al. (2012), which introduced the UTAUT-2 framework, served as a primary reference. The authors employed a questionnaire to measure constructs including Perf. exp. (three items), Eff. exp. (four items), Soc. inf. (three items), Fac. cond. (four items), Hed. mot. (three items), habit (four items), and Beh. int. (three items). The second instrument was the New General Self-Efficacy Scale (NGSES, Chen et al., 2001), which consists of eight items designed to assess self-efficacy across diverse contexts and tasks. In this study, the NGSES was utilized to evaluate SE ICT.

Each item from both instruments was translated into Greek and adapted to align with the specific requirements of the study. It has to be noted that the items examining Beh. int. were rephrased to better reflect the new definition of this factor as "behavioral intention to use or continue using ICT tools and applications for teaching." To ensure the rigor and validity of the adapted questionnaire, a process similar to the Decision Delphi method proposed by Rauch (1979) was implemented. The pool of items, including both the original English versions and their Greek translations, was shared with four experts in the field, who were instructed to evaluate the items and provide feedback, addressing the following key areas:

- The appropriateness of the wording for the target audience, with suggestions for alternative phrasing.
- Recommendations on whether specific items should be added or removed.
- Verification that each set of items represented the theoretical construct to which they were assigned.

After several rounds of review, discussion, and revision, consensus was achieved, and the panel finalized the proposed questionnaire. Next, to prevent any potential difficulties that future respondents might face, the instrument was piloted with a group of twenty teachers who were not part of the study's main sample. These teachers were asked to assess the clarity and comprehensibility of the questionnaire items and to provide comments. Based on their feedback, re-wording of some items was carried out. As an additional precautionary step, the revised items were resubmitted to the expert panel for final review and approval.

The items were presented in a five-point Likert-type scale (see Appendix A). Three additional items were included to capture participants' age, sex, and ICT cert.

6 Results

6.1 Initial Data Processing

As noted in a prior section, a total of 312 individuals participated in the study. The sample was predominantly composed of females ($n=286$, 91.67%), with an average age of approximately 40 years ($M=39.96$, $SD=10.35$). The imbalance between males and females was expected as the vast majority of kindergarten teachers are females (Organisation for Economic Co-operation and Development, 2023). In terms of ICT certification levels, 13.78% of the participants reported no certification, while 13.46% possessed beginner-level qualifications. Furthermore, 29.81% were classified as having intermediate-level certification, and the remaining 42.95% had advanced-level certification.

Given the study's research objective to explain the variance of endogenous constructs, alongside its exploratory nature with potential implications for new theory development, the use of PLS-SEM was identified as the appropriate statistical method for data analysis (Hair et al., 2019). Following the guidelines outlined by Hair et al. (2019), several assessments were performed prior to proceeding with the PLS-SEM analysis:

- Data quality: The dataset was reviewed for missing responses and unengaged participants (i.e., those exhibiting no variance in their answers, $SD=0.00$). No participants met the exclusion criteria.
- Item reliability: Indicator loadings were analyzed to ensure item reliability. While two items exhibited loadings below the ideal threshold of 0.70, their values exceeded 0.60, supporting the conclusion that item reliability was sufficient (Appendix B, Table 4).
- Internal consistency and reliability: Reliability metrics, including rho_A and Cronbach's α, were evaluated, revealing no concerns (Appendix B, Table 5).
- Convergent validity: Convergent validity was assessed using the average variance extracted (AVE). In line with established benchmarks, all constructs exhibited AVE values above 0.50, confirming the absence of convergent validity issues (Appendix B, Table 5).
- Discriminant validity: The heterotrait-monotrait (HTMT) ratio of correlations was used to examine discriminant validity. All HTMT values fell below the strict threshold of 0.85, providing evidence for discriminant validity (Appendix B, Table 6).
- Multicollinearity: The Variable Inflation Factor (VIF) of all items was assessed, with all VIF values falling well below the threshold of 5.0, demonstrating that multicollinearity was not a concern (Appendix B, Table 7).

6.2 PLS-SEM Results

The subsequent step involved evaluating the structural model by analyzing the PLS-SEM results. Please note that a Bias-Corrected and Accelerated bootstrap procedure, utilizing 10,000 subsamples, was employed to determine the significance of the path coefficients and to assess their values (Hair et al., 2019). The results are presented in Tables 1, 2 and 3, while Fig. 3 presents the final model.

The next phase of the analysis assessed the model's out-of-sample predictive accuracy using the PLSpredict procedure. Although PLSpredict offers a range of metrics to evaluate predictive performance on out-of-sample data, Hair et al. (2019) recommend to focus on comparing root mean squared error (RMSE) values derived from two analyses: predictions generated by the PLS-SEM model and those obtained from a naïve linear regression model (LM). In this study, the PLS-SEM model consistently produced lower RMSE values than the naïve LM across the vast majority of indicators (27 out of 31). These findings provide evidence that the model demonstrates moderate to strong predictive power.

For comparison, the analysis was run on the unmodified UTAUT-2 (including SE ICT). The results can be found in Appendix C, while Fig. 4 presents the unmodified UTAUT-2 final model.

6.3 Summary of the Results, Confirmation of the Research Hypotheses

Taking together the above results and in relation to the RHs, the following can be noted:

- RH1a–f. Fac. cond. significantly affected SE ICT, Eff. exp., Perf. exp., and Habit. On the other hand, this factor had no direct effects on Hed. mot. and Beh. int.
- RH2a–f. Soc. inf. significantly affected SE ICT, Eff. exp., Perf. exp., Hed. mot., and Beh. int. It did not have a direct effect on Habit.
- RH3a–e. SE ICT had significant effects only on Perf. exp. and Habit. No direct effects were observed on Eff. exp., Hed. mot., and Beh. int.
- RH4a–d. Eff. exp. had significant effects on Perf. exp. and Hed. mot. On the other hand, it had no direct effects on Habit and Beh. int.
- RH5a–c. Perf. exp. significantly affected Hed. mot. and Beh. int., though it had no effect on Habit.
- RH6a-b. Hed. mot. significantly affected both Habit and Beh. int.
- RH7. Habit had a significant effect on Beh. int.
- RH8a–h. Age significantly affected only Eff. exp. and Perf. exp. No direct effects were noted on Fac. cond., Soc. inf., SE ICT, Hed. mot., Habit, and Beh. int.
- RH9a-h. Sex did not affect any of the model's constructs.
- RH10a–h. ICT cert. significantly affected Fac. cond., SE ICT, and Hed. mot. It did not have significant direct effects on Soc. inf., Eff. exp., Perf. exp., Habit, and Beh. int.
- RH11. The model demonstrated more than satisfactory in- and out-of-sample predictive/explanatory power.

7 Discussion

The data analyses offered several rather interesting findings. On the other hand, please be reminded that the primary objective of this study was the introduction and validation of a revised UTAUT-2 model. Consequently, the discussion that follows focuses on the justification for incorporating and modifying specific factors, their direct and indirect effects, and the predictive and explanatory capabilities of the revised UTAUT-2 model, rather than

Table 1 The results of PLS-SEM, direct effects

Path	t	p	β	f^2	Interpretation
Age → Beh. int.	1.94	0.053	0.06	0.01	–
Age → Eff. exp.	2.36	0.018	−0.08	0.02	Weak path, small effect
Age → Fac. cond.	1.31	0.191	0.08	0.01	–
Age → Habit	0.44	0.662	0.02	0.00	–
Age → Hed. mot.	0.31	0.760	−0.01	0.00	–
Age → Perf. exp.	2.33	0.020	−0.09	0.02	Weak path, small effect
Age → SE ICT	0.53	0.600	−0.02	0.00	–
Age → Soc. inf.	0.03	0.975	0.00	0.00	–
Eff. exp. → Beh. int.	1.40	0.163	−0.08	0.01	–
Eff. exp. → Habit	0.35	0.730	0.02	0.00	–
Eff. exp. → Hed. mot.	3.06	0.002	0.22	0.05	Modest path, small effect
Eff. exp. → Perf. exp.	2.06	0.040	0.15	0.02	Modest path, small effect
Fac. cond. → Beh. int.	1.18	0.237	0.08	0.01	–
Fac. cond. → Eff. exp.	6.63	< 0.001	0.41	0.20	Moderate path, medium effect
Fac. cond. → Habit	2.42	0.015	0.18	0.03	Modest path, small effect
Fac. cond. → Hed. mot.	1.37	0.170	0.09	0.01	–
Fac. cond. → Perf. exp.	2.82	0.005	0.19	0.03	Modest path, small effect
Fac. cond. → SE ICT	12.53	< 0.001	0.60	0.51	Strong path, large effect
Habit → Beh. int.	5.18	< 0.001	0.34	0.14	Moderate path, small effect
ICT cert. → Beh. int.	0.79	0.428	0.03	0.00	–
ICT cert. → Eff. exp.	0.33	0.742	−0.01	0.00	–
ICT cert. → Fac. cond.	4.11	< 0.001	0.24	0.06	Modest path, small effect
ICT cert. → Habit	0.73	0.468	0.03	0.00	–
ICT cert. → Hed. mot.	2.71	0.007	0.09	0.02	Weak path, small effect
ICT cert. → Perf. exp.	0.06	0.954	0.00	0.00	–
ICT cert. → SE ICT	2.64	0.008	0.11	0.03	Modest path, small effect
ICT cert. → Soc. inf.	1.62	0.106	0.09	0.01	–
Hed. mot. → Beh. int.	6.52	< 0.001	0.36	0.15	Moderate path, medium effect
Hed. mot. → Habit	3.06	0.002	0.21	0.04	Modest path, small effect
Perf. exp. → Beh. int.	3.29	0.001	0.18	0.04	Modest path, small effect
Perf. exp. → Habit	1.73	0.084	0.11	0.01	–
Perf. exp. → Hed. mot.	5.19	< 0.001	0.36	0.16	Moderate path, medium effect
SE ICT → Beh. int.	1.50	0.133	−0.10	0.01	–
SE ICT → Eff. exp.	6.43	< 0.001	0.36	0.17	Moderate path, medium effect
SE ICT → Habit	4.37	< 0.001	0.30	0.09	Modest path, small effect
SE ICT → Hed. mot.	1.18	0.237	0.08	0.01	–
SE ICT → Perf. exp.	4.55	< 0.001	0.32	0.09	Moderate path, small effect
Sex → Beh. int.	0.00	0.998	0.00	0.00	–
Sex → Eff. exp.	1.15	0.251	−0.04	0.00	–
Sex → Fac. cond.	0.84	0.403	−0.03	0.00	–
Sex → Habit	1.40	0.161	0.06	0.01	–
Sex → Hed. mot.	1.21	0.225	−0.04	0.00	–
Sex → Perf. exp.	1.95	0.051	−0.08	0.01	–
Sex → SE ICT	1.79	0.074	−0.08	0.01	–
Sex → Soc. inf.	0.60	0.552	−0.03	0.00	–
Soc. inf. → Beh. int.	3.23	0.001	0.16	0.05	Modest path, small effect
Soc. inf. → Eff. exp.	2.66	0.008	0.15	0.04	Modest path, small effect
Soc. inf. → Habit	1.85	0.065	0.11	0.02	–

Table 1 (continued)

Path	t	p	β	f^2	Interpretation
Soc. inf. → Hed. mot.	3.43	0.001	0.18	0.05	Modest path, small effect
Soc. inf. → Perf. exp.	4.21	< 0.001	0.23	0.08	Modest path, small effect
Soc. inf. → SE ICT	2.83	0.005	0.15	0.03	Modest path, small effect

"–" Indicates not statistically significant results. For the interpretation of path coefficients, the following thresholds are applied: values of β ranging from 0 to 0.10 signify a weak path, β values from 0.11 to 0.30 indicate a modest path, β values between 0.31 and 0.50 represent a moderate path, and β values exceeding 0.50 denote a strong path (Hair & Alamer, 2022). Effect sizes are assessed using the following guidelines: $f^2 \geq 0.35$ indicates a large effect, $f^2 \geq 0.15$ reflects a medium effect, $f^2 \geq 0.02$ represents a small effect, and $f^2 < 0.02$ corresponds to a negligible effect (Cohen, 2013)

delving into a detailed interpretation of the results in relation to kindergarten teachers. In addition, it is important to acknowledge that the extensive reconfiguration of the UTAUT-2 framework, coupled with the scarcity of prior studies that have undertaken similar efforts, poses significant challenges to align the results with the findings of previous research.

7.1 Discussion of the Results Related to the Impact of the Perceived Facilitating Conditions and Perceived Social Influence (RH1 and RH2)

The results relating to RH1 shed light on how the perceived facilitating conditions influenced various constructs in the revised UTAUT-2 framework. The most pronounced direct effect was on SE ICT (β=0.60, p<.001, f^2 = 0.51), indicating that environmental support almost single-handedly shapes teachers' confidence in their ability to utilize ICT tools. This aligns with the assertion of others (Gálvez et al., 2018; Lin et al., 2022; Makeleni et al., 2023; Menno et al., 2024), who emphasized that institutional and resource-based support plays a key role in enhancing self-efficacy in professional contexts. This factor also significantly influenced Eff. exp. (β=0.41, p<.001, f^2 = 0.20), Perf. exp. (β=0.19, p=.005, f^2 = 0.03), and Habit (β=0.18, p=.015, f^2 = 0.03), further highlighting the importance of supportive environments in reducing the perceived complexity of technology usage, leading to an increased perception of its usefulness, and its habitual use. Interestingly, Fac. cond. did not exert direct effects on Hed. mot. or Beh. int. These omissions seem to challenge the view that support structures and accessible resources drive technology adoption and use (Mustafa et al., 2022; Palau-Saumell et al., 2019) and provide support to studies that suggested otherwise (Dwivedi et al., 2019; Kim et al., 2024; Marikyan & Papagiannidis, 2023; Zuiderwijk et al., 2015). They are also in antithesis with the UTAUT-2 model in which there is an effect of Fac. cond. on Beh. int (Venkatesh et al., 2012).

The above suggest that teachers' intentions to use ICT tools may rely on deeper psychological constructs (e.g., hedonic motivation) rather than environmental support alone. Indeed, Fac. cond. exhibited substantial indirect effects throughout the model, influencing Eff. Exp. (β=0.22, p<.001), Perf. exp. (β=0.28, p<.001), Hed. mot. (β=0.35, p<.001), Habit (β=0.34, p<.001), and Beh. int. (β=0.31, p<.001). These findings verify the cascading impact of environmental support across higher-order endogenous constructs. Moreover, the results related to Fac. cond. offer the first indication for the need to recognize indirect pathways and dynamic construct interactions in technology adoption models, as suggested in this study.

Table 2 The results of PLS-SEM, total indirect effects

Path	*t*	*p*	*β*	Interpretation
Age → Beh. int.	0.23	0.815	−0.01	–
Age → Eff. exp.	0.84	0.404	0.04	–
Age → Habit	0.11	0.917	0.01	–
Age → Hed. mot.	0.51	0.609	−0.03	–
Age → Perf. exp.	0.37	0.713	0.02	–
Age → SE ICT	1.11	0.267	0.05	–
Eff. exp.→ Beh. int.	3.45	0.001	0.16	Modest path
Eff. exp.→ Habit	2.78	0.005	0.07	Weak path
Eff. exp.→ Hed. mot.	1.97	0.049	0.05	Weak path
Fac. cond. → Beh. int.	5.50	<0.001	0.31	Moderate path
Fac. cond. → Eff. exp.	5.34	<0.001	0.22	Modest path
Fac. cond. → Habit	6.73	<0.001	0.34	Moderate path
Fac. cond. → Hed. mot.	7.08	<0.001	0.35	Moderate path
Fac. cond. → Perf. exp.	5.65	<0.001	0.28	Modest path
ICT cert. → Beh. int.	4.01	<0.001	0.19	Modest path
ICT cert. → Eff. exp.	4.27	<0.001	0.21	Modest path
ICT cert. → Habit	4.36	<0.001	0.21	Modest path
ICT cert. → Hed. mot.	3.53	<0.001	0.17	Modest path
ICT cert. → Perf. exp.	3.97	<0.001	0.18	Modest path
ICT cert. → SE ICT	3.71	<0.001	0.16	Modest path
Hed. mot. → Beh. int.	2.54	0.011	0.07	Modest path
Perf. exp. → Beh. int.	4.26	<0.001	0.20	Modest path
Perf. exp. → Habit	2.68	0.007	0.07	Weak path
SE ICT → Beh. int.	5.40	<0.001	0.28	Modest path
SE ICT → Habit	3.00	0.003	0.11	Modest path
SE ICT → Hed. mot.	4.23	<0.001	0.21	Modest path
SE ICT → Perf. exp.	2.11	0.035	0.05	Weak path
Sex → Beh. int.	1.95	0.051	−0.07	–
Sex → Eff. exp.	1.73	0.084	−0.06	–
Sex → Habit	2.58	0.010	−0.09	Weak path
Sex → Hed. mot.	2.66	0.008	−0.09	Weak path
Sex → Perf. exp.	1.85	0.065	−0.06	–
Sex → SE ICT	0.86	0.390	−0.03	–
Soc. inf. → Beh. int.	6.36	<0.001	0.24	Modest path
Soc. inf. → Eff. exp.	2.57	0.010	0.05	Weak path
Soc. inf. → Habit	4.45	<0.001	0.16	Modest path
Soc. inf. → Hed. mot.	4.86	<0.001	0.17	Modest path
Soc. inf. → Perf. exp.	3.07	0.002	0.08	Weak path

Notes. Effect sizes cannot be calculated for indirect effects

The second set of hypotheses (RH2) examined the direct and indirect effects of Soc. inf. The results revealed significant and positive direct relationships between Soc. inf. and several constructs, including SE ICT (β=0.15, p=.005, f^2 = 0.03), Eff. exp. (β=0.15, p=.008, f^2 = 0.04), Perf. exp. (β=0.23, p<.001, f^2 = 0.08), Hed. mot. (β=0.18, p=.001, f^2 = 0.05), and Beh. int. (β=0.16, p=.001, f^2 = 0.050), while there was no effect on Habit. These results provide support to the notion that social influence plays a crucial role. The substantial effect of Soc. inf. on Beh. int. reaffirms its critical role in guiding user intentions (Ain et al., 2016;

Table 3 The model's explanatory power/in-sample predictive power

Factor	Adj. R^2	Interpretation
Beh. int.	0.69	Strong explanation
Eff. exp.	0.64	Strong explanation
Fac. cond.	0.05	Weak explanation
Habit	0.61	Strong explanation
Hed. mot.	0.65	Strong explanation
Perf. exp.	0.57	Strong explanation
SE ICT	0.53	Strong explanation
Soc. inf.	0.00	Weak explanation

The interpretation of R^2 values aligns with the following thresholds: values ranging from 0 to 0.10 are considered a weak explanatory/predictive power, 0.11 to 0.30 indicate a modest one, 0.31 to 0.50 reflect a moderate one, and values greater than 0.50 denote a strong explanatory/predictive power (Hair & Alamer, 2022)

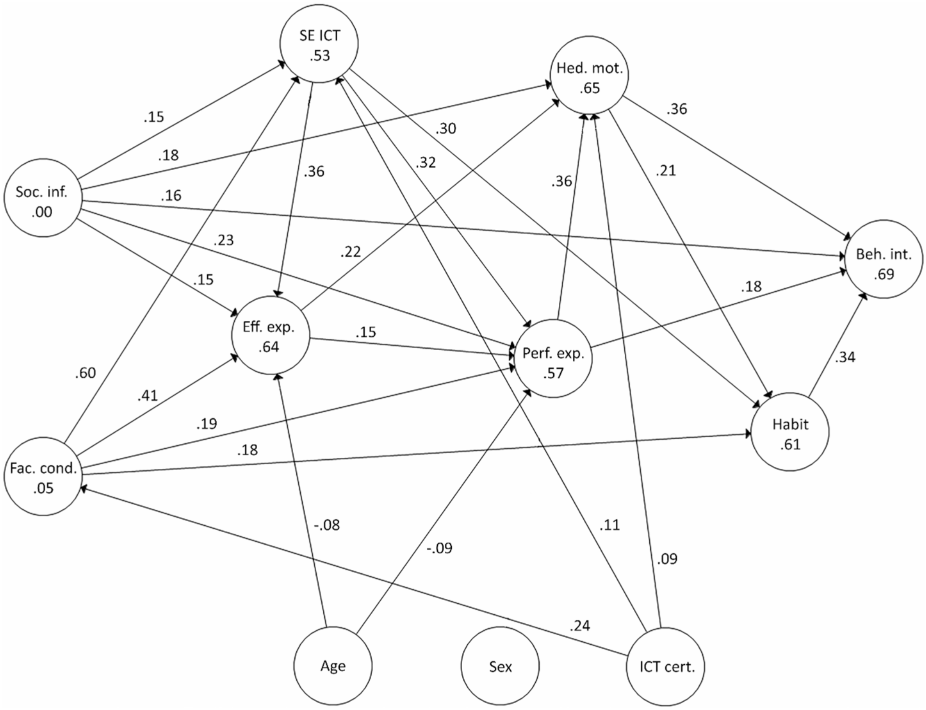

Fig. 3 The study's final model. For the sake of simplicity, only the statistically significant direct paths are shown. Path coefficients are indicated by the numerical values on the arrows, while the numbers in the circles represent the factors' R^2 values

Nikolopoulou et al., 2020; Palas et al., 2022; Sergeeva et al., 2025) and providing further support for its inclusion in the original UTAUT-2. In the context of education, this suggests that colleagues and institutional norms significantly encourage educators to adopt ICT tools. The path from Soc. inf. to SE ICT aligns with the assertion that social factors, such as peer support and collaboration, are instrumental in enhancing self-efficacy (Gálvez et al., 2018).

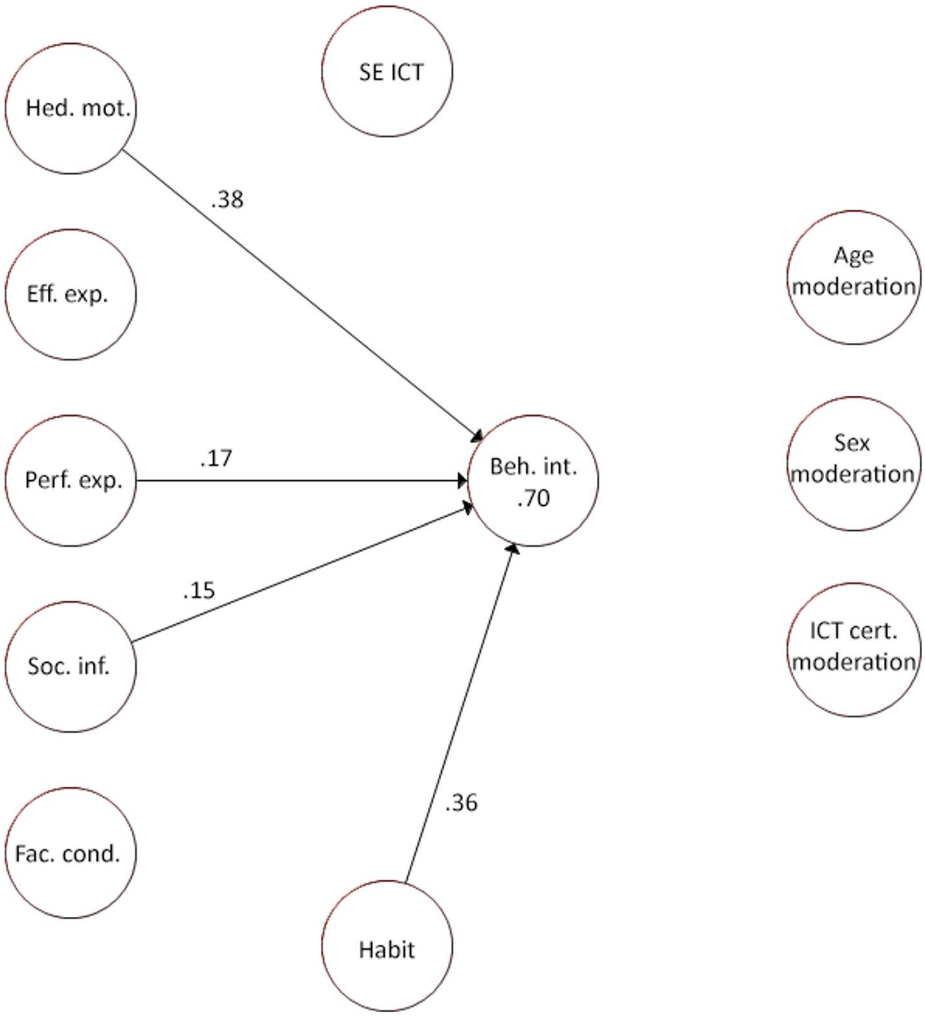

Fig. 4 The results of the unmodified UTAUT-2

The significant influence on Eff. exp. suggests that individuals are more likely to perceive ICT tools as easy to use when their peers and social networks express positive sentiments toward technology usage. Similarly, the significant effect on Perf. exp. stresses its role in shaping perceptions of technology as beneficial to professional goals (Guetz & Bidmon, 2022).

The analysis of the indirect effects indicated that Soc. inf. influenced constructs like Eff. exp. ($\beta=0.10$, $p=.010$), Habit ($\beta=0.16$, $p<.001$), Hed. mot. ($\beta=0.17$, $p<.001$), Perf. exp. ($\beta=0.08$, $p=.002$), and Beh. int. ($\beta=0.24$, $p<.001$). Soc. inf. demonstrated a significant indirect effect on Habit, despite its lack of direct impact on this factor. This implies that Soc. inf. indirectly molds habitual behaviors through its interactions with other factors. These subtle dynamics highlight Soc. inf.'s ability to function as an antecedent of more complex behavioral constructs, supporting the argument for a restructured UTAUT-2 model that considers direct and indirect pathways.

7.2 Discussion of the Results Related to the Impact of Self-Efficacy in Using ICT Tools and Applications for Teaching (RH3)

RH3 explored the direct and indirect impacts of SE ICT, a newly introduced factor in UTAUT-2. The results revealed significant direct paths to Eff. exp., Perf. exp., and Habit, while the paths to Hed. mot. and Beh. int. did not reach statistical significance. Regarding Eff. exp., SE ICT had a positive effect ($\beta = 0.36$, $p < .001$, $f^2 = 0.17$), which is consistent with prior research suggesting that individuals with higher self-efficacy perceive tasks associated with technology usage as less effortful (Fokides & Kapetangiorgi, 2022). Similarly, SE ICT significantly influenced Perf. exp. ($\beta = 0.32$, $p < .001$, $f^2 = 0.09$), indicating that self-efficacy directly shapes perceptions regarding the usefulness of ICT tools. This finding is in line with prior research highlighting how confidence in one's abilities leads to positive evaluations of technology's capacity to improve performance outcomes (Fokides, 2017). The direct impact on Habit ($\beta = 0.30$, $p < .001$, $f^2 = 0.09$) suggests that self-efficacy facilitates the development of habitual behaviors around ICT usage.

Contrary to what was theorized, SE ICT did not demonstrate a significant effect on Beh. int. Although this might be surprising, given that others suggested that this link exists (e.g., Fokides & Kapetangiorgi, 2022; Peng et al., 2024), it may reflect specific contextual dynamics in kindergarten teaching environments where educators with high self-efficacy in ICT perceive technology integration as complex, and, thus, do not intent to use it. The absence of statistical significance in the direct path from SE ICT to Hed. mot., probably indicates that this factor is less influenced by self-perceived capability and more reliant on other factors.

SE ICT indirectly and positively influenced Beh. int. ($\beta = 0.28$, $p < .001$). This observation suggests that while SE ICT has no direct impact on behavioral intention, its influence is channeled through intermediary constructs. Indirect paths were also found for Hed. mot. ($\beta = 0.21$, $p < .001$), Habit ($\beta = 0.11$, $p = .003$), and Perf. exp. ($\beta = 0.05$, $p = .035$). These indirect pathways reinforce previous findings that self-efficacy serves as a foundational factor in predicting outcomes related to technology adoption (Fokides & Kapetangiorgi, 2022; Peng et al., 2024). Overall, the direct and indirect effects of SE ICT provide support to the notion that it plays a key role in the revised model, suggesting research should consider its inclusion as a critical endogenous factor.

7.3 Discussion of the results related to the impact of effort expectancy and performance expectancy (RH4 and RH5)

Regarding RH4, Eff. exp. was found to have statistically significant direct effects on two constructs: Perf. exp. ($\beta = 0.15$, $p = .040$) and Hed. mot. ($\beta = 0.22$, $p = .002$). The effect sizes were classified as small ($f^2 = 0.02$ for Perf. exp.; $f^2 = 0.05$ for Hed. mot.). These findings confirm that when users perceive a technology as easy to use, they are more likely to consider it beneficial (Camilleri, 2024; Chu et al., 2022) and derive enjoyment from its use (Tamilmani et al., 2019). Contrary to what literature suggested (Beh et al., 2021; Huang, 2023), the direct effect of Eff. exp. on Beh. int. was not statistically significant. This outcome confirms the notions that it is a rather weak predictor of Beh. int. (Kittinger & Law, 2024; Tamilmani et al., 2021) and that it becomes non-significant after extended usage of technology or when the ICT tools are easy to use (Marikyan & Papagiannidis, 2023). The lack of impact on Habit may be understood in the context of habit formation requiring prolonged or repetitive exposure, rather than being solely driven by the perception of ease of use.

Eff. exp. demonstrated indirect effects on Beh. int. (β=0.16, p=.001), Habit (β=0.07, p=.005), and a rather weak one on Hed. mot. (β=0.05, p=.049). These pathways suggest that while Eff. exp. does not directly shape behavioral intention or habitual use, it does so indirectly by reinforcing more immediate constructs, such as users' perceived performance benefits and enjoyment in using technology. Additionally, the findings reaffirm the necessity to account for indirect interactions and mediatory pathways to fully capture the dynamics of technology adoption.

RH5 explored the effects of Perf. exp. It was found to have a direct impact on Beh. int. (β=0.18, p=.001, f^2 = 0.04), though a not so pronounced one as others suggested (Kittinger & Law, 2024). There was also an indirect effect on this factor (β=0.20, p<.001). These findings mirror the broader consensus within UTAUT-related research that perceived usefulness is a determinant of behavioral intention (Gimpel et al., 2020; Huang, 2023; Neves et al., 2025), albeit not as significant as others suggested (Nikolopoulou et al., 2021; Phibbs & Rahman, 2022; Vidal-Silva et al., 2024).

Perf. exp. had a direct effect on Hed. mot. (β=0.36, p<.001, f^2 = 0.16), indicating that heightened perceptions of the usefulness of ICT tools can elevate educators' intrinsic motivation to employ these tools. Although it did not have a direct impact on Habit, it had a weak indirect one (β=0.07, p=.007), through Hed. mot. This finding extends the scope of performance expectancy, as it reveals that behavioral routines related to the use of ICT tools can be reinforced if one believes that these tools are useful.

As with several other findings in this study, the results related to Perf. exp. illuminate overlooked dynamics in the original UTAUT-2 model. For example, past research suggested that Per. Exp., Hed. mot., and Habit work hand-in-hand in affecting Beh. int. (Nikolopoulou et al., 2021; Phibbs & Rahman, 2022; Vidal-Silva et al., 2024). Yet, the study's findings clearly demonstrate that Perf. exp. interacts dynamically with downstream factors such as Hed. mot., highlighting the necessity of rethinking its linear treatment in prior UTAUT-2 applications.

7.4 Discussion of the Results Related To the Impact of Hedonic Motivation (RH6) and Habit (RH7)

RH6 examined the influence of Hed. mot. on both Habit and Beh. int. The findings revealed that it impacted both (β=0.36, p<.001, f^2 = 0.15 for Beh. int. and β=0.21, p=.002, f^2 = 0.04 for Habit). The significant direct relationship between Hed. mot. and Beh. int. indicates the critical role that intrinsic enjoyment and pleasure derived from technology usage play in shaping intentions to adopt or continue using ICT tools. This result aligns with prior research emphasizing the importance of intrinsic motivation as key determinant of technology adoption behavior (Narayan & Naidu, 2024; Nikolopoulou et al., 2021; Plohl & Babič, 2024; Venkatesh et al., 2012), as it shifts the focus from extrinsic factors to enjoyment-driven factors that appeal to users' personal gratification.

The direct relationship between Hed. mot. and Habit, as well as the indirect impact of Hed. mot on Beh. int. through Habit (β=0.07, p=.011) are in line with expectations, as the interplay of these factors often shapes behavioral intentions (e.g., Marikyan & Papagiannidis, 2023; Narayan & Naidu, 2024; Nikolopoulou et al., 2021; Plohl & Babič, 2024). The above results reaffirm the role of Hed. mot. in UTAUT-2 inspired models.

As for RH7, the findings provide evidence that established behavioral patterns influence educators' willingness to continue using or adopting ICT tools for teaching activities, as Habit had a direct effect on Beh. int. (β=0.34, p<.001, f^2 = 0.14). This aligns with prior research emphasizing the role of habit in shaping technology-related decisions (e.g., Hagger et al., 2023; Tamilmani et al., 2019; Zheng et al., 2025). The finding might also signify the factor's broader applicability to educational domains, where routine behavior can mitigate decision-making complexities. As noted by others, teachers often struggle with insufficient technical training, lack of institutional support, and equipment failures (Alotaibi, 2023; Kerckaert et al., 2015), which can negatively affect habitual use of digital tools. Therefore, fostering habitual use may help alleviate these challenges as it enhances confidence and streamlining technology integration. This accords with the broader assumptions of the UTAUT-2 framework, where habit functions as an important addition to technology acceptance constructs, (Venkatesh et al., 2012). The study's results provide further justification for the inclusion of this factor in UTAUT-2 inspired models.

7.5 Discussion of the Results Related to the Impact of the Control Variables (RH8, RH9, and RH10)

RH8 examined the effects of age on the eight constructs of the revised UTAUT-2 model. The results provide evidence that it has a negligible direct impact, as it only modestly affected Eff. exp. (β = −0.08, p=.018) and Perf. exp. (β = −0.09, p=.020). This relationship is not indicative of a major influence. Moreover, the effect sizes observed were small (f^2 = 0.02 in both cases), signifying limited practical importance. In addition, results from the indirect effects analysis further demonstrated that age failed to influence any construct indirectly (see Table 2). This lack of influence might initially appear surprising, given the literature that found age-related differences (e.g., Chang et al., 2019; Marikyan & Papagiannidis, 2023; Venkatesh et al., 2012; Yap et al., 2022). On the other hand, as other studies also did not find age related differences in teachers' attitudes or intentions to use ICT (e.g., Papadakis, 2018), it might be viewed as an indicator that we have reached a point in which ICT (in general) have become such an integral part of education that these differences are diminishing (Fokides & Kapetangiorgi, 2022); therefore, age-specific effects in educational contexts have become less consequential than previously assumed. Thus, the question arises whether to retain this factor in future studies. The results suggest not to, as psychological and contextual factors proved to be the primary drivers of behavioral intention. Then again, this factor might be of interest in specific contexts (i.e., in the educational use of emerging technologies).

RH9 examined the impact of participants' sex. While there is research in which sex had moderating or direct effects, suggesting that males and females have different behaviors and attitudes toward technology adoption (e.g., Chang et al., 2019; Terblanche & Kidd, 2022; Venkatesh et al., 2012; Wang et al., 2009), the analysis revealed no direct effects on any construct. This finding can be attributed to the misrepresentation of males in the study's sample, which consisted of 91.67% females. On the other hand, three indirect effects emerged, illustrating its role in shaping ICT adoption. Specifically, sex exhibited weak indirect effects on

Hed. mot. (β = -0.09, p=.008), Habit (β = -0.09, p=.010), and a borderline effect on Beh. int (β = -0.07, p=.051). It had no effects on Eff. exp., Perf. exp., and SE ICT. These results add to the ongoing discourse regarding demographic influences in technology adoption, where prior studies have presented mixed findings. For instance, some suggested that sex impacts SE ICT (Clipa et al., 2023; Kölemen, 2023; Wu et al., 2020), while others suggested that it does not (Ghazali et al., 2024; Wang et al., 2024), as was the case in this study. This implies that attitudes and intentions vary, which may partially explain the absence of significant effects. From a practical perspective, while sex may not be a critical direct determinant of ICT adoption, its indirect effects suggest that it might still be a useful factor, especially in cases in which the intersection of technology and sex is of interest.

RH10 explored the effects of ICT cert. The PLS-SEM results revealed that its direct effects on UTAUT-2 constructs were mixed. It had no effect on Beh. int., Eff. exp., Soc. inf., and Perf. exp. On the other hand, it had modest direct effects on Fac. cond. (β=0.24, p<.001, f^2 = 0.06) and SE ICT (β=0.11, p=.008, f^2 = 0.03), and a weak effect on Hed. mot. (β=0.09, p=.007, f^2 = 0.02), all with small effect sizes. These results indicate that teachers with higher levels of ICT certification perceive their institutional, environmental, or context-related resources and support as more favorable for integrating technology into their teaching, consider themselves more self-efficient in the use of ICT, and are somehow more motivated to use them. However, the absence of direct effects on Beh. int. and other constructs suggests cultural, contextual, or attitudinal barriers that certification alone cannot address. Its indirect effects on Beh. int., Eff. exp., Habit, Hed. mot., Perf. exp., and SE ICT were statistically significant, yielding modest path coefficients between β=0.16 and β=0.21 (all p-values < 0.001). Therefore, it can be assumed that training programs are important as they function as foundational steps for technology adoption. Yet, the findings caution against relying exclusively on it as a singular solution for fostering widespread ICT adoption, as it proved to be insufficient on its own to impact beliefs. What is of importance is that the findings provide insights into the operationalization of certification levels. Unlike Venkatesh et al.'s (2012) use of "experience" as a measure, the shift to "ICT certification levels" reflects a more objective metric of expertise. Given that this adjustment captured some direct and several indirect pathways, it is suggested to retain this factor or use alternative methods to assess objective proficiency, in cases where proficiency in a given technology is of importance.

7.6 Discussion of the Results Related To the Predictive/explanatory Power of the Model (RH11)

RH11 hypothesized that the restructured UTAUT-2 model would exhibit sufficient in- and out-of-sample predictive/explanatory power. This hypothesis is strongly supported by the results, which demonstrate high levels of explanatory/predictive power across the endogenous constructs (Beh. int., R^2 = 0.69; SE ICT, R^2 = 0.53; Eff. exp., R^2 = 0.64; Perf. exp., R^2 = 0.57; Hed. mot., R^2 = 0.65; and Habit, R^2 = 0.61). Moreover, the PLSpredict procedure revealed that RMSE values were lower for the PLS-SEM model across most indicators (27 out of 31), affirming its moderate to strong out-of-sample predictive performance (Hair et al., 2019).

These findings are significant as they address limitations of the UTAUT-2 model. For instance, as noted earlier, UTAUT-2 was criticized for the neglection of the interplay between constructs. By restructuring the UTAUT-2 to include dynamic relationships, by refining definitions, and by replacing "experience" with ICT certification levels, this study addressed these shortcomings. As demonstrated by the results, a simple comparison between the suggested UTAUT-2 model (Fig. 3) and the unmodified one (Fig. 4) reveals that the latter is far more simplistic. In the modified version, several direct and indirect paths emerged that the original model disregarded, validating the study's argument that the revised model will allow for a better understanding of how behavioral intentions are formed.

7.7 Key Insights

The following summarize the study's key insights:

- Fac. cond. The strong direct impact on SE ICT suggests that institutional and environmental support are pivotal in shaping teachers' confidence in their ability to use ICT tools. The impact on Eff. exp., Perf. exp., and Habit, suggests that they can significantly reduce technology's perceived complexity, increase perceptions of its usefulness, and lead to its habitual use. The lack of direct effects on Beh. int. or Hed. mot., challenge the assumption that support structures inherently drive technology adoption; teachers' behavioral intentions appear to rely on psychological factors rather than external support alone. The cascading indirect effects on multiple constructs demonstrate the need to consider indirect pathways in technology adoption models.
- Soc. inf. The direct effect on Beh. int. suggests that peer and institutional norms critically shape educators' willingness to adopt ICT tools. Its effects on SE ICT, Eff. exp., Perf exp., and Hed. mot., underscore the importance of social encouragement in making educators view technology favorably. The indirect effects reflect its role as an antecedent of deeper behavioral constructs, further supporting the need to consider indirect pathways.
- SE ICT. It emerged as a significant factor in the revised model. The direct impact on Eff. exp., Perf. exp., and Habit, imply that educators with high confidence in their abilities view ICT tasks as less effort-intensive, more useful, and more likely to form routines around usage. It indirectly influenced Beh. int., Hed. mot., Habit, and Perf. exp., establishing its key role in guiding technology-related actions.
- Eff. exp. It exerted direct effects on Perf. exp. and Hed. mot., implying that ease of use increases perceptions of usefulness and enjoyment of ICT tools. It had indirect effects on Beh. int., Hed. mot., and Habit, providing evidence for its role in fostering positive evaluations that influence downstream behaviors. The lack of direct effects on Habit and Beh. int. suggests that ease of use alone does not create sustained routines or long-term adoption but reinforces perceptions of value through intermediary constructs.
- Perf. exp. It influenced (directly and indirectly) Beh. int., affirming its role as a determinant of educators' willingness to use ICT tools. The direct effect on Hed. mot. highlights its capacity to enhance intrinsic enjoyment. Its indirect influence on Habit reveals its potential to reinforce behavioral routines when ICT tools prove beneficial to everyday tasks.
- Hed mot. Its impact on Beh. int., reflects the importance of intrinsic enjoyment in driving technology adoption and continued use. The impact on Habit reaffirms the notion that these factors often shape behavioral intentions.
- Habit. Its influence on Beh. int. affirms the notion that routine behaviors are key drivers

in reinforcing behavioral decisions toward technology use.

- Age. It had negligible direct and indirect effects, implying that ICT tools have become integral to education, reducing generational differences in adoption metrics.
- Sex. Despite the absence of direct effects, sex shaped ICT adoption indirectly, particularly through Hed. mot., Habit, and Beh. int., supporting its retention in future models where demographic interactions are of interest.
- ICT certification levels. This factor influenced Fac. cond., SE ICT, Hed. mot. and exhibited modest indirect effects across all constructs. While certifications are foundational steps in adoption, they are insufficient alone to overcome contextual barriers.
- The suggested modified UTAUT-2 model provides a significantly more detailed picture of the dynamic interplay among the factors influencing educators' behavioral intentions to use ICT. It not only surpasses the original framework in its depth of understanding but also demonstrates strong predictive power across all critical constructs, rendering it a useful tool for examining technology adoption in educational contexts.

7.8 Implications for Research

The revised UTAUT-2 model not only enhances the theoretical understanding of technology acceptance but also addresses existing limitations of the original framework. These advancements offer valuable insights for researchers striving to optimize ICT integration in various domains. First, by reconceptualizing UTAUT-2, the study challenged the static treatment of its original constructs, suggesting that research exploring technology acceptance should not treat constructs in isolation. Indeed, the findings revealed previously unexplored pathways in the model that further influence user behavior and highlighted the need for more dynamic modeling approaches that reflect real-world complexities.

Second, the inclusion of indirect effects shed light on underexamined relationships. For instance, effort expectancy and performance expectancy emerged as impactful third- and fourth-order predictors of behavioral intention. These results suggest moving beyond examining direct effects alone and adopt an integrated perspective that addresses the cascading influences in technology acceptance frameworks. Moreover, the refinement of behavioral intention to include both adoption and continued use allows for a more inclusive and accurate assessment of users who are at different stages of technology engagement, a critical consideration for studies examining underrepresented populations, new adopters, or emerging technologies.

Third, the introduction of self-efficacy as an explicit construct into UTAUT-2 addresses a critical gap in the model, as it plays a crucial role in shaping user attitudes. This advancement, together with the impact it had on several factors, supports the integration of social cognitive theory into technology acceptance research and suggests that future studies should examine other context-specific psychological constructs to deepen theoretical insights into user behavior. Fourth, the replacement of "experience" with "ICT certification levels" addressed the discrepancies between duration of use and actual proficiency, providing a reliable metric for assessing skill variation. Research can benefit from adopting similar tailored approaches in contextualizing control factors, particularly in professions requiring certifications or standardized training. Lastly, given its high explanatory power, the revised model serves as a strong foundation for future studies seeking to expand the scope of UTAUT-based analyses.

7.9 Limitations and Future Work

The study has certain limitations that should be acknowledged. The first is related to the exclusivity of the study's participant pool, which consisted solely of Greek kindergarten teachers. While sufficient for the study's objectives, the findings lack generalizability across other educational contexts, including variation by geographical, cultural, or institutional factors. This highlights the need for future studies to replicate and validate the model with diverse participant groups, such as educators from other countries or broader K-12 segments, to assess the applicability and robustness of the framework in a wider context. Moreover, adapting the model to assess students' or parents' acceptance of technology in early-childhood education environments would offer a complementary perspective on ICT adoption dynamics.

Another limitation lies in the fact that data were captured at a single point in time. While the results demonstrated meaningful relationships between key constructs, it remains unclear whether these relationships evolve over time. Longitudinal studies could better assess the temporal dynamics and causal pathways of factors. Temporal data could also shed light on the sustainability of behavioral intentions to adopt ICT tools.

Additionally, while the study refined several constructs of the UTAUT-2 model, it did not account for other potential factors that could influence behavioral intention. For example, future studies can examine variables like institutional policies, workload pressures, content availability, or teacher adaptability to ICT innovations. These elements might further enrich the explanatory power of the model. Furthermore, adding psychological constructs may address the challenges teachers face when incorporating ICT into their classrooms, an underserved area in the existing literature.

Finally, future studies should employ qualitative research methodologies to complement the quantitative findings. For example, focus groups, interviews, or case studies could be employed to generate deeper insights into respondent perceptions, particularly concerning the barriers to improving low-performing yet critical factors.

8 Conclusion

This study brings advancements in understanding technology adoption through the refinement of the UTAUT-2 framework. By redefining key constructs and incorporating new ones, this modified model addressed limitations in the original UTAUT-2 structure, offering a new perspective on the dynamic interplay among its exogenous and endogenous variables. The results confirm the important role of social influence, performance expectancy, hedonic motivation, self-efficacy in the use of ICT tools and applications for teaching, and habit in shaping behavioral intention to use or continue using ICT tools and applications for teaching. Moreover, the analysis highlighted the model's strong explanatory and predictive power, particularly in the context of kindergarten educators. In conclusion, this study reinforces the applicability of UTAUT-2 in educational contexts while addressing theoretical gaps through significant conceptual innovations. By providing insights for researchers, it contributes to advancing technology integration strategies, especially for early childhood educators who often face barriers to successful ICT adoption.

Appendix A

The study's questionnaire [adapted from Venkatesh et al.'s (2012) paper]
Performance expectancy

- I find ICT tools and applications useful in my teaching.
- Using ICT tools and applications helps me accomplish my teaching more quickly.
- When teaching, the use of ICT tools and applications increases my productivity.

Effort expectancy

- Learning how to use ICT tools and applications for teaching is easy for me.
- My interaction with ICT tools and applications for teaching is clear and understandable.
- I find ICT tools and applications for teaching easy to use.
- It is easy for me to become skillful at using ICT tools and applications for teaching.

Perceived social influence

- People who are important to me think that I should use ICT tools and applications when teaching.
- People who influence my behavior think that I should use ICT tools and applications when teaching.
- People whose opinions I value, prefer that I use ICT tools and applications in my teaching.

Perceived facilitating conditions

- I have the resources necessary to use ICT tools and applications when teaching.
- I have the knowledge necessary to use ICT tools and applications when teaching.
- ICT tools and applications are compatible with other technologies I use during my teaching.
- I can get help from others when I encounter difficulties in using ICT tools and applications related to teaching.

Hedonic motivation

- The use of ICT tools and applications for teaching is fun.
- The use of ICT tools and applications for teaching is enjoyable.

- The use of ICT tools and applications for teaching is very entertaining.

Habit

- The use of ICT tools and applications when teaching has become a habit for me.
- I am addicted to using ICT tools and applications when teaching.
- I must use ICT tools and applications when teaching.

Behavioral intention to use or continue using ICT tools and applications for teaching

- I intend to use or continue using ICT tools and applications when teaching.
- I will try to use or continue using ICT tools and applications when teaching.
- I plan to use or continue using ICT tools and applications when teaching.

Self-efficacy in using ICT tools and applications for teaching [adapted from Chen et al.'s (2001) paper]

- I am confident in my ability to achieve most of the teaching goals I have set using ICT tools and applications.
- Even when I encounter difficulties in using ICT tools and applications in my teaching practices, I can handle them effectively.
- I believe that I can achieve my educational goals with the use of ICT tools and applications.
- I am convinced that I can succeed in most ICT-related educational endeavors that I pursue.
- I can successfully overcome the challenges that arise while using ICT tools and applications in educational settings.
- I am confident in my ability to perform effectively on a wide range of educational tasks that involve ICT tools and applications.
- Compared to other teachers, I excel in the utilization of ICT tools and applications for teaching.
- Even when challenges arise, I can perform my educational tasks effectively using ICT tools and applications.

Appendix B

See the Tables 4, 5, 6 and 7.

Table 4 Items' loadings

Items	Factors							
	Beh. int.	Eff. exp.	Fac. cond.	Habit	Hed. mot.	Perf. exp.	SE ICT	Soc. inf.
Beh. int1	0.93							
Beh. int2	0.93							
Beh. int3	0.92							
Eff. exp1		0.89						
Eff. exp2		0.86						
Eff. exp3		0.85						
Eff. exp4		0.91						
Fac. cond1			**0.69**					
Fac. cond2			0.86					
Fac. cond3			0.86					
Fac. cond4			**0.64**					
Hab1				0.89				
Hab2				0.93				
Hab3				0.92				
Hed. mot1					0.90			
Hed. mot2					0.92			
Hed. mot3					0.92			
Perf. exp1						0.90		
Perf. Exp2						0.94		
Perf. Exp3						0.90		
SE ICT1							0.81	
SE ICT2							0.81	
SE ICT3							0.84	
SE ICT4							0.85	
SE ICT5							0.87	
SE ICT6							0.87	
SE ICT7							0.76	
SE ICT8							0.81	
Soc. inf1								0.86
Soc. inf2								0.88
Soc. inf3								0.89

The bold values indicate lower than 0.70 loadings

Table 5 Internal consistency, reliability, and convergent validity

Factor	Cronbach's α	Composite reliability (rho_A)	AVE
Beh. int.	0.92	0.92	0.86
Eff. exp.	0.90	0.90	0.76
Fac. cond.	0.76	0.79	0.59
Habit	0.90	0.90	0.83
Hed. mot.	0.90	0.90	0.84
Perf. exp.	0.90	0.90	0.84
SE ICT	0.93	0.94	0.69
Soc. inf.	0.85	0.85	0.77

Table 6 Discriminant validity (HTMT analysis)

	Age	Beh. int.	Eff. exp.	Fac. cond.	Habit	ICT cert.	Hed. mot.	Perf. exp	SE ICT	Sex	Soc. inf.
Age											
Beh. int.	0.06										
Eff. exp.	0.04	0.64									
Fac. cond.	0.10	0.76	0.87								
Habit	0.04	0.80	0.71	0.81							
ICT cert.	0.05	0.22	0.19	0.26	0.25						
Hed. mot.	0.04	0.83	0.76	0.79	0.75	0.24					
Perf. exp.	0.08	0.76	0.72	0.77	0.72	0.16	0.81				
SE ICT	0.04	0.63	0.78	0.83	0.77	0.26	0.71	0.73			
Sex	0.10	0.04	0.08	0.05	0.04	0.13	0.10	0.13	0.08		
Soc. inf.	0.04	0.70	0.63	0.70	0.63	0.10	0.69	0.65	0.56	0.05	

Table 7 Multicollinearity diagnostics

Item	VIF	Item	VIF
Beh. int1	3.16	Hed. mot3	3.09
Beh. int2	3.34	Perf. exp1	2.85
Beh. int3	3.16	Perf. Exp2	3.96
Eff. exp1	2.82	Perf. Exp3	2.59
Eff. exp2	2.41	SE ICT1	2.45
Eff. exp3	2.20	SE ICT2	2.49
Eff. exp4	3.15	SE ICT3	2.80
Fac. cond1	1.35	SE ICT4	2.94
Fac. cond2	2.01	SE ICT5	3.41
Fac. cond3	2.07	SE ICT6	3.15
Fac. cond4	1.24	SE ICT7	2.00
Hab1	2.40	SE ICT8	2.38
Hab2	3.13	Soc. inf1	1.89
Hab3	3.09	Soc. inf2	2.22
Hed. mot1	2.54	Soc. inf3	2.29
Hed. mot2	3.08		

Appendix C

See the Table 8.

Table 8 The results of PLS-SEM for the unmodified UTAUT-2 model (SE ICT included)

Path	t	p	β	f^2	Interpretation
Age → Beh. int.	1.71	0.088	0.06	0.01	–
Eff. exp.→ Beh. int.	1.51	0.130	−0.09	0.01	–
Fac. cond. → Beh. int.	1.09	0.275	0.07	0.01	–
Fac. cond. * Age → Beh. int.	0.60	0.546	−0.03	0.00	–
Fac. cond. * ICT cert. → Beh. int.	0.05	0.964	0.00	0.00	–
Fac. cond. * Sex → Beh. int.	0.15	0.879	0.02	0.00	–
Habit → Beh. int.	5.46	<0.001	0.36	0.17	Moderate path, medium effect
Habit * Age → Beh. int.	0.47	0.642	0.03	0.00	–
Habit * ICT cert. → Beh. int.	1.22	0.221	0.08	0.01	–
Habit * Sex → Beh. int.	0.69	0.488	0.04	0.00	–
ICT cert. → Beh. int.	0.64	0.522	0.02	0.00	–
Hed. mot. → Beh. int.	6.00	<0.001	0.38	0.16	Moderate path, medium effect
Hed. mot. * Age → Beh. int.	0.33	0.745	−0.02	0.00	–
Hed. mot. * ICT cert. → Beh. int.	1.79	0.074	−0.12	0.02	–
Hed. mot. * Sex → Beh. int.	1.27	0.204	−0.12	0.01	–
Perf. exp. → Beh. int.	3.12	0.002	0.17	0.04	Modest path, small effect
SE ICT → Beh. int.	1.51	0.130	−0.10	0.01	–
Sex → Beh. int.	0.87	0.382	0.05	0.01	–
Soc. inf. → Beh. int.	2.95	0.003	0.15	0.04	Modest path, small effect

The asterisk (*) denotes moderating effect. Adj. R^2 for Beh. int. = 0.70

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Data Availability Data will be made available on reasonable request from the corresponding author.

Declarations

Competing Interests The authors declare that they have no conflict of interest.

Institutional Review Board Statement The research was conducted in compliance with all relevant legislative frameworks and institutional protocols. This study is an integral component of an ongoing research project, for which the Research and Ethics Committee of the Department of Primary Education at the University of the Aegean evaluated and approved its methodologies and practices.

Ethical Statement The authors declare that this manuscript is the result of their independent creation under the reviewers' comments. This manuscript does not contain any research achievements that have been published or written by other individuals or groups, or by AI tools.

Informed Consent The study's participants volunteered, understood that they could withdraw from the experiment at any time, and provided their informed consent. They were protected by hiding their personal information; no personal data were collected and/or processed.

Content for Publication During the preparation of this work the authors used Ghostwriter in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Abdunool, K., Ali, M., Muhammad, S., & Warda, S. (2024). The mediating effect of behavioral intention in the relationship between social influence and wireless technology usage. *International Journal of Wireless & Mobile Networks*, *16*(6), 37–46. https://doi.org/10.5121/ijwmn.2024.16603

Acosta-Enriquez, B. G., Ramos Farroñan, E. V., Zapata, V., Garcia, L. I. M., Rabanal-León, F. S., Angaspilco, H. C., J. E. M., & Bocanegra, J. C. S (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, *10*(19), e38315. https://doi.org/10.1016/J.HELIYON.2024.E38315

Ahadzadeh, A. S., Wu, S. L., Ong, F. S., & Deng, R. (2021). The mediating influence of the unified theory of acceptance and use of technology on the relationship between internal health locus of control and mobile health adoption: Uross-sectional study. *Journal of Medical Internet Research*, *23*(12), e28086. https://doi.org/10.2196/28086

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development*, *32*(5), 1306–1321. https://doi.org/10.1177/0266666915597546

Akyar, B. C., Monteiro, A., & Fernandes, P. (2024). Exploring Portuguese preschool educators' attitudes and practices on information and communication technology (ICT). *Education and Information Technologies*, *2024*, 1–22. https://doi.org/10.1007/s10639-024-12613-2

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Alotaibi, M. S. (2023). Factors influencing early childhood educators' use of digital educational aids: A sequential explanatory study. *SAGE Open*, *13*(4), 21582440231217727. https://doi.org/10.1177/21582440231217727

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall.

Barclay, D. W., Higgins, C. A., & Thompson, R. (1995). The partial least squares approach to causal modeling: Personal computer adoption and use as illustration. *Technology Studies*, *2*(2), 285–309.

Barni, D., Danioni, F., & Benevene, P. (2019). Teachers' self-efficacy: The role of personal values and motivations for teaching. *Frontiers in Psychology*, *10*, 1645. https://doi.org/10.3389/fpsyg.2019.01645

Baytar, E. M., Elyacoubi, H., Saqri, N., & Ouchaouka, L. (2023). Teachers' sense of competence in terms of ICT use: The case of secondary school teachers. *Research in Learning Technology*, *31*, 1–13. https://doi.org/10.25304/rlt.v31.2874

Beh, P. K., Ganesan, Y., Iranmanesh, M., & Foroughi, B. (2021). Using smartwatches for fitness and health monitoring: The UTAUT2 combined with threat appraisal as moderators. *Behaviour & Information Technology*, *40*(3), 282–299. https://doi.org/10.1080/0144929X.2019.1685597

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). Guilford Press.

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use chatgpt: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247. https://doi.org/10.1016/j.techfore.2024.123247

Chang, C. M., Liu, L. W., Huang, H. C., & Hsieh, H. H. (2019). Factors influencing online hotel booking: Extending UTAUT2 with age, gender, and experience as moderators. *Information*, *10*(9), 281. https://doi.org/10.3390/info10090281

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a new general self-efficacy scale. *Organizational Research Methods*, *4*(1), 62–83. https://doi.org/10.1177/109442810141004

Choudhury, A., & Shamszare, H. (2024). The impact of performance expectancy, workload, risk, and satisfaction on trust in chatgpt: Cross-sectional survey analysis. *JMIR Human Factors*, *11*, e55399. https://doi.org/10.2196/55399

Chu, T. H., Chao, C. M., Liu, H. H., & Chen, D. F. (2022). Developing an extended theory of UTAUT 2 model to explore factors influencing Taiwanese consumer adoption of intelligent elevators. *Sage Open*, *12*(4), 21582440221142209. https://doi.org/10.1177/21582440221142209

Clipa, O., Delibas, C. S., & Mâță, L. (2023). Teachers' self-efficacy and attitudes towards the use of information technology in classrooms. *Education Sciences*, *13*(10), 1001. https://doi.org/10.3390/educsci13101001

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic Press. https://doi.org/10.4324/9780203771587

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*, 719–734. https://doi.org/10.1007/s10796-017-9774-y

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fearnley, M. R., & Amora, J. T. (2020). Learning management system adoption in higher education using the extended technology acceptance model. *IAFOR Journal of Education*, *8*(2), 89–106. https://doi.org/10.22492/ije.8.2.05

Fokides, E. (2017). Pre-service teachers' intention to use MUVEs as practitioners. A structural equation modeling approach. *Journal of Information Technology Education: Research*, *16*, 47–68. https://doi.org/10.28945/3645

Fokides, E., & Kapetangiorgi, D. M. (2022). The use of computers by Greek educators. Did the COVID-19 pandemic change anything? *Journal of Information Technology Education: Research*, *21*, 217–244. https://doi.org/10.28945/4975

Fokides, E., & Klaoudatou, D. (2025). Using tablets to teach basic literacy skills to kindergarten students: A case study. *Applied Sciences*, *15*, 2252. https://doi.org/10.3390/app15052252

Gálvez, I. E., López-Martín, E., Ayuso, J. M., & López, J. M. V. (2018). Determining factors of teachers'self-efficacy in countries of the European Union. Results from TALIS 2013. *Educación xx1*, *21*(2), 225–248. https://doi.org/10.5944/educxx1.15875

García de Blanes Sebastián, M., Guede, S., J. R., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*, 993935. https://doi.org/10.3389/fpsyg.2022.993935

Ghazali, M., Makrakis, V., Kostoulas-Makrakis, N., Yakob, N., Rashid, R. A. A., Othman, W., & Fitriyanto, N. A. (2024). Predicting teacher's information and communication technology-enabled education for sustainability self-efficacy. *Sustainability*, *16*(13), 5323. https://doi.org/10.3390/su16135323

Gimpel, H., Graf, V., & Graf-Drasch, V. (2020). A comprehensive model for individuals' acceptance of smart energy technology—A meta-analysis. *Energy Policy*, *138*, 111196. https://doi.org/10.1016/j.enpol.2019.111196

Gordon, D., Bourke, T., Mills, R., & Blundell, C. N. (2024). Understanding how education reform influences pre-service teachers' teacher self-efficacy. *International Journal of Educational Research Open*, *7*, 100338. https://doi.org/10.1016/j.ijedro.2024.100338

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding university students' acceptance of chatgpt: Insights from the UTAUT2 model. *Applied Artificial Intelligence*, *38*(1), 2371168. https://doi.org/10.1080/08839514.2024.2371168

Guetz, B., & Bidmon, S. (2022). The impact of social influence on the intention to use physician rating websites: Moderated mediation analysis using a mixed methods approach. *Journal of Medical Internet Research*, *24*(11), e37505. https://doi.org/10.2196/37505

Hagger, M. S., Hamilton, K., Phipps, D. J., Protogerou, C., Zhang, C. Q., Girelli, L., Mallia, L., & Lucidi, F. (2023). Effects of habit and intention on behavior: Meta-analysis and test of key moderators. *Motivation Science*, *9*(2), 73. https://doi.org/10.1037/mot0000294

Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second Language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Herrero, Á., & San Martín, H. (2017). Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. *Computers in Human Behavior*, *71*, 209–217. https://doi.org/10.1016/j.chb.2017.02.007

Hickson, R. S. (2016). *The relationship between self-efficacy and teachers' ability to integrate technology* [Doctoral dissertation]. Liberty University. Retrieved from https://www.proquest.com/openview/e1b6fef06f05b42fe15b39fb7b780a15

Huang, T. (2023). Expanding the UTAUT2 framework to determine the drivers of mobile shopping behaviour among older adults. *PLoS ONE*, *18*(12), e0295581. https://doi.org/10.1371/journal.pone.0295581

Huang, K. Y., & Chuang, Y. R. (2017). Aggregated model of Ttf with utaut2 in an employment website context. *Journal of Data Science*, *15*(2), 187–204. https://doi.org/10.6339/JDS.201704_15(2).0001

Ikhlas, M., & Dela Rosa, E. D. (2023). Profile and predictors of high school teachers' attitude and self-efficacy in utilizing ICT: An investigation from Indonesia. *SN Social Sciences*, *3*(4), 71. https://doi.org/10.1007/s43545-023-00654-2

Kapoor, V., & Sohi, D. K. (2024). Teachers' acceptance of technology-based simulation games as teaching pedagogy in management education: An extended technology acceptance model. *Innoeduca: International Journal of Technology and Educational Innovation*, *10*(2), 93–112. https://doi.org/10.24310/ijtei.102.2024.18122

Kerckaert, S., Vanderlinde, R., & van Braak, J. (2015). The role of ICT in early childhood education: Scale development and research on ICT use and influencing factors. *European Early Childhood Education Research Journal*, *23*(2), 183–199. https://doi.org/10.1080/1350293X.2015.1016804

Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behavior in Korean companies: Applying the UTAUT model. *Behavioral Sciences*, *14*(11), 1035. https://doi.org/10.3390/bs14111035

Kittinger, L., & Law, V. (2024). A systematic review of the UTAUT and UTAUT2 among K-12 educators. *Journal of Information Technology Education: Research*, *23*, 17. https://doi.org/10.28945/5246

Kölemen, C. Ş. (2023). Self-efficacy perception of education faculty members on technology integration. *International e-Journal of Educational Studies*, *7*(14), 393–406. https://doi.org/10.31458/iejes.1258553

Lazarides, R., & Warner, L. M. (2020). Teacher self-efficacy. In *Oxford research encyclopedia of education*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190264093.013.890

Li, J. (2020). Blockchain technology adoption: Examining the fundamental drivers. In *Proceedings of the 2020 2nd international conference on management science and industrial engineering* (pp. 253–260). ACM. https://doi.org/10.1145/3396743.3396750

Lin, W., Yin, H., & Liu, Z. (2022). The roles of transformational leadership and growth mindset in teacher professional development: The mediation of teacher self-efficacy. *Sustainability*, *14*(11), 6489. https://doi.org/10.3390/su14116489

Makeleni, S., Mutongoza, B. H., Linake, M. A., & Ndu, O. G. (2023). Teacher self-efficacy and learner assessment: A perspective from literature on South African Indigenous languages in the foundation phase. *Journal of Curriculum Studies Research*, *5*(3), 44–64. https://doi.org/10.46303/jcsr.2023.30

Marikyan, D., & Papagiannidis, S. (2023). Unified theory of acceptance and use of technology: A review. In S. Papagiannidis (Ed.), *TheoryHub book*. TheoryHub.

Mehmood, N. (2019). Factors impacting EFL teachers' self-efficacy: A theoretical perspective. *English Language Teaching*, *12*(4), 39–48. https://doi.org/10.5539/elt.v12n4p39

Menno, A. W. M., Simanjuntak, Y. I. W., & Linda, D. (2024). Overcoming self-efficacy challenges in teachers and prospective teachers: Key factors and solutions. *Indonesian Journal of Educational Research and Review*, *7*(2), 285–297. https://doi.org/10.23887/ijerr.v7i2.77806

Motshegwe, M. M., & Batane, T. (2015). Factors influencing instructors' attitudes toward technology integration. *Journal of Educational Technology Development and Exchange (JETDE)*, *8*(1), 1. https://doi.org/10.18785/jetde.0801.01

Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, *12*(1), 20056. https://doi.org/10.1038/s41598-022-24532-8

Narayan, J., & Naidu, S. (2024). A new contextual and comprehensive application of the UTAUT2 model post-Covid-19 pandemic in higher education. *Higher Education Quarterly*, *78*(1), 47–77. https://doi.org/10.1111/hequ.12441

Narayanan, M., Ordynans, J. G., Wang, A., McCluskey, M. S., Elivert, N., Shields, A. L., & Ferrell, A. C. (2023). Putting the self in self-efficacy: Personal factors in the development of early teacher self-efficacy. *Education and Urban Society*, *55*(2), 175–200. https://doi.org/10.1177/00131245211062528

Neves, C., Oliveira, T., Cruz-Jesus, F., & Venkatesh, V. (2025). Extending the unified theory of acceptance and use of technology for sustainable technologies context. *International Journal of Information Management*, *80*, 102838. https://doi.org/10.1016/j.ijinfomgt.2024.102838

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: An investigation applying UTAUT2 model. *Education and Information Technologies*, *25*, 4139–4155. https://doi.org/10.1007/s10639-020-10157-9

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open*, *2*, 100041. https://doi.org/10.1016/j.caeo.2021.100041

Organisation for Economic Co-operation and Development. (2023). *Education at a glance 2023: OECD indicators*. OECD Publishing. https://doi.org/10.1787/e13bef63-en

Palas, J. U., Sorwar, G., Hoque, M. R., & Sivabalan, A. (2022). Factors influencing the elderly's adoption of mHealth: An empirical study using extended UTAUT2 model. *BMC Medical Informatics and Decision Making*, *22*(1), 191. https://doi.org/10.1186/s12911-022-01917-3

Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User acceptance of mobile apps for restaurants: An expanded and extended UTAUT-2. *Sustainability*, *11*(4), 1210. https://doi.org/10.3390/su11041210

Papadakis, S. (2018). Evaluating pre-service teachers' acceptance of mobile devices with regards to their age and gender: A case study in Greece. *International Journal of Mobile Learning and Organisation*, *12*(4), 336–352. https://doi.org/10.1504/IJMLO.2018.095130

Peng, R., Razak, R. A., & Halili, S. H. (2024). Exploring the role of attitudes, self-efficacy, and digital competence in influencing teachers' integration of ICT: A partial least squares structural equation modeling study. *Heliyon*, *10*(13), e34234. https://doi.org/10.1016/j.heliyon.2024.e34234

Perkmen, S. (2024). The role of self efficacy and school climate in motivation for technology integration in education. *Journal of Educational Technology and Online Learning*, *7*(4-ICETOL 2024 Special Issue), 358–366. https://doi.org/10.31681/jetol.1557095.

Phibbs, C. L., & Rahman, S. S. (2022). A synopsis of the impact of motivation, price, and habit on intention to use IoT-enabled technology: A correlational study. *Journal of Cybersecurity and Privacy*, *2*(3), 662–699. https://doi.org/10.3390/jcp2030034

Plohl, N., & Babič, N. Č. (2024). Using the UTAUT2 components and trust to predict consumer acceptance of smart home technology: A systematic review. *Human Technology*, *20*(1), 93–113. https://doi.org/10.14254/1795-6889.2024.20-1.5

Proedrou, A., Stankova, M., Malagkoniari, M., & Mihova, P. (2023). Self-efficacy and attitudes toward computers of general and special education teachers in Greece during the COVID-19 period. *European Journal of Educational Research*, *12*(4), 1645–1656. https://doi.org/10.12973/eu-jer.12.4.1645

Rauch, W. (1979). The decision Delphi. *Technological Forecasting and Social Change*, *15*(3), 159–169. https://doi.org/10.1016/0040-1625(79)90011-8

Rudhumbu, N. (2022). Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal*, *17*(1), 15–36. https://doi.org/10.1108/AAOUJ-08-2021-0084

Sadiq, S., Kaiwei, J., Aman, I., & Mansab, M. (2025). Examine the factors influencing the behavioral intention to use social commerce adoption and the role of AI in SC adoption. *European Research on Management and Business Economics*, *31*(1), 100268. https://doi.org/10.1016/j.iedeen.2024.100268

Schomakers, E. M., Lidynia, C., Vervier, L. S., Valdez, C., A., & Ziefle, M. (2022). Applying an extended UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps: Survey study. *JMIR mHealth and uHealth*, *10*(1), e27095. https://doi.org/10.2196/27095

Sergeeva, O. V., Zheltukhina, M. R., Shoustikova, T., Tukhvatullina, L. R., Dobrokhotov, D. A., & Kondrashev, S. V. (2025). Understanding higher education students' adoption of generative AI technologies: An empirical investigation using UTAUT2. *Contemporary Educational Technology*, *17*(2), ep571. https://doi.org/10.30935/cedtech/16039

Shukri, M. H. A., Effendi, M., & Matore, E. M. (2023). Trends and factors affecting self-efficacy among teachers: A systematic literature review. *International Journal of Academic Research in Business and Social Sciences*, *13*(2), 843–859. https://doi.org/10.6007/IJARBSS/v13-i2/16148

Söllner, M., Mishra, A. N., Becker, J. M., & Leimeister, J. M. (2024). Use IT again? Dynamic roles of habit, intention and their interaction on continued system use by individuals in utilitarian, volitional contexts. *European Journal of Information Systems*, *33*(1), 80–96. https://doi.org/10.1080/0960085X.2022.2115949

Songkram, N., & Osuwan, H. (2022). Applying the technology acceptance model to elucidate k-12 teachers' use of digital learning platforms in Thailand during the COVID-19 pandemic. *Sustainability*, *14*(10), 6027. https://doi.org/10.3390/su14106027

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2019a). Use of habit is not a habit in understanding individual technology adoption: A review of UTAUT2 based empirical studies. In *Proceedings of the smart working, living and organising: IFIP WG 8.6 international conference on transfer and diffusion of IT, TDIT 2018* (pp. 277–294). Springer. https://doi.org/10.1007/978-3-030-04315-5_19

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019b). The battle of brain vs. heart: A literature review and meta-analysis of hedonic motivation use in UTAUT2. *International Journal of Information Management*, *46*, 222–235. https://doi.org/10.1016/j.ijinfomgt.2019.01.008

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers*, *23*, 987–1005. https://doi.org/10.1007/s10796-020-10007-6

Tekin, Ö. G. (2024). Factors affecting teachers' acceptance of artificial intelligence technologies: Analyzing teacher perspectives with structural equation modeling. *Instructional Technology and Lifelong Learning*, *5*(2), 399–420.

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching chatbot. *Sage Open*, *12*(2), 21582440221096136. https://doi.org/10.1177/21582440221096136

Thommen, D., Grob, U., Lauermann, F., Klassen, R. M., & Praetorius, A. K. (2022). Different levels of context-specificity of teacher self-efficacy and their relations with teaching quality. *Frontiers in Psychology*, *13*, 857526. https://doi.org/10.3389/fpsyg.2022.857526

Tschannen-Moran, M., Hoy, A. W., & Hoy, W. K. (1998). Teacher efficacy: Its meaning and measure. *Review of Educational Research*, *68*(2), 202–248. https://doi.org/10.3102/00346543068002202

Van Raaij, E. M., & Schepers, J. J. (2008). The acceptance and use of a virtual learning environment in China. *Computers & Education*, *50*(3), 838–852. https://doi.org/10.1016/j.compedu.2006.09.001

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178. https://doi.org/10.2307/41410412

Vidal-Silva, C., Sánchez-Ortiz, A., Serrano-Malebrán, J., Arriagada, V., Flores, M., Godoy, M., & Vargas, C. (2024). Social influence, performance expectancy, and price value as determinants of telemedicine services acceptance in Chile. *Heliyon*, *10*(5), 1–15. https://doi.org/10.1016/j.heliyon.2024.e27067

Wang, Y. S., Wu, M. C., & Wang, H. Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology*, *40*(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Wang, Y., Pradubwate, R., & Sirawong, N. (2024). Factors affecting the use of ICT by teachers at Nan Yang technician college, China. *International Journal of Sociologies and Anthropologies Science Reviews*, *4*(6), 543–552. https://doi.org/10.60027/ijsasr.2024.4940

Wong, S. M., Leong, C. M., & Puah, C. H. (2020). Mobile internet adoption in Malaysian suburbs: The moderating effect of gender. *Asian Journal of Business Research*, *9*(3), 90–114. https://doi.org/10.14707/ajbr.190069

Wu, D., Zhou, C., Meng, C., & Chen, M. (2020). Identifying multilevel factors influencing ICT self-efficacy of k-12 teachers in China. In *Blended learning. Education in a smart learning environment: 13th international conference, ICBL 2020*, *Proceedings 13* (pp. 303–314). Springer. https://doi.org/10.1007/978-3-030-51968-1_25

Yang, J., & Lou, K. (2024). Exploring the nexus of self-efficacy in digital literacy and technology acceptance: Insights from L2 Chinese teachers. *Asia Pacific Journal of Education*, 1–19. https://doi.org/10.1080/02188791.2024.2336247

Yap, Y. Y., Tan, S. H., & Choon, S. W. (2022). Elderly's intention to use technologies: A systematic literature review. *Heliyon*, *8*(1), e08765. https://doi.org/10.1016/j.heliyon.2022.e08765

Yuliani, P. N., Suprapti, N. W. S., & Piartrini, P. S. (2024). The literature review on UTAUT 2: Understanding behavioral intention and use behavior of technology in the digital era. *International Journal of Social Science and Business*, *8*(2), 208–222. https://doi.org/10.23887/ijssb.v8i2.77311

Zheng, H., Han, F., Huang, Y., Wu, Y., & Wu, X. (2025). Factors influencing behavioral intention to use e-learning in higher education during the COVID-19 pandemic: A meta-analytic review based on the UTAUT2 model. *Education and Information Technologies*, *2025*, 1–39. https://doi.org/10.1007/s10639-024-13299-2

Zuiderwijk, A., Janssen, M., & Dwivedi, Y. K. (2015). Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology. *Government Information Quarterly*, *32*(4), 429–440. https://doi.org/10.1016/j.giq.2015.09.005