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# Using Rogers' diffusion of innovation theory to conceptualize the mobile-learning adoption process in teacher education in the COVID-19 era

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## Abstract

Using mobile learning (ML) has become exceedingly relevant in times of distant teaching. Although much is known about the factors affecting ML usage, less is known about the ML adoption process under constraints such as the COVID-19 pandemic. The aim of this exploratory case study was to gain insight into the ML adoption process using the lens of Rogers' Diffusion of Innovation Theory. Participants were in-service (32) and preservice (29) teachers who attended ML training. Data were collected using semi-structured interviews (20), focus groups (6), and participants' reflections (183) at three time points. Data underwent multilevel analysis (content and linguistic analysis), revealing 12 themes that denote the ML adoption process and demonstrated intergroup similarities and differences. The study provides theoretical insight into the ML adoption process under crisis and highlights the features that must be addressed to promote optimal ML adoption in teacher education in both routine and emergency conditions.

**Keywords** COVID-19 · Diffusion of innovation · Mobile learning · Distant learning · Multilevel analysis · Higher education

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"A season of loneliness and isolation is when the caterpillar gets its wings."

(Mandy Hale)

The COVID-19 pandemic has emphasized the need to prepare teachers to use technology effectively (Frei-Landau & Avidov-Ungar, 2022; Carrillo, & Flores, 2020; Lin & Johnson, 2021). Even before the pandemic erupted, the use of mobile and blended learning has grown rapidly (Tatnall & Fluck, 2022), and scholars have claimed that it is necessary to integrate technology into teacher education and to nurture teachers' techno-pedagogical skills (Voithofer & Nelson, 2021). Specifically, the importance of multiple tryouts using the technology, accompanied by opportunities to reflect on the process was advocated (Bruce & Chiu, 2015). The transition to online teaching during the Corona pandemic provided an opportunity to examine the process of adopting and implementing technology-based teaching in teacher education, particularly the use of digital mobile learning (ML), which involves the use of mobile devices within teaching and learning. Given the unique advantages of ML in remote teaching and considering the paucity of studies on the ML adoption *process* in times of crisis, the current research serves as a case study for enhancing theoretical understanding of the ML adoption process, to address this gap in the literature.

## 1 Literature review

There are numerous concepts in the teacher-education literature on online learning that encompass an array of overlapping meanings; hence, they are often used interchangeably (e.g., remote teaching, e-learning, distance education, online teaching, etc.). All of these refer to the learning process within environments that enable teaching and learning in a remote scenario (Carrillo & Flores, 2020). Some define online learning as "Education delivered through the web using online tools for learning" (Aguilera-Hermida et al., 2021), whereas Mobile Learning (ML) is one such tool, as it refers specifically to the integration of mobile computing devices into teaching and learning processes (Grant, 2019; Krouska et al., 2022). Studies have shown that ML provides a varied learning experience (Park et al., 2018), improves learning outcomes (Chen et al., 2020; Mitra & Gupta, 2020), enhances learners' motivation, learning efficacy, and learning involvement (Hatun Ataş & Delialioğlu, 2018; Ke et al., 2016). Several frameworks have been developed to provide a theoretical foundation for ML (Okai-Ugbaje, 2021). Some coined the term "Mobagogy," which represents the core function of pedagogy in implementing ML in the field of education (Schuck et al., 2013). Others offered theories of social collaborative learning (Danish & Hmelo-Silver, 2020), or self-determination theory (Yang et al., 2019) as theoretical frameworks for ML.

The use of ML has several advantages, especially during a period that requires distance learning (Eutsler, 2020). For example, the availability of smartphones in every household has the potential of reducing social gaps and inequality in learning (Ilgaz, 2021), which was a major concern during the pandemic (Frei-Landau et al., 2022; UNESCO, 2020). Likewise, the ability to adjust content and monitor learning through digital applications enables *personalized* learning (Gumbheer et al., 2022; Nedungadi & Raman, 2012) and addresses different learning styles. Given that ML is a form of ubiquitous learning (Aljawarneh, 2020), it can be used for future *situations of lockdown* and in routine times allows *learners who face a medical risk* to remain involved in learning from a distance. ML is an *active form of learning*, thus countering the concern regarding passive learning in the transition to online learning (Pimmer et al., 2021).

However, to date, aspects of ML have been examined during routine times (Lai, 2020), and less than one-third of the studies involved inservice teachers (Baran, 2014). Moreover, the majority of studies focused on examining factors that promote or inhibit the adoption of ML (Moya & Camacho, 2021), or on the attitudes and perceptions regarding the use of ML (Gikas & Grant, 2013), and the declared intention to buy or use it (Al-Rahmi et al., 2022; Buabeng-Andoh, 2021; Hao et al., 2017). Yet knowledge about the underlying *process* of adopting ML under restricted times such as the COVID-19 pandemic is insufficient (Lai, 2020). The current research explored the process of adopting and implementing ML in classroom teaching during the COVID-19 pandemic, as experienced by both inservice teachers (IST) and preservice teachers (PST), using Rogers' Diffusion of Innovation Theory (DIT) as a theoretical framework. Given that these processes are influenced first and foremost by the people experiencing them (Tatnall & Davey, 2003), we chose a qualitative approach that highlights one's subjective experiences.

### 1.1 Rogers' diffusion of innovation theory

Rogers' DIT (2003) is a well-established empirical framework (Miller, 2015) that conceptualizes the *process* of innovation diffusion, and can likewise be applied to the process of innovation adoption, specifically, to the adoption of educational technology in the field of education (Jwaifell & Gasaymeh, 2013). Most recently, DIT was applied to examine the adoption of online proctored examinations during the COVID-19 pandemic (Raman et al., 2021) and to the adoption of experiential learning via live-in-labs (Raman et al., 2020). It is worth noting that although various theoretical frameworks address innovation adoption, they all conceptualize the *factors* that affect the use or acceptance of the innovation, whereas this study's focus is on the entire *process* of innovation adoption. Thus, for instance, the Technology Acceptance Model (Venkatesh et al., 2003; TAM) describes two innovation factors (namely, perceived ease of use and perceived usefulness). The Unified Theory of Acceptance of Technology (UTAUT), which was developed by integrating theories such as the Theory of Reasoned Action (TRA), TAM, Theory of Planned Behavior (TPB), and the Diffusion of Innovation, explores additional innovation factors (Raman et al., 2021). Some of these theoretical frameworks were employed recently to examine the factors affecting the acceptance and usage of online educational tools in the context of the COVID-19 pandemic (Alshurafat et al., 2021; Wohlfart et al., 2021). However, after carefully reviewing these models, we focused on Rogers' DIT Theory, because it addresses not only the factors that affect ML adoption but also the entire process, which is described in terms of five consecutive stages. Thus, we found the DIT theory to be the most suitable framework for this study's purpose, which is to explore the *process* of ML adoption.

According to the DIT theory, the decision process for innovation adoption consists of the following five stages. (1) The Knowledge Stage involves gaining cognitive knowledge, during which the learner is exposed to the innovation, becomes aware of it (*awareness knowledge*), and seeks information about ways to use it efficiently (*how-to knowledge*). To increase the likelihood that individuals will adopt the innovation, they must have a sufficient level of *how-to knowledge* before attempting to use the innovation independently. (2) The Persuasion Stage is emotion-focused, as it is at this phase that attitudes about the innovation are formed. At this stage, the learner experiences uncertainty and, consequently, may be influenced by social encouragement to use the innovative tool, as well as by peer-group members' favorable subjective assessments of the instrument. (3) The Decision Stage is when the individual decides whether to adopt or reject the use of the innovation, whereby the likelihood of choosing to adopt it increases with the number of prior opportunities to try it out. Ultimately, the decision is affected by three types of motives: personal desire, peer pressure, and/or pressure from an authority figure. During the pandemic, the decision to adopt technology was derived from the unique social situation and was often dictated by authority figures (the school principal, the Ministry of Education); hence, it is interesting to examine how each aspect affected the adoption process. (4) The Implementation Stage is when the individual uses the innovation and examines the outcomes. Consequently, at this stage, it is essential that users receive feedback, as well as assistance and support, from those leading the transition, as this will help decrease uncertainty among the new users. Another facilitating element at this stage is "reinvention," whereby the users adapt and change the instrument according to their needs. The greater the number of adaptations introduced, the greater too is the likelihood that the tool will be used consistently. Given that ML inherently uses numerous apps, there are multiple ways to make adaptations, which makes it an optimal platform. (5) In the Confirmation Stage, the users reflectively examine the process and its outcomes, seeking confirmation for their decision as they consolidate their final attitudes.

The decision to adopt technology in general and that of ML, in particular, has been examined in previous studies using Rogers' theoretical framework (Sahin, 2006) and, recently, a questionnaire was developed based on this theory, to examine the adaptation of ML in the field of education (Celik et al., 2014). Nevertheless, as mentioned, only a few studies examined the adoption and implementation process among PSTs and ISTs in schools (Bano et al., 2018), and even fewer examined the *process* of adopting ML in times of crisis that involve the transition to distance learning. The comparison between PSTs' and ISTs' perceptions regarding ML adoption is especially important, given that previous studies have demonstrated that teachers and students are influenced by different factors when adopting technology (Mac Callum et al., 2014). More recently, a few studies have argued that conducting a comparative analysis of the views of teachers vs. students engaged in adopting innovative technology is imperative (Dolenc et al., 2021; Kovacs et al., 2021; Šorgo et al., 2021). Thus, for example, a study that examined educators' and students' views regarding the online education imposed during the COVID-19 pandemic found that while some views were shared by the two groups, in other respects, they differed substantially, thus underscoring the need to explore both perspectives to fully understand the issue. Specifically, students' views were usually related to the learning process (e.g., concentration), while educators focused mainly on organizational aspects and study materials (e.g., copyright). Another recent study showed that teachers scored higher than their students on measures of personal innovativeness in the context of adopting information technology. This kind of difference could lead to conflicting expectations between teachers and learners (Šorgo et al., 2021). Another recent comparative study explored the similarities and differences between teachers' and learners' perceptions at three different educational levels (Kovacs et al., 2021).

The examination of the ML adoption process is of particular interest given the advantages of ML and the need to enhance our theoretical understanding of the characteristics of this process in times of crisis. Gaining a better understanding of the adoption process can help improve the design of teacher education programs, to promote the effective use of ML in teaching, for both routine and emergency conditions. Specifically, gaining insight into the ML adoption process will help design better instructional approaches in the classroom, improve students' learning experience, as well as enhance teachers' ability to use mobile educational technology effectively when teaching. Additionally, understanding the ML adoption process may help online learning instructors and developers integrate ML into future hybrid or online programs (Aguilera-Hermida et al., 2021). Innovative use of digital technology, including mobile game-based learning, was mentioned by scholars as a leading principle for addressing many of the problems of modern civilization (Šorgo et al., 2021) and as a particularly relevant solution to the challenges posed by the COVID-19 pandemic (Abdel-Hameed et al., 2021; Krouska et al., 2022).

### 1.2 The research questions

1. In what ways are Diffusion of Innovation stages manifested in the process of ML adoption in the context of transition to distance learning during the COVID-19 pandemic?
2. What are the similarities and differences between inservice and preservice teachers' experiences during this ML adoption process?

## 2 Method

### 2.1 The study context

#### 2.1.1 The ML training

The ML training program is a short-term program that was constructed according to the principles of Rogers' theory (see Fig. 1), in an academic college for teacher education as part of a reform of innovation and entrepreneurship in The School of

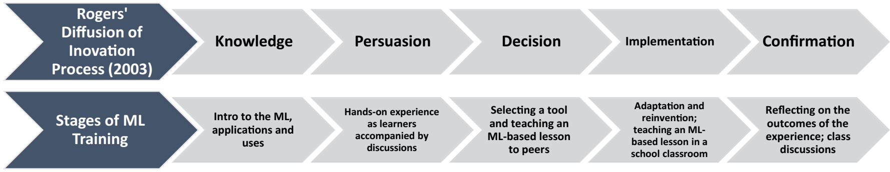


**Fig. 1** The Mobile-Learning training phases in light of Rogers' Diffusion of Innovation Theory

Education. During the ML training, the participants were introduced to five ML tools (see Appendix 1). As shown in Fig. 1, at first, the participants were introduced to the tools and used them as learners. Then they selected one of the tools and used it as teachers in an academic class (i.e., with their peers). Finally, they used this tool as school teachers, implementing it in an ML-based lesson plan. Each of these phases was accompanied by individual and group reflective processes.

### 2.2 The study design

Exploring experiences from the participants' viewpoints calls for qualitative inquiry. Specifically, an exploratory case study design was selected (Yin, 2014), as it allows for an in-depth investigation of the phenomenon using multiple data sources.

#### 2.2.1 Participants and data collection

Participants were 32 ISTs (out of 45 enrolled) in a Master's degree program, who agreed to partake in the study, and 29 PSTs (out of 41 enrolled) in a Bachelor's degree program, who agreed to participate. The rationale for selecting participants from these two groups is grounded in the professional literature, according to which age and teaching experience are factors related to readiness to incorporate ML (Mac Callum et al, 2014). The demographic characteristics of the study participants are presented in Tables 1 and 2.

Data were collected using multiple data sources throughout the program, to provide a deep understanding of the phenomenon (Bogdan & Biklen, 1998/2007), achieve trustworthiness, and enable cross-validity checks. The following modalities were used.

*Participants' reflections* were collected at three time points throughout the training. Participants were asked to elaborate freely on their learning experiences, share their feelings and thoughts, address issues they found relevant, and describe their experience of the process at that point. Overall, 183 reflections were analyzed, 96 were written by ISTs and 87 by PSTs.

Six *focus groups* were held, three of them after participants implemented the ML tool in a lesson taught to their peers and three after implementing it in a school classroom. In each focus group, the participants were requested to discuss their experiences and respond to each other's comments. The focus groups, which included 12–15 participants in each, were conducted and recorded using the ZOOM platform.

**Table 1** Inservice teachers' demographic characteristics

| Background variables | | Frequency in percentages ($N = 32$) |
|---|---|---|
| Gender | | |
| | Male | 3% |
| | Female | 97% |
| Age | | |
| | 21–30 | 9% |
| | 31–40 | 38% |
| | 41–50 | 53% |
| Years of teaching experience | | |
| | 1–5 | 6% |
| | 6–10 | 22% |
| | 11–15 | 34% |
| | 16–20 | 25% |
| | > 20 | 13% |
| Family status | | |
| | Single | 13% |
| | Married | 65% |
| | Divorced | 22% |
| Type of teacher | | |
| | Kindergarten | 28% |
| | Elementary school | 56% |
| | Middle school | 6% |
| | High school | 10% |

**Table 2** Preservice teachers' demographic characteristics

| Background variables | | Frequency in percentages ($N = 29$) |
|---|---|---|
| Gender | Male | 0 |
| | Female | 100% |
| Age | 20–22 | 19% |
| | 23–24 | 48% |
| | 25–29 | 33% |
| Year of studies | | |
| | Second year | 90% |
| | Third year | 10% |
| Family status | | |
| | Single | 86% |
| | Married | 14% |
| Practicum framework | | |
| | Elementary school | 85% |
| | Middle school | 15% |

Each group session lasted 45 min. The recordings were then transcribed by a human professional transcriber and coded as FG1-FG6.

*Semistructured interviews* were held with 20 participants (10 ISTs and 10 PSTs) on the ZOOM platform and lasted 25–50 min. All interviews were conducted by the same research assistant, a certified coach and group instructor, who additionally received professional training on conducting qualitative interviews for the purpose of this study. Participants were requested to provide a metaphor that described their learning experiences and then to describe the overall process. Interviews were videotaped, transcribed, and coded as follows: INW1–INW10 were the interviews conducted with ISTs, and INW11–INW20 were those conducted with PSTs. Figure 2 summarizes the time points of data collection throughout the process.

### 2.2.2 Procedure and ethics

The study was approved by the Ethics Committee of the higher education institute. The participants gave their informed consent and were informed that they could leave at will. All personal information was concealed, and WORD files were kept in a password-protected folder to ensure participants' anonymity. Additionally, focus groups and interviews were held by a trained research assistant, so participants would not feel pressured to participate.

### 2.2.3 Data analysis

Multilevel analysis (Muchnik-Rozanov & Tsybulsky, 2019) involved qualitative content analysis (conducted by the first and third author using ATLAS.ti software) and linguistic analysis (conducted by the second author using AntConc software). Trustworthiness was ensured by the triangulation of multiple research instruments (i.e., interviews, focus groups, and reflections), multilevel analysis, as well as the authors' recurrent brainstorming sessions. In cases of disagreement, the issue was pursued until full agreement was reached. Furthermore, member checks were conducted to

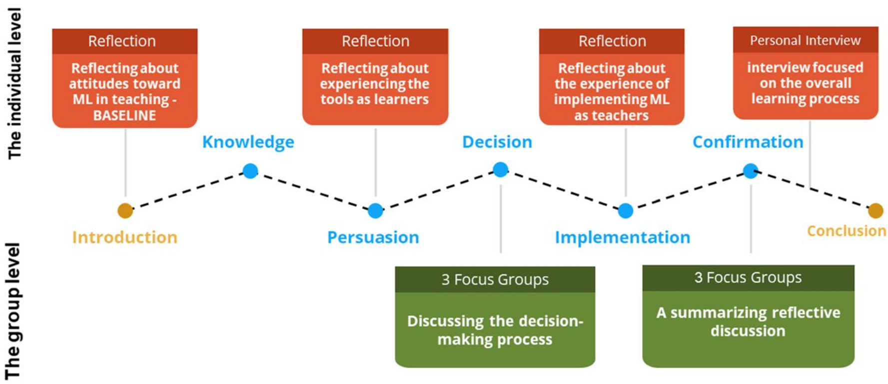


**Fig. 2** Data-collection points throughout the ML training

further enhance trustworthiness (Kornbluh, 2015). This method is frequently used in qualitative inquiry to enhance trustworthiness (Frei-Landau et al., 2020c).

### 2.2.4 Content analysis

The data obtained from the reflections, interviews, and focus groups were analyzed through both deductive and inductive content analysis (Fereday & Muir-Cochrane, 2008), using ATLAS.ti 9 software (Muhr, 1991, 2004), which is suitable for qualitative analysis in education (Smit, 2002). The analysis was conducted by the first and third authors, in a two-step, thematic analysis procedure: first, we performed a deductive analysis, using the DIT as an interpretative lens, to capture participants' perceived innovation-adoption process, while we remained open to additional aspects not mentioned in Rogers' theory. Specifically, we searched for phrases and discourse segments that characterized the participants' accounts of their learning process, with a focus on descriptions of learning corresponding to Rogers' five stages theory. In the second step, we employed an open inductive thematic analysis. During this analytic phase, data segments that were identified in the previous round as reflecting Rogers' DIT phases were analyzed, as we searched for salient themes emerging from the texts. Then, the data were read to identify meaningful units, which was followed by open coding. During this process, we carefully read and reread the data, to further identify and consolidate relevant themes, which were later conceptualized. Next, the list of codes was reviewed, and similar or related codes were grouped together. Finally, the main themes representing each code were conceptualized and textual examples were found for each of them. This microanalysis was conducted to ensure that no important ideas or themes had been overlooked. Throughout the process, each step was conducted collaboratively by the two researchers (first and third authors) followed by recurrent brainstorming sessions to enhance trustworthiness. In cases of disagreement, the issue was pursued until full agreement was reached. This process yielded 12 main themes. Eventually, we were able to organize the emergent themes that represented participants' ML adoption process along Rogers' DIT.

### 2.2.5 Linguistic analysis

Participants' verbal expressions from the 20 interview transcripts were examined by the second author using Laurence Anthony's software AntConc (Anthony, 2013). Overall, 66,070 words were analyzed. The linguistic analysis was focused on discursive self-positioning analysis. Self-positioning is defined as an identification act (Kupferberg & Gilat, 2012; Wortham, 2004). Discursive self-positioning refers to features related to the identity of the speaker throughout the discourse of interaction. Analyzing the discursive self-positioning of the ISTs and PSTs was intended to enhance our understanding of the way they present and perceive themselves throughout the process of ML adoption. Situations of discursive self-positioning were identified through the speakers' use of first-person pronouns (I). Next, the number of segments that represent self-positioning was calculated and they were analyzed using a qualitative approach. Finally, we examined the instances of linguistic self-positioning as expressed among the ISTs and compared them to those expressed by the PSTs. The comparative analysis was conducted separately by the second author before the findings of the content analysis became available so that the comparison findings could serve to validate the content-analysis findings.

# 3 Findings

The multilevel analysis suggests that the ML adoption process in the context of the COVID-19 era involved a process that comprises Roger's DIT aspects. This finding was supported by both the linguistic and the content analysis. The analysis revealed 12 themes that denote the characteristics of the process of adopting ML during the COVID-19 pandemic along Rogers' DIT stages. Seven of these themes were shared by both groups (PSTs and ISTs), whereas five of the themes were uniquely manifested in each group. Figure 3 presents a model of the study's findings that highlights the similarities and differences between the PSTs and the ISTs. In the following sections, the main themes are explained in detail, using quotations from the participants' data (all names used in the findings section are pseudonyms).

## 3.1 Stage 1: Knowledge

Rogers' first stage involves knowledge acquisition and awareness of the innovation, which is likely to engage the learner in the process. The analysis demonstrated that the exposure to the ML applications served as an initial essential stage in the process: "A major thing was the initial exposure in the classroom and being introduced to the various software programs and digital tools" (Rose, FG5). For the ISTs, this stage included, first and foremost, discovering the existence of the various tools,

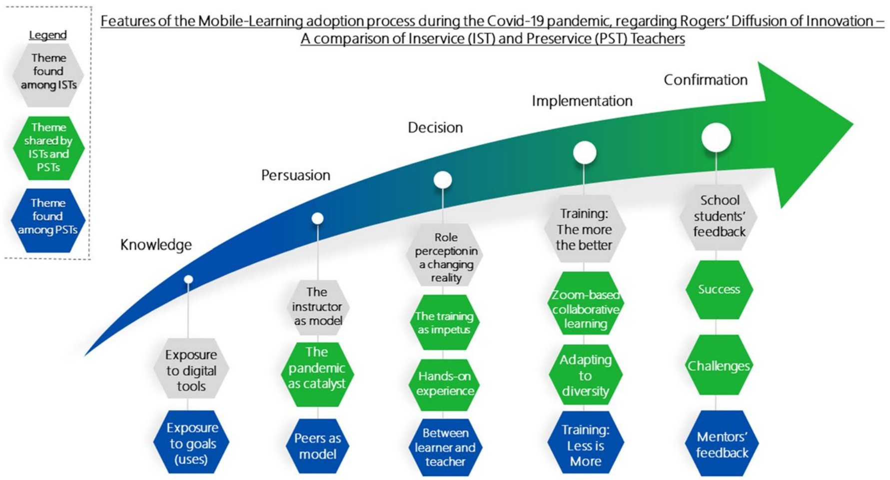


**Fig. 3** Features of the Mobile-Learning adoption process during the Covid-19 pandemic, regarding Rogers' diffusion of innovation-A comparison of Inservice (IST) and Preservice (PST) teachers

which Rogers referred to as "awareness knowledge." By contrast, for the PSTs, who were familiar with these tools (most likely because of their younger age), the discovery involved the understanding that these can be used for diverse pedagogical functions, rather than for entertainment alone.

> At first, I thought that using technology was intended to make the lesson entertaining, giving students time to play… That's what I was familiar with. But then I saw that students' assessments could be documented and analyzed. (Leah, INW11).

Rogers described this as "how-to knowledge," i.e., knowing how to use innovations effectively. Given that how-to knowledge is critical for the adoption of innovative technologies in complex situations (Sahin, 2006), and considering that the pandemic created a complex situation, it appears that the PSTs were more advanced than the ISTs. However, when referring to their exposure to the new tools, both groups mentioned their need for guidance on how to identify the most appropriate tool, so as not to feel overwhelmed by the multiple possibilities.

> The number of digital tools is endless, and while you want to learn more and more, it can also be overwhelming, so that you're not sure what you actually should choose… So, that is something that needs to be addressed, i.e., how to filter my choices, by learning what--from the plethora of options-- is appropriate for use in my area of expertise (Shira, INW9).

Shira highlights that it is not enough to expose trainees to the instruments, but rather, they need guidance on how to select an appropriate tool for use in their discipline.

### 3.2 Stage 2: Persuasion

Rogers' second stage deals with the factors related to persuading the learners to adopt the innovation. It should be noted that ISTs and PSTs alike commented that prior to reaching a decision independently, their initial attitude about using technology was a complex one. Some noted their lack of technological tendencies: "It took a while before I was convinced; I'm not attracted to technologies; rather, I try to avoid them" (Rose, INW6). Others described themselves as technophobes: "I'm quite afraid of technology… I'm always afraid I won't be able to manage" (Tal, INW13). Only a few participants did not express anxiety about using technology: "I was very soon persuaded that this is worthwhile… Maybe because I feel connected to technology" (Sharon, INW8).

What, then, were the factors in the persuasion stage that convinced the participants to get involved in the process despite their complicated feelings about technology? The analysis revealed two themes at this stage: one was shared by ISTs and PSTs, namely, the pandemic as a catalyst for innovation adoption. The second theme involved modeling but was manifested differently in each group: the instructor as a model among ISTs, and the peers as models among PSTs.

### 3.2.1 The pandemic as a catalyst

Both the ISTs and the PSTs mentioned the Corona pandemic as a significant stimulus that convinced them to get involved in the learning. Yafit, a PST, described it thus: “It’s like you have no choice at this time [the COVID-19 period]; you have to engage with the technology; you have to learn and get to know it.” (FG4). The pandemic served as a stimulus for a change in perception of technology:

> Our world is constantly edging in that direction, and what better proof than the pandemic? … teachers find change difficult and there are always objections. But in the end, despite our resistance, we discovered how it works. And mind you, I am not a big fan of ICT, but still, I realized it can be learned (Shira, IST, FG6).

According to Shira, the pandemic changed her attitude about the necessity of technology and about her ability to learn to use it.

### 3.2.2 Learning from a model: The instructor as a model versus the peers as model

All participants referred to the element of learning through modeling, which helped persuade them to adopt the technology. While the ISTs viewed the instructor as their model for ML-based teaching, the PSTs referred to the peer group. Thus, for example, in FG2, Dena, an IST, said: "The instructor’s approach is innovative… She adapted quickly to the new situation… she serves as a true model." Sharon reacted to Dena’s words, adding: "I really have to give her credit –she is always looking for ways to adapt the contents or adapt herself… So now I want to give it a try too". Thus, it appears that the participants identified the instructor as a model of flexibility and adaptation to changes which, to them was a persuasive factor that led them to adopt innovation by teaching with ML. By contrast, for the PSTs, it was the peer group that persuaded them to adopt ML, specifically, witnessing a peer who applied ML to teaching in a successful and effective manner:

> I thought, “What do I need technology for?!”… But then I saw my friend. she demonstrated the things she did in class with her students, and I realized I also want to be such a teacher, I also want to be current, influential, interesting… And then I realized I too want to use it (Leah, INW11).
> At first… I lacked confidence… I didn’t even try. And then I saw in class that a friend of mine was using it and I said to myself, “Maybe it’s not all that scary? Maybe I will try it?” (Yael, INW16).

It appears that the PSTs’ initial avoidance of ML was accompanied by a tendency to discount its value, perhaps masking their fear of it. However, viewing their peers in class use technology successfully was a convincing element that led the participants to get involved in the process. Indeed, according to Rogers, in the persuasion stage, the learners are uncertain about their attitudes towards the innovation, yet these are likely to change upon receiving social reinforcement, or upon witnessing their colleagues give positive assessments about the innovation. This study demonstrates that peer modeling is of crucial importance for the PSTs, compared to the ISTs, although the latter did mention the importance of learning from peers in the context of collaborative learning in the implementation stage, rather than in the context of learning from a model in the persuasion stage.

### 3.3 Stage 3: Reaching a decision

The analysis revealed three themes that relate to the decision whether to adopt ML. Two of these, namely, the training program as impetus, and the impact of hands-on experience, were shared by the two groups, whereas the third theme, which referred to the perceived role of the teacher, was expressed differently by each group (the ISTs perceived the role as adaptive, whereas the PSTs' perception was still unformulated).

#### 3.3.1 The training program as impetus

In both groups, it was noted that despite the change in attitude related to the coronavirus pandemic, they would not have decided to integrate new technologies in their teaching had they not enrolled in this training program.

> To be honest, I had a phobia of technology, and this pandemic created very difficult challenges for me. So, I let my colleagues prepare things for me. I avoided it at all costs. But in this program… I had to dive in, headfirst. So of course, in the beginning, we worked in groups, and I let my colleagues take charge, until we were each assigned to work in our separate classrooms, and [giggles], I had to try it.… Truth be told? I was very surprised. The software we were taught suited my class … And I understood that it isn't all that terrible. (Sarah, INW2)

As Sarah stated, despite the reliance on technology during the pandemic, she found workarounds so she wouldn't have to learn to use it. Even at the beginning of the training, she refused to leave her comfort zone. Only at a later stage, when there was no other option, did she decide to try her hand at technology, at which point she had to "jump in, headfirst." Hence, it appears that imposing this learning framework provided the final impetus for the teachers to cope with their fears and aversion to technology. Nevertheless, participants described the need for autonomy, for example in choosing the instrument or the topic. This autonomy was described as promoting the decision to get involved.

> My decision to use this was first of all related to the freedom to choose the topic. Choosing something that I felt strongly about and that corresponds to my interests out of the variety of options … I believe that I would have been much less motivated if I had to tackle one particular topic or use a specific instrument. (Nina, INW4)

Thus, it appears that the participants' decision to adopt the use of technology required a balance between necessity and autonomy, whereby the latter was created by providing a context in which one can choose from a limited selection. Rogers claimed that the decision to adopt an innovation may be related to three motives: a personal desire, peer pressure, and pressure from an authority figure. In fact, during the pandemic, the decision to adopt technology resulted from a given social situation (Reimers et al., 2020) that functioned as a type of peer pressure and from pressure exerted by authority figures (e.g., the school principal and the Ministry of Education). However, the findings underscore that even under these circumstances, there is a need to include personal choice, which corresponds to Roger's motive of personal desire.

### 3.3.2 The impact of direct experience

The hands-on experience of using ML was described as an element that significantly advanced the decision to adopt technology and especially when the experience was a positive one. Lee described it thus: "I was very much opposed… But after I experienced it, I simply realized how easy it really is… It turned out to be more successful than I expected. So I said to myself, 'Okay, I'll do this again'." (INW17). Indeed, Rogers claimed that the likelihood of adopting an innovation increases if there are opportunities for hands-on experience with it. It should be noted that in the current study, the participants emphasized the importance of gaining hands-on experience in an environment where they could receive support when needed. For example, Rebecca responded to the question about what influenced her decision: "I think that the fact that the instructor let us experience it hands-on, here, and now, while she accompanied us– so that if needed, she was there to answer questions" (INW19). The hands-on experience was described as advancing participants' understanding of the advantage of using this tool: "Once you try it, there's no turning back. You can see the advantages, so there's no point in being opposed" (Sarah, FG2). Additionally, the experience was described as strengthening participants' sense of self-efficacy:

> It's all about the hands-on experience. As soon as you experience it… Despite all your fears – I am a technophobe, and I was worried, but then it went smoothly. So, this experience is something that ultimately leads to belief in myself, discovering that despite all my anxieties, it is doable (Daniela, INW3).

Thus, our findings demonstrate that experiencing the ML, especially when the experience is successful, addresses the initial anxieties and has a crucial role in the decision-making process.

### 3.3.3 Perception of the teacher's role – adaptive versus unformulated

Another relevant aspect of participants' decision to adopt ML was related to their perception of their role as teachers. The IST group spontaneously noted the significance of the change in their professional role perception, which occurred vis-à-vis the pandemic, and its contribution to their decision to adopt the use of technology.

Thus, for example, they realized that they must “advance with the times” and accept the new developments:

> I think that educators must march with the times and progress; we can’t stay behind in the traditional and familiar realm… So, yes, that is also part of the role of the teacher, to educate for progress and stay in tune with the changes that take place in our world (Sarah, INW2).

In addition, ISTs described realizing that the role of the teacher also involves communicating with students through technology, which became a consideration in their decision to adopt the technology.

> Listen, we live in an entirely digital world -- it can’t be avoided; children are constantly exposed to screens, and this is even more true now, during the pandemic. So, I decided that if I, as a teacher, can engage students by using websites and online content, then I stand to gain, as my students are likely to be more motivated to learn. (Shira, INW9)

Thus, whereas it is evident that the ISTs were considering their perceived role as part of the process of deciding whether to adopt ML, by contrast, among the PSTs, it was clear that their perception of the teacher’s role in adopting technology was insufficiently formulated. They were ambivalent and, along with their understanding of the importance of integrating technology as teachers, they noted the need for support from their supervisors: “Yes, it’s mostly up to me to adopt the technology, but I do need the support of those above me in rank” (Yafit, INW14). Interestingly, the PSTs tended to consider the situation from a point of view situated between learners and teachers. Thus, for example, in describing their decision to adopt the technology, they first referred to their personal experience with technology as high school students.

> Not too long ago, I too was a student and, in fact, the lessons I remember most were those that integrated the use of technology. So, I realize how important it is… I’m a very visual person: the teacher can talk for hours and then show a clip that summarizes it all and I suddenly understand it much better. So my decision to use these applications we learned is very much related to understanding how much technology contributed to my own learning experience. (Tal, INW13)

Interestingly, soon after the PSTs described the influence of their own experience as learners on their decision to adopt technology, they concluded the description by reverting to the teacher’s perspective:

> I remember myself as a pupil enjoying each time there was something that did not involve the blackboard or the notebook. I realized it is important to use it [ML]. And it’s much more fun – ultimately the teacher enjoys it more too. (Yafit, INW14)

Yafit began by describing her experiences as a student and ended by describing the experiences of the teacher. This duality suggests that she views herself between these two positions—between learner and teacher, which influences her decision to adopt the ML. It appears that her past learning experiences and an earlier encounter with technology in the classroom affected her decision to adopt it. Hence, referring back to childhood experiences, especially for the PSTs, should be further explored and employed as a useful strategy that encourages the decision to adopt ML.

### 3.4 Stage 4: Implementation

According to Rogers, at this stage, the individual applies the use of the innovation to consider its outcomes. Our analysis revealed three themes denoting the experience of applying the ML, two of which were shared by the ISTs and the PSTs (specifically, collaborative learning via the ZOOM platform and making adaptations), whereas the third theme, which dealt with the training needs, was manifested differently by each group (namely, "the more the better," for the ISTs, and "less is more," for the PSTs).

#### 3.4.1 Collaborative learning via the ZOOM platform

When participants described the application of ML in the school classroom, they reiterated and emphasized the importance of first implementing it in small groups in the college classroom, which allowed them to apply it optimally: "What helped me personally was that … She let us work in pairs or triads and I found that gave me a sense of confidence; I had someone to consult with and that facilitated the overall process" (Rose, FG 6). Furthermore, participants noted the advantage of being able to apply communal or group learning on the ZOOM platform, by breaking out into rooms, and especially when they were able to select a teammate: "Practicing in the breakout rooms was helpful and I particularly appreciated being allowed to choose my group members" (Rina, INW20). Interestingly, again—the need for autonomous choice (in selecting teammates) is desired alongside the need for group collaboration.

#### 3.4.2 Making adaptations

An important aspect of the implementation stage was the ability to make adjustments, which included adjusting the use of the ML to the learner's style, to the teaching methodology, and/or to the content area.

> At first, what guided me was whatever was easiest… Then I started thinking about what worked for me, for my students, for their needs… and it was successful! I told them we would do more of this later on. (Nina, INW4)

As seen, Nina begins with a desire to choose whatever was easiest for her, but then she made adjustments to her particular learning population, which turned out as a success. This reinforced her to continue using the ML. One of the participants described making adaptations to the tool to create a variety of tasks on different levels, tailored to the different learners in her classroom, which is known as personalized teaching (Nedungadi & Raman, 2012):

> The activity is adjusted according to levels, that is, some of the activities would not work for lower-level students, while other tasks would be tailored to higher-level students. So, I can "play" with these adjustments for individual students' needs (Ben, INW1).

All in all, making adjustments increases the successful implementation and the desire to continue using the innovation in the future. Indeed, Rogers referred to this as "reinvention," i.e., adapting the innovative tool to the user's needs, and noted that the more adjustments are made, the greater the chance that the innovation will be adopted permanently.

#### 3.4.3 Training needs: The more the better vs. less is more

According to Rogers, the uncertainty during the implementation stage can be unnerving and, therefore, receiving assistance from agents of change is mandatory at this stage. The analysis demonstrated that when participants described the implementation stage, the aspect of the training was underscored. "Training is absolutely necessary… I don't think we were ever offered a program like this, which was truly needed" (Daniela, INW3). Daniela's comment represents the voice of many of the ISTs, who noted the absence of sufficient training in the use of technology. According to their perception, it was important that the training should include active implementation, without which the exposure to numerous digital tools would be useless:

> Last year, when it [the pandemic] just began, we addressed the principal and noted that we feel ill-prepared and need to learn to use technology. Throughout the years we had a few professional development training sessions that presented all kinds of software programs… I can't tell you that I learned much from that –I don't remember anything, because we didn't have the chance to implement and use it. (Rachel, INW7)

Unlike the ISTs, the PSTs were overwhelmed by the number of tools simultaneously taught to them in college and felt that there was too much repetition:

> This year's program includes so many courses about technology… At first, I thought this program was much like another one that we already had, and I wondered why we needed it…When we spoke [about this] with the instructor, she made changes and added things… But repetition should be avoided. (Debbie, PST, interview 15)

In terms of the training, the ISTs felt that the more exposure they would get, the better they would do, whereas the PSTs perceived a need to limit and coordinate the technology courses and their contents and, hence, less is more. These findings highlight the need to design different training programs according to the learning experience of the trainees.

### 3.5 Stage 5: Confirmation

In the fifth and last stage in Rogers' theory, the individuals reflect on the process and its outcomes and seek support for their decision to formulate their attitudes. Our analysis revealed three themes that denote the ML confirmation stage, two of which were shared by both groups (success factors and challenges), and one was manifested differently by each group (school students' feedback among ISTs and authority figures' feedback among the PSTs).

#### 3.5.1 Experiencing success

A major aspect that concerned both ISTs and PSTs at this stage of confirmation was success versus failure.

> So yes, eventually I could see the excitement all around and that made me want to do more. My friend and I--separately from the group--initiated more activities on another topic without being asked by the instructor. We just did it. (Daniela, INW3)

The experience of success at the summarizing stage encouraged further adoption of the ML. Daniela mentioned an additional activity that she created although it was not a required assignment. That is, this process began with impetus from an outside source (external motivation) and following a successful experience, it ended with further use of the ML derived from an internal motivation. This internalization reflects the confirmation stage in the ML adoption process.

#### 3.5.2 Challenges

Alongside reflecting on success, PSTs and ISTs alike mentioned difficulties, whereby the most significant ones were related to the availability and quality of the technological equipment.

> I work at a school where I have to connect the cables and bring the projector and it is a nightmare, so I gave up in advance… So, you can talk all you want about content websites or digital books but there is little we can do about it, unfortunately. (REF67)

Sometimes the difficulty was related to the lack of time-related resources needed to prepare the lesson and conform to the many demands of the system, especially given the number of students per class, and the frequent changes to the curriculum.

> We don't have a lot of time, to put it mildly. So even though I want to introduce the use of digital tools, it takes up so much time… And I also have to prepare for different levels… And the textbooks are changed about every three years, so even once I have prepared materials, they constantly must be changed,

> and it becomes an enormous task that takes up a lot of time and is not being rewarded. (Dena, INW10)

Dena's description makes the sense of burden palpable and her frustration is evident. These challenges should be attended to by policymakers to prevent a situation of avoiding the adoption of ML due to such technical barriers.

#### 3.5.3 Responsive feedback – from the school students or the training mentor

Both the ISTs and PSTs described responsive feedback as an important factor that summarizes their experience. Nonetheless, whereas the ISTs referred to school students' feedback as a criterion that influences their overall experience and their decision whether to continue using ML, the PSTs referred to the authority figures' feedback.

> You see the students' excitement and you can see it really touches others. For example, a student who up until this point was not particularly interested suddenly became absorbed… So, I'm definitely going to integrate this into my teaching (Rose, IST, INW6)

Although the PSTs also mentioned students' feedback as an element that motivates them to continue using ML, they attributed a great deal of importance to feedback from the authority figure, namely, the training teacher or the pedagogical mentor. "The training teacher was extremely enthusiastic, and she wanted me to teach her… she wanted me to keep on using it" (REF132). Feedback from the pedagogical mentor was also mentioned: "My pedagogical mentor started to consult with me about technology… So, I think gaining her attention was also motivating" (REF 78). However, some of the training teachers felt threatened by the PSTs' familiarity with technology, which led to negative responses and caused frustration: "The teacher commented that my lessons are full of pyrotechnics, that is, there are too many computer-related activities. But why not? What's wrong with that?" (REF 154). Thus, it appears that an authority figure's feedback is uniquely significant for PSTs. Overall, at the end of the process, both the PSTs and the ISTs were engaged in assessing their experience, using outside feedback to formulate their final attitude regarding ML-based teaching.

### 3.6 Findings of the linguistic analysis – self-positioning in the two groups following the ML training

The linguistic analysis, which was conducted separately, revealed a picture similar to that found through the content analysis, thus validating the findings of the latter. As reported, the content analysis identified 12 themes that correspond to the five stages of Rogers' theory, seven of which were shared by the two groups, while five others were expressed differently by each. The linguistic analysis revealed a similar pattern in terms of the similarities and differences between the two groups. Findings of the linguistic analysis are reported in Table 3.

**Table 3** Findings of the linguistic analysis – self positioning in the two groups following the ML training

| Theme No | Verbalized meaning | ISTs | PSTs |
|---|---|---|---|
| 1 | Acknowledging the importance of trying out the digital tools | 174 (15%) | 89 (13.5%) |
| 2 | Concerns and negativity regarding the use of the digital tools | 122 (11%) | 68 (10%) |
| 3 | The impact of COVID-19 on teaching | 86 (8%) | 56 (8.5%) |
| 4 | "Who am I as an educator?" | 103 (9%) | 31 (5%) |
| 5 | Effects of the program on familiarity with technology | 109 (9.6%) | 67 (10%) |
| 6 | Dissatisfaction with the program (time slot, technology, workload) | 30 (2.5%) | 39 (6%) |
| 7 | Program outcomes and training necessity for the digitalization of teaching | 304 (27%) | 105 (16%) |
| 8 | Need for exposure to digital tools | 27 (2.4%) | 44 (7%) |
| 9 | Challenges faced while implementing the digital tools | 85 (7.3%) | 46 (7%) |
| 10 | Adaptations to digital tools for use in special education | 25 (2%) | 63 (10%) |
| 11 | Acknowledging group support in the process of learning | 25 (2.2%) | 22 (3%) |
| 12 | Feeling motivated following successful engagement with the digitalization | 35 (3%) | 7 (1%) |
| 13 | Feeling discouraged due to lack of support from schools and pedagogical mentors | – | 20 (3%) |
| Total | Total instances of self-positioning (N) | 1,136 | 657 |
| Total | Uses of "I" as a linguistic self-positioning resource | 1,295 | 742 |
| Total | Total words analysed | 35,925 | 30,145 |

An examination of Table 3 reveals that the linguistic analysis identified 13 categories related to the self-positioning of the participants by the end of the program. As in the content analysis results, in the linguistic analysis too, no frequency differences were found between the two groups regarding recognition of the effect of the pandemic (theme 3), the effect of the training program (theme 5), the importance of the hands-on experience (theme 1), the collaborative learning (theme 11), the experience of success (theme 12), and the challenges encountered (theme 9). However, the linguistic analysis did find differences between the groups in terms of the adaptations made (theme 10), such that the PSTs were more concerned with making adjustments for students with special needs, as compared to the ISTs. This difference was not identified in the content analysis. Furthermore, the linguistic analysis found a similar level of initial concerns about using the ML tool in both groups (theme 2) as was found in the content analysis and which was reported in relation to the persuasion stage (relating to concerns prior to persuasion).

In addition, the linguistic analysis found a difference between the two groups concerning four of the dimensions of self-positioning: role perception (theme 4), training needs (themes 6 and 7), the need for exposure to technology (theme 8), and the effect of feedback from the training instructor (theme 13). This means that by the end of the training program, the ISTs and PSTs differed in their perceptions of their role as teachers who implement technology and in their perceptions of their training needs and benefits. There were differences in the importance attributed to the feedback from the training instructor, given that the ISTs did not receive feedback from the instructor and instead considered the feedback from their students. There were also differences between the groups in terms of their self-positioning on the question of the degree of exposure to the innovation, whereby the PSTs felt overwhelmed by the amount of exposure compared to the ISTs.

In summary, the linguistic analysis, which focused on linguistic expressions that represented participants' self-positioning, revealed findings that were essentially similar to those revealed through the content analysis, thus validating the latter.

Finally, the findings revealed the features that characterize the process of adopting ML-based teaching in the context of transitioning to distance learning during the coronavirus pandemic, as viewed through Rogers' theory. The model of the study's results presents the main issues relevant to each of the stages of the process, which were validated through the use of multiple analyses (content and form), thus enhancing the reliability of the findings.

## 4 Discussion

This study provides insight into the Mobile-Learning adoption process in teacher education in the context of the COVID-19 pandemic, examined through the lens of Rogers' Diffusion of Innovation Theory (2003).

The study contributes in three ways to the theoretical and practical knowledge of technology adoption under crisis conditions. First, as arises from the findings regarding the COVID-19 context, the study highlights the importance of providing a framework that serves as a catalyst for teachers to face their aversion to technology.

The study highlights that such a framework should maintain a delicate balance between necessity and autonomy. On the one hand, in the COVID-19 situation, adopting the use of technology became a necessity; yet, given the circumstances, this transition was perceived as unavoidable (rather than planned and dictated by one's superiors) and hence did not arouse opposition. It is essential to create such "natural" frameworks that act as catalysts for teachers to engage in ML. On the other hand, precisely because of the circumstantial constraints, it is essential to balance the sense of the "unavoidable," by allowing for a modicum of autonomy and choice. The study suggests that this careful balance served as an optimal combination for promoting the adoption of ML. To date, the research literature has examined the way the use of ML promotes the learners' autonomy (Alzieni, 2020), whereas the current study illuminates the opposite aspect, namely, the need for autonomy as part of the process of adopting ML in teaching and learning.

Second, the current study provides a model that conceptualizes the relevant aspects throughout the stages of the ML adoption process, while emphasizing the similarities and differences between the ISTs' and PSTs' adoption process. The study underscores the differential needs of these two groups along this process, providing essential information for policymakers in teacher education to promote the design of efficient ML training. Figure 4 illustrates the similarities and differences between the groups in their ML adoption process. Some of the differences that require attention include their differential *training needs* (PSTs need better coordination of materials, whereas ISTs welcomed more training and need to be rewarded for their time); their *modeling source* (PSTs found a model in their peers, whereas the training instructor was the ISTs' model); and their *feedback sources* (PSTs needed feedback from an authority figure, whereas ISTs relied on their pupil's feedback). Previous studies have documented some of the differences between PSTs' and ISTs' concerning the ML adoption process (Mac Callum et al, 2014), as well as differences between university teachers and students regarding the use of online learning in general (Dolenc et al., 2021; Šorgo et al., 2021). However, the current study further demonstrates

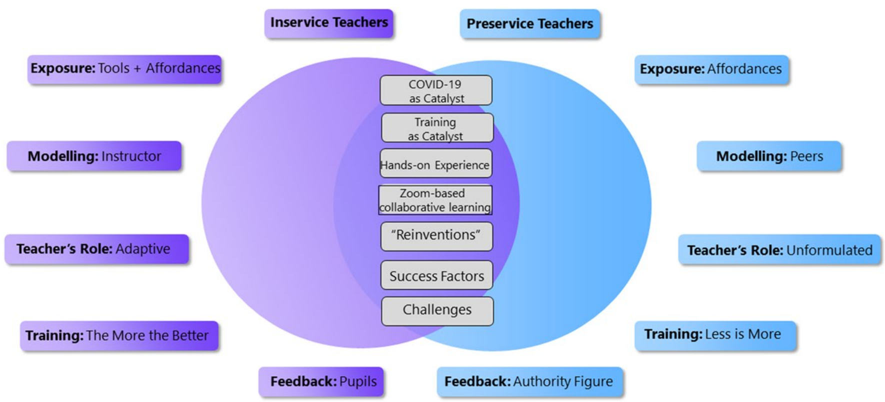


**Fig. 4** A visual representation of the similarities and differences in the ISTs and PSTs process of ML adoption

that this is also the case in the particular adoption of ML during a crisis such as the pandemic. Thus, designing optimal ML training programs could be improved by considering and attending to these differences.

Third, the study underscores the importance of developing PSTs' role perception. While the ISTs' role perception shifted naturally with the changes related to the pandemic, the PSTs' role perception, to begin with, was not sufficiently mature, even though their exposure to and familiarity with technological tools was more extensive than that of the ISTs. These findings emphasize that familiarity with the tools is not a sufficient condition to become "a teacher that implements technology in teaching"; efforts should be made to formulate teachers' role perception to be "teachers who implement technology in the classroom". Given the finding that the PSTs' perspective when deciding whether to adopt the technology was described in terms of their transition from learner to teacher when formulating their role perception, they should be encouraged to take into consideration their past experiences as learners. Previous studies that examined the teachers' role perception in relation to technology use, in general (e.g., Avidov-Ungar & Tsybulsky, 2021), and ML in particular, focused on the way students perceive the role of their teacher as the figure who is responsible to teaching them about technology (Kan, 2018). However, there is a paucity of studies on the PSTs' role perception of themselves as future teachers adopting the ML approach. This aspect should be further investigated in future research.

In addition to the abovementioned three main contributions, the study echoes previous findings regarding Rogers' innovation adoption theory. As noted, apart from Rogers' innovation adoption stages, the theory claims that individuals evaluate innovation in light of its relative advantage, compatibility, complexity, trialability, and observability. Recent studies showed that these five aspects are relevant to the adoption of online proctored examinations during the COVID-19 pandemic (Raman et al., 2021) and to the adoption of experiential learning via live-in-labs (Raman et al., 2020). Likewise, these five elements are evident also in the current study, but they manifest in a different form. For instance, "observability" is mentioned in the fifth stage – confirmation, when participants reflect on their experience and search for feedback; "trialability" is reflected in the third stage – decision, wherein participants try out the technology and express their training needs, and also later, in the fourth stage, that of implementation; "relative advantage" and "compatibility" are evident in the second stage – persuasion, when participants discuss the role of the pandemic in promoting their understanding of the necessity and benefits of technology to maintain their values of learning; and "complexity" appears in our findings under the first stage, when participants are exposed to knowledge about the technology and its uses and appreciate its ease of use. All in all, the current study further strengthens the abovementioned previous studies (Raman et al., 2021); however, the current study's emphasis is on the overall *process* rather than on the *factors* that promote the ML adoption.

This study also reinforces prior findings regarding the factors that affect technology adoption, demonstrating their relevance also in times of crisis. For instance, the role of the instructor (Dennen et al., 2007); the importance of hands-on experience with technology (Meishar-Tal & Ronen, 2017) and the benefit of collaborative learning when adopting technology (Johnson et al., 2010); the effects of exposure to pedagogical affordances on teachers' attitudes toward ML (Moya & Camacho, 2021),; and finally, the importance of experiencing success, addressing barriers, and establishing an organizational climate that encourages technology use (Moya & Camacho, 2021).

### 4.1 Limitations and future research

Longitudinal studies over several years could further our understanding of the adoption and implementation process of ML in the field, demonstrating whether these develop and/or change over time and with increased experience. In addition, it should be noted that all self-report measures may have been influenced by social desirability bias. Nevertheless, we believe that the triangulation of data sources and the fact that the data were collected by an external research assistant helped minimize the chance of bias as far as possible.

Future research may opt to focus on the process of ML adoption under routine conditions, rather than during a crisis, to explore whether this adoption process manifests similarly or differently in the IST and PST groups. Another possible focus for future research could be to examine the reasons why ISTs rely on the instructor as a role model whereas PSTs prefer to rely on their peers. This may be related to the age gap between the groups as well as to their role perception. Finally, future research may be conducted among ISTs and PSTs of various cultures and minority groups with limited access to technology (Frei-Landau & Avidov-Ungar, 2022), as participants' background was found to be an essential factor affecting their adjustment to sudden or traumatic changes (Frei-Landau et al., 2020a, b).

In conclusion, this study illuminates Rogers' DIT aspects as manifested in the ML adoption process, in the context of distance learning during the COVID-19 pandemic. As such, it contributes to the ongoing conversation regarding the ways in which ML adoption can be understood and supported to promote teachers' best practices. This is imperative both in routine and emergency times, and particularly considering the COVID-19 era (and future emergencies), when opportunities for face-to-face teaching are limited.

## Appendix 1 A List of the technological tools experienced by the training program participants and their pedagogical uses

- https://he.padlet.com

  A shared virtual whiteboard where visual information can be displayed, allowing for brainstorming and a shared discussion, thus encouraging active participation.
- https://quizizz.com

  An online quiz enabling the immediate monitoring of learning achieved at the end of a curricular unit. It can be used for review purposes in a synchronic lesson or as homework practice.
- https://nearpod.com

Enables the planning of online interactive lessons based on a slide presentation. It can include a virtual tour, three-dimensional objects, surveys, etc., and can be used to monitor students' understanding of the material.

- https://app.biteable.com

  An application for preparing a film clip that can be used to teach a given topic.
- https://www.mentimeter.com

  An interactive tool for assessing learners' attitudes and prior knowledge on a given topic, so as to choose an appropriate focus. It can also be used for discussing social and emotional issues.

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## Declarations

**Conflict of interest** None: The authors declare no conflict of interest.

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