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“Development and validation of the ICAP Technology Scale to measure how teachers integrate technology into learning activities”

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ABSTRACT

Previous research investigating the use of technology in school has focused mainly on the frequency of use of digital tools during lessons rather than investigating how technology is integrated with respect to different kinds of learning activities.

Since the impact of technology use on learning depends on how it is used and on what activities supported by technology are implemented in lessons, a measurement instrument assessing how technology is integrated into learning activities is necessary to investigate its impact on teaching and learning processes. According to the interactive, constructive, active, and passive (ICAP) framework, which distinguishes four different learning activities based on the level of students' cognitive engagement, we developed the 12-item ICAP Technology Scale (ICAP-TS) that accounts for all four dimensions of technology integration in lessons. We used confirmatory factor analysis to validate the four-factor structure of the ICAP-TS with a sample of 1059 upper-secondary school teachers from Switzerland. We also examined reliability using classical test theory and Rasch model analysis to assess the scale's psychometric characteristics. We then analyzed the associations between the ICAP-TS and a general use frequency measure of 12 educational technologies to test the criterion validity. The results confirmed the four-factor structure of the ICAP-TS and revealed good instrument accuracy. The most difficult items to endorse are those describing the integration of technology into interactive learning activities. Furthermore, all 12 items significantly correlated with the frequency of use of 12 educational technologies. We recommend the ICAP-TS as a short and reliable measurement scale for assessing how technology is integrated into lessons, considering different learning activities based on the ICAP theoretical model.

1. Introduction

Digital transformation has become one of the most pressing issues in the educational context (Egloffstein & Ifenthaler, 2021; Iivari et al., 2020). As new educational technologies have developed and become more widely available, teachers have started to use

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technology more frequently in their lessons (EU European Commission, 2013; European Commission, 2019; Schmitz et al., 2022). The introduction of digital technologies affects education as they provide new opportunities for learning and influence pedagogical approaches to teaching and learning (Deepika et al., 2021). Indeed, the integration of technologies into teaching requires teachers to modify their pedagogical approach and teaching strategies, which determine the extent to which the use of technologies improves students' cognitive outcomes (OECD, 2019). The potential of digital technologies for teaching and learning does not primarily depend on the type of technology or its frequency of use but rather on *how* digital technologies are used to cognitively stimulate and engage students in learning activities (Chien et al., 2016; OECD, 2015; Tamim et al., 2011; Wekerle et al., 2020). Although it has been stressed that the effects of technology on learning depend on how technology is integrated into learning contexts (Fütterer et al, 2022; Hamilton et al., 2016; Petko et al., 2017), previous studies have adopted simplified and techno-centric strategies to assess technology integration, mainly focusing on the frequency of technology use without revealing any information on how technology is integrated in learning activities (Franklin & Bolick, 2007). Among these, large scale studies such as PISA or ICILS have condensed frequency items into composite indices that reflect an overall use of technology and are sometimes difficult to interpret (Schmitz et al., 2022). Another research strand investigated the Technology Acceptance Model and Unified Theory of Acceptance and Use Technology in education (Dwivedi et al., 2020; Habibi et al., 2020; Scherer et al., 2019) considering teachers' personal factors (e.g., attitude toward technology, beliefs, knowledge) as influencing technology integration; however, these studies examined only one overall index of technology use as outcome variable (e.g., the use frequency of a specific technology or general technology use) that is not sufficient for the understanding of technology integration from a qualitative perspective.

According to Backfisch et al. (2021) the quality of technology integration can be operationalized as the extent to which technology is used to transform and redefine learning activities and the level of teaching quality that comprehends task-specific strategies (e.g., cognitive activation, individual learning support), and task-general strategies (e.g., classroom management). Thus, to understand how technology is integrated in lessons requires the implementation of a measurement tool that assesses teaching and learning activities in which technology is integrated, and whether technology is used as a substitute for traditional teaching or to transform and support more complex learning activities. A recent attempt in this direction was undertaken by analysing teachers' lesson plans (Backfisch et al., 2020). However, lesson plans analysis is time-demanding, and teachers do not always perfectly implement what is reported in their plan (Chi et al., 2018). Furthermore, this qualitative research methodology is usually limited to small populations. Thus, we recognized the need for a short and reliable scale for evaluating teachers' digital integration practices on a large sample. However, a theoretically based and reliable measurement instrument that effectively assesses how teachers qualitatively integrate technology in different types of learning activities in upper secondary schools is not available, and we aim to develop and validate such a scale. For classifying learning activities supported by technology, we referred to the interactive constructive active passive (ICAP) framework by Michelene Chi (Chi, 2009; Chi & Wylie, 2014), which differentiates learning activities in terms of observable activities (i.e., the degree of learners' activation) and underlying learning processes (i.e., learners' cognitive engagement). Based on the ICAP taxonomy, we developed a 12-item scale assessing how frequently teachers integrated technology to conduct different learning activities in their lessons.

Before introducing our newly developed ICAP-Technology Scale (ICAP-TS), we present a review of the literature on the measurement of technology integration in lessons, the ICAP framework, and its application in the context of technology integration in education.

1.1. *The measurement of technology integration in lessons*

Since the early days of educational technology integration research, most survey-based studies have operationalized the integration of technology by assessing how often teachers and students use different digital devices and software in the classroom, whether they feel comfortable using different technologies, whether they have positive attitudes toward these technologies, or as a mix of these aspects (Christensen & Knezek, 2001; Gomez et al., 2022; Scherer et al., 2020). Although these measures can be used to analyze the frequency and familiarity of technology use, they can hardly be taken as indicators of the quality of using teaching and learning. As a recent example, in the European Survey of Schools Information and Communications Technology in Education, the use of digital technology was measured by asking teachers to report the average percentage of time teachers and students spent using technologies in lessons. In the IEA International Computer and Information Literacy Study (ICILS; Fraillon et al., 2020), some items assessed how often students used digital tools in the classroom (e.g., word-processing and presentation software; computer-based information resources; concept mapping software; multimedia production tools). Similarly, the teachers' questionnaire of the Programme for International Student Assessment (PISA; OECD, 2018) includes items assessing the teachers' use of 14 digital tools and software (e.g., digital learning games; simulations and modeling software; drawing software). The limitation of these 'techno-centric' scales is that they focus on the use of specific digital tools, and this focus does not reveal any information on how the technology is integrated to support different learning activities. Indeed, even if a technology was not developed for specific teaching and learning purposes, teachers can integrate it in different ways that promote learning (Parker et al., 2019). Furthermore, the indicator of the frequency of digital devices or software use in the classroom is not enough to understand the pedagogy underlying the integration of technology and thus does not allow investigation of the implications of technology use in sustaining teaching and learning. It is well established that the effect of technology use on learning outcomes does not depend on what technology or how often technology is used; rather, learning outcomes depend on how learning activities induce deep cognitive learning processes (Fütterer et al., 2022). Thus, investigating the type of learning activities supported by technology would be a more appropriate benchmark for assessing technology integration, with a focus on how often different types of learning activities involving technology have been implemented by teachers instead of asking only about the frequency of technology use.

1.2. Interactive, constructive, active, and passive (ICAP) framework

The ICAP framework identifies four different types of learning activities (Chi et al., 2018): interactive, constructive, active, and passive. Each of these activities subsumes cognitive processes that are involved in building knowledge structures (i.e., storing, activating, linking, and inferring) and reflects different levels of learners' cognitive engagement, which is defined as the investment of cognitive effort in the learning process (Chi, 2009; Chi et al., 2018).

In *passive* learning activities, students work with knowledge in a merely receptive manner (e.g., students watch an instructional video without having any possibility to interact or manipulate the instructional material). This type of passive learning activity can be efficient for the acquisition and storage of simple procedures and for the recall of declarative information in a similar context (Chi et al., 2018).

Active learning occurs when students have hands-on opportunities to interact and practice with the given instructional material and content (e.g., pausing or forwarding the video or highlighting a text). In contrast to passive learning, students practice, apply, and use the new knowledge they have been taught. From a cognitive perspective, students are thus activating previous knowledge, allowing new information to be linked, and more deeply integrated into the structure of existing knowledge (Chi & Wylie, 2014).

In *constructive* learning, students individually create new knowledge and new links between elements of knowledge (e.g., creating concept maps, comparing information, solving problems), going beyond the given instructional material or the content that has been taught by the teacher. The underlying cognitive processes are the activation of prior knowledge to deduce and infer new knowledge, guessing, and testing new knowledge components, and storing the new inferred knowledge. This type of cognitive engagement occurs when acquiring complex skills and solving problems that require the creation of elaborate and interrelated internal structures of knowledge.

Interactive learning happens when learners interact and collaborate with others with the purpose of building knowledge inferred from their own prior knowledge and from the information provided by the partner(s) (e.g., sharing ideas, discussing their argumentations, constructing a joint point of view). This interactive and collaborative exchange results in enriched knowledge structures for all participants and can also facilitate the development of complex social-cognitive skills, such as argumentation skills.

The ICAP framework suggests that cognitive learning processes become increasingly sophisticated, moving from passive to interactive learning activities. Interactive learning activities should facilitate the acquisition of domain-specific knowledge to a greater extent than constructive knowledge. Constructive learning activities should facilitate the acquisition of knowledge to a higher degree than active learning activities, which are expected to be more strongly associated with knowledge acquisition than passive activities. Various studies have already confirmed this assumption (Chi & Wylie, 2014; Chi et al., 2018; Morris & Chi, 2020; Wiggins et al., 2017).

1.3. ICAP learning activities supported by technology

Since the use of technology to support teaching and learning is only an advantage for students' learning if it is aligned with the pedagogical learning activity and goal, the integration of technology in teaching requires a deep reflection on the pedagogical principles underlying technology use. For this purpose, the ICAP framework can provide insights on the quality of technology integration in teaching and learning activities, as it can distinguish the activities supported by technology use based on the level of students' cognitive engagement (for examples of categorizing activities with technology according to the ICAP framework, see Deepika et al., 2021). In this direction, Stegmann's (2020) meta-analysis shows that student activities with digital technologies can be classified according to the ICAP framework, and it provides empirical evidence that digital technologies that are used to increase the probability of the occurrence of certain cognitive processes within an engagement mode have a positive effect on students' learning outcomes. Moreover, there have been few recent attempts to use the ICAP framework as a conceptual model for developing measures of the quality of technology integration in teaching. Based on the ICAP model, Sailer et al. (2021) developed a scenario-based self-assessment instrument to address different kinds of technology use that had not been considered in previous research. They asked teachers to report the percentage of time spent using technology into four different types of learning activities (i.e., students' passive, active, constructive, and interactive learning activities). More precisely, short descriptions of the learning scenarios were presented, and the teachers were asked to indicate how often they used digital technologies in a similar manner for each scenario. Given that the four ICAP dimensions have been evaluated by only one item, each item description comprises several examples of activities and behaviors, which makes it difficult to estimate the frequency of use. Another limitation that the authors acknowledge is that scenario-based assessment is time-demanding. Overall, even if the measurement instrument by Sailer et al. (2021) showed good reliability, it did not provide enough detailed information about technology integration across the four ICAP dimensions.

Moreover, Wekerle et al. (2020) developed a scale to assess the students' engagement in technology-supported activities built on the ICAP theoretical model. They used 16 items to ask students to report the frequency of technology use for passive (e.g., to read content), active (e.g., to copy content), constructive (e.g., to reflect on content), and interactive (e.g., to debate with others) learning activities. This was the first step in validating an item-based instrument for assessing the students' engagement in technology-supported learning activities. However, due to the focus on students' perspective, we cannot rely on this measurement scale for insights on the quality of teachers' technology integration.

Although these studies represent the first attempts to provide a quality measure for educational technology use in line with the ICAP framework, a reliable, consistent and more detailed measurement scale for teachers is still not available. Thus, the assessment of how technology is integrated to accomplish the ICAP principles of pedagogy could allow for the examination of the effectiveness of technology on learning outcomes. In accordance with the ICAP hypothesis, depending on which type of learning activity technology supports, it is possible to trigger more or less sophisticated cognitive processes. In a study by Wekerle et al. (2020), technology-supported constructive and interactive learning activities were found to be the most powerful significant predictors of the acquisition of domain-specific knowledge. This evidence highlights the need for teachers to use technology in their lessons to support the students' engagement in more constructive and interactive learning activities than passive and active ones.

1.4. The present study

Driven by the research gap about the measurement of the quality of educational technology integration in upper secondary education, we aimed to develop and validate a scale to measure how teachers integrate technology in teaching. After a literature review of the measures for educational technology use and the ICAP theoretical framework, we developed 12 items to measure the frequency of different learning activities supported by technologies implemented by teachers and students in lessons, and we assumed that these items are equally distributed across the four dimensions of learners' cognitive engagement identified by the ICAP taxonomy. More precisely, the study aimed to address the following research objectives:

(1) To develop and validate a new ICAP-Technology Scale (ICAP-TS) on technology integration in lessons, assessing the frequency of interactive, constructive, active, and passive learning activities implemented with the support of technology.
(2) To examine the correlations of the ICAP-TS overall and subscale scores with a general frequency measure of the use of educational tools and software.

The main contribution of the validation of the ICAP-TS is providing researchers with a valid measurement tool to assess teachers' technology use in the upper-secondary level of education.

2. Methods

2.1. Procedure and sample

The questionnaire was developed by the authors with the feedback of ten in-service teachers to assess the face validity of the instrument early on. For content validity, we asked three researchers in the field of educational technology who were familiar with the concept under investigation to evaluate the items with respect to problems, ambiguity, proper use of terms and comprehensibility. After assessing face and content validity, a survey study using the items was conducted. Data were collected between September 2021 and November 2021 through an online survey hosted on the Unipark platform. The study employed a cross-sectional design. The target group for our study was in-service teachers of 54 upper secondary schools in the Canton of Zurich; thus, the entire questionnaire was developed in German. No missing data were found, as a force-choice function was used to ensure that each item was answered. Teachers were recruited via school's administration contact. In total, 1074 teachers completed the survey. After the data cleaning based on the criteria of compiling time, the final analytical sample consisted of 1059 teachers (47.3% female, 50.0% male, 2.6% other) ranging in age from 24 to 66 years ($M = 46.36$, $SD = 9.88$). 496 (46.8%) participants were teaching in dual vocational education tracks, and 563 (53.2%) were teaching in gymnasiums and other upper secondary schools. The participating teachers had, on average, 15.56 years of teaching experience ($SD = 9.63$).

2.2. Measures

2.2.1. ICAP Technology Scale

The ICAP-TS consists of 12 items describing the integration of technology in different learning activities implemented by teachers and students during lessons. The items are equally distributed in four subscales, each reflecting passive, active, constructive, and interactive learning activities supported by technology, as defined by the ICAP taxonomy. The four subscales are described as follows:

> 'Passive' learning subscale comprises three items that describe activities where teachers use technology to present predefined knowledge and explain learning contents, and students learn merely in a receptive manner.
>
> 'Active' learning subscale is defined by three items describing the active use of technology by students to apply previously taught knowledge.
>
> 'Constructive' learning subscale comprises three items describing learning activities where students acquire new knowledge individually and independently.
>
> 'Interactive' learning subscale comprises three items describing collaborative learning activities where students acquire new knowledge together with other students.

For each item, we asked teachers to indicate how often they and their students used technology to accomplish the activities described by the items. The response answers range on a 5-points Likert Scale, form 'Almost never' (0) to 'Almost every lesson' (4). A full list of the items per subscale can be found in Table 1.

2.3. Educational technologies' use

We also asked teachers to report how often they use the following 12 educational technologies in their teaching activities: (1) presentation software, (2) specific-subject learning software, (3) online test and quizzes, (4) word-processing software, (5) spreadsheet and calculation software, (6) games, (7) drawing and image editing software, (8) video recording and editing software, (9) online research software, (10) online communication software, (11) students' work presentation/publication software, (12) learning management system. The response scale ranged from 'Never' (1) to 'Nearly every day' (5).

2.4. Personal information

Teachers' personal information, such as gender, age, and years of teaching experience, were collected in the last section of the questionnaire. We reported the entire questions and items in Appendix A.

2.5. Data analysis

The data analyses included (1) descriptive statistics of single items and subscales as well as a reliability analysis; (2) polytomous Rasch model to examine the psychometric quality of the ICAP-TS; (3) exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to explore and validate the four-factor structure of ICAP-TS; (4) correlation analysis between the four dimensions of ICAP-TS and the frequency of educational technology use to test the criterion validity; (5) multiple linear regression analysis to explore the impact of personal variables (i.e., gender, age, teaching practice) on ICAP-TS. Statistical analyses were conducted using the analytics software IBM SPSS Statistics (Version 27), the lavaan package (0.6–7) and TAM package in R (4.1.2).

2.5.1. The Rasch model

The Rasch model (Rasch, 1960) has been widely used for constructing a measurement, analyzing questionnaires, and construct validity (Baghaei, 2008). The Rasch measurements model refers to a family of models that compute the probability of a certain response to each item given the amount of the latent construct the individual possesses (trait level) and the relation between each item and the construct (item difficulty). The Rasch model scales both persons and items according to the strength of an individual's relation with the latent construct. As a preliminary analysis, we compared the Rasch Partial Credit Model (PCM) with the polytomous Rasch Rating Scale Model (RSM). Then we computed item- and person-reliability statistics. Infit and outfit mean square statistics were used to assess the fit of the 12 items to the Rasch PCM. According to Linacre (2018, pp. 582–588), the ideal value of an item infit/outfit mean square statistic should fall between 0.50 and 1.50, and values exceeding 2.00 may suggest a noisy problematic item. Moreover, for a rating scale survey, the reasonable range for infit and outfit is 0.6–1.4 (Bond et al., 2021; Wright et al., 1994). For the estimation of the infits and outfits, we used the TAM package in R and applied PCM2, a classical parametrization introduced by Andrich (1978) and Masters (1982), which has also been implemented in ConQuest. The person-item map or Wright map was plotted to investigate the construct hierarchy of the ICAP-TS. The map visually represents the relative difficulty of the items. Items are ranked from the hardest to endorse to the easiest to endorse.

Table 1
Documentation of the ICAP-TS

Dimension/Item code	Question	Item
Passive/ICAP_P1	For which teaching and learning activities do you use digital technologies?	To inform about learning objectives and content.
Passive/ICAP_P2	"	to demonstrate learning content vividly.
Passive/ICAP_P3	"	to explain learning content in a comprehensible way
Active/ICAP_A1	For which learning activities do your learners/students use digital media in your lessons?	So that they write down and record the knowledge imparted.
Active/ICAP_A2	"	so that they actively repeat and practice the knowledge imparted.
Active/ICAP_A3	"	so that they can solve simple tasks with the knowledge imparted.
Constructive/ICAP_C1	"	so that they can acquire new knowledge individually.
Constructive/ICAP_C2	"	so that they can develop individual solutions for complex problems.
Constructive/ICAP_C3	"	so that they become individually creative and produce something new.
Interactive/ICAP_I1	"	so that they develop new knowledge together with others.
Interactive/ICAP_I2	"	so that they can discuss different points of view with others.
Interactive/ICAP_I3	"	so that they work in working groups on complex problems.

Note. Answer format is a five-point Likert scale: 0 Almost never – 4 Almost every lesson.

3. Results

3.1. Descriptive results

Descriptive results for the single items showed a good variation within the response patterns of all items with neither ceiling nor floor effects (Table 2). Passive activities were carried out most often, followed by active, constructive, and interactive activities that involved digital technologies for teaching and learning.

Cronbach's alpha reliability coefficients of the four subscales ranged from 0.834 to 0.908, which can be interpreted as a good consistency of the measurement: passive, $\alpha = 0.834$; active, $\alpha = 0.897$; constructive, $\alpha = 0.871$; and interactive, $\alpha = 0.908$. Furthermore, Mc Donald's Omega ranged from 0.858 to 0.908, indicating good to excellent internal consistency of the four factors: passive, $\omega = 0.858$; active, $\omega = 0.900$; constructive, $\omega = 0.874$; and interactive, $\omega = 0.908$.

We calculated mean statistics for the ICAP-TS subscales and the 12 educational technologies' use frequency (Table 3) to give the readers an overview of how technology was integrated in lessons and how frequently educational technologies were used by Swiss teachers and students in upper-secondary schools.

3.2. Results of the partial credit model

The comparison between the PCM (BIC = 31018, AIC = 31018) and RSM (BIC = 31139, AIC = 31155) revealed a better fit for PCM. Furthermore, a Chi-square test confirmed that the PCM fit the data significantly better than the RSM (χ^2 (33) = 350.49, $p < .01$). The Rasch PCM model allows us to establish the relative difficulty (or relative endorsability) of the 12-item statement with regard to its latent construct (i.e., ability to integrate technology in learning activities). We chose the Rasch PCM, which is an extension of the Rasch model (Rasch, 1960) for polytomous data and which allowed us to assess technology integration on a continuum from a low sophisticate level ('passive' learning activities supported by technology use) to a high level of technology integration ('interactive' learning activities supported by technology use). The PCM is less restrictive than the RSM, as it allows for different response categories in different items. Despite identical response categories, the meaning and gradation of the response categories usually vary strongly depending on the concrete statement or the attitude object. Whereas the PCM model makes no assumptions about the width of the 'bands' between thresholds, the RSM assumes identical spacing or parallel threshold trajectories for all items in each case, indicating that the meaning and gradation of the answer options do not vary for the different statements. These requirements of the RSM are difficult to meet. To estimate the reliability of the Rasch model, weighted likelihood estimates (WLE) and expected a posteriori (EAP) reliability measures were calculated. Whereas maximum likelihood estimators (MLE) overestimate the variance of the person parameters, and EAP estimators tend to underestimate the variance of the person parameters, WLE estimators are slightly corrected toward the mean and are therefore the most accurate estimators (Adams, 2006; Bond & Fox, 2015). Following the criteria recommended by Bond and Fox (2015), the results indicated that all items fit the model well. The WLE reliability of the PCM was .91, and the EAP reliability was .93, indicating a very good accuracy of the measurement. High item reliability suggests that the items have a wide range of endorsability and distinguish well among low and high frequency learning activities supported by technology use, whereas high person reliability indicates that teachers have a wide range in the frequency of technology use in learning activities. Nearly all items had a good infit and outfit and lay within the range of 0.6–1.4 (see the table in Appendix B), as expected for items of rating scales (see Bond et al., 2021; Wright et al., 1994). Exceptions are the outfits of the first item measuring passive technology use and the outfit of the third item measuring constructive use. However, the infits lay within the range of 0.6–1.4. For the decision on the suitability of items, the weighted deviations (infit MNSQ) were of greater importance than the unweighted deviations (outfit MNSQ). For the outfit, deviations on items with difficulty that lay far away from the person parameter have just as much weight as those that lay very close to the person parameter. The infit, on the other hand, is not sensitive to outliers, since it is more sensitive to deviations on items whose difficulty is close to the person parameter. These are weighted more heavily than on items whose difficulty is far from the person parameter. Therefore, the value of the infit was weighted higher in our decision to keep the items (Wright et al., 1994). Moreover, the outfits of the items did not exceed the value of 2.00 indicating that the items are not too noisy and problematic (see Linacre, 2018).

Table 2
Descriptive statistics of ICAP-TS.

Item code	N	Min	Max	M	SD	α if item deleted	Corr.
ICAP_P1	1059	1	5	3.80	1.327	.908	.573
ICAP_P2	1059	1	5	4.12	1.103	.716	.759
ICAP_P3	1059	1	5	4.06	1.154	.688	.782
ICAP_A1	1059	1	5	3.63	1.389	.899	.746
ICAP_A2	1059	1	5	3.46	1.280	.829	.825
ICAP_A3	1059	1	5	3.45	1.318	.830	.822
ICAP_C1	1059	1	5	3.32	1.207	.835	.735
ICAP_C2	1059	1	5	2.82	1.292	.761	.814
ICAP_C3	1059	1	5	2.82	1.220	.852	.715
ICAP_I1	1059	1	5	2.78	1.242	.874	.810
ICAP_I2	1059	1	5	2.37	1.276	.867	.818
ICAP_I3	1059	1	5	2.57	1.239	.864	.821

Table 3
Descriptive statistics of educational technology use.

	Mean	SD	Min	Max
Passive	3.99	1.04	0	4
Active	3.51	1.21	0	4
Constructive	2.98	1.11	0	4
Interactive	2.57	1.16	0	4
Presentation software	4.46	0.957	1	5
Specific-subject learning software	3.04	1.389	1	5
Online test and quizzes	2.30	1.119	1	5
Word-processing software	3.39	1.420	1	5
Spreadsheet and calculation software	2.23	1.309	1	5
Games	2.01	1.056	1	5
Learning management system	4.00	1.219	1	5
Drawing and image editing software	1.95	1.182	1	5
Video recording and editing software	1.89	0.948	1	5
Online research software	3.63	1.161	1	5
Online communication software	2.39	1.296	1	5
Students' work presentation/publication software	2.85	1.073	1	5

Thus, we decided not to remove these two items from the questionnaire. The Wright map (Fig. 1) illustrates the person's abilities on the left and the item difficulties on the right, arranged along the same logit scale. The item categories of the responses are presented in ascending order according to their difficulty. The map shows that the likelihood of answering the highest response option (i.e., every lesson) increased as the latent trait of the respondents (i.e., technology integration ability) increased. For an average level of person ability, the chances of answering the highest category (high frequent integration of technology) for all items was lower than 50% and even lower (<25%) for items assessing the integration of technology in interactive learning activities. Instead, the chances of answering all items selecting the lower categories (low frequent integration of technology) were higher than 50%. As respondents' ability increased, the chance of answering the highest categories even for the 'constructive' and 'interactive' items increased. In line with the ICAP hypothesis, the highest category of response of 'interactive' items was the most difficult to endorse and subsumed a higher person ability, followed by 'constructive' and 'active' items. Instead, the highest categories of the three 'passive' items were the easiest to endorse and required an average level of person ability.

Note. The items describing the passive learning activities supported by technology (i.e., P_1, P_2, and P_3) are the easiest to endorse; then, the items included in the active dimension of ICAP taxonomy are a bit more difficult (i.e., A_1, A_2, and A_3), followed by the items of the constructive dimension (i.e., C_1, C_2, and C_3). Items I_1, I_2, and I_3, which encompass the interactive dimension, are the

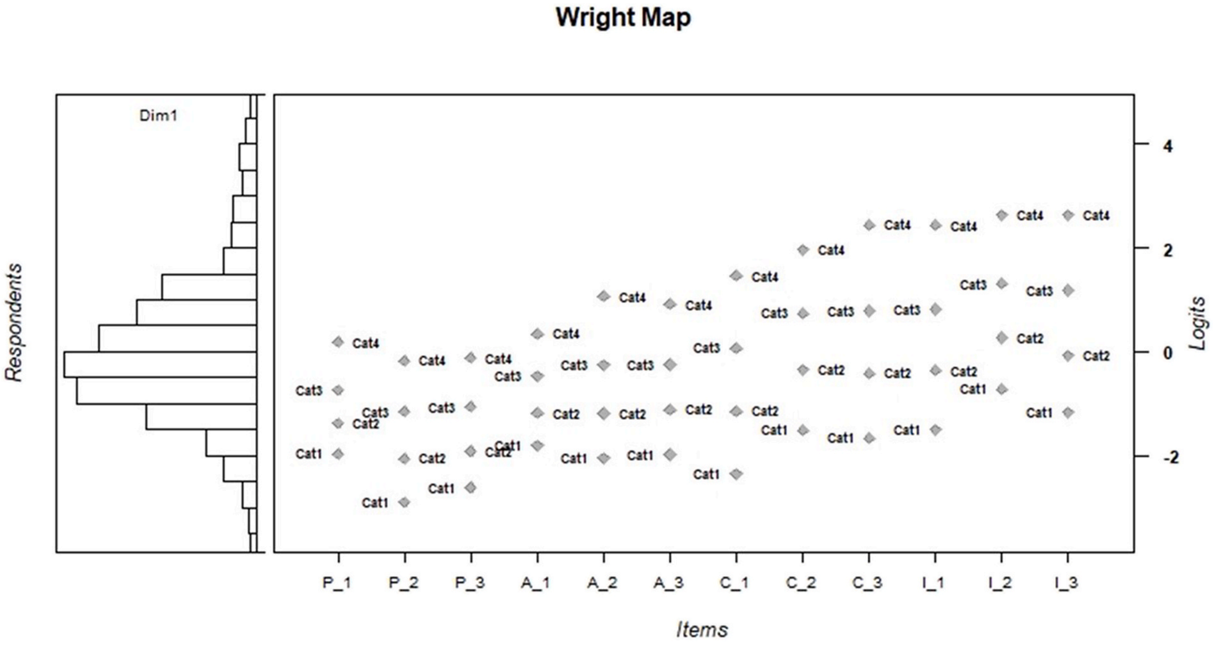

Fig. 1. The Wright map. *Note*. The items describing the passive learning activities supported by technology (i.e., P_1, P_2, and P_3) are the easiest to endorse; then, the items included in the active dimension of ICAP taxonomy are a bit more difficult (i.e., A_1, A_2, and A_3), followed by the items of the constructive dimension (i.e., C_1, C_2, and C_3). Items I_1, I_2, and I_3, which encompass the interactive dimension, are the most difficult.

most difficult.

We used the Thurstonian thresholds to analyze all polythomous items with regard to their threshold parameters. Ordered thresholds for each item indicate that the response scale has an ordinal scale level. Analyses of threshold parameters (see the Table of Thresholds in Appendix B) indicate that the item response scales had an ordinal scale level because the thresholds per item for the categories were ordered in ascending order.

3.3. Results of the EFA and CFA

First, an EFA was conducted using the maximum likelihood extraction method in combination with Oblimin rotation. The solution explained the 69.3% of the total variance. The results, which are reported in Table 4, confirmed that each item had a clear primary loading on one factor (factor loadings $> |0.40|$). Factors 1, 2, 3 and 4 were loaded by three items of 'passive', 'active', 'constructive', and 'interactive' dimensions respectively.

Then, to validate the structure and internal consistency of the ICAP Technology Scale, a first-order and a second-order CFA were used to evaluate the dimensionality and the validity of the measurement model. Before running the analysis, the assumption of univariate and multivariate normality was tested to select the estimation method. Nine multivariate outliers were deleted.

According to the ICAP theoretical framework, we estimated the fit of the 12 items in the four dimensions to test whether the data fit the theoretically expected four-factor structure. We conducted a first-order CFA with the four correlated first-order latent variables (i.e., 'passive', 'active', 'constructive', and 'interactive'). We then assessed the factorial validity by employing a second-order CFA model that assumed a second-order factor reflecting the overarching construct of 'technology integration in lessons'. Different goodness-of-fit indices were used to examine the fit of the models: the chi-square test assesses the absolute fit of the model, but it can be influenced by sample size, correlation, and variance unrelated to the model. Thus, we considered the comparative fit index and Tucker-Lewis index (CFI and TLI; good fit ≥ 0.95; see Brown, 2015), the standardized root means squared residual (SRMR; good fit ≤ 0.08; see Hu & Bentler, 1999), and the root mean square error of approximation (RMSEA; acceptable fit $\leq .08$; see Browne & Cudeck, 1992). Residual correlations were added according to the modification indices, where necessary, to improve the model fit. Then, we compared the two nested models (second-order CFA was nested in the first-order CFA), computing the chi-square difference test to evaluate which model fit the data significantly better.

Since the assumption of data normality distribution was violated, a robust maximum likelihood estimation method was used. According to the modification indices, we added two residual covariances to improve the fit of the first-order CFA. Only inter-item correlations within the same dimension were added. As a result, the first-order CFA model showed a good fit: χ^2 (46) = 187.886, CFI = 0.980, TLI = 0.971, RMSEA = 0.061, 90% confidence interval (CI) [0.052, 0.070], SRMR = 0.028. Although the chi-square test was significant ($p < .001$), we did not reject the model because the test significance was influenced by the sample size while the other fit indices were satisfactory. Standardized factor loadings ranging from 0.669 to 0.915 are presented in Table 5.

In the second-order CFA model, according to the modification indices, we added two covariances between two items of the 'passive' dimension, between two items of the 'interactive' dimension, and one correlation between the 'constructive' and 'interactive' first-order latent factors. The standardized coefficients among latent and manifest variables are depicted in Fig. 2. The second-order CFA showed good fit indices: χ^2 (47) = 190.849, CFI = 0.980, TLI = 972, RMSEA = 0.054, 90% confidence interval (CI) [0.054, 0.061], SRMR = 0.028.

We compared the fit indices of the two models (reported in Table 6), computing the scaled chi-square difference test, $\chi s^2 = (\chi r^2 * c_r - \chi l^2 * c)/cd$. The comparison suggested that the larger model (first-order CFA) did not fit data significantly better ($p >$. 05) than the narrower one (second-order CFA).

3.4. Correlation results

We calculated Pearson correlation coefficients between the overall measure of person ability of the ICAP-TS, mean scores of the

Table 4
Factor loadings from EFA.

	Factor			
	1	2	3	4
ICAP_P1	0.332	**0.430**	0.114	−0.105
ICAP_P2	−0.037	**0.892**	0.007	0.018
ICAP_P3	0.002	**0.945**	−0.015	0.002
ICAP_A1	**0.786**	−0.013	0.118	−0.091
ICAP_A2	**0.846**	0.009	−0.009	0.092
ICAP_A3	**0.881**	0.018	−0.033	0.047
ICAP_C1	0.301	0.067	0.044	**0.532**
ICAP_C2	0.128	0.079	0.065	**0.720**
ICAP_C3	−0.055	0.020	0.287	**0.607**
ICAP_I1	0.084	0.008	**0.601**	0.266
ICAP_I2	0.013	0.004	**0.931**	−0.059
ICAP_I3	0.021	0.045	**0.732**	0.134

Table 5
Results of the first-order CFA.

Factor	Indicator	Estimate	*p*	Stand. Estimate
Passive	ICAP_P1	1.056	<.001	.793
	ICAP_P2	0.740	<.001	.669
	ICAP_P3	0.824	<.001	.712
Active	ICAP_A1	1.090	<.001	.783
	ICAP_A2	1.175	<.001	.915
	ICAP_A3	1.182	<.001	.894
Constructive	ICAP_C1	1.001	<.001	.826
	ICAP_C2	1.148	<.001	.886
	ICAP_C3	0.975	<.001	.797
Interactive	ICAP_I1	1.138	<.001	.913
	ICAP_I2	1.054	<.001	.823
	ICAP_I3	1.052	<.001	.846

Note. Covariances added according to the modification indices: ICAP_P2 and ICAP_P3 (0.680, $p < .001$); ICAP_I2 and ICAP_I3 (0.261, $p < .001$).

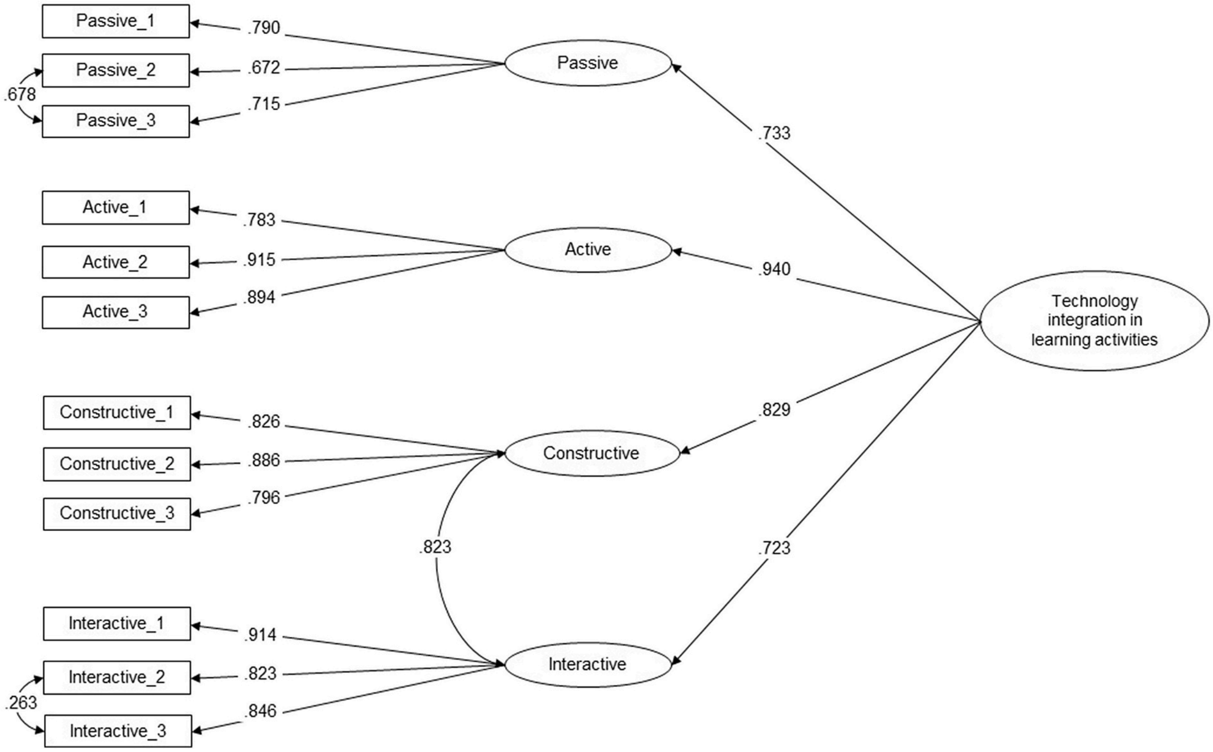

Fig. 2. Results of the second-order CFA. *Note.* All standardized coefficients are displayed. All coefficients are significant at $p < .001$.

Table 6a
Fit statistics of the first-order and second-order CFA.

	χ^2	df	*p*	CFI	TLI	SRMR	RMSEA	RMSEA 90% CI Lower	RMSEA 90% CI Upper
First-order	187.886	46	<.001	.980	.971	.028	.061	.052	.070
Second- order	190.849	47	<.001	.980	.972	.028	.054	.054	.061

Note. CI = Confidence Interval; df = degree of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; SRMR = Standardized Root Mean Square Residual; RMSE = Root Mean Square Error of Approximation.

four ICAP subscales, and the 12 educational technologies used. We also analyzed the correlation matrix to investigate whether any trend or pattern was observable among the correlations. Furthermore, we used Psychometrica's online calculator (psychometrica.de, 2017) to compare the correlation coefficients of a dependent sample for significance, according to Eid et al (2011). Given the multiple correlations estimated, the Bonferroni correction was applied to the p-value, dividing the ordinary cut-off of 0.05 by the number of coefficients estimated, thus lowering the level of significance at $p < .001$. The correlation analysis (Table 6) showed that the overall measure of person ability (i.e., ICAP-TS theta) and the mean scores of the four subscales significantly ($p < .001$) and positively correlated with the use of 12 educational technologies. For each of the four ICAP dimensions, we selected the largest correlation with educational technology use and compared the magnitude of this correlation coefficient with the correlation coefficients of the other dimensions and educational technology use. The passive dimension showed the greatest correlation with the frequency of using presentation software. We found that the correlations of 'presentation software' with 'passive' was significantly greater than the correlations of presentation software with 'active' ($z = 6.863$, $p < .001$), 'constructive' ($z = 9.04$, $p < .001$), and 'interactive' ($z = 10.244$, $p < .001$). The largest correlation of the 'active' dimension was with the learning management system. This correlation was significantly greater than the correlations of the 'learning management system' with 'passive' ($z = 3.680$, $p < .001$), 'constructive' ($z = 5.889$, $p < .001$), and 'interactive ($z = 6.648$, $p < .001$). Regarding the constructive subscale, the highest correlation can be observed with 'online research software'. This correlation was also significantly higher than the correlations of online research software with 'passive' ($z = 4.749$, $p < .001$), 'active' ($z = 3.388$, $p < .001$), and 'interactive' ($z = 3.015$, $p < .001$). Lastly, the highest correlation for the 'interactive' dimension is reported for 'students' work presentation software'. In turn, this correlation is significantly greater than the correlation of 'students' work presentation' with Passive ($z = 4.536$, $p < .001$) and Active ($z = 4.527$, $p < .001$). However, the correlation coefficient for Interactive was not significantly greater than the correlation coefficient for Constructive ($z = 0.748$, $p = .227$).

3.5. Multiple linear regression results

Results (from Tables 7–11) revealed that gender and age do not have any significant effects on the four dimensions of technology integration, or on ICAP-TS overall score. Indeed, the number of teaching years negatively and significantly affect the Passive and Interactive dimensions, and the ICAP-TS overall measurement score.

4. Discussion

In the present study, we validated the newly developed ICAP-TS, a 12-item self-report scale to address technology integration with regard to four different learning activities (i.e., passive, active, constructive, and interactive), as defined by the ICAP theoretical model.

The CFA analysis of the ICAP-TS dimensionality yielded excellent fit indices, and the four subscales demonstrated excellent reliability. The results showed that the ICAP-TS is a psychometrically valid measure aligned with the ICAP model. The scale consists of four highly reliable dimensions of technology integration in different learning activities that identify an overall dimension of technology integration, as confirmed by the results of the second order CFA.

Next to the classical test theory, the item response theory is useful in providing a quantitative assessment of the ICAP-TS and its 12 items. The Rasch PCM analysis supported the psychometric properties of the scale items and confirmed the items' reliability and the discrimination power of the ICAP-TS items. Considering the ease and difficulty in endorsing the items, the ordering reliability coefficients of the items reflect the complexity of learning activities as described in the ICAP taxonomy. Indeed, the items comprised in the 'passive' dimension were perceived as the easiest items to endorse by teachers, followed by the items in the 'active' dimension. The items included in the 'constructive' and 'interactive' dimensions were the most difficult to endorse. From the analysis of the Wright map, we can affirm that the chance of reporting frequent integration of technologies in lessons increases as the overall level of ability in integrating technology increases, particularly for the integration of technology in constructive and interactive activities. The frequent use of technology in these two types of learning activities seems to be very challenging to achieve.

Therefore, the ICPA-TS is a tool that could help discriminate the different levels of technology integration in learning activities and allows distinguishing higher levels of technology integration (i.e., constructive and interactive) from less sophisticated activities (i.e., active and passive).

In addition to testing the validity of the instrument, the use of the ICAP-TS also allowed additional considerations about teachers'

Table 6b
Correlation matrix between ICAP-TS and educational technology use.

	ICAP-TS (theta)	ICAP- TS subscales (mean score)			
		Passive	Active	Constructive	Interactive
Presentation software	.398	**.559**	.387	.314	.267
Specific-subject learning software	.407	.353	**.384**	.377	.350
Online test and quizzes	.406	.365	**.378**	.367	.360
Word-processing software	.450	.379	**.441**	.432	.418
Spreadsheet and calculation software	.392	.303	**.359**	.322	.311
Games	.343	.268	**.312**	.308	.305
Learning management system	.470	.440	**.536**	.412	.377
Drawing and image editing software	.365	.259	.306	.340	.309
Video recording and editing software	.318	.172	.219	.334	.317
Online research software	.500	.391	.448	.519	.470
Online communication software	.453	.344	.397	.409	**.431**
Students' work presentation/publication software	.516	.345	.410	.506	**.518**

Note. All correlations are significant at $p < .001$. In bold are the highest correlation coefficients among the four subscales.

Table 7
Multiple linear regression on the Passive dimension.

						95% Confidence Interval	
Predictor	Estimate	SE	t	*p*	β	Lower	Upper
Intercept	4.061	0.051	79.187	<.001			
Age	−3.22e−4	0.000	−0.945	.345	−.031	−.095	.033
Teaching years	−0.004	0.001	−3.72	<.001	−.121	−.185	−.057
Gender [a]	0.060	0.064	0.936	.350	.029	−.032	.090

Note. [a] 0 = male, 1 = female.

Table 8
Multiple linear regression on the Active dimension.

						95% Confidence Interval	
Predictor	Estimate	SE	t	*p*	β	Lower	Upper
Intercept	3.591	0.061	59.266	<.001			
Age	−8.32e−5	0.000	−0.207	.836	−.007	−.071	.058
Teaching years	−0.002	0.001	−1.293	.196	−.042	−.107	.022
Gender [a]	−0.056	0.076	−0.74	.459	−.023	−.085	.038

Note.[a] 0 = male, 1 = female.

Table 9
Multiple linear regression on the Constructive dimension.

						95% Confidence Interval	
Predictor	Estimate	SE	t	*p*	β	Lower	Upper
Intercept	3.008	0.055	54.311	<.001	−.019	−.083	.046
Age	−2.09e−4	0.000	−0.569	.569	−.044	−.109	.020
Teaching years	−0.002	0.001	−1.343	.180	.026	−.036	.087
Gender [a]	0.057	0.069	0.824	.410	−.019	−.083	.046

Note. [a] 0 = male, 1 = female.

Table 10
Multiple linear regression on the Interactive dimension.

						95% Confidence Interval	
Predictor	Estimate	SE	t	*p*	β	Lower	Upper
Intercept	2.614	0.058	45.252	<.001			
Age	0.000	0.000	0.978	.328	.032	−.032	.096
Teaching years	−0.003	0.001	−2.269	.023	−.074	−.139	−.010
Gender [a]	−0.038	0.072	−0.529	.597	−.017	−.078	.045

Note. [a] 0 = male, 1 = female.

Table 11
Multiple linear regression on the ICAP-TS measure (theta).

						95% Confidence Interval	
Predictor	Estimate	SE	t	*p*	β	Lower	Upper
Intercept	0.166	0.124	1.34	.180			
Age	0.001	0.001	0.963	.336	.032	−.033	.096
Teaching years	−0.005	0.003	−2.111	.035	−.069	−.134	−.005
Gender [a]	−0.080	0.155	−0.517	.605	−.016	−.078	.045

Note. [a] 0 = male, 1 = female.

integration of technology in Swiss upper secondary schools. Descriptive statistics revealed how frequently teachers integrated technology into their learning activities. The findings showed that technologies were mostly integrated in activities in which students were passively involved, whereas integration in activities in which students were actively and interactively engaged was less frequently reported. These results are consistent with the international studies investigating the integration of technologies in educational contexts (e.g., ICILS, PISA) that reported a high frequency level of digital tools for presenting and sharing content, and a low use of more sophisticated software and devices that enable the implementation of constructive and interactive learning activities (European Commission, 2013, 2019; Fraillon et al., 2020). Similarly, studies conducted in higher education revealed that teachers use technology more often in activities that entail a passive role of students (e.g., to support presentation or demonstration) rather than in activities that require students' active and interactive role (see Marcelo et al., 2015 in Spain; Newman et al., 2018 in the UK; Sailer et al., 2018 in Germany). The predominant implementation of passive learning activities supported by technology can be explained by the fact that the technological devices and software available in educational settings mainly address teacher-centered and lecture-style technology use. Another explanation could be that less time, resources, and competence are required to implement passive learning activities; instead, constructive and interactive activities require more time from teachers (and students), effort, and high abilities in using more sophisticated technologies (Cattaneo et al., 2022; Lohr et al., 2021). Overall, it seems that teachers did not utilize the full potential of the technologies to provide students with constructivist or collaborative learning.

Furthermore, we analyzed the correlations among the ICAP-TS subscales and the use of several educational technologies. Although all the associations were positive and significant, we observed some correlational trends. For example, the passive dimension highly correlates with the use of presentation software. This is consistent with the fact that this type of software is very useful for learning activities in which teachers inform, demonstrate, and explain lesson content to students. The use of subject-specific learning software, online test and quizzes, word-processing software, spreadsheets and calculation software, games, and learning management systems highly correlated with the active sub-dimension. A possible interpretation is that teachers who more frequently implement learning activities in which students are required to use technology for writing down knowledge, solving simple tasks, and training allow students to use these types of technologies in lessons. Indeed, the use of the aforementioned technologies allows students to interact with the already-made instructional material and given knowledge. By contrast, the use of drawing and image editing software, video recording and editing software, and online research software is coherent with the implementation of constructive learning activities in which students are asked to create new knowledge that goes beyond the given material and contents. Then, the use of software for online communication and students' work presentation highly correlated with the implementation of interactive learning activities supported by technology. Even if these results may suggest that techno-centric measurement instruments could provide some indications about the pedagogical activities implemented by teachers in lessons, they cannot be reliable to assess the quality of technology integration. Rather, our results may provide a preliminary clue as to which technological tool or software is better suitable for one type of learning activity than another. The association between what technologies and how they can be used should be further investigated with the aim of identifying the appropriate use of technology for the implementation of constructive and interactive learning activities. Furthermore, the multiple regressions results revealed that teachers' gender and age do not affect the level of technology integration. However, years of teaching negatively correlate with the overall ICAP-TS measure and the Passive and Interactive dimensions. These results are in line with previous findings revealing that the more experienced teachers tended to use technology less frequently (Inan & Lowther, 2009; Mathews & Guarino, 2000) and suggests that novice teachers, who recently graduated from a teachers education program, would be more ready to integrate technology in learning activities.

4.1. *Limitations*

The findings of this study have to be seen in light of several limitations. First, the ICAP-TS has been validated only with a German-speaking sample. Second, the participants in our study were all upper secondary school teachers, thus representative only of this schooling level. A third limitation of the study is the use of a self-report questionnaire which is susceptible to self-assessment bias. However, as the items require teachers to report on the frequency of their objective behaviour related to the use of technologies, and not to self-assess their skills or subjective opinions, we expect the answers are likely to reflect the actual behaviour of technology integration. Fourth, we applied Rasch model analysis to examine the ICAP-TS, although we did not administer a performance test. However, the use of Rasch modeling is becoming more and common also in survey research (Andrich & Marais, 2019; Boone, 2016; Royal et al., 2010).

4.2. *Implications for research and practice*

To overcome the study's limitations, future studies should validate the ICAP-TS in different languages and among teachers from different levels of education to assess whether this scale could also be applied for research in primary and higher education. In order to address the limitations of self-report questionnaires for assessing the quality of technology integration, it would be worthwhile to combine qualitative measures such as classroom observations, interviews and analysis of lesson plans, albeit more time-consuming than questionnaires.

Furthermore, since the understanding of how technology is integrated in education is the first step to further investigate the effect of technology on learning outcomes, the ICAP-TS scale could be used in future research that investigates the effects of technology integration on students' achievement. Future research should also investigate correlations between the use of technology in ICAP learning activities and teachers' digital competence, beliefs and attitudes toward technology to identify the most significant predictors of high-quality technology integration. Indeed, this information could be useful to design teacher training for digital education. From a practice perspective, the ICAP-TS can be used as a metric of the digital transformation progress in secondary schools and for self-evaluation by teachers who can use the instrument to reflect on their own teaching practices.

5. Conclusion

This study is a first attempt to validate the ICAP-TS developed on the basis of a theoretical pedagogical model. Our validation study contributes to addressing the need for a valid measurement instrument for assessing the quality of technology integration in schools. Based on the ICAP theoretical model, the ICAP-TS has been shown to be a reliable short scale for fulfilling this need. The advantage of using a short scale is that it is economically suitable in terms of time and cost when a large number of people are surveyed. This could open up new perspectives for technology integration research in schools. Instead of measuring the quantity of device use, the ICAP-TS provides both a theoretical framework and a valid self-report measure to address the quality instead of the mere quantity of technology integration in schools.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

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