Article

A Latent Class Analysis of University Lecturers' Switch to Online Teaching during the First COVID-19 Lockdown: The Role of Educational Technology, Self-Efficacy, and Institutional Support

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Abstract: The switch to emergency remote teaching (ERT) due to the first COVID-19 lockdown demanded a lot from university lecturers yet did not pose the same challenge to all of them. This study sought to explain differences among lecturers (*n* = 796) from universities in France, Germany, Switzerland, and the UK in their use of educational technology for teaching, institutional support, and personal factors. Guided by the Social Cognitive Theory (SCT), lecturers' behavior (educational technology use), environment (institutional support), and personal factors (ERT self-efficacy, continuance intentions, and demographics) were examined. Latent class analysis was employed to identify different types of lecturers in view of educational technology use, while multinomial regression and Wald chi-square test were used to distinguish classes. The largest latent class were *Presenters* (45.6%), who focused on content delivery, followed by *Strivers* (22.1%), who strived for social interaction, *Routineers* (19.6%), who were ready for online teaching, and *Evaders* (12.7%), who evaded using technology for educational purposes. Both personal factors and perceived institutional support explained class membership significantly. Accordingly, *Evaders* were older, less experienced, and rarely perceived institutional support as useful. *Routineers*, the *Evaders'* counterparts, felt most self-efficient in ERT and held the highest continuance intentions for educational technology use. This research suggests that universities engage lecturers in evidence-based professional development that seeks shared visions of digital transformation, networks and communities, and design-based research.

Keywords: COVID-19; educational technology; higher education institution; university teaching; faculty; self-efficacy; technology-enhanced learning; professional development; institutional support; Social Cognitive Theory

1. Introduction

The lockdown of universities had an immediate impact on the digitalization of teaching and learning at universities. Strict measures were implemented to flatten the epidemic curve. As a result, educational practices changed dramatically in terms of teaching and learning. For conventional—brick and mortar—universities, the lockdown meant that teaching and learning had to be spatially distanced. Shortly thereafter, the term "emergency remote teaching" (ERT) became established in this new educational context [1,2].

In this research, the empirical focus lies on lecturers, who had to fulfil the difficult task of transforming their teaching norms into a new online format—within days. Many of

the lecturers were inexperienced in online teaching and had likely only previously used Learning Management Systems (LMS) in combination with their conventional teaching. Although the rapid transition to ERT allowed for continuity of education, preparing a high-quality online course would typically have required much more preparation time and pedagogical and technological thought [1,3]. For example, lecturers for whom teaching in an online-only environment was new, used educational technology trying to replicate their conventional teaching. The need for more student-centered approaches to teaching and the benefits of educational technology to enhance learning was not visible or attainable to the initial ERT [3–5].

As Achen and Rutledge [4] aptly noted in their research on the transition from ERT to quality online teaching, institutional efforts to achieve this particular leap in instructional performance within a short period of time are far-reaching. The role of lecturers shifted from probably being skilled and experienced educators in the conventional teaching setting before the pandemic to novices in online teaching. Now lecturers lacked a set of competencies and attributes for quality online teaching [6]. However, in the new ERT reality, lecturers were faced with new demands as they suddenly had to incorporate academic, technical, guidance, social, and organizational functions related to online teaching. In addition, a new set of pedagogical, cognitive, technological, communicative, and personal skills was necessary to convey quality online teaching [6]. Overall, studies showed that lecturers were able to adapt to the new situation by adopting new and expanding the usage of already known technologies for the initial ERT [7,8]. However, lecturers from conventional universities had different personal and institutional prerequisites for the switch to ERT [1,9]. Looking at personal factors, a positive attitude towards digital technologies in teaching [10,11], as well as a strong self-efficacy expectancy for online teaching [12–14], facilitated the switch to ERT. Besides that, studies showed that especially lecturers with prior experience with digital technologies had an advantage for a successful shift to ERT [15–17].

In fact, lecturers experienced ERT differently, as studies with person-centric approaches show. A mixed-methods study identified three types of lecturers during the first lockdown, namely *Experienced*, *Enthusiastic*, and *Cautious* lecturers. The researchers conclude that the most influential factor for profile affiliation was prior experience and competence with educational technology in teaching [17]. At the same time, surprisingly little research applied person-centric approaches such as cluster analysis, latent class, or latent profile analysis to investigate different patterns of lecturers' adaptation to ERT [18,19]. Rutherford et al., for example, also identified three groups of lecturers during ERT: *Highly supportive*, *instructor-centered*, and *more detached*. The latter group accounted for more than half of the participants. According to the results, the more detached lecturers reported educational technology use on a low level. The instructor-centered lecturers focused on conveying teaching material and lecturing, whilst the highly supportive lecturers also made sure to enable social interaction in the digital space [18]. Overall, recent research suggests that lecturers approached ERT differently depending on their prior experiences with educational technology use. However, it is evident that there is a research gap in person-centric approaches that focus on additional personal (e.g., self-efficacy, continuance intentions) and environmental factors (institutional support) in the switch to ERT.

Even before the pandemic, empirical research on educational technology use with person-centric approaches was sparse. Using latent profile analysis, Yukhymenko-Lescroart et al. [20] found five types of lecturers in relation to educational technology use: *Technology enthusiasts*, *knowledgeable adopters*, *knowledgeable skeptics*, *prospective adopters*, and *non-adopters*. The researchers used the constructs of the Technology Acceptance Model (TAM) [21] as latent profile indicators. In another person-centric study, although using a K-12 teacher sample, researchers distinguished between four evenly size-distributed groups of lecturers using latent class analysis: *Dexterous*, *Presenters*, *Assessors*, and *Evaders*. The first and last group of lecturers contrasted the most regarding educational technology use in teaching. Dexterous lecturers were flexible in using it and did so on a high level. Presenters focused on

conveying the teaching content, and assessors used the benefits of educational technology to assess student achievements [22].

Following the person-centered approaches, the present study seeks to analyze data from lecturers during the first COVID-19 lockdown to classify them based on how they used educational technology for ERT. Qualitative studies have shown how differently faculty members have experienced the transition to ERT [4–6,23]. In this study, we use quantitative data and analyses to enrich these research findings and highlight the importance of individual experiences and progress related to digital transformation in higher education. By identifying unobserved groups in our data, we seek to explain correlations between these and personal, institutional, and technological factors.

Therefore, lecturers self-reported use of eight technologies will serve as indicators for a latent class analysis (LCA). Based on the assumptions of the *Social Cognitive Theory* (SCT) [24], which describes the interaction between a person's behavior, personal factors, and environment, it is assumed that the lecturer's educational technology use (behavior) depended on the institutional support (environment) and lecturers' self-efficacy, etc. (personal factors). This study is therefore intended to complement an existing research gap in person-centered approaches in university teaching [20]. In the following sections, the three factors mentioned above will be explained from an empirical perspective and then consolidated in a theoretical framework.

1.1. Educational Technology to Close the Spatial Distance

Educational technology was the means for lecturers that ensured the continuity of education during the COVID-19 lockdowns through teaching and learning in an online environment. In a more traditional sense, technology is used for educational purposes in order to achieve teaching and learning goals. Educational technology consists of "a broad variety of modalities, technologies, and strategies for learning" [25]. To highlight the importance of educational technology for ERT, Moore [26] stated that "distance education is not simply a geographic separation of learners and lecturers, but, more importantly, is a pedagogical concept." However, as Hodges et al. [1] rightfully point out, ERT was the first response of universities to the political and social demand for continuing education at all costs. The theoretical and empirical foundations of online teaching, which had been built over decades, were largely left aside. Therefore, "ERT is a temporary shift of instructional delivery to an alternate delivery mode due to crisis circumstances" [1]. Educational technology as a practice "involves the reasoned and effective integration of technology to support or facilitate learning, performance, and instruction" [27]. It is, therefore, essential to differentiate digital technologies or simply technology, such as computers, smart and wearable devices, software, and applications, from educational technology, which includes the integration of such digital technologies in a pedagogical context to enhance learning. For example, in a comprehensive second-order meta-analysis, Schneider and Preckel [28] have shown that educational technology in higher education has the strongest effects on learning when it complements classroom-based teaching and learning. The results further revealed that only very advanced, subject-specific, and high-cost digital technologies such as virtual reality games had high effect sizes on learning outcomes. On the contrary, when human instruction was replaced by computer instruction, academic performance decreased. In the end, educational technology use should improve the quality of teaching and learning by providing stimulating activities that are adapted to learners' individual needs and enable social learning [29].

Puentedura's [30] substitution, augmentation, modification, and redefinition (SAMR) model categorizes educational technology use. The SAMR model consists of four levels in consecutive order; hence, with each step, learning is enhanced and teaching digitally transformed. The lowest level, substitution, corresponds to technology integration that substitutes an analog teaching method, such as reading an online lexicon instead of a hardcopy version. On the augmentation level, technology augments a learning opportunity, e.g., watching an educational video on portable devices for each student and the possibility

to stop and rewind rather than on the pace for all the students at once. One step upwards, modification means that technology allows the substantial redesign of a task, for example, writing and editing a text simultaneously as a group on an online pad. At last, the redefinition level accords to technology integration that creates a unique and interactive learning environment in the form of software, virtual game, or an app that, for example, allows self-directed learning and an individualized learning experience [31]. Manifold digital technologies are not only openly accessible, often at no monetary cost, but also often include multiple use cases. Consequently, the extent to which learning is enhanced through digital technologies greatly depends on how well it is integrated and what subject-specific and pedagogical goal the lecturer wants to achieve by its integration [3,32]. A qualitative study [33], which was conducted during the first lockdown period in 2020, has shown that lecturers' initial reaction to ERT was to keep students informed and guarantee access to content. More so, lecturers zealously tried to enable social learning through digital technologies such as synchronous collaboration tools (sharing of audio-video, chat, text discussion) or asynchronous collaboration tools (forums, note taking, document creation). However, as shown in a systematic review study, "recreating physical learning spaces in cyberspace was a common approach to dealing with in-class engagement issues. Zoom featured as a popular tool for replicating F2F instruction online" [34]. Alternatively, to put it into the perspective of the SAMR model [30], during ERT, digital technologies have been integrated to substitute conventional classroom practices in the online space rather than enhancing learning [32].

In another qualitative study by Chiasson et al. [35], lecturers reported that online courses take more time to prepare than face-to-face ones. Furthermore, the involvement of instructional designers is perceived as helpful for the effective integration of technology and that colleagues could deliver pedagogical support. The lecturers increasingly took an accompanying role in the lessons, which was paralleled by the perceived loss of control over students' learning. Especially lecturers who primarily taught synchronously during ERT reverted to substituting conventional teaching methods. Lastly, studies display that those lecturers were worried that the quality of teaching suffered due to the sudden switch to an online environment [11,36,37].

Taken together, educational technology use is meant to enhance student learning. However, in the case of ERT, the purpose switched to ensure continuity of education in an online space due to the spatial distance between lecturer, learner, and the classroom.

1.2. Self-Efficacy in Emergency Remote Teaching

According to Bandura (1986) [24], a person's performance is mediated by self-efficacy, as "perceived self-efficacy is defined as people's judgements of their capabilities to organize and execute courses of action required to attain designated types of performances." In the context of teaching, a positive appraisal of teaching capabilities corresponds to the lecturer's confidence in creating an effective learning environment to promote learning outcomes [38]. In addition, perceived self-efficacy is a significant determinant of performance that operates partially independently of underlying skills [24]. In other words, a person's belief in his or her capabilities also influences actual performance, to some extent, independently of previously acquired skills, which was the case for a lot of lecturers during the switch to online teaching due to COVID-19. Four sources of self-efficacy beliefs have been postulated, namely mastery experiences, vicarious experiences, social persuasion, and physiological and psychological cues [38]. Mastery experiences have the greatest effect on self-efficacy beliefs. Successful performances, therefore, increase self-efficacy beliefs, whereas failures decrease expectations of a person's ability to master a specific task to succeed.

As displayed in a recent meta-analysis [39], a large body of studies exists that describes a positive correlation between teaching self-efficacy and students' academic achievements. Furthermore, the positive relationship between teaching self-efficacy and the quality of teaching and learning in a classroom has been researched and confirmed extensively [40]. Reverting to the self-efficacy theory, people who believe they can integrate educational

technology into their teaching to reach instructional goals are more inclined to integrate educational technology [41,42]. Especially in difficult times such as a pandemic, lecturers with high self-efficacy beliefs in teaching are more persistent and remain flexible to alter their plans and surmount emerging obstacles [43,44], such as immediately switching to ERT [45].

Numerous studies have attempted to explain the role of self-efficacy in teaching for face-to-face but also online learning and teaching. According to Klassen and Chiu [46], teaching self-efficacy beliefs become more positive through experiences in teaching. However, the relationship is curvilinear, meaning that the positive correlations peak after 20 years of experience and begin to decline. In this research vein, Chang et al. [47] have found that female professors had greater self-efficacy than males and greater self-efficacy among professors from educational disciplines or social sciences [42,46]. Besides demographic factors, also attitudes towards online teaching have been researched. Horvitz, Beach, Anderson, and Xia [42] found that the perception of learning in an online environment influenced several dimensions of teaching self-efficacy, such as student engagement, instructional strategies, and class management. Moreover, lecturers' intention to online teaching in the future also influenced the self-efficacy score positively.

Another prominent research branch around has evolved around lecturers' *Technological Pedagogical Content Knowledge* (TPACK) framework introduced by Mishra and Koehler [48]. It assesses lecturer competence to successfully integrate educational technology into their teaching and thereby evaluates lecturers' knowledge in terms of digital technologies, pedagogy, and subject matter. More importantly, it highlights the intersection of these three areas to identify factors that are central to teaching quality and students' academic achievement. Applying the TPACK framework, studies reported a positive correlation between teaching self-efficacy and TPACK [49]. In a recent study, researchers have found that lecturers' who had greater self-efficacy and held positive attitudes towards online teaching during COVID-19 measures were less psychologically strained. In terms of ERT, the lecturers with higher scores perceived their teaching as more successful and felt more confident in their teaching abilities [50]. In the context of ERT, Ma, Chutiyami, Zhang, and Nicoll [13] have found that, while lecturers' self-efficacy did not increase, the extent to which lecturers integrated educational technology did. In the qualitative part of the mixed-methods study, lecturers reported the lack of experience with educational technology as a barrier to the transition to ERT. Moreover, the assessment of student achievement and time for preparation of ERT were negatively reported. For ERT, studies showed that prior experience with online teaching and educational technology was beneficial [12,16].

Overall, teaching self-efficacy is influenced by prior experience in teaching with and attitudes towards educational technology and, to a lesser degree, by demographics and institutional support [42,45]. More important, teaching self-efficacy is a predictor of teaching quality, students' academic achievement, the integration of educational technology, and intentions to integrate educational technology in the future [39,42]. Seetal et al. [51] argue that teaching self-efficacy is a primer for ERT and online teaching in general. A basic prerequisite for a self-effective approach to educational technology is the digital maturity of a university and the associated digitization strategy. However, the availability of technology is not enough. Implementation must be guided and sustainable. This is the only way to improve the quality of teaching and strengthen student learning [29]. However, research on teaching self-efficacy is primarily conducted within the K-12 context. There is a need for more quantitative and qualitative research in higher education [52].

1.3. Institutional Support

Lecturers' efforts and successful technology integration depend on personal and institutional factors. The latter contains types of resources, such as infrastructure, time, professional development, and technological-pedagogical support. Each factor can vary based on the digital maturity of a particular university. According to Ertmer [53], who labels these potential resources as "first-order barriers", a lack of sufficient pedagogical

and technological support as well as access to soft- and hardware can be frustrating, especially when lecturers face multiple problems at a time. Therefore, even if a lecturer wants to implement modern technology and create new learning opportunities, the advancement can be disturbed due to first-order barriers. However, studies have shown that the perceived usefulness of institutional support depends on lecturers' readiness for online teaching. Comparing three different types (high, low, and inconsistent online teaching readiness) of lecturers, Scherer, Howard, Tondeur, and Siddiq [45] have found that lecturers with low competencies for online teaching also perceived weak support from their institution, whereas lecturers who were ready for online teaching perceived sufficient institutional support. Especially for ERT, which had to be conducted by both trained and inexperienced lecturers, the availability of directed technological and pedagogical support combined with strong leadership was crucial for a successful shift from conventional to online teaching [10,54,55].

In a qualitative study, Guilbaud et al. [56] have identified three sources of institutional support for lecturers: professional development, collaboration with colleagues, and administrative support and encouragement by the institution. More specifically, the interviewed lecturers wished for individualized professional development, the opportunity for social learning and sharing, reasonable expectations, more time for preparation as well as recognition for efforts. In many studies, the same problem areas, or issues of resources for online teaching recured, namely professional development, technical and pedagogical support, access to technology, and time [10,57–59]. These findings were also displayed in a study by Marek [36]; results showed that lecturers who had to learn to teach online benefited from time and financial compensation for preparation, pedagogical and technological support from the institution, formal professional development, and support through colleagues. Furthermore, the value and shared vision of online teaching at a university was crucial for educational technology use in teaching [11]. In contrast to the studies above, Weidlich and Kalz [60] found in their cross-sectional study during COVID-19 restrictions, no evidence that institutional support played a significant role in ERT.

In short, institutional support can be available and still useless to the cause of quality online teaching if it remains unused. Lecturers' wish for individualized support is a sign that a one-support-fits-it-all is not sufficient [58]. This accords with studies that found types of lecturers that differ regarding their experience and competence in educational technology use [17,19,20].

1.4. Conceptual Framework and Research Questions

So far, extraordinarily little attention has been paid to what facilitated lecturers' shift to ERT and the role of educational technology, self-efficacy, and institutional support. We assume that these three factors interact with and influence the lecturer's capability for ERT reciprocally [24]. Therefore, the conceptual framework of this study is derived from Bandura's [24] *Social Cognitive Theory*, which explains the interaction between a person's behavior, environment, and personal factors.

First, in the present study, behavior corresponds to the lecturers' use of educational technology for ERT. Second, the university environment corresponds to the lecturers' perceived usefulness of institutional support. Third, personal factors correspond to online teaching self-efficacy, continuance intentions for educational technology use, and further covariates (age, gender, discipline, and prior experience in educational technology use) (see Figure 1). It is assumed that optimal support on the part of the university and a high level of conviction in the lecturers' own abilities had a decisive influence on the integration of digital technologies. Conversely, it is also assumed that the integration of digital technologies has a positive impact on skills in using them and, in the longer term, on the digital maturity of universities, which displays through the technical and pedagogical support offered, professional development, and technology infrastructure for teaching at universities [29].
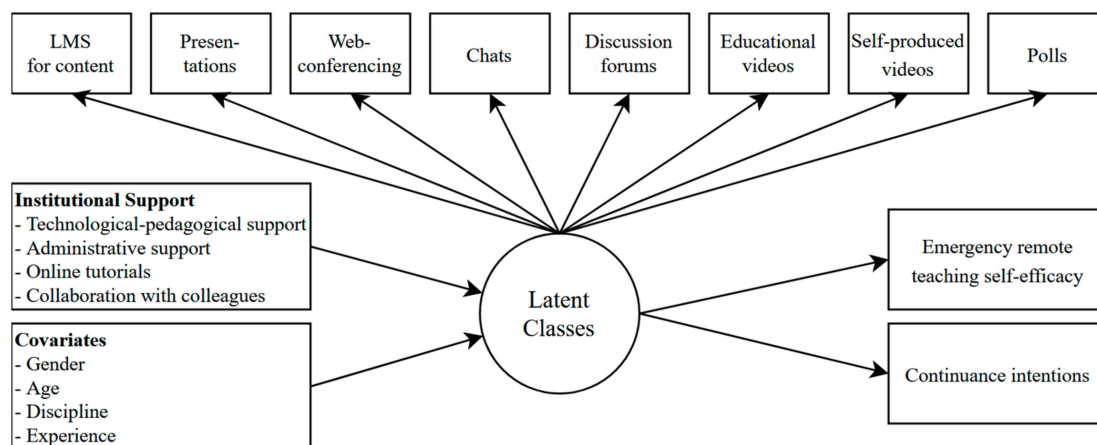
Figure 1. Latent class model.

As noted earlier, the sudden switch to ERT demanded a lot from lecturers: quickly shifting to online teaching and learning environments, adopting new digital technologies, shifting working environments, collaboration, and communication [34]. However, not all experienced this pressure and handled the teaching situation in the same way [61]. Based on the theoretical and empirical implications presented above, the following questions arise:

RQ1. Which latent classes can be identified based on lecturers' educational technology use during ERT (behavior)?

RQ2. In how far do lecturers' demographic and professional variables explain latent class membership (personal factors)?

RQ3. In how far are lecturers' ERT self-efficacy and continuance intentions related to latent class membership (personal factors)?

RQ4. In how far does institutional support for ERT explain latent class membership (environment)?

2. Materials and Methods

2.1. Participants

Participants were *n* = 796 lecturers who actively taught during the first COVID-19 lockdown in 2020. In total, five conventional face-to-face universities participated and invited all their lecturers to partake in the survey. The universities were in the UK, France, Germany, and Switzerland.

The French sample consisted of 398 lecturers, which accounted for exactly 50% of the analyzed sample. Followed by the Swiss (*n* = 157, 19.7%), the German (*n* = 154, 19.3%), and lastly the UK (*n* = 87, 10.9%). 381 (47.9%) lecturers described themselves as female, and 388 (48.7%) as male. 27 (3.4%) lecturers chose not to self-describe. For further analysis, two age groups were formed, which were of comparable size: 360 (45.2%) lecturers were 45 years old or younger, whereas 432 (53.3%) were older than that. More lecturers from Non-STEM (*n* = 488, 61.3%) participated than from STEM (*n* = 308, 38.7%) disciplines. Regarding prior experience, about half of the lecturers reported having used educational technology only to a small extent or not at all (*n* = 407, 51.1%). The other half had used educational technology to a moderate or large extent (*n* = 385, 48.4%).

After approval by appropriate ethic committees and rectorates, a link to the questionnaire was distributed to all lecturers at the participating universities, regardless of their academic position. Participants received information about the data processing of the study, which they confirmed with written consent. In addition, participants could end the survey or skip questions at any time. The survey was open from mid-May to mid-June. In addition, a reminder for participation was sent out after two weeks.

2.2. Instruments

The questionnaire consisted of three parts: Use of educational technology and experiences before and during the pandemic and a post-pandemic outlook. Because lecturers at the universities spoke different languages, the questionnaire was translated and back-translated from English into French and German. Then, the questionnaire was piloted on a sub-sample at each university. The collected feedback was then incorporated into the next version of the questionnaire before it was tested by university experts for content and face validity [16].

2.2.1. Covariates

Gender, age, discipline, and prior experience in using educational technology in teaching were included as covariates in the statistical analysis. Within the theoretical framework, however, they fall under the category of personal factors and are therefore of theoretical relevance, which is addressed by Research Question 2.

2.2.2. Educational Technology Use

As depicted in Table 1, the eight items that assessed lecturers' educational technology use during ERT functioned as indicators for LCA. Lecturers were asked to report their educational technology use on eight different types of technology. The 4-point Likert scale was dichotomized for LCA. Values 1 and 2 represent no or little use, whereas values 3 and 4 represent moderate or extensive use. The frequencies of use are shown in Table 1, along with a classification of educational technology according to the four dimensions of the SAMR model [30,31].

Table 1. Frequencies of self-reported educational technology use during lockdown.

Educational Technology	Not At All/ to a Small Extent	To a Moderate/ Large Extent	SAMR Classification
LMS for content	14.3%	85.7%	Substitution
Presentations	22.1%	77.9%	Substitution
Web-conferencing	36.8%	63.2%	Substitution/ augmentation
Chats	63.9%	36.1%	Substitution/ augmentation
Discussion forums	59.0%	41.0%	Augmentation/ modification
Educational videos	63.0%	37.0%	Augmentation/ modification
Self-produced videos	75.0%	25.9%	Augmentation/ modification
Polls	57.5%	42.5%	Augmentation/ modification

Note. SAMR = Substitution, Augmentation, Modification, Redefinition.

2.2.3. Emergency Remote Teaching Self-Efficacy

Lecturers' self-efficacy was assessed using a unidimensional 4-point Likert scale (1 = not at all, 4 = completely agree) consisting of 8 items (e.g., "I feel confident I am able to use digital tools as a means to maintain the same quality of teaching."). It was adapted and modified by the research team to capture lecturers' experiences more reliably during ERT. The original scale was derived from the *Online Teaching Self-Efficacy Inventory* [62] and the *College Teaching Self-Efficacy Scale* [63]. In this study, however, it is labeled as the *Emergency Remote Teaching Self-Efficacy* scale (ERT-SE). Internal consistency proved to be at a good level with Cronbach's α = 0.87.

2.2.4. Continuance Intention

The continuance intention scale assesses whether lecturers plan to continue using educational technology for teaching after the pandemic. The research team developed it solely for the purpose of this study. The scale consists of four items rated on a 4-point Likert scale from "not at all" to "to a large extent" (e.g., "To what extent will your new experience in using digital tools affect your pedagogical practice?"). Factorial analyses demonstrated unidimensionality. The reliability was assessed using Cronbach's alpha. The score was acceptable, $\alpha = 0.73$.

2.2.5. Institutional Support

Four questions were developed to measure lecturers' perception of various aspects of their respective institutional support, which functioned as single items. The items were rated on a 4-point Likert scale (1 = "not at all", 4 = "to a large extent"). For further analysis, the items were dichotomized from 4 to 2 values (see Table 2).

Table 2. Dichotomized institutional support variables.

Usefulness of Institutional Support	Scale	n (%)
Technological-pedagogical support	Not at all/to a small extent	421 (52.9)
	To a moderate/large extent	330 (41.5)
Administrative support	Not at all/to a small extent	529 (66.5)
	To a moderate/large extent	214 (26.9)
Tutorials	Not at all/to a small extent	452 (56.8)
	To a moderate/large extent	280 (35.2)
Collaboration with colleagues	Not at all/to a small extent	354 (44.5)
	To a moderate/large extent	394 (49.5)

2.3. Statistical Analysis

Once collected, the data were imported into SPSS 27 for cleansing and initial descriptive analysis. In the first step of statistical analysis, a latent class analysis (LCA) was conducted using Mplus 8.8 LCA is a statistical method for empirically identifying an appropriate number of latent subgroups in a sample. As a person-centered mixture modeling approach, it aims to classify individuals based on their responses to a set of indicators [64]. The latent class indicators were the self-reported educational technology use presented in Section 2.2.2. above. The procedure for selecting a class solution was to run a series of models, starting with one class. Then, in an iterative process, models with one more class were each compared to the previous model. This procedure was repeated until a statistically sound solution was found that was also acceptable in terms of theoretical interpretability [65]. Statistical conformity was determined using the recommended information criteria [64], namely Aikake Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample size adjusted Bayesian Information Criterion (aBIC). In addition, likelihood-based tests such as Lo-Mendell-Rubin (LMRT) and bootstrap likelihood ratio test (BLRT) were used as a source of information for model comparison [64]. After identifying the optimal class solution, each lecturer was assigned to a class based on their posterior class membership probabilities. For the next analytical steps, the parameters of the model were fixed, so that class assignments could not be changed anymore [66].

The second step of the analysis was to examine associations between latent classes, personal factors, and the environment. Multinomial logistic regression was performed to examine how covariates and environmental factors predicted class membership using a three-step approach proposed by Vermunt [67]. For the continuous personal factor variables, ERT self-efficacy, and continuance intentions, the automated Bolck-Croon-Hagenaars method (BCH) was applied [68–70]. The automatic BCH approach independently estimates the mean of the distal outcome variables per class and evaluates mean differences with the Wald chi-square test [68].

With 0.5 to 8.0% missing values at the item level, the impact of the missing values on the statistical results was marginal. However, due to the multiple steps of the multinomial logistic regression [66] and the BCH approach [67,69,70] methods, missing values were imputed at the item level. Missing data of distal outcome variables, as well as the environment variables, were handled beforehand using the *Fully Conditional Specification Method* (FCSM) in SPSS. Twenty imputed data sets were generated. Further analyses were then conducted based on the aggregated data from the twenty imputed data sets. To account for missing values of the eight indicator variables, models were estimated using *Full Information Maximum Likelihood* (FIML), which is standard in Mplus 8.8 [71].

3. Results

3.1. Research Question 1: How Many Latent Classes Can Be Identified for Educational Technology Use?

Based on multiple fit indices combined with theoretical interpretability, a 4-class solution was found that best explained differences between lecturers. Table 3 allows for reconstructing the iterative procedure of comparing the class solutions with six latent class models. As for the information criterion AIC, BIC, and aBIC, a smaller value corresponds to a better statistical fit of the latent class model [64,72]. The likelihood-based tests indicate with a *p*-value whether the class solution with one more latent class has a better statistical fit than the previous solution. Entropy is an omnibus index that indicates the accuracy of the individuals' classification into classes, where values > 0.60 are acceptable and >0.80 good [65]. Finally, individuals' average posterior probabilities, and therefore their most likely class membership, indicate how well the model classifies individuals into their class, with values > 0.70 indicating good differentiation between classes, as shown in Table 4 [72].

Table 3. Model fit indices to evaluate the class solution.

Model (*K*-Class)	AIC	BIC	aBIC	LMRT *p*-Value	BLRT *p*-Value	Entropy
1-class	7388.470	7425.907	7400.502	-	-	-
2-class	6965.198	7044.751	6990.766	<0.000	<0.000	**0.687**
3-class	6910.981	**7032.651**	6950.087	0.104	<0.000	0.678
4-class	6876.799	7040.585	**6929.441**	**0.004**	**<0.000**	0.630
5-class	**6876.402**	7082.305	6942.581	0.428	0.286	0.608
6-class	6876.611	7124.629	6956.325	0.345	0.098	0.595

Note. Bold values indicate the model fit criteria endorse. *K* = number of classes; AIC = Aikake Information Criterion; BIC = Bayesian Information Criterion; aBIC = adjusted BIC; LMRT = Lo-Mendell-Rubin test; BLRT = bootstrapped likelihood ratio test.

Table 4. Classification probabilities for the most likely class membership and class counts.

| *K*-Class	Class-1 *Presenters* *n* = 363 (45.6%)	Class-2 *Strivers* *n* = 176 (22.1%)	Class-3 *Routineers* *n* = 156 (19.6%)	Class-4 *Evaders* *n* = 101 (12.7%)
Class-1	0.824	0.064	0.043	0.069
Class-2	0.203	0.721	0.130	0.023
Class-3	0.126	0.109	0.826	0.000
Class-4	0.064	0.025	0.000	0.772

Table 3 shows that the fit indices provide incongruent information, which is generally not uncommon for LCA [72]. The AIC value was lowest for the 5-class solution, BIC for the 3-class solution, and aBIC for the 4-class solution. However, both LMRT (*p* = 0.004) and BLRT (*p* < 0.000) *p*-values were significant for the 4-class solution. Accordingly, based on the aBIC and the likelihood-based tests, the 4-class solution showed a better statistical fit compared to the other models. Furthermore, too much interpretable information would have been lost with a 3-class solution. In a simulation study, researchers have shown that the BLRT is the most accurate indicator for statistical fit for latent class

models [64]. Finally, the 4-class model was chosen based on the above considerations and theoretical interpretability.

The results of the 4-class model are looked at in more detail here, from the largest to the smallest class count to answer the first research question (see Table 3).

The four latent classes differed in terms of class count. Class-1 was the largest group with $n = 363$ lecturers. They were likely to use LMS for content delivery, presentations, and web conferencing for ERT. Although on a low level, lecturers were more likely than two other classes to use educational videos and self-produced videos. Class-2 consisted of $n = 176$ lecturers. They were likely to use chats and forums moderately or extensively in their teaching, besides utilizing LMS, presentations, and web conferencing. However, compared to Class-1 lecturers, they were less likely to use videos. $n = 156$ lecturers belonged to class-3. They used all educational technology likely to a moderate or large extent for ERT and did so more frequently than lecturers from other classes. Lastly, class-4 lecturers, the smallest group with $n = 101$, very rarely used other educational technology besides LMS, presentations, and web-conferencing.

In this step, labels and short descriptions were given to the lecturers of the respective classes, which derived from an earlier person-centered study [22] and our own interpretations (see Figure 2).
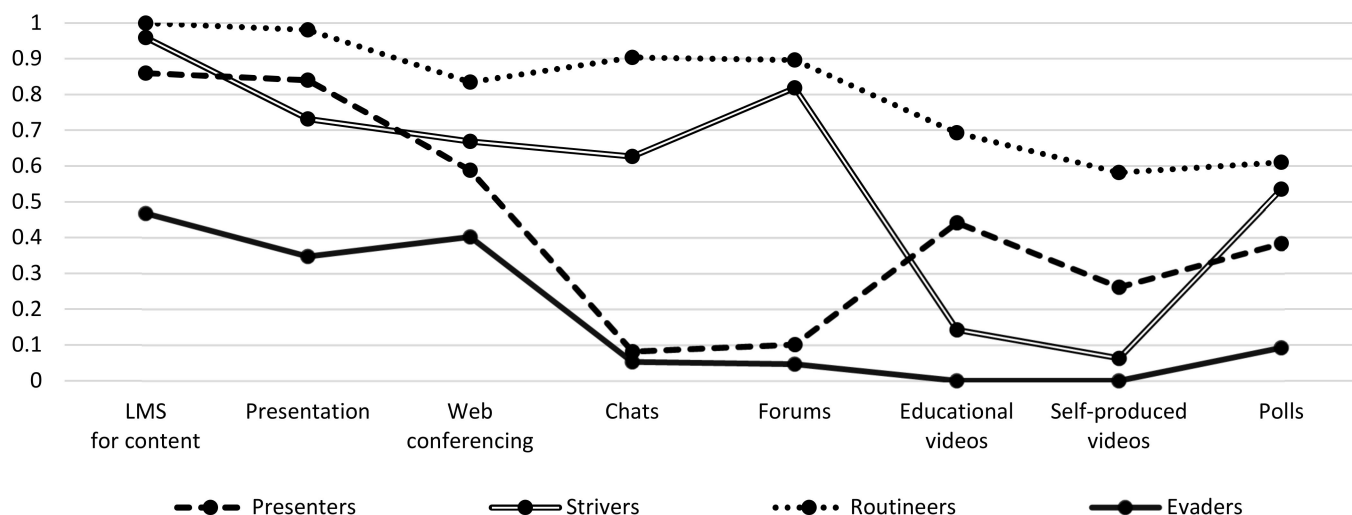
Figure 2. Latent classes of lecturers regarding educational technology use during ERT. Note. The figure shows the characteristics of the four classes based on responses to the eight indicators. The Y-axis represents the probability that lecturers responded that they used educational technology to a moderate or large extent.

Class-1: Presenters: Lecturers in this class were highly likely to use LMS and presentations to convey teaching materials. Also, they were more likely than two other classes to integrate educational videos and self-produced videos into their teaching. Chats and forums were rarely used whatsoever.

Class-2 Strivers: Although they were likely to integrate LMS and presentations during the lockdown, educational videos and self-produced videos were not. However, they integrated chats and forums for social interaction in their teaching.

Class-3 Routineers: Routineers were more likely to integrate all the assessed digital technologies in their teaching during lockdown than lecturers from the other classes.

Class-4 Evaders: Evaders were unlikely to integrate digital technologies in their teaching in a moderate or extensive way. Also, they did not adopt educational videos and self-produced videos at all.

3.2. Research Question 2: In How Far Do Lecturers' Demographic and Professional Covariates Explain Latent Class Membership?

A three-step approach [66] to conduct a multinomial logistic regression was employed to answer research Question 2, using *Presenters* as a reference to explain latent class membership.

Table 5 shows the results of the multinomial logistic regression of the demographic covariates (gender, age, discipline) and the prior experience with educational technology use (Educational technology use). When comparing *Presenters* and *Strivers*, none of the observed covariates explained significant differences. Lecturers from Non-STEM disciplines (humanities and art, social sciences, law, business and economics, theology, psychology, education, languages) were more likely to be members of *Routineers* ($OR = 2.468$, $p = 0.006$). Accordingly, the odds ratio of these lecturers belonging to *Routineers* was 2.468 higher compared to *Presenters*. The same goes for lecturers who integrated educational technology to a moderate or large extent before the pandemic. They were likely to be *Routineers* ($OR = 4.790$, $p < 0.000$). As for the *Evaders*, age ($OR = 2.612$, $p = 0.300$) as well as previous experience with educational technology use ($OR = 0.183$, $p = 0.006$) were class membership predictors. According to these findings, on the one hand, older lecturers were more likely to be assigned to this class. On the other hand, lecturers with experience in educational technology use were unlikely to be assigned to this class. Lastly, gender did not explain any class membership ($p > 0.050$).

Table 5. Multinomial logistic regression of lecturer background and institutional support for ERT.

	Strivers	Routineers	Evaders
Covariates	*OR* **[95%** *CI*]**,** *p***-Value**	*OR* **[95%** *CI*]**,** *p***-Value**	*OR* **[95%** *CI*]**,** *p***-Value**
Gender, male	0.844 [0.491, 1.590], 0.680	0.811 [0.461, 1.430], 0.470	1.787 [0.762, 4.188], 0.182
Age ≥ 46	0.836 [0.468, 1.493], 0.544	0.710 [0.394, 1.277], 0.253	2.612 [1.099, 6.208], 0.030
Discipline, Non-STEM	0.921 [0.503, 1.686], 0.790	2.468 [1.303, 4.675], 0.006	1.300 [0.608, 2.780], 0.499
Experience	1.025 [0.570, 1.845], 0.933	4.790 [2.570, 8.929], < 0.000	0.183 [0.054, 0.620], 0.006
Institutional support			
Usefulness: Tech.-ped. supp.	0.850 [0.424, 1.706], 0.648	2.564 [1.317, 4.991], 0.006	0.995 [0.439, 2.258], 0.991
Usefulness: Admin. supp.	0.555 [0.269, 1.143], 0.110	0.982 [0.519, 1.856], 0.995	0.346 [0.126, 0.944], 0.038
Usefulness: Tutorials	0.868 [0.472, 1.597], 0.648	1.104 [0.610, 1.997], 0.744	0.308 [0.107, 0.881], 0.028
Collab. with colleagues	1.868 [0.628, 0.967], 0.063	1.528 [0.824, 2.833], 0.178	1.035 [0.475, 2.256], 0.931

Note. $n = 767$; *OR* = odds ratio; *CI* = confidence interval; Tech.-ped. supp. = Technological-pedagogical support; Admin. supp. = Administrative support; Collab. with colleagues = Collaboration with colleagues.

3.3. Research Question 3: In How Far Does Institutional Support for ERT Explain Latent Class Membership?

To answer the research Question 3, again, a three-step approach [66] to conduct a multinomial logistic regression was employed. *Presenters* functioned as a reference to explain latent class membership. Covariates and institutional support variables were computed in a single equation.

In the lower section "Institutional support" of Table 5, the results of four sources of institutional support are listed. These covariates contextualize lecturers' educational technology use during the COVID-19 lockdown. None of the analyzed institutional support sources were significant in explaining *Strivers* class membership. There is a slight tendency for an intensive collaboration with colleagues to possibly have an influence, although not significant ($OR = 1.868$, $p = 0.063$). Lecturers who found the technological-pedagogical support useful during lockdown were more likely to be assigned to *Routineers* ($OR = 2.564$, $p = 0.006$). A high perceived usefulness of administrative support ($OR = 0.364$, $p = 0.038$) and tutorials for educational technology use ($OR = 0.308$, $p = 0.028$) corresponded with unlikely class-4 *Evaders* membership compared to *Presenters*.

3.4. Research Question 4: In How Far Are "Intention to Adapt Teaching in the Future" and "Emergency Remote Teaching Self-Efficacy" (Distal Outcomes) Related to Latent Class Membership?

The means of lecturers' emergency remote teaching self-efficacy (ERT-SE) and continuance intentions for educational technology use (intention) are presented in Table 6. Overall, the Wald chi-square test was significant for both ERT-SE (Wald $\chi2$ = 49.219, p < 0.000) and lecturers' intention (Wald $\chi2$ = 47.857, p < 0.000) between classes. *Routineers* scored the highest means in both distal outcome variables (ERT-SE: M = 2.91, SE = 0.036; intention: M = 2.58, SE = 0.045). On the other end, the *Evaders* scored the lowest (ERT-SE: M = 2.65, SE = 0.082; intention: M = 2.13, SE = 0.091). In between were the *Presenters* and *Strivers*, whose means did not differ significantly. However, both classes had significantly higher scores on both distal outcome variables than the *Evaders* and significantly lower scores than the *Routineers*. Consequently, the Wald chi-square test was highly significant for *Routineers'* and *Evaders'* ERT-SE (Wald $\chi2$ = 36.091, p < 0.000) as well as continuance intentions (Wald $\chi2$ = 45.148, p < 0.000).

Table 6. Distal outcome analysis using the BCH method.

	ERT-SE	Intention	Strivers		Routineers		Evaders	
			ERT-SE	Intention	ERT-SE	Intention	ERT-SE	Intention
	M(SE)				*Wald* $\chi2$, *p*-Value			
Presenters	2.91 (0.036)	2.58 (0.045)	1.221 0.269	0.013 0.909	22.824 <0.000	12.732 <0.000	7.318 0.007	16.184 <0.000
Strivers	2.99 (0.054)	2.57 (0.068)	-	-	7.253 0.007	7.996 0.005	12.018 0.001	14.655 <0.000
Routineers	3.21 (0.048)	2.87 (0.062)	-	-	-	-	36.091 <0.000	45.148 <0.000
Evaders	2.65 (0.082)	2.13 (0.091)	-	-	-	-	-	-

Note. M = mean value; SE = standard error; ERT-SE = emergency remote teaching self-efficacy; Intention = continuance intention for educational technology use.

4. Discussion

The purpose of this study was to examine whether there are distinct types of lecturers regarding educational technology use during COVID-19 lockdown measures and, thus, the spatial distancing of lecturers, learners, and the classroom (Research Question 1). In addition, and in accordance with the theoretical framework, relationships between class membership and personal factors (Research Questions 2 and 4) and institutional support (Research Question 3) were further examined. To answer the research questions, lecturers who were actively teaching during the first COVID-19 lockdown measures in 2020 were questioned. Data were analyzed using a person-centric approach to derive latent classes of lecturers. The results of the iterative LCA procedure pointed to a four-class solution: *Presenters*, *Strivers*, *Routineers*, and *Evaders*. Three key findings emerge when looking at the four classes.

Besides the *Evaders*, the other lecturers reported moderate and extensive use of educational technology during ERT. In order to achieve this, two premises needed to be met by their technological environment and personal factors. Drawing on the *Social Cognitive Theory* [24], using educational technology goes hand in hand with institutional support (educational technology environment) and personal factors (prior experiences, self-efficacy, continuance intentions).

First, it may be rated as a success that most of the lecturers were able to continue delivering education to students, despite having to switch to ERT within a short period of time [73] and being exposed to new sources of physiological and psychological strain because of the lockdown [74]. *Presenters* account for the largest part of the sample. Moreover, they are a good example of how lecturers tried to replicate their conventional teaching in the online space by delivering content in LMS, presentations, and web conferencing. Digital technologies were the means to substitute [31] what was before. The focus hereby

laid on the lecturer, disregarding the students' needs for autonomy, competence, and relatedness [75]. The second largest group, the *Strivers*, however, integrated technologies such as chats and discussion forums, accounting for students' need for relatedness to peers and lecturers. A recent study revealed that students felt the social aspect of studying dramatically suffered during the COVID-19 measures [37,75,76], which had an immediate effect on motivation [77]. *Routineers* could also be labeled as tech-savvy since they integrated educational technology more than the other classes and were highly likely to do so for any type of assessed technology. In this case, it would have been interesting to see if they had also integrated more advanced technologies such as educational games or virtual reality. The sentiment of the *Evaders* is best illuminated by a comment in an open-ended survey question: "A frustrating experience; to teach you have to perceive the reactions of the audience, even in large lecture halls. Online teaching is dehumanizing." The loss of social interaction, in combination with lack of ICT-competences and prior experience, made the switch to ERT a frustrating experience for them [15].

Putting these findings into the research context of educational technology use with person-centric approaches, the identified classes accord somewhat: *Experienced*, *Enthusiastic*, and *Cautious* [17] or *Highly supportive*, *Instructor centered*, and *More detached* [18] during the pandemic. In addition, person-centric research before the pandemic found *Technology enthusiasts*, *Knowledgeable adopters*, *Knowledgeable skeptics*, *Prospective adopters*, and *Non-adopters* [20]. The most convergence of results was found compared to the study of Graves and Bowers [22], who found similar classes based on educational technology use as indicators: *Dexterous*, *Presenters*, *Assessors*, and *Evaders*. Consequently, it becomes apparent that there is repetition in the way researchers label classes and profiles, which may indicate a certain empirical consensus and validity of the present study.

Second, class membership was determined by three demographic and socio-professional variables, namely age, discipline, and prior experience in educational technology use. These findings are in line with empirical studies, stating that older lecturers, on the one hand, have lower self-efficacy beliefs, a lack of ICT competencies, and less experience in educational technology use [16,78,79]. Regarding prior experience, this finding broadly supports the work of other studies in this area. Accordingly, prior experience is a crucial factor for further educational technology use. From this standpoint, it is arguable that lecturers will continue using certain technologies and methods, especially if perceived as successful for teaching and learning [80]. However, experience and "better" online teaching must not per se correlate linearly. Scherer et al. [81] show a curvilinear correlation, meaning that experience and readiness, perceived institutional support, and self-efficacy increase until a peak and then decreases over time. During COVID-19, however, the situation was different, and lecturers who had, for example, experience in web-conferencing were certainly at an advantage [73]. Age and prior experience in educational technology use are interwoven with the perceived usefulness of the online teaching support the universities offered [19,82,83]. Another important finding revealed that lecturers who perceived the technological-pedagogical support as useful were more likely to be classified as *Strivers*, whereas *Evaders* rarely perceived administrative support and tutorials as useful. At first glance, this result could appear surprising, expecting that lecturers struggling with ERT would seek help. Nevertheless, these results are indeed in line with those of previous studies establishing that lecturers were already under immense time pressure in order to additionally seek support and may have been aware of what their institution had to offer [19]. However, the empirical ground regarding the role of support remains inconsistent, as some stress the necessity for individualized teaching support [84], and others find no evidence that the supports reached the right audience [60] and thus was perceived as not useful for ERT.

Third, how lecturers integrated educational technology was related to self-efficacy beliefs and continuance intentions. *Routineers* had not only the highest self-efficacy beliefs but also the strongest intentions to continue integrating educational technology in their future teaching. As the name suggests and results underline, *Routineers* had a certain

routine of educational technology use before the pandemic, which helped them navigate through ERT and will most likely do so for post-pandemic teaching. In contrast, the *Evaders* are cause for concern since personal, environmental, and behavioral factors reciprocally influence each other, as proposed in the theoretical framework in Section 1.4. Accordingly, these lecturers did likely have no prior experience in educational technology use, perceived no usefulness or did not know about the capacities of the institutional support, and did consequently evade the usage of educational technology to create an online learning environment for students. This is tantamount to giving up on the students' needs and right to education. Looking at this case with a magnifying glass, it becomes apparent that these lecturers had most likely no accessible sources for positive self-efficacy beliefs [38] and therefore lacked the capacity to endure especially stressful times, being in spite flexible and able to alter plans [43]. This would include, for example, seeking technological and pedagogical support from the institution or collaborating with experienced colleagues. Taking *Presenters*, *Strivers*, and *Routineers* together, however, a positive trend regarding continuance intentions is recognizable, which accords with other studies [20,33].

5. Conclusions, Limitations, and Future Research

Two years after the first COVID-19 lockdown and ERT at universities, lecturers' capabilities and their technological environment have changed. Now, in this post-pandemic phase of digital transformation at universities, the question is how sustainable the enforced digitalization boost was for technology-enhanced learning. The person-centric approach of the present study revealed that lecturers started their journey into online teaching from different starting points. Personal factors, educational technology, and institutional support diverged among them, as reflected in the classification of lecturers into the four classes found in this study. Based on lecturers' experiences and study findings, it is likely that professional development happened due to this emergency. At least the ice has been broken in regard to educational technology use. In other words, lecturers had the chance to gather experiences, which is a great advantage for moving forward in the digital transformation of university teaching [16,45].

As the *Social Cognitive Theory* [24] suggests, it is crucial that all of the factors listed therein be considered in the development of post-pandemic university teaching. On the one hand, lecturers must be prepared on an individual level, as they have different prerequisites like experience, self-efficacy, competencies, and beliefs [12,34,42,48,85]. Professional development with the scope of the TPACK framework [48] would ensure that the interweaving of pedagogical, technical, and professional knowledge serves the quality of teaching and learning [29]. On the other hand, universities must deliver a solid technological environment for lecturers, including a variety of digital technologies, but also technological and pedagogical support regarding educational technology use [23,56]. It is gratifying that most of the lecturers studied were able to pass on their teaching content to the students during ERT. However, there remains the group of *Evaders* who need special attention in the development of post-pandemic university teaching. These hold a particularly evading and resisting stance when it comes to educational technology use. These facts once more stress the importance of lecturer professional development that is enabled through a solid technological foundation that goes hand in hand with a shared vision for educational technology use, networks and communities, and design-based research [86].

This study has limitations in the following aspects. Lecturers could partake voluntarily in this study. Considering the stressful time of the first COVID-19 lockdown, it is probable that lecturers who had spare resources filled out the survey, which manifested in the low response rate of below 20% per each university. This could have resulted in a positive bias towards educational technology use and the related constructs. In addition, person-centric approaches are prone to sample-specific results, damping generalizability. However, the latent class analysis conducted is a model-based method controlled by fit indices, which is a strength of the study. Furthermore, despite low response rates, the lecturers who participated in this study varied in their backgrounds, experiences, and disciplines, which

allowed for a holistic display of latent classes. Another strength is the sound theoretical foundation of this study. The *Social Cognitive Theory* makes it possible to place relevant factors and outcomes in a strong theoretical framework that enables interpretation. The results are consistent with other studies and thus confirm the theoretical approach, which underlines the importance and validity of the results of this study, not to mention the replicability of the approach.

Second, the cross-sectional study design only allows for exploratory analysis of the data to answer the research question, and no causal conclusions can be drawn. Third, the indicators of the latent class analysis are based only on self-reported integration of digital technologies. Future studies could assess how lecturers create technology-enhanced learning environments more objectively and fine-grained, e.g., through observational and video studies.

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