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Profiling teachers' readiness for online teaching and learning in higher education: Who's ready?

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ABSTRACT

The COVID-19 pandemic has forced a shift to online teaching and learning (OTL) in colleges and universities across the globe, requiring teachers to adapt their teaching in a very short time—independent of whether they were prepared. Drawing from an international sample of $N = 739$ higher education teachers in 58 countries, the present study sheds light on teachers' readiness for OTL at the time of the pandemic by (a) identifying teacher profiles based on a set of key dimensions of readiness; (b) explaining profile membership by individual teacher characteristics, contextual aspects of the shift to OTL, and country-level indicators representing educational innovation and cultural orientation. We conducted latent profile analysis and identified three teacher profiles with consistently high or low readiness or an inconsistent readiness profile—hence, teachers in higher education are not a homogeneous group. Importantly, key individual and contextual variables, such as teachers' gender and prior OTL experience, the context of the OTL shift, the innovation potential in education, and cultural orientation, explained profile membership. We discuss these findings with respect to the nature of the profiles, how they can be understood with respect to key determinants, and their implications for OTL in higher education.

1. Introduction

Online teaching and blended learning have been part of teaching in higher education for nearly two decades (e.g., Singh & Thurman, 2019). However, while these modes of teaching and learning have been present in universities, their actual implementation and adoption have been persistently inconsistent—this resulted in high levels of variation in student learning experiences, within institutions, disciplines, and even programs (Bernard et al., 2014). In an effort to ensure that all students have the same access to high-quality teaching and learning, it is therefore necessary to explore a wide range of factors related to university teachers' adoption and use of online teaching, especially to help institutions better support teaching and learning in online spaces (Kebritchi et al., 2017).

The event of the COVID-19 pandemic and the respective implementation of social distancing protocols resulted in a rapid transition to OTL (Online Teaching and Learning) between March and April 2020 for most higher education institutions around the world, independent of whether teachers were prepared (UNESCO IESALC, 2020). This rapid transition of all teaching consequently provides a unique opportunity to observe the extent to which teachers actually felt prepared for OTL (Brooks & Grajek, 2020). It is important to acknowledge that higher education teachers' perceptions of their readiness for OTL represent a multifaceted problem (Martin et al., 2019). Particularly in relation to the rapid transition to full online teaching, this shift constituted major changes in teaching practice. Such changes in practice, or the willingness to engage in change at any level, is a complicated organization of individual, institutional, and cultural factors (Kukulska-Hulme, 2012). To understand teachers' readiness for OTL in more detail, examining its relations to these factors is critical (Hung, 2016). Moreover, these factors may not affect all teachers in the same way. Teachers in higher education are not a homogeneous group, the different important relationships affecting one group may be completely different for another, given different backgrounds, experience with OTL, and academic disciplines. To be able to provide appropriate support, understanding some of the reasons why teachers do or do not adopt new OTL practices is necessary (Bruggeman et al., 2020).

In the present study, we explore higher education teachers'

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perceptions of their readiness for OTL and a range of related individual background and contextual variables (for a detailed discussion on such factors, please see Sailer et al., 2020). To do this, we present three profiles of OTL readiness. In this context, profiles are referred to groups of teachers which share similar levels of readiness for OTL. Readiness is explored in relation to teachers' perceptions of their own confidence to teach in an online space ("personal readiness") and their perceptions of how well their institution is prepared to support OTL ("contextual readiness"). We argue that profiles can provide key insights into (a) the differences among teachers' perceptions of readiness so more targeted support can be provided by institutions, (b) some key determinants to predict how teachers may feel about OTL and to begin personalizing support, and, ultimately, (c) a strong basis for further investigation into teachers' perceptions of moving learning online, to develop better policies for quality OTL.

2. Theoretical framework

2.1. Conceptualizing teachers' readiness for OTL in higher education

Readiness to teach online can be broadly defined as "the state of faculty preparation" to teach online (Martin et al., 2019). Therefore, teachers' perceptions of their readiness and that of their institution relates to beliefs about their preparedness. Perceptions of online readiness will therefore include a mixture of attitudes and experience, which are impacted by a range of individual characteristics, contextual, and cultural factors (Hung, 2016). For individuals, such perceptions may specifically rely on their future-oriented projections of their knowledge and skills concerning OTL, which are manifested in their sense of self-efficacy and experiences (Tschannen-Moran et al., 1998)—these aspects represent *personal readiness*. For institutions, the context in which OTL is implemented is key to readiness and may include the support structures, resources, and professional development opportunities (Kebritchi et al., 2017)—these aspects represent *contextual readiness*. With this in mind, we explore three dimensions of higher education teachers' readiness for OTL: (a) Technological and pedagogical content knowledge (TPACK) self-efficacy as an indicator of perceived OTL competence, (b) Online teaching presence as an indicator of OTL teaching practices, (c) Institutional support as an indicator of the contextual readiness for OTL.

2.1.1. Technological and Pedagogical Content Knowledge (TPACK)

Teachers' self-efficacy to teach online has been examined in the present study through the lens of the TPACK framework (Koehler et al., 2014). In this framework, TPACK comprises several knowledge domains, including domain-general and technology-specific aspects, that are relevant for teachers to implement technology in teaching and learning processes (Voogt et al., 2013). Specifically, the following technology-lean dimensions are key to the framework (Scherer et al., 2018): TPCK—"knowledge about the complex relations among technology, pedagogy, and content that enable teachers to develop appropriate and context-specific teaching strategies" (Koehler et al., 2014, p. 102); TPK—knowledge about the use of ICT to implement instructional practices, principles, and strategies; TCK—knowledge about how the subject matter can be represented with the help of technology; TK—knowledge of and about technology. TPCK, TPK, and TCK represent the key pedagogical and didactical aspects of TPACK, while TK represents a purely technological domain (Schmidt et al., 2009). This distinction was evident in studies showing that the factor structure of TPACK self-efficacy scales was comprised of a general TPACK factor and a specific TK factor (Scherer et al., 2018; Tondeur et al., 2017). Teachers' TPACK is relevant for OTL because integrating technology, pedagogy, and content is key to training educators for OTL (Brinkley-Etzkorn, 2018).

2.2. Online teaching presence

In the current study, we further focus on teaching presence—a concept addressing the online learning elements of time, distance, and interaction (Gurley, 2018). According to Law et al. (2019), the depth of OTL is related to presence, conceptualized as social, cognitive, and teaching presence. More specifically, online teacher presence emphasizes teachers' responsibilities of the design, organization, facilitation, and instruction in the online learning space so that educational purposes can be fulfilled while learners and teachers are not co-located or working at the same time (Martin et al., 2019; Rapanta et al., 2020). Key components of teaching presence are active communication, providing feedback, and learner-learner interaction (Wilson & Stacey, 2004) and relate to instructional practices that are associated with teaching quality (e.g., Praetorius et al., 2018). To illustrate, Gurley (2018) examined these components of teacher presence in relation to teachers' behaviors in blended and online learning environments. Behaviors related to feedback, clear instruction, and assessment were found to relate to teachers' perceptions of high teaching presence (Rapanta et al., 2020).

2.2.1. Institutional support for online teaching and learning

Researchers highlighted that institutional support is vital for teachers in higher education when transitioning to OTL (Naylor & Nyanjom, 2020). In this respect, several studies showed that the integration of online teaching can be associated with technical and pedagogical support, the school vision about online learning, and strong leadership (Bao, 2020; Rapanta et al., 2020). To illustrate, a shared vision to integrate online technologies in educational processes can motivate teachers to change, while a lack of commitment to change at an organizational level can demotivate teachers and limit change (e.g., Tondeur et al., 2019). Clearly, the transition to OTL because of the COVID-19 pandemic pushed fast considering a range of key issues related to institutional support: how lecturers were trained to teach online, if the institution had a pedagogical vision about online learning, how to support students to learn online, etc. However, Bolliger et al. (2019) have shown that teachers in higher education report limited support to design, implement, and sustain online teaching program. It is therefore necessary to examine both perceptions of teachers' knowledge and skills and their perceptions of the readiness of their institution. In the present study, we examined teachers' perceptions of institutional support for OTL in general and specifically at the time of the COVID-19 pandemic together. Because of the rapid transition to online learning, in many cases, there was very limited time for institutions to provide online materials, technical infrastructures, and the necessary pedagogical support for OTL (Bao, 2020). Therefore, teachers' perceptions of the degree to which pedagogical support, leadership, and vision building about OTL and the technical and pedagogical support specific to the transition to OTL during the pandemic are both important components of contextual readiness.

2.3. Determinants of the readiness for online teaching and learning in higher education

In addition to considering teachers' perceptions of readiness, such as their TPACK and online presence, it is necessary to understand some of the other possible factors related to readiness and online teaching. By considering a wider array of factors it is possible to better understand the heterogeneous experiences of higher education teachers and therefore design more personalized support. Previous research in the field of online teaching and learning has identified gender, academic disciplines, previous teaching experiences, and perceived institutional standing and support as potential sources of variation (e.g., Tondeur et al., 2019). Moreover, cultural and innovation differences across countries have been identified as factors which are positively related to new ways of teaching (Huang et al., 2019; Seufert et al., 2020). In this section, we summarize some selected research findings.

2.3.1. Online teaching experience

Prior teaching experience is positively related to teachers' general self-efficacy and their attitudes toward OTL. For instance, Muñoz Carril et al. (2013) showed that more experienced "online" teachers also have higher self-confidence in their pedagogical competences to teach online. Similarly, Shea (2007) showed that prior experience (measured by the frequency of OTL) was critical to teachers' motivation for continuing with OTL; moreover, more experience in online teaching was associated with higher self-efficacy in this study. At the same time, teachers with little experience reported high levels of struggle related to communication and interaction, and unfamiliarity with effective online pedagogy and technology. A recent study by Martin et al. (2019) on teachers' perceptions of their readiness for OTL showed that experience from teaching online impacts online course design and facilitation, that is, aspects of teaching practice and presence. However, little or no online teaching experience was associated with lower self-efficacy. Bolliger et al. (2019) confirmed these results in their study on faculty members' perceptions of online program community and their efforts to sustain it. Their findings showed that faculty members with no or less than three years of OTL experience were less aware of building program community, and the systems and activities used to support it. These examples show that OTL experience is not only a determinant of OTL adoption and practice but also teachers' self-efficacy.

2.4. Gender differences

Gender differences in attitudes toward and competence in OTL are diverse. While some studies indicated differences in favor of female teachers in higher education, in particular regarding the importance of online course design (Briggs, 2005), motivation to teach online (Shea, 2007), value of program community, involvement and support to build online program community (Bolliger et al., 2019), other studies could not identify any gender differences in constructs related to OTL readiness (e.g., Aydın, 2005; Schmid et al., 2021; Teddy So & Swatman, 2010). For instance, Martin et al. (2019) found substantial gender differences favoring women on some constructs (e.g., perceived importance of online course design, communication, and time management), yet not on others (e.g., teachers' attitudes on the importance of technical competence, and their perceptions of own ability to teach online). These observations are, however, not surprising: Researchers have argued that technology-related attitudes are context-dependent (Tondeur et al., 2016). When examining gender differences, it is therefore essential to consider possible contextual effects. Moreover, most research in this area portrays a time in which the transition to OTL may have been slower, introduced in only some courses, with more time for planning the course design etc.—the time portrayed in our study, however, is quite different. As a consequence, we examined the extent to which the profiles of teacher readiness for OTL at the time of the COVID-19 pandemic were subject to gender differences.

2.4.1. Academic disciplines

Tracing OTL in higher education, Baran (2011) emphasized that "we need to consider how students learn and develop in different disciplines and how the teachers can encourage these learning experiences with online technologies" (p. 48). However, to our best knowledge, teachers' readiness for OTL has hardly been evaluated in relation to academic disciplines. Bolliger et al. (2019) surveyed teachers in education and engineering, two representatives of the "soft" and "hard" sciences, and assessed their perceptions of the value of online program community and their strategies for supporting and sustaining it. Their results showed that teachers of education scored significantly higher on all items than the teachers of engineering, suggesting the possible subject-specificity of the constructs. Baran (2011) conducted a case study on exemplary teachers in different disciplines to examine how different discipline cultures influence teachers' OTL experiences and needs. She concluded that, among other factors, the discipline is an important aspect of successful teachers' planning and implementation of online courses. What is needed, then, is the creation of transformative learning experiences for faculty who would "engage in pedagogical problem-solving and discovery about online teaching" within their disciplines (Kreber & Kanuka, 2006, p. 122). In this sense, the academic disciplines teachers in higher education operate in create not only subject-specific demands, but also frame a culture in which OTL is implemented.

2.4.2. Context of the OTL shift

As Sailer et al. (2020) suggested in their Cb-model for online and offline learning environments in higher education, the context of OTL is largely shaped by the facilitating conditions higher education institutions provide, besides the cultures inherent to academic disciplines. In fact, a plethora of evidence suggests that such conditions, including the technological infrastructure and resources, are directly and indirectly related to the adoption of OTL and technology in general (Granić & Marangunić, 2019). In the context of educational systems' responses to the COVID-19 pandemic, different degrees of the shift to OTL at higher education institutions have been implemented (UNESCO IESALC, 2020). For instance, while some institutions have demanded moving their teaching to OTL entirely, others offered hybrid solutions with only parts of the teaching being moved. Moreover, while some institutions issued an immediate shift to OTL, leaving most teachers with only a few days to prepare for OTL, others delayed the shift due to, for instance, the lack of teacher preparation or infrastructure (Dhawan, 2020). These and other indicators framing the OTL shift at the time of the COVID-19 pandemic may further explain variation in teachers' readiness profiles.

2.5. Culture and innovation

It is a well-established finding in educational psychology that self-efficacy beliefs, which are considered key elements of teachers' readiness, are subject to cultural differences, both for students and teachers (Bonneville-Roussy et al., 2019; Vieluf et al., 2013). Such differences have not only surfaced in the context of general teaching but also for teaching with technology. For instance, Srite and Karahanna (2006) argued that the behavioral models describing technology acceptance may not hold to the same extent across different cultures. Among other moderating effects, they showed that the effects of subjective norms on the intentions for technology use were stronger in countries with high uncertainty avoidance. Aparicio et al. (2016) found that the differences with respect to individualism and collectivism were key determinants of e-learning success and identified this aspect of cultural orientation as a moderator of the link between OTL use and performance. In their comparative study of Chinese and Spanish university teachers, Huang et al. (2019) observed substantial differences in the subjective norms and technology usage intentions between the two cultures and argued broadly that cultural orientations are key to understanding technology acceptance. Zhao et al. (2020) synthesized this line of reasoning, focusing on the link between culture and OTL adoption. Their meta-analytic findings suggested that culture, indicated by core orientations such as individualism vs. collectivism or norms, moderated the relations among technology acceptance constructs. For instance, subjective norms and technology self-efficacy were more salient predictors of technology use in collectivist cultures, while the perceived usefulness played a larger role in individualistic cultures. This selection of findings on the link between culture and technology acceptance constructs, including self-efficacy as a key dimension of teachers' readiness for OTL, shows the importance of the cultural context for understanding the heterogeneity between teachers.

Next to the cultural context in which OTL is implemented, the potential for innovation in a country may play a role for teachers' readiness, especially in countries with limited coverage of OTL. For such countries, the shift to OTL represents an educational innovation and requires both individual and organizational innovativeness (OECD, 2019a). Moreover, several stakeholders (e.g., policy-makers, researchers, practitioners) emphasized that new digital technologies could potentially have a catalyzing role in accelerating educational innovations (Carretero et al., 2018). Further, a country's innovation potential in education is positively associated with its capability to adopt new technology and transition to new ways of teaching and learning (OECD, 2016). Besides the observation that innovation and digital technologies and OTL practices are linked, the extant body of literature suggests a connection between culture and innovation, especially for individualism vs. collectivism, uncertainty avoidance, and normative orientation (e.g., Handoyo, 2018; Jang et al., 2016). We therefore included measures of countries' innovation potential in education to potentially explain variation in the readiness profiles.

2.6. The present study

As noted earlier, the shift to OTL in higher education institutions at the time of the COVID-19 pandemic has put teachers in a unique and demanding situation—this situation required quickly adopting forms of technology-based teaching, communication, and collaboration which were new to many of them. In light of this need for adaptability and change, the question about the extent to which teachers were in fact prepared for the shift surfaced (Hung, 2016). The present study identified the profiles of higher education teachers' readiness for OTL at the time of the COVID-19 pandemic. Specifically, taking the person-centered approach of latent profile analysis (LPA) and utilizing key dimensions of the readiness construct (i.e., TPACK self-efficacy, perceived online presence, and perceived institutional support), we first examined whether latent profiles of teachers' readiness for OTL existed and what characterized them (see Fig. 1):

RQ 1. Which profiles of teachers exist with respect to their TPACK self-efficacy, perceived online teaching presence, and perceived institutional support?

To further understand the nature of the profiles, we selected possible determinants that covered teachers' background next to contextual factors—the latter included factors describing the academic discipline, the context of the OTL shift, the cultural orientation, and the innovation potential of countries (see Fig. 1). While most of the previous studies identifying teacher profiles and levels for variables indicating readiness focused mainly on individual teacher characteristics as possible profile determinants (e.g., technology-related self-efficacy; Hung, 2016; Schmid et al., 2021; Tondeur et al., 2019), the present study extended this line of research by examining contextual and country-level determinants. However, the list of these determinants was by no means complete, yet represented a theory-driven selection. We utilized extensions of the latent profile analysis framework, including LPA regression and multilevel LPA, to address the following research questions:

RQ 2. (a) To what extent do teacher characteristics and the context of the shift to OTL at higher education institutions explain profile membership? (b) To what extent is profile membership associated with countries' innovation potential in education and cultural orientation?

Although the importance of teachers' readiness for OTL has been well-established, the degree of heterogeneity between teachers in higher education and the possible determinants of this heterogeneity have not. The present study examined in detail the profiles of teachers' readiness for OTL—that is, groups of teachers that may otherwise remain unobserved. In short, we extended the existing body of research on readiness for OTL by (a) focusing on a unique sample of teachers at the time of the COVID-19 pandemic who had to transition to OTL, and (b) identifying and exploring the individual and contextual heterogeneity within this sample.

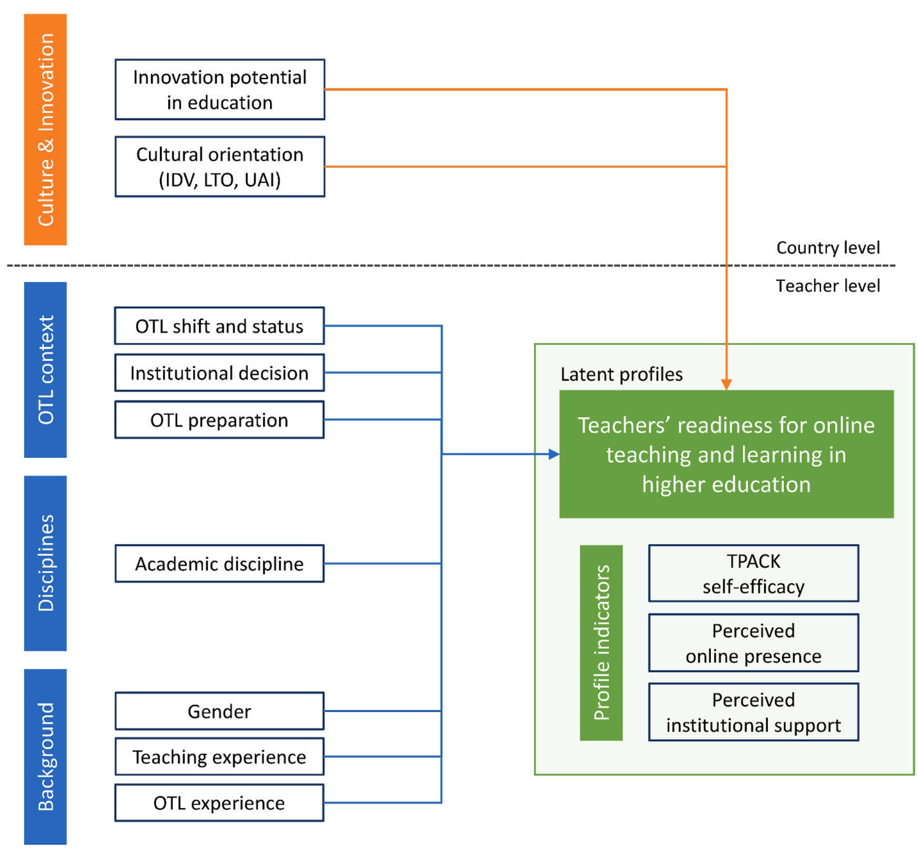

Fig. 1. Research model underlying the identification and description of latent profiles of teachers' readiness for online teaching and learning in higher education. Note. IDV = Individualism vs. collectivism, LTO = Long-term orientation vs. short-term (normative) orientation, OTL = Online teaching and learning, TPACK = Technological and Pedagogical Content Knowledge, UAI = Uncertainty avoidance index.

3. Method

3.1. Sample and procedure

Between March and May 2020, we launched an online survey assessing teachers' readiness for online teaching around the world at the time of the COVID-19 pandemic in primary, secondary, tertiary, adult, and vocational education. We distributed the anonymized survey questionnaire via several channels, including social media, collaborating universities, and higher education institutions, and invited teachers to participate. Participants were provided with information about the study, they were asked to approve that they understood and informed that completion of the questionnaire was tacit consent for their data to be used in the study. We extracted the data from 1144 educators in 64 countries (as of May 31, 2020). Intentionally, we did not restrict the participants to a specific country, language group, or culture to achieve a sufficiently large heterogeneity and variation in the readiness constructs, individual and contextual characteristics, and OTL practices. This heterogeneity could inform the interplay between constructs and the identification of overall rather than context-specific teacher profiles.

The target population from which the sample for the present study was drawn represented teachers in higher education who were actively teaching in the spring of 2020. In this context, higher education referred to tertiary education at universities, colleges, and graduate schools (ISCED levels 5–8; OECD et al., 2015), yet excluded institutions offering adult education, vocational education, or professional development for in-service teachers. We subset the data to higher education teachers and retrieved a final sample of $N = 740$ teachers (54.4% women) from 58 countries distributed across the seven world regions, yet with most teachers from Europe and Central Asia (84.2%). A detailed account of the distribution of teachers across countries is given in the Supplementary Material S4 (number of teachers per country: $M = 12.7$, $Mdn = 2$, $Min = 1$, $Max = 368$). On average, teachers were 48.2 years old ($SD = 9.9$) and reported 19.4 years of teaching experience ($SD = 10.8$) across a broad range of academic disciplines (see Supplementary Material S2). About 37.2% of the teachers indicated that they had gained some prior experience with OTL. For 80.7% of the teachers, the shift to OTL was mandatory, for 16.6%, the shift was expected yet not mandatory, and about 2.6% reported that shifting to OTL was neither mandatory nor expected. Most teachers (80.8%) indicated that their institutions asked them to move their entire teaching to OTL, while 14.9% were asked to move parts of the teaching, and only 4.3% of the teachers reported that none of their teaching had to be moved to OTL due to institutional decisions. On average, higher education teachers were given 6.8 days to prepare the transition to OTL, and, at the time of the survey, teachers were about 1.9 days into OTL after the transition.

3.2. Measures

In the present study, we measured the core construct of teachers' readiness for OTL in higher education using three indicators: Teachers' TPACK self-efficacy, their perceptions of the online presence they create during OTL, and their perceptions of the institutional support. These indicators formed the basis for the identification of profiles and were derived from teachers' responses to a survey questionnaire. To further understand the nature of these profiles, we assessed additional teacher-level predictors, such as variables characterizing teachers' background, their academic discipline, and the context of the shift to OTL. Finally, we extracted two country-level predictors, representing the countries' cultural orientation and their innovation potential in education. In our study, the "context of OTL" can be described and represented by teachers' perceptions of the institutional support, the variables describing the OTL shift, and the country-level characteristics. Fig. 1 summarizes these categories of measures.

3.2.1. Teacher-level variables

TPACK self-efficacy. We represented the pedagogical and content-related aspects of online teaching readiness, focusing on the three TPACK-dimensions of TPCK, TPK, and TCK. To assess these dimensions, we administered the validated TPACK self-efficacy scale (Archambault & Crippen, 2009) and adapted it to the context of OTL. The respective stimulus referred to teachers' perceptions of the confidence in TCK (2 items; e.g., "implement curriculum in an online environment"), TPK items (4 items; e.g., "implement different methods of teaching online"), and TPCK items (4 items; e.g., "use technology to predict students' skills/understanding of a particular topic"). Participants indicated their confidence on a 5-point scale ranging from 0 (*strongly disagree*) to 4 (*strongly agree*). The internal consistencies of the overall scale were high, Cronbach's $\alpha = 0.93$, Omega total $\omega_t = 0.95$.

Perceived online teaching presence. We measured teachers' perceptions of their online presence in three core dimensions (Gurley, 2018): Clarity of instruction (POPCLA; e.g., "Overall, I can clearly communicate important course goals"; 4 items), cognitive activation (POPCOG; e.g., "Overall, I help to keep course participants on a task in a way that helps students to learn"; 7 items), and student feedback and assessment (POPFED; e.g., "Overall, I provide feedback in a timely fashion"; 2 items). Teachers indicated their agreement with these statements on a 5-point scale ranging from 0 (*strongly disagree*) to 4 (*strongly agree*). The resultant three subscales showed high internal consistencies (POCLA: $\alpha = 0.91$, $\omega_t = 0.95$; POPCOG: $\alpha = 0.93$, $\omega_t = 0.93$; POPFED: $\alpha = 0.83$, $\omega_t = 0.88$).

Perceived institutional support. Six items of the validated scale by Philipsen (2018) indicated teachers' perceptions of the institutional support for OTL. These items addressed several aspects, such as the schools' vision for OTL (e.g., "In my institution, there are clear objectives as regards online learning") and the opportunities for professional development (e.g., "In my institution, there is a supportive environment as regards professional development for online learning"). Participants indicated their agreement on a 6-point scale (from 0 = *strongly disagree* to 5 = *strongly agree*). The reliability coefficients were high and indicated sufficient internal consistency of the scale, $\alpha = 0.94$, $\omega_t = 0.96$.

To further assess teachers' perceptions of the technical and pedagogical support specific to the transition to online teaching during the COVID-19 pandemic, we administered two additional items with the stimulus "If your institution has asked you to transition your teaching from face-to-face to online, have you been provided with the following …": Item PISCO1 ("Additional technical support has been provided to transition face-to-face teaching to online because of COVID-19") and item PISCO2 ("Additional pedagogical support has been provided to transition face-to-face teaching to online because of COVID-19"). These two items were not integrated into the existing, more general scale of perceived institutional support.

Teacher background characteristics and academic disciplines. We collected data on key background variables, that is, individual characteristics that were consistently associated with teacher self-efficacy and their perceptions of their instruction and work environment (e.g., Klassen & Tze, 2014; Scherer et al., 2016). These background variables included teachers' age (in years), gender (coded as *0* = *Male*, *1* = *Female*), teaching experience (in years), online teaching before the COVID-19 pandemic (coded as *0* = *No prior experience*, *1* = *Yes, teachers had prior experience*), and their main discipline (coded as categories: *Arts & Humanities, Social Sciences, Medicine & Health, Engineering, Science, Business*, and *Law*).

Online teaching and learning context. We described the context of OTL by the days teachers were given to prepare for OTL after the decision for the shift (in days), the days into online teaching after the shift (in days), the extent to which teaching had to be shifted to OTL (coded as *0* = *No, none of it*, *1* = *Some of my teaching*, *2* = *Yes, all of it.*), and the degree to which the shift to OTL was mandatory (*0* = *It was not mandatory*, *1* = *It was expected*, *2* = *It was mandatory*).

3.2.2. Country-level variables

Innovation potential in education. To represent a country's innovation potential in education, we used three sub-indices of the Global Innovation Index in the area of human capital and research (Dutta et al., 2018): (a) *Global innovation index in education 2019*—an index informed by the expenditure on education, government funding per secondary student, school life expectancy, assessment in reading, mathematics, and science, and the pupil-teacher ratio in secondary schools; (b) *Global innovation index in tertiary education 2019*—an index informed by the tertiary enrolment, graduates in science and engineering, and the tertiary level inbound mobility; (c) *Global innovation index in research and development 2019*—an index informed by the number of researchers, the gross expenditures on research and development, average expenditures of the top 3 global research and development companies, and the average ranking score top 3 universities. At the time of writing, these indices were available for 55 of the 58 countries represented in the teacher sample (see globalinnovationindex.org). Please find the respective indices in Supplementary Material S4.

Cultural orientation. Drawing from the extant body of literature on the connection between national culture and innovation, the link between subjective norms and culture in the context of technology acceptance, and considering that the OTL shift at the time of the COVID-19 pandemic required substantial adaptation of countries' educational approaches, we selected three indicators of the well-established Hofstede's dimensions of cultural orientation (Hofstede, 2020): (a) *Individualism vs. collectivism (IDV)*—high scores on the IDV-dimension indicate that countries tend to expect individuals to make choices and decisions (i.e., a tendency toward individualism); (b) *Long-term orientation vs. short-term normative orientation (LTO)*—high scores on the LTO-dimension indicate a strong short-term normative orientation in a culture; (c) *Uncertainty avoidance index (UAI)*—high scores on the UAI-dimension indicate that members of a society tend to feel uncomfortable with uncertainty and ambiguity. Given the limited number of countries and to keep the country-level model as parsimonious as possible, we were not able to include all six dimensions of Hofstede's framework. We extracted the scores of the dimensions from hofstede-insights.com. Please find the respective scores in Supplementary Material S4. Notice that utilizing these scores as country-level characteristics is based on the assumption that the higher education institutions within a country are homogeneous in their cultural orientation—this assumption may not represent reality (e.g., Burnett & Huisman, 2009), but could not further be addressed due to the lack of information about the institutions.

3.3. Methodological approaches

3.3.1. Step 1: confirmatory factor analysis

As a first step, we evaluated the measurement models describing teachers' TPACK self-efficacy, perceived online presence, and perceived institutional support via confirmatory factor analyses. This step was key to (a) evaluating the psychometric quality of these scales, (b) establishing the number of factors representing the respective constructs, and (c) extracting factor scores which would ultimately serve as indicators in the subsequent latent profile analyses (Morin & Marsh, 2015). Specifically, we estimated the reliability coefficients to indicate the internal consistency of a scale (i.e., Cronbach's α and Omega total ω_t) and evaluated the factor structures, specifying and comparing confirmatory factor analysis models with different assumptions on the factor structures (Brown, 2015). For all scales, these assumptions were represented by a baseline, single-factor model and modified, single- or multiple-factor models that followed our hypotheses on the specific structure of the scale. In all models, we allowed for residual covariances to represent item dependencies beyond the latent trait and accommodate possible similarities in item formulations and the resultant responses. We evaluated the respective model fit following the common guidelines for the goodness-of-fit indices (for an acceptable fit: Comparative Fit Index CFI $\geq$ 0.95, Root Mean Square Error of Approximation RMSEA $\leq$ .08, Standardized Root Mean Residual SRMR $\leq$ 0.10; e.g., Marsh et al., 2005). However, these guidelines have been validated only on a limited set of conditions and should therefore not be considered "golden rules" (Marsh et al., 2004).

Once we had identified a well-fitting factor model, we extracted the respective factor scores. Morin and Marsh (2015) argued that the using factor scores has at least three advantages: First, they partially control for measurement error and can easily be scaled to continuous variables with a mean zero, thus facilitating their interpretation. Second, the subsequent latent profile analyses must no longer rely on full measurement models with many parameters to be estimated but on a more parsimonious set of continuous variables. Third, factor scores are based on a well-fitting measurement model and account for the specific nature of that model (e.g., residual covariances, cross-loadings). As a consequence, we followed their recommendation and used the factor scores as observed (i.e., manifest) representatives of the scales and constructs.

To account for possible deviations from the multivariate normality assumption, we utilized robust maximum-likelihood (MLR) estimation and derived robust standard errors of all model parameters (Maydeu-Olivares, 2017). Model comparisons were consequently based on the Yuan-Bentler adjusted chi-square (YB- χ^2) difference test (Satorra & Bentler, 2010). We performed all confirmatory factor analyses in the R packages 'lavaan' version 0.6–6 (Rosseel, 2012) and 'psych' version 1.9.12.31 (Revelle, 2019), with the full-information-maximum-likelihood procedure to handle missing item responses (Enders, 2010). Please find the details of these analyses in the Supplementary Material S2.

3.3.2. Step 2: latent profile analysis

Identifying the profiles. As a second step, we conducted latent profile analyses (LPA) to identify the (latent) profiles of higher education teachers' readiness for OTL, using the factor scores of TPACK self-efficacy (*g*TPACK), the three dimensions of perceived online presence (POPCLA, POPFED, POPCOG), perceived institutional support (*g*PIS), and the two grand-mean centered items PISCO1 and PISCO2 as profile indicators. In general, LPA represents a person-centered approach that identifies unobserved homogeneous groups in a sample (Lubke & Muthén, 2005) and offers a more flexible and model-based approach to identifying groups than cluster analysis (Marsh et al., 2009). LPA offers relative fit indices, including the Akaike information criterion [AIC], the Bayesian information criterion [BIC], and the sample-size-adjusted BIC [aBIC], thus allowing researchers to compare LPA models with different assumptions on the number, shape, and size of profiles. Circumventing the restrictive assumption of equal variances of profile indicators across profiles, we freely estimated these variances.

Identifying the number of latent profiles in a sample is based on a series of LPAs varying numbers of profiles (Masyn, 2013). These LPAs are then compared via the information criteria (i.e., the smaller their values, the better the fit) and likelihood-ratio tests, such as the adjusted Lo-Mendell-Rubin [LMR] and the Vuong-Lo-Mendell-Rubin [VLMR] likelihood-ratio tests [LRT]. Besides, researchers can gather information on the classification accuracy, that is, the entropy (acceptable values above 0.70; Jung & Wickrama, 2008). However, the decision for the number of profiles is also based on the theoretical considerations of researchers, in particular the interpretability and sizes of the profiles (Howard & Hoffman, 2017). An optimal profile solution should reveal conceptually meaningful and interpretable profiles of substantial size (Marsh et al., 2009). We thus considered these conceptual criteria next to the statistical indices.

Teacher-level covariates. Once the best profile solution had been established, we extended the respective model by adding the teacher-level covariates that may predict teachers' profile membership. We used the indirect auxiliary-variables approach ("R3STEP") to estimate the regression and odds ratio coefficients (Asparouhov & Muthén, 2014). Both the LPA and the LPA with teacher-level covariates were performed in the software package M*plus* version 8.3 (Muthén &

Muthén, 1998–2017), using MLR estimation and the full-information-maximum-likelihood procedure. Due to a large number of missing responses and thus factor scores, the data obtained from one participant had to be excluded, resulting in an overall sample of $N = 739$ teachers available to the LPAs. Given that our data followed a hierarchical structure with teachers nested in countries, we accounted for this nesting by adjusting the standard errors and chi-square statistics with the M*plus* option TYPE = MIXTURE COMPLEX.

3.3.3. Step 3: multilevel latent profile analysis

As a third step, we extended the optimal LPA model with teacher-level explanatory variables to a multilevel LPA model in two stages (Henry & Muthén, 2010): First, we allowed the intercepts of the latent categorical variables indicating the profile membership for each teacher to have an intercepts and a variance at the country level. This model represents a so-called parametric random-intercept model and represents the assumption that average probabilities of being assigned to one or the other profiles may vary between countries. Second, we added the country-level variables to explain this variation and ultimately examine the link between the average profile membership probabilities, innovation potential, and cultural orientation. Again, we conducted these analyses in the software package M*plus* version 8.3 (Muthén & Muthén, 1998–2017), using MLR estimation, the full-information-maximum-likelihood procedure, and the M*plus* option TYPE = TWOLEVEL MIXTURE.

4. Results

4.1. Descriptive statistics, measurement models, and correlations

The descriptive statistics of teachers' item responses on TPACK self-efficacy, perceived online presence, and perceived institutional support neither indicated substantial deviations from normality nor any strong tendencies, such as floor or ceiling effects (see Supplementary Material S2). However, we accounted for marginal deviations from normality by utilizing robust maximum-likelihood estimation in all measurement models. Item responses representing the subscales of the same construct were positively and significantly correlated, supporting their internal consistency. The full item-level correlation matrices for each of the scales are presented in Supplementary Material S2.

Next, we specified, estimated, and evaluated the measurement models of the respective scales. The model describing *TPACK self-efficacy* contained a general TPACK factor and two specific factors which explained covariation among the residuals of the TPCK and the TPK items. This model exhibited a good fit to the data, YB- χ^2 (29) = 75.4, $p < .01$, CFI = 0.985, RMSEA = 0.047, SRMR = 0.019. Neither a single-factor model nor a correlated-traits model distinguishing between TPCK, TPK, and TCK exhibited good fit to the data (see Supplementary Material S2). The latter showed high factor correlations between $\rho = 0.89$ and $\rho = 0.94$. The measurement model distinguishing between three factors of *perceived online teaching presence* (POPCLA, POPFED, POPCOG) exhibited a good fit to the data, YB- χ^2 (57) = 165.1, $p < .01$, CFI = 0.977, RMSEA = 0.051, SRMR = 0.033. This model resulted in factor correlations between $\rho = 0.73$ and $\rho = 0.80$. Five residual covariances for items with similar formulations were part of this model. Moreover, the model outperformed a single-factor and correlated-traits model without any residual covariances (see Supplementary Material S2). Finally, the *perceived institutional* support scale was best represented by a single factor and two residual covariances. The respective model showed an excellent fit to the data, YB- χ^2 (7) = 10.9, $p = .15$, CFI = 0.998, RMSEA = 0.027, SRMR = 0.009.

On the basis of these measurement models, we extracted the corresponding scores of the general TPACK self-efficacy factor (*g*TPACK), the general perceived institutional support factor (*g*PIS), and the three correlated factors representing perceived online presence (POPCLA, POPCOG, and POPFED). The correlations among these factor scores and the two standalone items of perceived institutional support during the COVID-19 pandemic are shown in Table 1. Overall, these variables were correlated positively and significantly. TPACK self-efficacy showed the highest correlations with perceived online presence; the two standalone items PISCO1 and PISCO2 were substantially correlated with the general perceived institutional support factor (Table 1).

4.2. Latent profile analysis (RQ1)

4.2.1. Identifying the number of profiles

To identify the number of latent, that is, initially unobserved profiles, we specified and estimated a series of LPA models with freely estimated variances of the profile indicators and the number of profiles varying between one and six. The resultant information criteria, entropies, and the *p*-values of the likelihood-ratio tests are shown in Table 2. Overall, the more profiles were estimated, the lower the absolute log-likelihood values and information criteria. This trend suggested the preference of the models with increasing number of profiles. At the same time, the differences in the log-likelihood values between the models with one and two profiles were insignificant; yet, adding another profile resulted in a significant decrease in the absolute log-likelihood values and pointed to the preference of the three-profile solution. Adding even more profiles did not suggest any further significant likelihood-ratio test results. Concerning the entropies, the models with four and five profiles showed the highest values (entropies = 0.921 and 0.920), followed by the three-profile solution (Entropy = 0.912). Concerning the decrease of the information criteria, the elbow plot showed a bend and suggested a profile solution with three or four profiles (see Fig. 2). Finally, concerning the profile sizes, the LPA models with more than three profiles contained at least one small profile (with about 3.6% of the sample size), and some of these profiles were very similar and could hardly be distinguished substantively. Considering this evidence, we decided for the three-profile model as the final model.

To further back this decision, we conducted a multivariate analysis of variance with the profile indicators as the dependent variables and the profile grouping variable as the independent variable. These analyses should support the significant differences in the indicators between the three profiles and thus their distinction. The overall multivariate test indicated statistically significant mean differences, Pillai's trace $V = 0.63$, F (7, 716) = 171.1, $p < .001$. These differences explained about 62.6% of the variation in the profile indicators. Further univariate post-hoc tests indicated significant profile differences in all indicators (*F*s > 257.9, Bonferroni-adjusted *p*s < .00071), explaining between 26.3% and 43.7% of variation.

4.2.2. Characterizing the profiles

Fig. 3 depicts the three latent profiles and shows the means and standard errors of the respective profile indicators. Profile 2 formed the largest group ($n = 385$), followed by profile 1 ($n = 291$); profile 3 formed the smallest group of teachers ($n = 63$). The three profiles can be characterized as follows (see also Supplementary Material S1):

- *Profile 1 (low readiness):* This profile describes teachers with consistently low ratings on all profile indicators, that is, TPACK self-efficacy, perceived online presence during OTL, and the perceived institutional support. Teachers especially perceived the institutional support—both in general and at the time of the COVID-19 pandemic—as weak and had little confidence in their abilities to teach online and create an online presence during their teaching. Given these low ratings, this group of teachers indicated that they were not or hardly ready for OTL.
- *Profile 2 (inconsistent readiness):* This profile describes teachers with consistently low ratings of their TPACK self-efficacy and perceived online presence, but high ratings on the perceived institutional support. In contrast to profile 1, profile 2 indicates a disconnect between the levels of TPACK self-efficacy and perceived online

Table 1
Descriptive statistics and correlations between the profile indicators (N = 739).

Variable	*M*	*SD*	1	2	3	4	5	6
1. TPACK self-efficacy (*g*TPACK)	0.00	0.96						
2. Perceived institutional support in general (*g*PIS)	0.00	1.15	.40** [.33, .46]					
3. Perceived institutional support: Technical support during COVID-19 (PISCO1)	3.36	1.46	.34** [.27, .40]	.65** [.61, .69]				
4. Perceived institutional support: Pedagogical support during COVID-19 (PISCO2)	2.69	1.55	.33** [.27, .40]	.66** [.62, .70]	.69** [.65, .73]			
5. Perceived online teaching presence: Cognitive activation (POPCOG)	0.00	0.65	.71** [.68, .75]	.38** [.32, .44]	.29** [.22, .36]	.28** [.21, .35]		
6. Perceived online teaching presence: Clarity of instruction (POPCLA)	0.00	0.55	.72** [.68, .75]	.35** [.29, .41]	.33** [.26, .39]	.29** [.22, .35]	.85** [.83, .87]	
7. Perceived online teaching presence: Feedback to students (POPFED)	0.00	0.76	.64** [.59, .68]	.34** [.28, .41]	.28** [.21, .35]	.25** [.19, .32]	.87** [.85, .89]	.82** [.79, .84]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. $^{**}p < .01$.

Table 2
Information criteria, entropies, and results of the likelihood-ratio tests for the LPA models with up to six profiles.

Model	LL	Npar	SCF	AIC	BIC	aBIC	Entropy	*p* (VLMR-LRT)	*p* (LMR-LRT)
One profile	−6994.237	14	1.7821	14,016.474	14,080.948	14,036.493	1.000	–	–
Two profiles	−6179.609	29	1.8153	12,417.217	12,550.771	12,458.686	0.836	0.1545	0.1567
Three profiles	**−5580.048**	**44**	**1.2440**	**11,248.096**	**11,450.729**	**11,311.013**	**0.912**	**0.0002**	**0.0002**
Four profiles	−5218.206	59	1.5504	10,554.412	10,826.125	10,638.779	0.921	0.3631	0.3654
Five profiles	−4971.323	74	1.2876	10,090.645	10,431.437	10,196.461	0.920	0.2318	0.2336
Six profiles	−4791.262	89	1.4282	9760.523	10,170.395	9887.789	0.906	0.5363	0.5377

Note. LL = Log-likelihood value, Npar = Number of parameters, SCF = Scale correction factor, AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, aBIC = Sample size-adjusted BIC, *p*(VLMR-LRT) = *p*-value of the Vuong-Lo-Mendell-Rubin (VLMR) likelihood-ratio test, *p*(LMR-LRT) = *p*-value of the Lo-Mendell-Rubin (LMR) likelihood-ratio test. The suggested number of profiles is highlighted in bold.

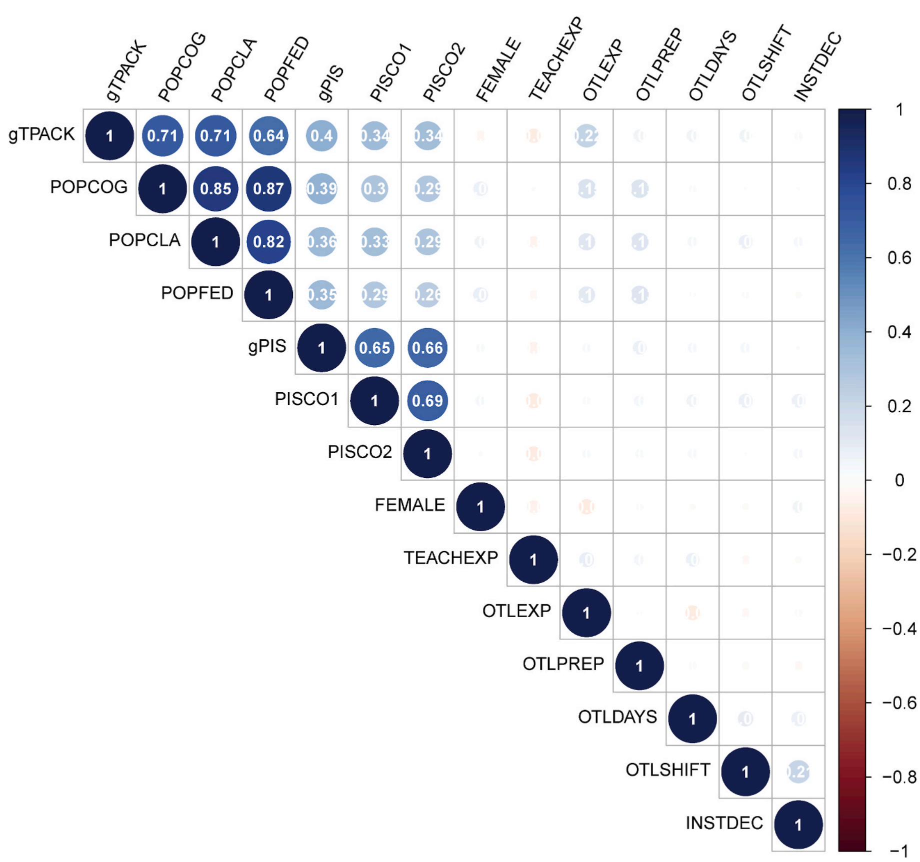

Fig. 2. *Elbow plot of the information criteria extracted from the LPA with up to six profiles, Note.* AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, aBIC = Sample size-adjusted BIC. Please find the specific values of these LPA models in the Supplementary Material S1.

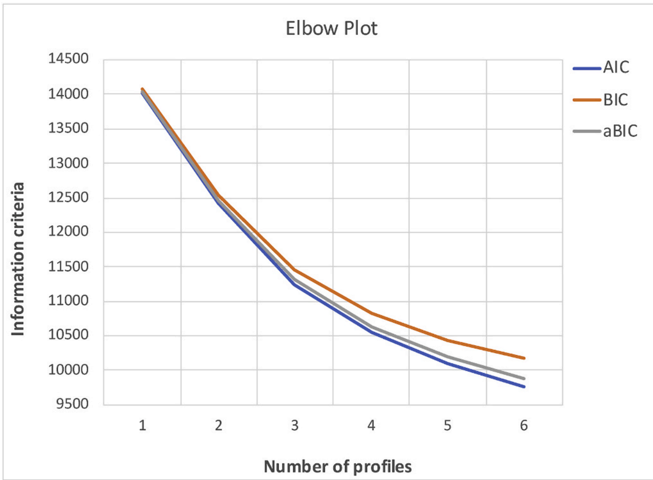

Fig. 3. *Profiles describing higher education teachers' readiness for online teaching and learning, Note.* gTPACK = TPACK self-efficacy, POPCLA = Perceived online teaching presence: Clarity of instruction, POPFED = Perceived online teaching presence: Feedback to and assessment of students, POPCOG = Perceived online teaching presence: Cognitive activation, gPIS = Perceived institutional support in general, PISCO1 = Perceived institutional support: Technical support during COVID-19, PISCO2 = Perceived institutional support: Pedagogical support during COVID-19. Please find the specific means and variances for each of the variables and profiles in the Supplementary Material S1.

presence vs. perceived institutional support. Teachers in this group reported sufficiently high support from their institution (i.e., the context in which OTL is implemented), yet had little confidence in their OTL abilities and instructional practices. In this sense, these teachers exhibited "contextual" readiness, yet no "personal" readiness.

- *Profile 3 (high readiness):* This profile describes teachers with consistently high ratings of their TPACK self-efficacy and perceived online presence and medium to high ratings on the perceived institutional support. These teachers showed both personal and contextual readiness for OTL. Their TPACK self-efficacy ratings were considerably high and indicated a strong confidence in their OTL abilities.

Considering the teacher characteristics and the context of the shift to OTL, the profiles can be characterized as follows (see Table 3):

- The distribution of age and teaching experience were uniform across the three profiles. Profile 3 contained 68% women, while the other profiles were balanced.
- Most teachers assigned to profiles 1 and 2 reported that they did not have any prior OTL experience—in contrast, most teachers in profile 3 reported such experience.
- Teachers in profile 1 were given the shortest time to prepare for OTL (about 6 days), and teachers in profile 3 were given up to 8 days on average. On average, teachers were about two days into OTL across the profiles.
- Consistently across profiles, almost all of the teaching had to be shifted to OTL, and the institutions made this shift mandatory for most teachers.
- All profiles were dominated by teachers in the social sciences. Most law teachers were assigned to profile 3, while profile 1 contained the least business teachers. The distributions of academic disciplines varied across profiles for the arts & humanities, business, law, medicine & health, and science—in contrast, they were homogeneous for engineering and social sciences.
- All profiles contained teachers mostly from European and Central Asian countries. A substantial proportion of teachers in profile 3 were located in East Asian and Pacific, North American, and Sub-Saharan African countries.

Table 3
Characteristics of the teachers within the three profiles.

Teacher characteristics	Profile 1 (n = 291)	Profile 2 (n = 385)	Profile 3 (n = 63)
Background variables			
Age in years *M* (*SD*)	48.9 (9.8)	47.8 (10.2)	47.7 (8.8)
Gender			
Women	51.4%	54.3%	67.7%
Men	48.6%	45.7%	32.3%
Teaching experience *M* (*SD*) in years	20.0 (11.1)	19.0 (10.8)	20.1 (9.9)
Online teaching and learning			
Prior online teaching experience			
Yes	31.4%	37.9%	60.3%
No	68.6%	62.1%	39.7%
Days of preparation for online teaching *M* (*SD*)	6.0 (6.8)	7.2 (6.8)	8.4 (10.8)
Shift to online teaching due to COVID-19			
No, none of the teaching was shifted.	2.4%	2.1%	6.3%
Some of the teaching was shifted.	18.2%	16.1%	12.7%
Yes, all of the teaching was shifted.	79.4%	81.8%	81.0%
Days into online teaching after the shift *M* (*SD*)	1.8 (1.2)	2.0 (1.1)	2.0 (1.3)
Institutional decision of the shift			
It was not mandatory.	5.3%	3.5%	5.0%
It was expected, but not mandatory.	15.3%	14.9%	13.3%
It was mandatory.	79.4%	81.6%	81.7%
Academic disciplines			
Arts & Humanities	16.4%	12.5%	11.3%
Business	8.5%	12.5%	14.5%
Engineering	17.8%	17.8%	16.1%
Law	3.2%	2.4%	6.4%
Medicine & Health	7.8%	10.3%	8.1%
Science	10.3%	12.4%	9.7%
Social Sciences	36.0%	32.1%	33.9%
World regions[#]			
East Asia & Pacific	5.8%	3.7%	9.5%
Europe & Central Asia	83.2%	87.5%	69.8%
Latin America & Caribbean	2.8%	2.1%	4.8%
Middle East & North Africa	2.4%	3.1%	0.0%
North America	1.0%	2.6%	7.9%
South Asia	2.1%	0.5%	1.6%
Sub-Saharan Africa	2.7%	0.5%	6.4%

Note. [#] World regions were created on the basis of the World Bank's classification of countries (The World Bank, 2020).

Overall, these teacher and OTL contextual characteristics indicated, in most instances, homogeneity, yet some heterogeneity across profiles. To further substantiate this heterogeneity and understand which of these characteristics may explain profile membership, we extended the LPA model with three profiles by explanatory, teacher-level variables (RQ2a).

4.2.3. Replication and cross-validation of the profiles

To further back the decision for the three-profile model, we replicated the latent profile analyses on the basis of random samples drawn from the original sample (Scherer, Rohatgi, & Hatlevik, 2017). Specifically, we drew 100 random samples corresponding to the size of 90% of the original sample (N = 666) and conducted the latent profile analyses with one to four profiles. Evaluating the resultant information criteria, entropies, profiles sizes, and likelihood-ratio tests, we found that: (a) the three-profile model showed substantially better convergence rates than the four-profile model—specifically, the LPA with three profiles did not converge for only 3 out of the 100 samples, while the LPA with four profiles did not converge for 27 samples; (b) in 90% of the samples, the three-profile model was favored over the two-profile model; (c) the minimum profile sizes in the three-profile model were substantial (12.8%), while they were considerably smaller in the four-profile model (7.7%); (d) the decision for a model with three profiles was reasonable for more than 95% of the samples. These findings indicated a high degree of replication of the three-profile model for random subsamples.

In addition to this replication, we further examined the degree to which the entropy of the three-profile model could be validated for random subsamples—cross-validating key parameters in statistical model is critical to crafting a validity argument in any empirical study (de Rooij & Weeda, 2020). Specifically, we drew 100 random samples corresponding to 80% of the overall sample size ($N = 592$) and estimated the three-profile model fixing the model parameters to those obtained from the three-profile model of the full sample. We then studied the deviation of the entropies between the random- and the full-sample data. Overall, the average entropy extracted from the 100 random samples was 0.912 ($SD = 0.003$, $Mdn = 0.911$, $Min = 0.903$, $Max = 0.920$) and matched the estimate of the full sample, that is, 0.912. This result provided some evidence for the validity of the entropy value of the final, three-profile model. Please find the details of the replication and cross-validation in the Supplementary Material S1.

4.3. Latent profile analysis with teacher-level variables (RQ2a)

To further explain profile membership (RQ2a), we added teacher-level variables describing teachers' background, academic disciplines, and the context of OTL as predictors. These variables exhibited overall small relations to the profile indicators (see Fig. 4). Specifically, teachers' experience with OTL and the days they were given to prepare for OTL were positively correlated with all profile indicators. Gender differences favored men for the indicators POPFED ($d = -0.17$, 95% CI [-0.31, −0.02]) and POPCOG ($d = -0.16$, 95% CI [-0.30, −0.01]), but were negligible for all other indicators. Teachers who had to shift most or all of their teaching to OTL tended to show slightly higher values in perceived online presence; yet, these relations were small (see Supplementary Material S2). Besides, the relations among the teacher-level and OTL context characteristics were small and did not indicate potential issues of multicollinearity in the subsequent LPA regression models.

Utilizing the multinomial logistic regression framework within LPA, we obtained (unstandardized) regression coefficients, along with their standard errors, and odd ratios to test which teacher-level variables may explain profile membership. Comparing the pairs of profiles, we obtained the following results (for the detailed results, see Table 4):

- *Profile 1 vs. 2:* Teachers with more teaching experience (independent of OTL) were more likely to be assigned to profile 1, while teachers who reported some prior OTL experience were less likely to be assigned to this profile. Both the days of preparing for OTL as a result of the COVID-19 pandemic and the days after the transition to OTL had been made predicted profile membership, and teachers who reported more days on these two variables were less likely to be assigned to profile 1. Academic disciplines showed marginal effects, that is, science teachers were less likely to be assigned to profile 1. Neither gender nor the variables describing the OTL shift (i.e., amount of teaching that had to be shifted and the type of the shift) were significantly related to membership in profile 1 as compared to profile 2.
- *Profile 2 vs. 3:* Women were less likely to be assigned to profile 2 as compared to profile 3, and so were teachers who reported prior OTL experience or who taught law. All other teacher-level predictors did not show significant relations to profile membership.
- *Profile 1 vs. 3:* Again, women were less likely to be assigned to profile 1 as well as teachers with prior OTL experience and teachers of law. The more days teachers were given to prepare the shift to OTL, the less likely they were assigned to profile 1 as compared to profile 3. We could not identify any additional significant effects. These findings confirm the initial description of profile 3 as being composed of mainly female teachers, teachers with prior OTL experience, and teachers of law.

To further substantiate the effects of gender and OTL experience, we examined the extent to which the three profiles were similar across gender and OTL experience groups through a series of multi-group LPA models with similarity constraints (see Morin et al., 2015). The results of these additional analyses are shown in the Supplementary Material S1 and suggested that, for both gender and OTL experience, at least so-called dispersion similarity could be assumed. This level of similarity assumes the same number of profiles, means, and variances across these groups. Hence, the effects of gender and OTL experience were not biased by profile dissimilarity. Overall, teachers' gender, teaching experience, prior OTL experience, the days of preparing for the OTL shift, the days into OTL after the shift, and the academic disciplines (i.e., science and law) explained differences in the probabilities of profile membership.

4.4. Multilevel latent profile analysis with country-level variables (RQ2b)

To address RQ2b, we extended the LPA regression model with the teacher-level predictors (RQ2a) to models of multilevel LPA. We found that the variation in profile membership probabilities could be

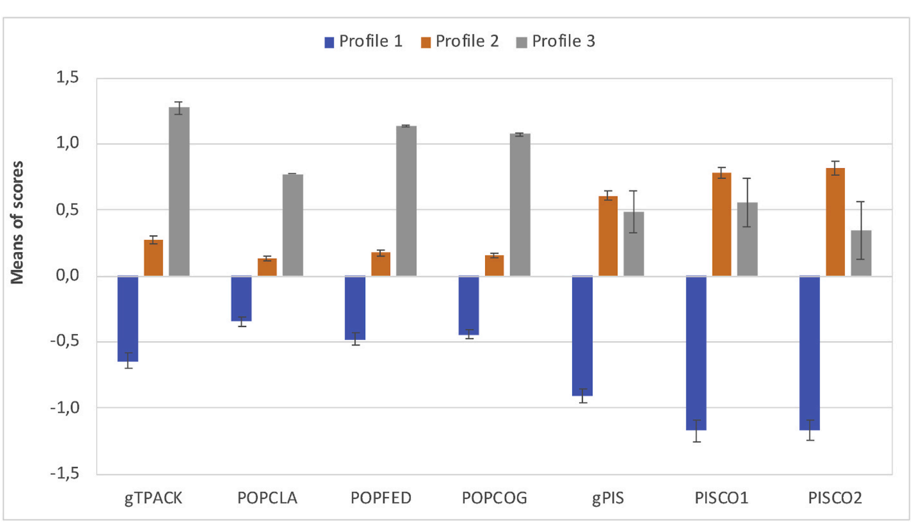

Fig. 4. *Correlogram of the profile indicators and the background variables, Note.* gTPACK = TPACK self-efficacy, POPCLA = Perceived online teaching presence: Clarity of instruction, POPFED = Perceived online teaching presence: Feedback to and assessment of students, POPCOG = Perceived online teaching presence: Cognitive activation, gPIS = Perceived institutional support in general, PISCO1 = Perceived institutional support: Technical support during COVID-19, PISCO2 = Perceived institutional support: Pedagogical support during COVID-19, TEACHEXP = Teaching experience, OTLEXP = Online teaching experience, OTLPREP = Online teaching preparation (in days), OTLDAYS = Days into online teaching due to the COVID-19 pandemic, OTLSHIFT = Online teaching shift, INSTDEC = Institutional decision for online teaching and learning. Please find the full correlation matrix in the Supplementary Material S2.

Table 4
Results of the multinomial logistic regression predicting profile membership (teacher level).

Variable	B	SE	OR	p
Profile 1 vs. 2				
Gender (*0 = Male, 1 = Female*)	−0.116	0.138	0.89	0.401
Teaching experience (*in years*)	0.012	0.006	1.012	0.041
Online teaching experience (*0 = No, 1 = Yes*)	−0.461	0.166	0.631	0.006
Online teaching preparation (*in days*)	−0.039	0.015	0.962	0.010
Days into online teaching due to the COVID-19 pandemic	−0.166	0.073	0.847	0.023
Online teaching shift	−0.027	0.141	0.973	0.849
Institutional decision for online teaching and learning	−0.131	0.121	0.877	0.279
Academic disciplines				
Arts & Humanities	−0.023	0.203	0.977	0.908
Medicine & Health	−0.348	0.511	0.706	0.496
Engineering	−0.318	0.411	0.727	0.439
Science	−0.372	0.159	0.690	0.019
Business	−0.619	0.519	0.538	0.232
Law	0.016	0.451	1.016	0.972
Profile 2 vs. 3				
Gender (*0 = Male, 1 = Female*)	−0.723	0.306	0.485	0.018
Teaching experience (*in years*)	−0.008	0.015	0.992	0.612
Online teaching experience (*0 = No, 1 = Yes*)	−0.980	0.331	0.375	0.003
Online teaching preparation (*in days*)	−0.018	0.025	0.982	0.462
Days into online teaching due to the COVID-19 pandemic	−0.013	0.103	0.987	0.896
Online teaching shift	−0.269	0.726	0.764	0.711
Institutional decision for online teaching and learning	0.052	0.187	1.053	0.782
Academic disciplines				
Arts & Humanities	−0.159	0.418	0.853	0.703
Medicine & Health	0.205	0.782	1.228	0.793
Engineering	−0.423	0.330	0.655	0.200
Science	0.025	0.502	1.025	0.961
Business	−0.614	0.383	0.541	0.109
Law	−1.460	0.332	0.232	0.000
Profile 1 vs. 3				
Gender (*0 = Male, 1 = Female*)	−0.839	0.338	0.432	0.013
Teaching experience (*in years*)	0.004	0.019	1.004	0.824
Online teaching experience (*0 = No, 1 = Yes*)	−1.441	0.278	0.237	0.000
Online teaching preparation (*in days*)	−0.057	0.021	0.945	0.008
Days into online teaching due to the COVID-19 pandemic	−0.179	0.105	0.836	0.089
Online teaching shift	−0.296	0.696	0.744	0.671
Institutional decision for online teaching and learning	−0.079	0.204	0.924	0.698
Academic disciplines				
Arts & Humanities	−0.183	0.397	0.833	0.645
Medicine & Health	−0.143	0.463	0.867	0.758
Engineering	−0.741	0.539	0.477	0.169
Science	−0.347	0.494	0.707	0.483
Business	−1.233	0.786	0.291	0.117
Law	−1.444	0.574	0.236	0.012

Note. Academic disciplines were coded dichotomously with the Social Sciences as the reference.

explained by the country-level variables as follows (Table 5):

- *Profile 1 vs. 2*: Neither the indicators of innovation in education nor the indicators of cultural orientation explained the variation in the profile membership probabilities for profiles 1 vs. 2 across countries.
- *Profile 2 vs. 3*: The higher a country scored on the global innovation index in education 2019, the higher the average probabilities of being assigned to profile 2 as compared to profile 3 ($B = 0.086$, $SE = 0.023$, $p < .01$). In other words, university teachers in highly innovative countries were, on average, more likely to be assigned to profile 2 than to profile 3. Similarly, the higher the uncertainty avoidance index, the lower the average probabilities of being assigned to profile 2 vs. 3 ($B = -0.025$, $SE = 0.013$, $p = .048$). Finally, the more a country tended to be oriented toward short-term goals, the higher the probabilities of being assigned to profile 2 vs. 3 ($B = 0.023$, $SE = 0.009$, $p = .010$).

Table 5
Results of the multilevel latent profile analysis explaining between-country variation in the average probabilities of profile membership (country level).

Variable	B	SE	p
Profile 1 vs. 2			
Innovation potential in education			
Global innovation index in education 2019	−0.039	0.022	0.081
Global innovation index in tertiary education 2019	0.006	0.025	0.808
Global innovation index in research and development 2019	0.014	0.019	0.460
Cultural dimensions			
Individualism vs. collectivism (IDV)	0.004	0.012	0.720
Uncertainty avoidance index (UAI)	0.003	0.009	0.751
Long-term orientation vs. short-term normative orientation (LTO)	−0.001	0.008	0.902
Profile 2 vs. 3			
Innovation potential in education			
Global innovation index in education 2019	0.086	0.023	0.000
Global innovation index in tertiary education 2019	0.019	0.022	0.383
Global innovation index in research and development 2019	−0.022	0.018	0.234
Cultural dimensions			
Individualism vs. collectivism (IDV)	−0.021	0.017	0.209
Uncertainty avoidance index (UAI)	−0.025	0.013	0.048
Long-term orientation vs. short-term normative orientation (LTO)	0.023	0.009	0.010
Profile 1 vs. 3			
Innovation potential in education			
Global innovation index in education 2019	0.048	0.021	0.021
Global innovation index in tertiary education 2019	0.025	0.021	0.231
Global innovation index in research and development 2019	−0.008	0.013	0.559
Cultural dimensions			
Individualism vs. collectivism (IDV)	−0.017	0.012	0.155
Uncertainty avoidance index (UAI)	−0.022	0.010	0.022
Long-term orientation vs. short-term normative orientation (LTO)	0.022	0.006	0.001

- *Profile 1 vs. 3*: The significant effects identified for the comparison between profiles 2 and 3 also existed for the comparison between profiles 1 and 3. Specifically, teachers in countries with a high innovation potential in education were more likely to be assigned to profile 1 than profile 3 ($B = 0.048$, $SE = 0.021$, $p = .021$). Moreover, in countries with a tendency toward short-term orientation, the average probability of being assigned to profile 1 rather than 3 was significantly higher ($B = 0.022$, $SE = 0.006$, $p < .01$). In contrast, this probability was lower for countries with a tendency toward uncertainty avoidance ($B = -0.022$, $SE = 0.010$, $p = .022$).

Overall, the indicators of the innovation potential in education and the cultural orientation explained cross-country variation of profile membership probabilities, especially for the comparisons involving profile 3. These comparisons clarified the composition of profile 3 as being mainly comprised of teachers in countries with a tendency toward uncertainty avoidance and long-term orientation, yet a limited innovation potential in education (relative to other countries). The other two profiles were homogeneous with respect to the country-level variables and were comprised of teachers in countries characterized by a tendency toward uncertainty tolerance, short-term orientation, and innovation potential in education.

5. Discussion

The main goal of the present study was to identify teachers' profiles of readiness for OTL in higher education at the time of the COVID-19 pandemic. Our study specifically focused on profiles based on a set of key dimensions of readiness, and we explored possible determinants of profile membership, including teacher characteristics, contextual aspects of the shift to OTL, and country-level indicators of innovation and cultural orientation (see Fig. 1). In contrast to the rapid transition to OTL as a result of the pandemic, previous institutional policies, such as the expectations that each teaching instance (e.g., a subject or course) would have an online component, provided significant space for teachers to utilize online learning as they felt comfortable (Dhawan, 2020). The forced shift to OTL, given the circumstances, thus provided a unique context for studying teachers' readiness. To our best knowledge, this study is the first to identify latent profiles of teachers in higher education during a crisis situation.

5.1. Teachers' profiles under a magnifying glass (RQ1)

Our first research question was aimed at identifying higher education teachers' profiles of readiness for OTL and ultimately explore possible heterogeneity in the teacher sample (RQ1). Latent profile analysis allowed us to make visible this heterogeneity that was caused by the diversity in the readiness construct (Morin & Marsh, 2015). As opposed to variable-centered approaches to describing readiness, that is, approaches focusing on the interplay between readiness and related variables (Hung, 2016; Özgür, 2020), the person-centered approach we were taking circumvented the strong assumption that higher education teachers are homogeneous in their readiness. In fact, some existing evidence suggested that teachers are heterogeneous with respect to their TPACK self-efficacy (Seufert et al., 2020; Tondeur et al., 2019), which represents only one of the three readiness dimensions we examined. The "one-size-fits-all" assumption on teacher readiness for OTL may thus not be reasonable. Clearly, any knowledge about the existence and shape of initially unobserved (latent) profiles can identify opportunities to tailor support for teachers and potentially promote quality OTL (Bruggeman et al., 2020).

In the following, we discuss the three profiles identified in our study. Profile 1 included teachers with low ratings on all profile indicators. To illustrate, these teachers had little confidence in their abilities to teach online and create an online presence during their teaching and they perceived the institutional support as weak and at the same time. This is in line with the findings of Bao (2020) who found that there was very limited time for institutions to provide online materials, technologies, and the necessary pedagogical support for OTL at the time of the COVID-19 pandemic. Besides, the fact that some teachers may hold poor beliefs about their competences for teaching online is well-established (Klassen & Tze, 2014; Tondeur et al., 2019). Interestingly, however, these poor self-beliefs went hand in hand with negative perceptions of their teaching presence and the institutional support. The former also represents a well-established finding in the extant body of research on the link between teaching self-efficacy and teaching practices (Klassen & Tze, 2014); the latter suggests a link between two quite different types of readiness (i.e., personal vs. contextual). In the recent Teaching and Learning International Survey, a similar link had been observed: Teachers who reported low teaching self-efficacy also reported little satisfaction with their work environment and the respective support (OECD, 2019b). This link seems to also hold for the context of OTL (e.g., Özgür, 2020).

Profile 3 contrasted profile 1 and was identified as the high-readiness profile. Teachers who were assigned to this profile perceived themselves ready for OTL and reported good support from their institutions in general and at the time of the COVID-19 pandemic. This group, however, formed the smallest group of teachers—this is an observation not new to the study of teacher preparedness and the shift to OTL during crisis (Bao, 2020; Rapanta et al., 2020). Moreover, the fact that profile 3 exhibited high readiness does not necessarily imply that teachers within this profile were indeed ready for OTL. Our study has shed light only on the *perceptions of readiness*, yet not teachers' actual readiness, which would have to be assessed by objective measures, such as TPACK performance, the quality or effectiveness of the OTL teaching practices (e.g., Bernard et al., 2014; Lachner et al., 2019). Besides, teachers' responses to our survey questions on their self-efficacy and online presence may have been influenced by the experiences they have made with the students in their classes. Specifically, while determining their readiness, teachers may have relied to some extent on the success in OTL up until the time of our survey—this success may have been indicated by their students' responsiveness, achievement, or persistence whilst engaging in OTL. In this sense, the sources of teachers' self-reports may not only have been projections of future mastery but also prior experience informed by students' learning (Tschannen-Moran & Hoy, 2007).

The participants involved in the current study interpreted the move to online learning according to their specific profile. It is necessary to understand how teachers think about the innovation, because it is impacting their decision making. At the same time, the static and quantitative nature of the data, gathered to develop the profiles, also posed difficulties to grasp the actual uptake of online teaching. Future research should therefore adopt a more qualitative and iterative approach to explore the teachers' profiles. In this respect, their observed (online) TPACK could be used as a determinant to measure the extent to which teachers in higher education. It would also be possible to move beyond self-efficacy and teaching presence and create a deeper understanding of the institutional context, through approaches such as cultural-historical activity theory (e.g., Foot, 2014).

The observation of a high- and low-readiness profile aligns well with the previous study by Tondeur et al. (2019) on teacher profiles in constructs related to readiness. Specifically, the authors found two profiles on the basis of TPACK self-efficacy and some indicators of the institutional strategies to support teacher educators. Despite the congruency with our results, the identification of a binary set of profiles only bears the information about which teachers may require support. It does however not provide information about the specific aspects teachers may need support for. In this sense, our results extend this body of evidence as they shed light on a distinctive, inconsistent profile of teacher readiness. This profile exhibited high levels of perceived institutional support (i.e., contextual readiness), yet low levels of TPACK self-efficacy and teaching presence (i.e., personal readiness). We argue that this inconsistency has at least two implications: (a) Readiness for OTL in higher education may not be uniform across all its dimensions, and (b) even though the facilitating conditions may be perfect, teachers being assigned to this profile may still require specific personal support to strengthen their self-efficacy and teaching presence, for instance, via gaining mastery experiences or engaging in professional development (Rapanta et al., 2020; Tschannen-Moran & Hoy, 2007).

5.2. Explaining profile membership (RQ2)

Our second research question was aimed at examining the individual and contextual determinants of teachers' profile membership (RQ2). As noted earlier, we explored the extent to which teachers' background and contextual variables explained variation between individual teachers and countries in the profile membership probabilities (see Fig. 1). In our study, gender, OTL experience, academic disciplines, and the days of preparing for the OTL shift explained differences in the probabilities of profile membership, but also pointed to the heterogeneous nature of the profiles. Besides, we found support for the importance of contextual determinants, including academic disciplines, the context of the OTL shift, cultural orientation, and the innovation potential in education. These results testify to the fact that the context of the shift to OTL is associated with readiness profiles and, ultimately, explains heterogeneity between them. Moreover, these results extend the extant body of research by the perspective of the context—so far, teachers' readiness profiles have been mainly explored with respect to individual rather than contextual determinants (Tondeur et al., 2017, 2019). In the following, we discuss selected determinants in greater detail.

5.2.1. Gender differences and prior OTL experience

Our overall results showed significantly different probabilities of profile membership related to gender. Men were more likely to belong to profiles 1 and 2, and members of profile 3 were more likely to be women.

However, there was really no effect of gender between profiles 1 and 2. In this sense, gender differences do not appear as consistent predictors of the profiles—an observation in line with variable-centered approach which identified gender difference for some but not all OTL constructs in higher education (Briggs, 2005; Martin et al., 2019). One possible explanation for this inconsistency may lie in the context-dependence of gender differences (Salleh & Laxman, 2015), that is, differences and ambiguities may not only exist between gender groups, but also within gender groups (Briggs, 2005, p. 261).

Notably, female teachers were more likely to be members of profile 3, the profile with the highest personal readiness. On the one hand, these results are consistent with some studies indicating that women hold more positive attitudes toward OTL, perceive it as important, and have higher self-efficacy in designing and implementing online teaching (Bolliger et al., 2019; Martin et al., 2019; Shea, 2007). On the other hand, these results contrast studies which identified higher TPACK self-efficacy for men (Ergen et al., 2019; Scherer, Tondeur, & Siddiq, 2017). To this end, the possible mechanisms underlying these gender differences in profile membership are still to be clarified, especially in light of the OTL context during the pandemic.

Another key finding was that teachers with prior OTL experience were more likely to be assigned to the high-readiness profile. Once again, this finding is in line with previous studies showing that prior experience in online teaching is positively related to attitudes toward technology and forms a source of self-efficacy (Bolliger et al., 2019; Muñoz Carril et al., 2013). Given the sudden circumstances due to the transition to OTL that many lecturers in higher education faced during the COVID-19 pandemic, this is important knowledge. The situation might have contributed to feelings of stress or low self-esteem in online teaching for some teachers (Özgür, 2020). Besides, given the little time teachers had to prepare the transition, the willingness to adapt and adjust their teaching to the demands of OTL may play a key role as well (Bruggeman et al., 2020). Hence, there is a need for professional development and sufficient time to design and practice OTL to become a competent and self-confident online teacher (Baran & Correia, 2014; Kebritchi et al., 2017). This is also in line with the viewpoint that online teaching is different from face-to-face teaching in several aspects (Ko & Rossen, 2017). Downing and Dyment (2013) showed in their study that experienced and self-confident higher education teachers in face-to-face teaching became suddenly deskilled when transitioning to online teaching. Feelings, such as disempowerment, vulnerability, and frustration were reported with regard to technological and pedagogical challenges when constructing and supporting students' learning, participation and engagement, assessment and feedback. To meet some of these challenges, researchers have highlighted mentoring as a successful approach to support teachers' professional development in OTL (Baran & Correia, 2014). Also, working in teacher design teams, in which teachers from different profiles support each other may be a significant approach to ease the transition to OTL. The teachers working in such teams can potentially motivate and mentor each other, share experiences, strategies, and learning (Downing & Dyment, 2013; Naylor & Nyanjom, 2020).

5.2.2. *Academic disciplines*

Academic disciplines come along with their own disciplinary cultures, norms, and orientations (Kreber & Kanuka, 2006). As these cultures frame the context into which OTL is implemented, teaching practices, beliefs, and effects on student learning may be discipline specific. Our results suggested that academic disciplines explained differences in the probabilities of profile membership to some degree and confirmed that some degree of discipline-specificity in the readiness profiles exists (Bolliger et al., 2019). However, we find it challenging to explain this discipline-specificity, especially because the mechanisms behind it are complex and manifold and involve not only the specific disciplinary cultures, but also teachers' beliefs about how OTL would be best implemented as well as their self-beliefs within the disciplines (Ball & Lacey, 2012; Tschannen-Moran et al., 1998). These additional factors may mediate the disciplinary differences in profile membership. Our study corroborates the idea that preparation and support of online teachers may need to focus on transformative learning experiences, including engagement in pedagogical problem-solving and discovery about OTL, *within* their disciplines (Baran, 2011). Nevertheless, further research is needed to investigate the roles and needs of the academic disciplines in the process of transitioning to OTL.

5.2.3. *Culture and innovation*

Indicators of the innovation potential in education and the cultural orientation explained cross-country variation of profile membership probabilities. Specifically, profile 3 (i.e., the high-readiness profile) was mainly comprised of teachers in countries with a tendency toward uncertainty avoidance and long-term orientation, yet a limited innovation potential. This finding does not only point to the importance of national strategies resulting from cultural orientation to deal with the shift to OTL in terms of preparing teachers for OTL in higher education (UNESCO IESALC, 2020), but also emphasizes the dealing with uncertainty and goal-setting at the time of the COVID-19 pandemic are key to facilitate teachers' readiness. Notably, the individualism-collectivism indicator of cultural orientation was not associated with membership in profile 3. This finding seems unexpected, because the profile indicators contain self-efficacy beliefs—beliefs that are partly sourced by collaborative experiences (Tschannen-Moran et al., 1998). At the same time, the link between collectivism and teacher collaboration is still to be substantiated.

Besides, we observed that high innovation potential was not necessarily associated with membership in the high-readiness profile. This finding may have several explanations: First, the present study was based only on indicators of the innovation potential, yet not indicators of actual innovation during the pandemic. Second, the potential of innovation in education may not directly result in innovative educational strategies at higher education institutions, let alone specific courses or classrooms. In fact, realizing this potential heavily depends on teachers' adaptive attributes and the institutional innovativeness (Bruggeman et al., 2020; OECD, 2019a).

Despite these findings, we argue that the profiles we identified may not fully generalize across countries, although some evidence exists on the stability of TPACK self-efficacy as a key indicator of OTL readiness (Castéra et al., 2020). The three profiles were based on an international sample and served as a lens through which readiness could be described. The dependencies of profile membership on some country-level variables may, however, indicate that the profiles are to some extent country-specific. To back this specificity or, depending on the outcome, transferability of the teacher profiles, a much larger sample with sufficiently large samples representing the different countries would be needed. Such a large-scale follow-up investigation could shed further light on the profile invariance (e.g., Morin et al., 2015) and could link universities transition to OTL to cultural or even political aspects to a larger degree (e.g., Burbules & Callister, 2000).

5.3. *Limitations and future directions*

Several limitations of the present study should be noted: First, the sample of university teachers represented a convenience sample rather than a randomly drawn and stratified sample. Cross-validating the latent profiles and the effects of their determinants with a random sample procedures could shed light on the extent to which our results may be subject to selection bias (de Rooij & Weeda, 2020). However, the observation that the profiles could be replicated with randomly drawn subsamples suggests that this bias may be low. Nonetheless, we encourage future research that examines systematically the effects of different sampling strategies on the number, shape, and prediction of the profiles. Second, we represented teachers' readiness for OTL by three core components—TPACK self-efficacy, perceived institutional support, and perceived online presence. Given that readiness may have additional components (Hung, 2016), we encourage researchers to extend the representation and measurement of this concept in future studies. Such extensions could include, but are not limited to participation in professional development (Lidolf & Pasco, 2020), expectancy and value beliefs (Cheng et al., 2020), or performance-based TPACK measures (Lachner et al., 2019). Moreover, in this study, we aimed at measuring TPACK in the context of the current situation (i.e., transition to OTL in higher education due to the COVID-19 pandemic). Nevertheless, other contexts of designing OTL activities in specific subject disciplines could not be covered. Hence, we encourage future studies to take a more design-based approach to investigate online TPACK, for instance, following the TPACK in-situ model (Pareto & Willermark, 2018). Third, we assessed teachers' readiness, the respective individual and contextual characteristics at only one measurement occasion. While this design provides information on the nature and shape of the profiles (e.g., levels of the constructs across profiles, predictive variables), longitudinal follow-up measurements could shed further light on teachers' transitions between profiles, the changes in the readiness constructs, and contextual adaptations. Concerning the latter, multilevel study designs could also allow researchers to estimate actual contextual effects and understand better the influences of the organizational characteristics. Fourth, all items in our survey were administered in English, irrespective of the participants' first language. Given that many teachers may have been second-language English speakers, some terms or items in our survey may have been understood differently across countries. While the impact of such language bias is hard to quantify in the aftermath, it may indeed be small, given the focus on higher education teachers—in fact, it is likely that the participating teachers had a sufficient English language proficiency to understand the key terms and items. Nonetheless, we argue that the possible language bias in the readiness scales should be quantified and documented (Zavala-Rojas & Saris, 2018).

6. Conclusion and implications

Overall, the results of our study suggest that teachers in higher education are not a homogeneous group with respect to their reported readiness for OTL—yet, different subgroups of teachers exist which may require different approaches for support. Identifying such profiles is key to making visible the heterogeneity between teachers and, ultimately, facilitate tailored support for implementing OTL. The profiles we identified in our study did not only exhibit consistently high or low levels of readiness, but also showed that personal and contextual readiness may not necessarily go together. As such, we argue that the readiness construct is indeed multifaceted and requires taking an individual and contextual perspective. Moreover, the determinants explaining profile membership may not affect all teachers in the same way—the different important relationships affecting one group of lectures may be completely different for another, given different backgrounds and experience with OTL. Besides, as one of the profiles in our study showed, perceived support and self-efficacy may not necessarily go hand in hand—specifically, good institutional support may not compensate for little confidence in teaching online. This observation points to the need that both aspects may have to be addressed in strategies to support teachers in times of OTL. To understand these profiles, a broad scope on the possible determinants must be taken, going beyond individual teacher characteristics and including factors that describe the context of OTL, culture, and innovation. Specifically, we argue that the organizational level is key to facilitate the capacity building at institutions to support OTL. Clearly, a better insight into the profile of teachers' readiness is an important step towards understanding how to best support them in the transition to online learning. In sum, teachers' readiness for OTL goes beyond their self-efficacy and teaching presence and depends on the institutional, cultural, and innovation context.

CRediT Statement

Ronny Scherer: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization; Sarah K. Howard: Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Project administration; Jo Tondeur: Conceptualization, Methodology, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Project administration; Fazilat Siddiq: Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2020.106675.

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