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Transitioning to Emergency Online University Education: An Analysis of Key Factors

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Restrictions and lockdown measures implemented in response to the Covid-19 pandemic exerted unprecedented pressure on higher education institutions to switch to online-only teaching. This transition was characterised by swift implementation of policy, and the adoption of a wide range of information technologies at extraordinary speed and scale. Our aim was to explore which factors contributed to a successful switch and to what extent. We collected data from university students related to their experience with the deployment of emergency remote teaching. Using a framework of Person, Artefact, and Task factors as indicators, we conducted a hierarchical logistic regression analysis to predict problem-free transition to online-only university education. Transparency of tasks and difficulties with practicals emerged as the most important predictors, among factors related to IT equipment (availability, experience, and attitude), and teachers' availability to communicate with students. We present an impact-prevalence analysis of the predictors to provide guidance for managerial decision-making and prioritisation for future intervention and research. The findings are used to provide an evaluative reflection of the transition, and to promote improvement and planning. Knowledge generated within the pandemic context is especially valuable for future contingencies, such as natural emergencies and disasters, times of conflict, and other unforeseen events.

Keywords: covid-19, digital education, emergency remote teaching, higher education, online education

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INTRODUCTION

Background

Since the World Health Organization declared Covid-19 a pandemic on 11 March 2020 (WHO, 2020), governments around the world responded by placing various aspects of public life in lockdown in an attempt to curtail the spread of the virus. Consequently, the education sector in general, and the higher education sector in particular, came under urgent and unprecedented pressure to adopt courses previously delivered face-to-face to be taught remotely.

Although the role of digital technologies and online tools had seen a rapid increase in the past two decades (e.g., Goodyear, 2002, Bates & Poole, 2003, Bates, 2019), the nearly instantaneous and mandatory switch to online-only education during the Covid-19 pandemic constitutes a different case. According to Hodges et al. (2020), it is important to distinguish online university courses, which are typically planned and developed for several months before the course is delivered, from emergency remote teaching, which is a (temporary) shift to an alternative delivery mode due to crisis circumstances.

Research into emergency remote teaching may be especially relevant during the pandemic, however, it is important to point out that there are several circumstances where knowledge generated in this context can be applied, such as remote education during times of natural disasters (Quezada et al., 2020) and conflict (Hodges et al., 2020). Emergency remote teaching has been used frequently in the past, but it was the pandemic that brought about its widespread application. Although we may hope that a mandatory switch to online-only education will not be necessary again at a global scale, Covid-19 presented a conspicuous precedent, and it seems reasonable to expect an increased role of remote teaching in the future.

Emergency remote teaching was implemented rapidly in an improvised manner at the onset of the pandemic; it was intended to be a temporary solution, as opposed to online courses and programs planned well in advance and with strong institutional backing. This speedy deployment of remote teaching may come at an expense of quality, with potential deficits in aspects of online teaching related to interactions between students and teachers, such as knowledge building, challenging each other's thinking to promote deeper understanding, community development, and the creation of online presence (Wallace, 2010). Courses delivered by professional online educators may not be affected, however, throwing untrained or insufficiently prepared educators into online environments have been found to be detrimental to quality (Tobin et al., 2015).

Challenges to education during the pandemic has prompted a swift response from practitioners and researchers around the world. Some pointed out that this global context may provide a unique opportunity to research and evaluate the effectiveness of online instruction in higher education (see Zimmerman, 2020, but also see Tobin, 2020 for a critique), while others described the situation in their institutions, shared their experiences with emergency online teaching, and provided guidance for best practice.

For example, Rapanta et al. (2020) emphasised the role of pedagogical content knowledge needed to teach online, which may be lacking in university lecturers with little or no previous experience in online teaching. To address this, they conducted interviews with experts in online teaching and learning to draw guidance for the benefit of educators under stress to prepare and deliver classes from their homes. Quezada et al. (2020) described switching a university teacher education program to online emergency education during the Covid-19 pandemic in California (US) and the many challenges related to it. They found synchronous teaching to be the most effective, but reported 'Zoom fatigue' during long sessions, and concluded with a call for developing instructional response plans for future contingencies. Similarly, Smith et al. (2020) described the experiences of students and staff at a historically black university department through the analysis of narratives collected after switching to emergency remote teaching. They summarised their findings in a list of challenges and related lessons learned, with an emphasis on community building, compassionate teaching, and a responsive and reflexive organisation of learning content in collaboration with students. Hazaymeh (2021) reported that university students in the United Arab Emirates learning English as second language were successful in developing sufficient skills in an exclusively online context during lockdown, however, technical problems and a lack of physical contact had curtailed their learning experience. Alomyan (2021) explored the impact of the rapid transition to distance learning on university students in Jordan and found that students in their third and fourth year, as opposed to those in their first year, and those with higher computer skills experienced more positive psychological and learning effects.

In line with the global trend, and in response to the same pressure, higher-education institutions in Hungary rallied to migrate all teaching activities online from March 2020. Our institution, the Faculty of Education and Psychology at Eötvös Loránd University (ELTE PPK), published guidelines to promote the ease of transition on 16 March 2020 (Bereczki et al., 2020), and offered online courses for teachers in the use of various learning management systems (e.g., Canvas and Moodle), video conferencing services (e.g., MS Teams and Zoom), and software for developing course content (e.g., Panopto), as well as methods workshops tailored for online education.

ELTE PPK implemented a mentor system where teachers were assigned mentors under the supervision of coordinators in order to provide continuous assistance specifically in online teaching (see Káplár-Kodácsy, 2020). This system was predominantly used to discuss and disseminate best practice. Additionally, there was an explicit emphasis in everyday practice on eliciting student feedback on remote teaching, both informally and through feedback forms within the central learning management system (Neptun; *https://neptun.elte.hu/*) used by the university.

To further support transition, the Faculty of Education and Psychology moved spring break forward to provide a week-long buffer and conducted a survey to assess access to IT equipment and services among teachers and students. During the remainder of the spring semester, as a quick-fix solution, previously synchronous lectures were delivered asynchronously, often with presentation slides accompanied by audio recordings. During the fall semester, most of these lectures were held synchronously using teleconferencing tools. All seminars were held synchronously in remote settings.

The academic community reacted quickly to the situation. For example, the largest annual pedagogy conference in Hungary held in November 2020 featured two dozen talks and posters dedicated to discussing the effects of lockdown in education (see Engler et al., 2020). Most studies either had a qualitative focus, or presented descriptive quantitative analysis of cross-sectional data collected in surveys (e.g., Grajczjár et al., 2021).

In this paper, we go beyond descriptive analysis by fitting a statistical model to quantitative data. Specifically, we formulate a logistic regression model predicting problem-free transition to online-only university education from answers to factual questions collected from a large number of students. The primary benefit of this approach over descriptive quantitative analysis is that it allows for assessing the strength of the relationship between each predictor and the outcome while controlling the effects of other predictors. Additionally, the overall fit of the model allows to estimate the extent to which a phenomenon (here: problem-free transition) is explained by the predictors. Note that this modelling approach is taken not to compete with, but to complement existing qualitative and interpretative work that focus on providing in-depth and experiential descriptions.

Theoretical Framework and Research Questions

We used the Person-Artefact-Task model (PAT) as theoretical framework for identifying factors that may influence students' transition to online-only education. The PAT model was originally developed by Finneran and Zhang (2003) to study flow experience in computer-mediated environments and has been applied in the research of user experience with interactive systems, such as web navigation (van Schaik & Ling, 2012), online news (Aranyi, 2012), collaborative learning in a virtual environment (van Schaik et al., 2012), and game-based learning (Elsattar, 2017).

The model categorises antecedents of experience into Person, Artefact, and Task factors, as well as the interactions of these components; the (flow) experience, in turn, leads to (flow) consequences. We adapted this model for the purpose of the current exploratory work by treating PAT factors as antecedents to the online learning process, which lead to online learning outcomes (Figure 1).

Using the PAT model as framework, Artefact factors (e.g., the availability of IT devices and systems), Task factors (e.g., attending lectures or seminars) and Person characteristics (here: teacher characteristics) all influence the online learning process. Additionally, Finneran and Zhang note that the effects of Person, Artefact, and Task factors on the process are not independent. For example, the appropriateness of an artefact (such as a learning management system) for supporting various learning activities (e.g., accessing learning material, collaborative learning, or communicating with teachers) constitutes an Artefact-Task interaction, which may be analysed in terms of the capability of the system to perform particular tasks.

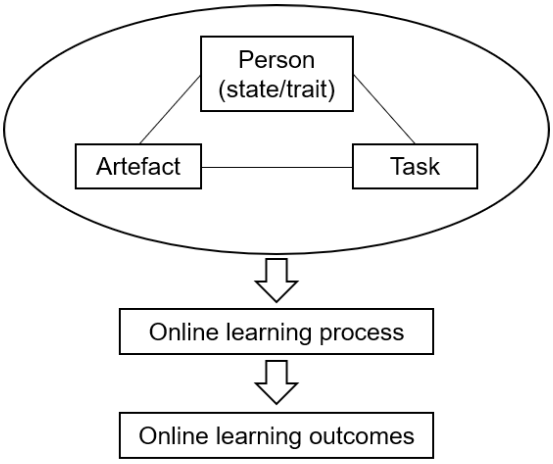

Figure 1
Person-Artefact-Task framework (adapted from Finneran & Zhang, 2003)

The online learning experience leads to online learning outcomes, which can be categorised as subjective (e.g., course satisfaction, rating, and evaluation) and objective (e.g., exam performance and learning outcomes). For the purpose of the current study, we used as outcome metric the students' subjective evaluative judgement of their experience of transitioning to emergency online education. Accordingly, we formulated two research questions.

Research question 1: which factors contribute to successful transition to online-only education and to what extent?

Research question 2: how can the findings be used to reflect on the transition and aid improvement?

In the following sections, we address Research question 1 through the analysis of a questionnaire completed by university students after transitioning to online-only university education. Specifically, we present a logistic regression analysis, where students' responses whether they had experienced a problem-free transition (no/yes) are regressed onto a set of Person, Artefact, and Task factors. Research question 2 is addressed in the Results section, where we analyse the effect of each predictor in detail and identify possible avenues of practical intervention. In the Discussion section we present an impact-prevalence analysis of each predictor in the research model to aid managerial decision-making and prioritisation for research and intervention. The paper concludes with a reflection on limitations, conclusions, and recommendations for future work.

METHOD

We conducted an online survey in Hungary after all university students had to switch to emergency online education as part of the Covid-19 lockdown measures enacted by the government. Answers were collected in December 2020 and January 2021. The aim of the survey was to ascertain the success of transitioning to emergency online education from the students' perspective. We regressed respondents' perceptions of problem-free transition to online-only education onto a set of indicators (online survey items) selected according to the PAT framework. The following sections provide a description of the sample, the grouping of model indicators, and details of analysis design.

Participants

From the authors' institution, 317 respondents gave a valid response to the survey. The majority of respondents were female (n = 229, 72.2%). Most were undergraduates (n = 238, 74.6%). The majority (n = 240, 75.7%) reported transition to emergency online education to be problem-free.

One hundred and twenty (37.9%) participated in teacher training, 16 (5%) participated partly in teacher training, and 181 (57.1%) did not participate in a teacher-training program. There was no statistically significant association between participation in teacher training (no/yes/partly) and problem-free transition (no/yes), $\chi^2(2) = 3.019$, $p = .221$, $V = 0.098$ (small)[1]; therefore, further analyses were conducted regardless of participation in teacher training.

The majority (n = 247, 77.9%) attended a full-time course. We found no statistically significant association between type of course (full-time/part-time/evening/distance) and problem-free transition (no/yes), $\chi^2(3) = 5.701$, $p = .127$, $V = 0.134$ (small); therefore, further analyses were conducted regardless of type of course.

Finally, we found no statistically significant association between gender (female/male) and problem-free transition (no/yes), $\chi^2(1) = 0.483$, $p = .487$, $V = 0.039$ (small).

Indicators

We selected indicators to predicting problem-free transition to emergency online education from the questions using the PAT framework and assigned them to one of three categories: (1) teacher factors (Person), (2) factors related to IT equipment (Artefact), and (3) learning/task factors (Task). None of the items were measured psychometrically; most items were factual questions with either nominal categories, binary choice (no/yes) or ordinal (4-point Likert-type scales). The selected items are presented in the Appendix.

Teacher factors include questions addressing how quickly teachers responded to the students during online education (*Teacher reaction time*), whether the respondents felt it important for teachers to be present at all (*Teacher presence*), how flexible the teachers were in switching to online teaching (*Teacher flexibility*), how proficient the teachers had been in using IT tools (*Teacher IT competence*), and how many teachers the respondents had contact with during online-only education (*Number of teachers*).

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[1] We interpret Cramer's V effect sizes according to Cohen (1988): .10 – small, .30 – medium, .50 – large.

Factors related to IT equipment include the variables *IT availability*, *IT experience*, and *IT negative attitude*, covering topics whether the respondent had access to all necessary IT equipment to support online learning, whether they used the same tools as they had before switching to online education, and if they had a negative attitude towards digital tools in general.

Learning/task factors include questions related to the difficulty of learning practical content online (*Learning difficulty*), whether the respondents had problems in learning seminar material (*Practicals difficulty*), and whether the learning tasks were transparent during online-only education (*Transparency of tasks*).

Design

We regressed the outcome variable (problem-free transition: no/yes) onto the indicators in a hierarchical binary logistic regression using the statistical software R (version 3.4.3)[2]. The hierarchy had 3 blocks, into which predictors were entered with forced entry method. We first estimated a separate model for each predictor category (IT equipment, teacher factors, and learning/task factors; see Appendix), then submitted only those predictors to the hierarchical analysis that had a regression coefficient statistically significantly different from zero (based on the Wald statistic).

The first block included variables in Category 1: IT equipment. We decided to enter predictors related to IT equipment in the first block, because they constitute so-called hygiene factors. According to Zhang and von Dran (2000), hygiene factors in the context of technology use are those that lead to dissatisfaction when they are not met; however, their presence does not lead to satisfaction[3]. Additionally, in an interview with expert online educators to advise non-expert university teachers on emergency online education during Covid-19, Rapanta et al. (2020) reported that accessibility to proper devices, connection, and software may be considered the most important to online teaching success from the perspective of the students. We argue that the effects of other factors need to be considered over those of IT-related factors that serve as a basis for online learning and interactions.

Because we did not posit a theoretical rationale for including teacher and task/learning factors in any particular order, we decided to add the blocks based on model fit (in terms of residual deviance) when including all statistically significant predictors in the block, entering the block with the lower fit first.

Analysis

Step 1: IT factors. Each variable in the first block was a statistically significant predictor of problem-free transition. Therefore, we added *IT availability*, *IT experience, and IT*

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[2] We used the glm function from the stats package for fitting the regression models with logit as link function.
[3] By contrast, the presence of so-called motivator factors leads to satisfaction and promotes the quality of experience.

negative attitude to Model 1 (Table 1) and retained each variable for the second step. We describe the effect of each variable as part of the complete model in the Results section below (see Field et al., 2012 for interpreting logistic regression metrics).

Step 2: teacher factors. Only the variables *Teacher reaction time* and *Teacher IT competence* returned a statistically significant Wald statistic; therefore, only these variables related to teacher factors were added to Model 2 (see Table 1) and retained for the third step. Each predictor remained statistically significant at the 5% level, model fit improved (in terms of chi-square goodness of fit and deviance), the parsimony-adjusted measure of fit improved (in terms of the Akaike Information Criterion, or AIC for short), and there was a notable improvement in each pseudo-R^2 metric.

Step 3: learning/task factors. The variables *Learning difficulty* and *Practicals difficulty* (see Appendix) were strongly correlated, S_{pb} = .67, p < .001, and led to high multicollinearity in the model. We retained the variable *Practicals difficulty* to describe students' problems with learning the material of practicals, because it yielded a lower AIC value than including Learning difficulty in the regression model, and its binary coding yielded a simpler interpretation of its effect. Model 3 (see Table 1) yielded an improved fit, AIC decreased, and each pseudo-R^2 metric increased.

Including all statistically significant learning/task factors at the third step of the regression hierarchy (Model 3) suppressed the effect of *Teacher IT* competence from Model 2, and the variable *Practicals difficulty* in Step 3 also lost statistical significance. The two variables were moderately and negatively correlated, τ = -.31, p < .001. Since *Teacher IT competence* had the smaller effect of the two, we removed it from the final model solution and re-estimated the model. Parameters of the complete model are presented in Table 2.

Table 1
Hierarchical logistic regression analysis to predict problem-free transition to emergency online education

DV: Problem-free transition (1)	Model 1 (IT factors)	Model 2 (IT + Teacher factors)	Model 3 (IT + Teacher + Tasks)
	b (*SE*)	*b* (*SE*)	*b* (*SE*)
Intercept	-0.811 (0.678)	-4.125*** (1.013)	-3.223** (1.114)
IT availability	1.736*** (0.455)	1.330** (0.512)	1.504** (0.560)
IT experience	0.385* (0.159)	0.396* (0.168)	0.360* (0.174)
IT negative attitude	-0.576*** (0.169)	-0.560** (0.186)	-0.477* (0.191)
Teacher reaction time		0.701*** (0.209)	0.565** (0.218)
Teacher IT competence		0.573** (0.192)	0.306 (0.206)
Transparency of tasks			1.093** (0.357)
Practicals difficulty			-0.578$^+$ (0.324)
Deviance	315.00	286.54	271.47
AIC	323.00	298.54	287.47
Model χ^2(df)	χ^2(3) = 36.491***	χ^2(5) = 64.948***	χ^2(7) = 80.024***
R^2 (Hosmer-Lemeshow)	0.104	0.185	0.228
R^2 (Cox-Snell)	0.109	0.185	0.223
R^2 (Nagelkerke)	0.162	0.276	0.333

Notes. * p < .05; ** p < .01; *** p < .001; $^+$ p < .10.

The complete research model addresses *Research question 1* by listing statistically significant determinants of problem-free transition to online-only education, and the extent to which each determinant influenced transition in terms of odds ratios. In the following section, we focus on the effect of each predictor in detail to address *Research question 2*.

Table 2
Parameters, effect sizes, and measures of fit of the complete model

DV: Problem-free transition (1)	*b* (*SE*)	Odds ratio [95% confidence limits]		
		Lower	Odds ratio	Upper
Intercept	-2.55* (1.010)			
IT availability	1.607** (0.551)	[1.694]	4.990	[14.693]
IT experience	0.341* (0.174)	[1.001]	1.406	[1.976]
IT negative attitude	-0.460* (0.188)	[0.437]	0.631 (1.58)	[0.912]
Teacher reaction time	0.618** (0.215)	[1.218]	1.855	[2.826]
Transparency of tasks	1.222*** (0.346)	[1.722]	3.392	[6.683]
Practicals difficulty	0.665* (0.319)	[0.276]	0.514 (1.95)	[0.961]
$\chi^2(6) = 77.804$***	*AUC*: = 0.797 (Area Under Curve)	$R^2 = 0.221$ (Hosmer-Lemeshow)	$R^2 = 0.218$ (Cox-Snell)	$R^2 = 0.325$ (Nagelkerke)

Notes. The multiplicative inverse of the odds ratios for predictors negatively related to the outcome variable are presented in parentheses to promote the direct comparability of effect sizes. * $p < .05$; ** $p < .01$; *** $p < .001$.

FINDINGS

Over three-quarter of respondents ($n = 240$, 75.7%) indicated that their transition to online-only education was free of hurdles. It is difficult to make sense of this proportion in absolute terms. On the one hand, it is expected that some would experience problems even in an ideal scenario. On the other hand, there is clearly room for improvement: nearly a quarter of students reporting problems in a transition process that had a profound effect on their access to education calls for a closer examination of the factors influencing this transition.

IT availability. The odds of problem-free transition were nearly five times higher for students who had access to all necessary IT equipment for online-only education than the odds for those who lacked some equipment. We treat this predictor as a hygiene factor (Zhang & von Dran, 2000) that serves as a basis for successful transition. Although only a relatively small number of students were affected (see Figure 2 for the distribution of predictor variables), their transition was hindered most of the time. Cross-tabulating problem-free transition with *IT availability* showed that of the 25 respondents (8% of the full sample) who reported not having access to all necessary IT equipment, 16 (64%) reported problems in transitioning to online-only education.

Respondents were asked to indicate in a free-text response the IT tools that were missing. Sixteen participants reported missing computer peripherals: eight microphones, two headsets, and six cameras. These devices are relatively easy to replace and explains why missing IT equipment was not associated with transition problems in all cases. Ten participants reported not having access to an appropriate Internet connection from home. Solving this problem is not always trivial, especially in rural parts of Hungary, and highlights the importance of providing public access to high-speed Internet. Finally, eleven participants (3.5% of the full sample) reported that they lacked an appropriate computer (desktop, laptop, or tablet) for online learning. We believe this is a serious problem that needs to be identified in the future in advance. As switching to online-only education was mandatory, support should have been given to provide the means for compliance. Lacking quick procurement for IT equipment for the use of disadvantaged students, a possible intervention would be to loan computers from the institution's computer labs that were not in use during lockdown.

IT experience. Those students who used the same IT tools (hardware and software) during online-only education as before were less likely to experience problems during transition. Specifically, one unit change in the predictor (measured on a 1-4 scale) was associated with a 1.4-times increase in the odds of problem-free transition. Nearly half of students (n = 146, 46%) reported to have used the same IT tools as before, and 120 (38%) reported to have used mostly the same tools as before. Fifteen respondents (5%) reported to have used entirely different tools during online education, and 36 (11%) reported to have used more new tools than previously used ones.

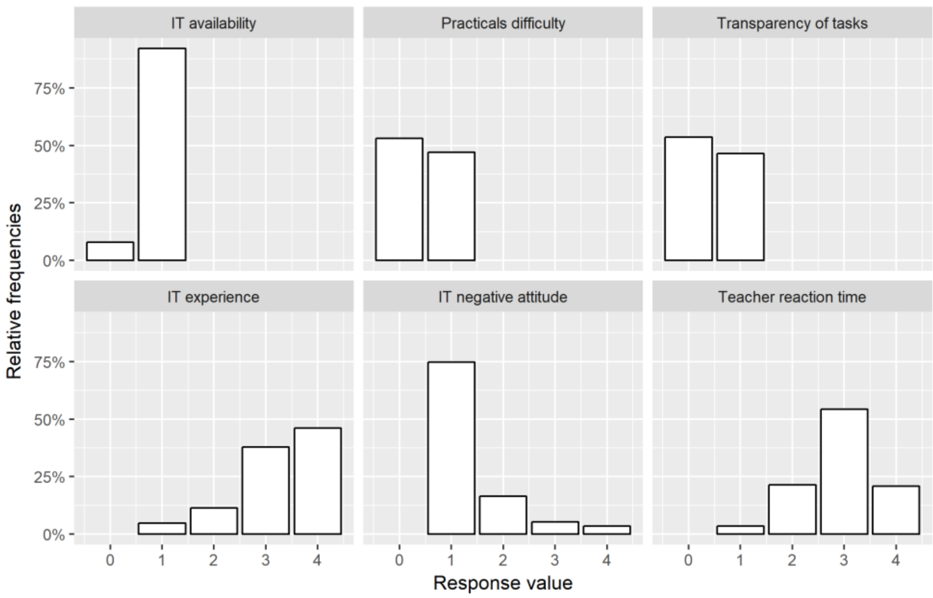

Figure 2
Distribution of predictors
Notes. Binary predictors are coded 0 – "no", 1 – "yes". See the Appendix for the coding of ordinal variables.

From the perspective of the PAT framework, *IT experience* can be viewed as an interaction between Person and Artefact factors (i.e., lack of experience of a person with a particular system), and it is theoretically related to the concept of internal control conceptualised as computer self-efficacy in the context of technology use (see Venkatesh, 2000). Over half of the students were affected to some extent, but only 16% to a serious degree. An intervention to address this factor would be to identify those affected in due time, as well as the tools in question, and offering (online) courses.

IT negative attitude. One unit change in the predictor (measured on a 1-4 scale, reverse-coded) was associated with a 1.6-times increase in the odds of problem-free transition. We found that the majority (n = 247, 75%) of respondents had a strong positive attitude towards IT tools in general. However, eleven participants (3%) reported a strong negative attitude, and seventeen (5%) a negative attitude, amounting to 8% of the respondents being affected by this factor. According to the PAT framework, this constitutes a Person factor, which has a long history in Human-Computer Interaction literature. For example, in an extension of the Technology Acceptance Model (TAM) based on a series of longitudinal field studies (Venkatesh & Davis, 2000), such general negative attitudes were conceptualised as computer anxiety, which (along with factors such as computer playfulness and perceived enjoyment) served as an antecedent of perceived ease of use, a key factor in predicting intention to use a computer system. A study with students in higher education in Hungary (Faragó et al., 2016) found IT competence (here: *IT experience*) and IT attitude as independent factors, and linked attitude towards IT tools to external locus of control, based on the findings of Woodrow (1990). To mitigate the effect of negative IT attitudes, we recommend offering (technical) support for affected students.

Teacher reaction time. One unit change in the predictor (measured on a 1-4 scale) was associated with a 1.9-times increase in the odds of problem-free transition. Eleven participants (3%) reported to have received responses from their teachers very slowly, and 68 (21%) reported to have received slow online responses for the queries from their teachers, amounting to nearly a quarter of the students being negatively affected. This finding highlights the importance of maintaining timely online communication with students, which, according to our own experiences, requires considerable time and effort, especially as there was little time to prepare and organise before the rapid transition to online-only teaching. Teachers need to be provided the means and the necessary time to respond to an increase in online-communication load. While online education had already blurred the boundaries between real-world and digital experience (see Fawns, 2019 for a postdigital perspective on education), learning (and working) from home during the pandemic has further blended the boundaries between home and school (and the workplace), with severe effects on mental health and well-being (Dawson & Golijani-Moghaddam, 2020). Therefore, we argue that the increased workload for teachers resulting from maintaining continuous online communication with students needs to be explicitly taken into account when organising tasks.

Transparency of tasks. The odds of problem-free transition were 3.4 times for students who had clearly defined tasks during online-only education. This factor had the second largest effect size in the research model after *IT availability*; however, it affected the most students among all the factors. More than half of the participants (n = 170, 54%) reported that their online learning tasks were not transparent. According to the PAT framework, we treat *Transparency of tasks* as a Task factor, and as the most important predictor of problem-free transition in terms of the combination of its effect size and the proportion of students affected. Clear learning objectives are a key part of instructional- and learning design, and are strongly related to desired learning outcomes (Bates, 2019); therefore, teaching transparency needs to be explored in more detail, preferably through content analysis of qualitative data (e.g., see Anderson et al., 2013). Although this factor is conceptually related to institutional communication and organisation, we also see a key role of learning management systems to promote clear and transparent communication of learning tasks and requirements (Nakamura et al., 2017).

Practicals difficulty. The odds of problem-free transition were double for students who reported no particular difficulties in learning seminar material during online-only education. This factor was the second-most important in terms of the number of students negatively affected: 149 (47%) reported to have had problems in learning for practicals online. This factor has also had the third largest effect size, and we treat it as the second-most important predictor of problem-free transition (after *Transparency of tasks*) in terms of the combination of its effect size and the proportion of students affected. We posit that this factor needs to be approached primarily from the organisation of learning material, with a strong role of learning management systems (Blyth & Verhaart, 2007).

DISCUSSION

The previous section presented the results of our analysis in detail, describing each statistically significant factor of problem-free transition to online-only education, in connection with relevant research and recommendations for intervention. Here, we present a high-level summary of the predictors and discuss the findings from the perspective of managerial decision-making, and prioritisation for research and intervention.

Figure 3 shows the effect size of each predictor plotted against the proportion of students in our sample whose experience we identified as seriously influenced by the effect of each predictor in the Results section above. We refer to the proportion of students affected as the prevalence of a factor. The effect sizes are in terms of odd ratios, which allows for comparing the effect of each predictor on the outcome. An odds ratio of one represents no relationship (i.e., the odds of problem-free transition are the same, regardless of any change in the predictor). We present the multiplicative inverse of odds ratios for predictors negatively related to the outcome variable to promote a direct comparability of the magnitude of the effects. Based on impact-performance matrices (see Martensen & Grønholdt, 2003, Aranyi & van Schaik, 2015), where effect sizes are plotted against standardised scores of continuously measured scales, we refer to this analysis as an impact-prevalence matrix.

The horizontal dashed line in Figure 3 shows the average prevalence (i.e., the proportion of students seriously affected across all factors), while the vertical dashed line represents the average of odds ratios across the factors. The two lines separate the figure into four quadrants. The lower-left quadrant contains predictors that had a relatively low effect coupled with a relatively low prevalence. Although these predictors are important in driving problem-free transition, they are less important from a decision-making point of view than other factors. *IT experience* and *IT negative attitude* both fall into this quadrant, along with *Teacher reaction time* with a slightly higher effect size and a notably higher prevalence. The figure shows, for example, that it may not be worth addressing *IT negative attitude* (unless it can be done at a reasonably low cost and effort), since it has a relatively low effect size (i.e., improvement is not expected to lead to a large change in the outcome), and only a few people are affected. In general, factors in the lower-left quadrant should be targeted for intervention if resources are readily available and more important factors are also being addressed. From a managerial point of view, factors in this quadrant have a relatively low priority.

The lower-right quadrant of Figure 3 contains the factor *IT availability*, which affects a low proportion of students, however, its effect is profound. This factor calls for intervention by virtue of its large effect. We have identified the availability *of IT equipment* as a hygiene factor that serves as a basis of problem-free transition to online-only education, therefore, it is imperative to prioritise intervention in this area in order to prevent dropout. The associated costs should be favourably influenced by the low proportion of students who are seriously affected.

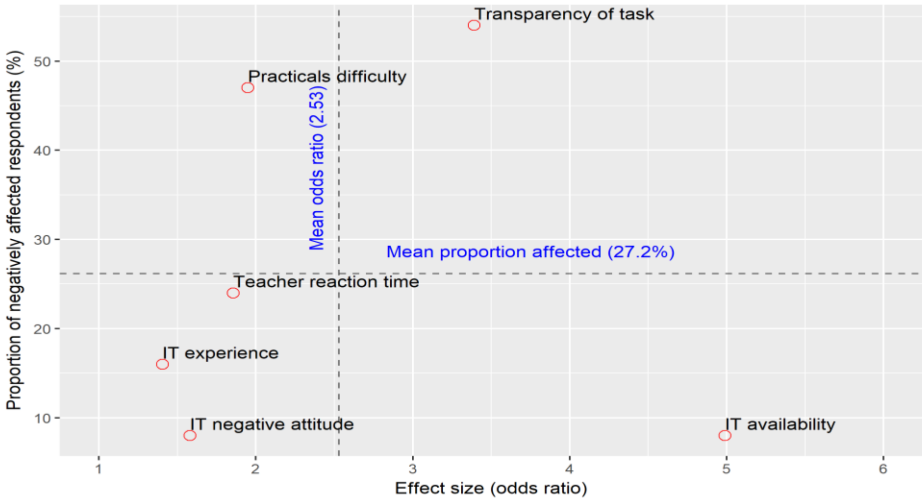

Figure 3
Impact-prevalence analysis of the factors affecting problem-free transition to online-only education.

Notes. Multiplicative inverses of the odds ratios are presented for predictors negatively related to the outcome variable: *IT negative attitude* and *Practicals difficulty*. An odds ratio of one represents no relationship between the outcome and the predictors.

The upper-left quadrant contains *Practicals difficulty*, a variable with relatively modest effect, but with a large prevalence (nearly half of the students affected). We suggest assigning this area a high priority, both in terms of intervention and research. The difficulty of learning practical material online is a key issue in the effectiveness of remote learning, and our findings corroborate its prevalence in the context of emergency online teaching.

Finally, the upper-right quadrant should be the focus of most immediate intervention, as it is associated with a large effect and large prevalence relative to other factors. The predictor *Transparency of tasks* falls into this quadrant, which makes it the most important factor in our research model. As discussed in the Results section, teaching transparency is strongly related to desired learning outcomes, and is conceptually related to both institutional communication and to the application and usability of learning management systems. Promoting the transparency of tasks in online teaching is expected to have the highest impact on the successful implementation of online teaching.

LIMITATIONS, AND FUTURE WORK

A methodological limitation related to the formulation of the research model was the treatment of ordinal variables as continuous, instead of dummy-coding them into dichotomous predictors. Although the latter is not complicated in execution, we opted against it in order to promote the ease of interpretation of the results (each four-level predictor would have had to be replaced by dummy variables for each level). We believe the current treatment of the variables is sufficient for exploratory purposes and delivers essentially the same results.

Another limitation related to methods would be the simplicity of model structure. We tested a single-stage model solution, where each factor was a direct predictor of the outcome variable. No interactions between the factors were hypothesised nor tested, although the PAT framework suggests and allows such interactions. We hold that moderation (and mediation) analyses are subjects for future work, where specific hypotheses are formulated for them. Here, the intention was to provide an exploratory account, with a description of effect sizes that can be directly interpreted and compared; we have achieved this objective and answered *Research question 1*.

We refrained from including statistically non-significant predictors in the research model in a trade-off between descriptive scope and generalisability. For example, *Teacher IT competence* was a significant predictor in Model 2 (see Table 1) with an effect size comparable to many other factors (exponentiate the reported regression coefficient to get the odds ratio) and it was conceptually relevant; we excluded it from the final model solution as it was no longer statistically significant in the presence of other effects.

Future (modelling) work may also use psychometrically measured factors, as well as outcome measures that address the quality of experience of students and/or their satisfaction. For example, psychometric scales for measuring perceptions of internal control when interacting with computer systems and attitudes towards computer systems are available, such as computer self-efficacy and computer anxiety, respectively (see

Venkatesh, 2000). We assert that the short and factual questions and the simple, single-item evaluations for each factor used in the current study fitted the exploratory nature of the enquiry. We also note that we did not cover certain areas integral to online university teaching and learning, such as (online) examinations and assessment (see Munoz & Mackay, 2019), which needs to be addressed in future work.

CONCLUSION

We presented an exploratory study of factors influencing problem-free transition to online-only university education implemented post-haste in response to the Covid-19 pandemic. *Research question 1* asked which factors contributed to a successful transition to online-only university education and to what extent, and was answered by formulating a logistic regression model with Person, Artefact, and Task factors as predictors. Transparency of tasks and difficulties with practicals emerged as the most important predictors of problem-free transition, in terms of the combination of their effect size and the proportion of students affected; both predictors were Task factors according to the PAT framework. Predictors related to the availability of, experience with, and attitudes towards IT equipment (Artefact factors) were associated with a low number of students affected, and were identified as hygiene factors, the absence of which lead to dissatisfaction, while their presence is insufficient for satisfaction. Among Person factors, teachers' availability to communicate with students emerged as a significant factor in driving problem-free transition.

The question of how the findings can be used to reflect on the transition and aid improvement (*Research question 2*) was addressed via an impact-prevalence analysis of the predictors, summarising the research model in a format that allows for drawing guidance for managerial decision-making and prioritisation for practice and research. According to this analysis, promoting the transparency of tasks in online teaching should receive the highest priority (high impact and high prevalence), followed by mitigating the difficulty of learning practical material online (low impact and high prevalence), providing support to access IT equipment (high impact and low prevalence), managing teachers' workload to support continuous online communication with students (low impact and low prevalence), and the provision of IT courses and support for students (low impact and low prevalence).

We sincerely hope that the pressing need for implementing emergency online teaching at such a large scale will not arise again, even if it occurs regularly outside the Covid-19 context, for example, during times of conflict and natural disasters. As a silver lining to the black clouds that are hopefully well behind us, we believe that the knowledge generated during the pandemic will benefit future education research and practice in the global context of persistent digitisation and the ever-increasing share of online activities in our lives.

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APPENDIX

Outcome variable and indicators of problem-free transition to online-only education.

Variable name	Question text	Response and coding
Outcome variable		
Problem-free transition	Was transitioning to online education free of problems for you?	Nominal, binary 0 – no, 1 – yes
Category 1: IT equipment		
IT availability	Did you have access to all the sufficient IT equipment to switch to online education?	Nominal, binary 0 – no, 1 – yes
IT experience	Did you use the same IT tools for online education as you used before?	Ordinal 1 – no, 2 – many were new, 3 – mostly, 4 – yes
IT negative attitude	I hate digital tools.	1-4 Likert Verbal anchors: 1 – not at all, 4– completely
Category 2: teacher factors		
Teacher reaction time	How quickly did you receive replies to your questions from your teachers during online education?	1-4 Likert Verbal anchors: 1 – very slowly, 4– very quickly
Teacher presence	Do you consider it important in learning for a teacher to be present?	Nominal, binary 0 – no, 1 – yes
Teacher flexibility	How would you rate your teachers' flexibility in switching to online education?	1-4 Likert Verbal anchors: 1 – not at all, 4– completely
Teacher IT competence	Did your teachers use IT tools adequately after switching to online education?	1-4 Likert Verbal anchors: 1 – not at all, 4– completely
Number of teachers	How many teachers did you have during online education?	Ordinal, 1-3 1: 1-5; 2: 6-10; 3: 10+
Category 3: learning/task factors		
Learning	How difficult did you find learning course	1-4 Likert

difficulty	material with a practical content during online education?	No verbal anchors
Practicals difficulty	Did you have any problems in learning seminar material during online education?	Nominal, binary 0 – no, 1 – yes
Transparency of tasks	Were your learning tasks transparent during online education?	Nominal, binary 0 – no, 1 – yes