Modelling Students' Adoption of E-Learning During the COVID-19 Pandemic: Hungarian Perspective

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Abstract—This research examines the impact of gender and age differences on the attitude towards online education in universities and colleges during the COVID-19 pandemic in Hungary. The answers were evaluated using Partial Least Squares estimation technique by involving age and gender as moderator variables. The research model is based on a modified version of the Technology Acceptance Model (TAM) proposed by Davis, Warshaw, and Bagozzi (1989) and expanded by a good teaching scale. Apart from perceived ease of use, other variables illustrated significant direct relationships. Moderating effect of age and gender of the surveyed Hungarian students influence formulation of attitude towards e-learning. The results illustrate that the gender and age of the respondents influence the perceived usefulness → behavioral intention pathway. Also, the age of respondents has an impact on the relationship between perceived ease of use and perceived usefulness.

Keywords—e-learning, TAM, moderating effect of gender, moderating effect of age, COVID-19

1 Introduction

In many countries, online education was the only correct choice for trying to keep the COVID-19 virus under control and keep up with teaching [1]–[3]. 'Remote teaching' is a specific concept born of the pandemic situation. It combines the features of distance and online learning. Although it has many possibilities (flexibility, individual learning paths), its limitations and difficulties may also arise (low digital competence of the participants; lack of tools and personal connection) [4], [5]. The transition to remote teaching took place in a sudden and unplanned way, so it is safe to use the term 'emergency remote teaching' (ERT) [6].

The current study aims to build up the model that might explain Hungarian university students' attitude towards remote online education (with the application of e-learning tools) during the COVID-19 pandemic as well as to determine the influence of age and gender. For achieving this purpose, Technology Acceptance Model/TAM [7] was chosen as the theoretical framework of the study, and a good teaching scale was included in the model. The study aims to find answers to the following research questions:

- RQ1. Is TAM appropriate for understanding the attitude of students in higher education towards e-learning tools in Hungary?
- RQ2. Does gender/age play an essential role in the formulation of behavioral intention and actual use of e-learning tools during COVID-19?

2 Literature review

2.1 Education and COVID-19

The terms distance education, online education as well as e-learning emerged in the 1980s [8]. Distance learning is a form of education where the teacher and the student are not in the same place and teaching process occurs through specially designed education platforms [9]. The learner studies alone, independently for most of the training time, and participates in consultations for a smaller part, with the help of teachers, i.e., tutors, through personal contact and direct supervision.

As opposed to the traditional learning environments, which is tied to a location and the presence of the instructor and the student, takes place in real-time, controlled by the instructor, applying linear teaching methods [10], online environments are unbound and dynamic by using evolving information and communication technologies, asynchronous communication and real-time information, allowing a diverse range of pedagogical practices, active learning, and a student-centered attitude [11]–[13].

In the scientific literature, e-learning is characterized as a combination of technological tools (i.e., web-based, web-distributed, or web-capable) for achieving the main goal [14], [15] – to provide education any time from any place in the world [16], [17]. If previously, the application of online tools in education/learning process was believed to be "non-formal education" [18], the current circumstances changed people's opinions. In order to have interesting classes and explain topics in detail, these changes required a combination of different skills [19].

Some studies [2], [20] were interested in understanding teachers' attitudes towards e-learning. Students' lifestyles were changed as well, as they had to adapt to the new circumstances [21]. This paper focuses on students' acceptance of changes and their interaction with e-learning tools as well as identifies influence of gender and age on students' intention and actual use of e-learning tools.

2.2 Hungarian context for online learning during COVID-19

In Hungary, prior to the onset of the coronavirus epidemic, higher education mainly used to be in a traditional, presence-based, full-time schedule [22]. Following the appearance of the new type of coronavirus on March 4, 2020, the Government of Hungary declared an emergency situation throughout the country on March 11. A government decree prohibited students from visiting higher education institutions. Universities and colleges took measures to combat the spread of the coronavirus, as part of which they ordered the transition to digital education for teachers and researchers [23]. According to a survey by the International Association of Universities (IAU), 91% of higher education institutions have a well-established communication infrastructure, however, respondents said that it was a challenge to ensure clear and effective communication processes with staff and students [24].

Deés [25] draws attention to the results of the COVID-19 Global Student Survey, according to which Hungary ranks first among the countries of the world in terms of students (in their own opinion) being able to increase their performance in the new educational environment, second in student satisfaction as regards the presentation of the curriculum from faculty to students. Hungarian students also rate the performance of universities in the new situation as the second best (69%) [26].

As found by the questionnaire surveys conducted by the National Union of Students in Hungary (HÖOK), according to Hungarian students participating in higher education, around 70 per cent of contact classes and exams could be replaced by digital education. The discussed proportion of replaceable classes is mostly dependent on the satisfaction with online education, while work schedule does not cause significant differences in the above-mentioned terms. Respondents with lower monthly data limit tend to replace less, but considerable share of contact classes [27].

Numerous Hungarian authors [4], [22], [23], [25], [28]–[30] surveyed university students on the online education during the pandemic, in majority from an educational science and policy perspective. A common finding of the studies is that institutions adapted quite well to the remote teaching, although the transition meant an increased burden, especially for teachers, however, students were rather dissatisfied with the lecturers' preparedness for online teaching and using digital tools. It turned out that personal contact cannot be fully replaced by the virtual environment.

2.3 Theoretical background

The model developed for examining e-learning context during COVID-19 is an extension of the Technology Acceptance Model (abbr. TAM) which was developed based on the Theory of Reasoned Action [31] aiming to explain the behavior [32] towards information systems (IS). It was originally used for measuring the acceptance of technology in a workplace.

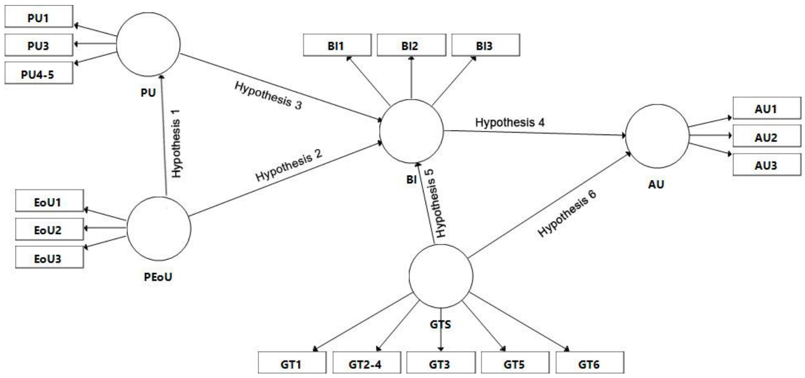

Fig. 1. Proposed model (only direct relationships illustrated, Source: own editing)

The modified version of the model [7] included ease of use (PEoU), perceived usefulness (PU), behavioral intention (BI), and actual use (AU). Perceived usefulness and ease of use were the main two dependent variables influenced by different characteristics (i.e., technology, individual/group, task, and situational) of technological products/services [33]. Appendix 1 illustrates some of those numerous studies in the field used TAM for analyzing behavior towards digital learning. Some studies reported poor use of moderators such as experience [34], age, and gender [35]. Also, there was criticism regarding the model's explanatory power [36] and insensitiveness to causal directions in the case of SEM [37].

Even if a large number of studies are based on the TAM framework [14], some authors tend to use a relatively new model [38] called the unified theory of acceptance and the use of technology or its extension (abbr. UTAUT/UTAUT2). Unlike TAM and its extensions [7], [34], [39], the original and extended versions of UTAUT [38], [40] involve moderator variables such as gender, age, voluntariness. Also, a limited number of studies [16], [41] used innovation diffusion theory for e-learning context.

3 Hypothesis development

3.1 Perceived usefulness and perceived ease of use

Davis [7] explains the concept behind perceived ease of use (abbr. PEoU) as "the degree to which a person believes that using a particular system would be free of effort" [7, p. 320] whereas perceived usefulness (abbr. PU) is explained as "the degree to which a person believes that using a particular system would enhance his/her job performance" [7, p. 320]. The mentioned variables are strong determinants of behavioral intention (BI) in the framework of the technology acceptance model (abbr. TAM).

Moreover, studies conducted before COVID-19 [14]–[16], [42]–[44] proved the relationships between determinants (PU and PEoU) and BI as well as the confirmed impact of perceived ease of use on usefulness in the e-learning context. During COVID-19, the results were much more contradictory; some studies showed partially [3], [45] the others fully [42], [46]–[48] significant outcomes.

In the mentioned conditions, usage of e-learning tools might not be optional (i.e., it was an obligatory choice considering that personal interaction would increase the number of infected people), the authors expect to see the impact of ease of use and usefulness on intention to use e-learning tools during COVID-19 lockdown. Therefore, the authors propose the following hypotheses:

H1: Perceived ease of use (PEoU) has a positive influence on students'perceived usefulness (PU) to use e-learning tools during the COVID-19 pandemic. (PEoU → PU).

H2: Perceived ease of use (PEoU) has a positive influence on students'behavioral intention (BI) to use e-learning tools during the COVID-19 pandemic. (PEoU → BI).

H3: Perceived usefulness (PU) has a positive influence on students'behavioral intention (BI) to e-learning tools during the COVID-19 pandemic. (PU → BI).

Behavioral intention. Behavioral intention (abbr. BI) to use e-learning can be defined as the "degree to which a learner without prior experience of e-learning intends to switch over to the innovation or increases his use in the future" [41, p. 1410]. Various studies proved the significant direct impact of behavioral intention on the actual use of e-learning tools before [15], [41] and during COVID-19 [3], [14], [47]. Therefore, the authors propose the following hypothesis:

H4: Behavioral intention (BI) has a positive influence on students'actual use (AU) of e-learning tools during the COVID-19 pandemic. (BI → AU).

Good teaching scale. Good Teaching Scale (abbr. GTS) is defined as helpful feedback of teaching staff about a student's studies. It was designed [49] as a part of the Course Perceptions Questionnaire, aimed to analyze students' approaches to studying. Later, Ramsden [50] designed the Course Experience Questionnaire that also included Good Teaching Scale. The reason for including GTS in the proposed model was to understand how well the new system suits the expectations of Hungarian university students. Therefore, the authors propose:

H5. Good teaching scale (GTS) has a positive influence on Behavioral Intention (BI) of the e-learning tools during the COVID-19 pandemic (GTS →BI).

H6. Good teaching scale (GTS) has a positive influence on Actual Use (AU) of the e-learning tools during the COVID-19 pandemic (GTS →AU).

Moderation: Influence of gender. Previous studies [38], [40], [51], [52] illustrated that gender is one of the main factors that influence the attitude and behavior of young adults towards adoption of the IS-related products and services. The main divergence in decision-making is based on the socialization patterns caused by cognitive structures [51]. Originally, the gender of respondents was not used as the moderator of relationships between variables in the case of TAM [7], [34], [39]. Also, it was reported that using gender as a moderator significantly increases the explanatory power of the model [38], [53].

Even if the impact of gender on PEoU and PU pathway was also reported in the literature [51], it was not previously applied for the e-learning context. Moreover, considering the limited number of studies examining the effect of gender as well as the involvement of new variables in the model, it was interesting to report results for PEoU → PU relationship and to compare the result with the previous studies. Therefore, the authors propose:

H7A. The relationship between Perceived Ease of Use (PEoU) and Perceived Usefulness (PU) is moderated by gender (i.e., PEoU → Gender → PU).

However, there is scientific evidence that males and females react differently to PU and PEoU [51]. In more detail, males are more influenced by PU (i.e., PU → BI) while females value PEoU (i.e., PEoU → BI). Within the e-learning context, the study conducted by Tarhini et al. [54] illustrated that one of the pathways (i.e., PEoU → BI) was influenced by moderating effect of gender. When adopting UTAUT to the case of mobile learning, gender moderated only the relationship between Performance Expectancy (the equivalent of Perceived Usefulness) and Behavioral Intention [35]. As result, the authors propose:

H7B. The relationship between Perceived Ease of Use (PEoU) and Behavioral Intention (BI) is moderated by gender (i.e., PEoU → Gender → BI).

H7C. The relationship between Perceived Usefulness (PU) and Behavioral Intention (BI) is moderated by gender (i.e., PU → Gender → BI).

Moderation: Influence of age. Some studies emphasize the importance of age as a demographic variable that affects behavioral intention, as well as technology adoption/diffusion [35], [38], [40]. Moreover, while part of scientists offered involvement of age to TAM [54], [55], others build up a new model and included it as a moderator [38], [40].

The relationship between PEoU and PU has not been previously examined within an educational context. Unfortunately, the moderating effect of age also was not calculated for the mentioned pathway. Therefore, the current study aims to explore whether the age of respondents plays a role within an educational context. Therefore, the authors propose:

H8A. The relationship between Perceived Ease of Use (PEoU) and Perceived Usefulness (PU) is moderated by age.

Also, the researchers were interested in the influence of age on PEoU → BI pathway. In the case of the UTAUT, the variable that had almost the same characteristics as perceived ease of use (i.e., effort expectancy/EE) was used as a determinant of behavioral intention; age was illustrated as one of the moderators of relationship. Considering that measurement of Effort Expectancy is similar to perceived ease of use [54], the outcome of UTAUT related studies might also be used in the literature review. As result, there is a piece of evidence regarding the influence of age on PEOU/EE and BI pathway in the case of e-learning [35], [54].

H8B. The relationship between Perceived Ease of Use (PEoU) and Behavioral Intention (BI) is moderated by age (i.e., PEoU → Age → BI).

The authors are also interested in determining the influence of age on PU → BI pathway. In the UTAUT, Venkatesh et al. [38] proved that the relationship between Performance Expectancy (the equivalent of Perceived Usefulness) and Behavioral Intention is moderated by age. However, in the case of e-learning, researchers reported contradictory results. Some researchers [35] illustrated a significant relationship between Performance Expectancy (which is similar to Perceived Usefulness) and Behavioral Intention while others reported the opposite [54].

H8C. The relationship between Perceived Usefulness (PU) and Behavioral Intention (BI) is moderated by age (i.e., PU → Age → BI).

4 Methodology

4.1 Sampling and data collection

The authors of the current study aimed to understand qualitative aspects of influencing online education during the Covid-19 spread in Hungary. The data collection method of the current research was a survey using an online questionnaire. The target population was Hungarian university students, the sampling frame consisted of those who had access to the questionnaire sheet through social media (Facebook). The disadvantages of voluntary response survey are that "the researcher has no control over the make up of the sample" and "the sample is likely to be comprised of strongly opinionated people" [56].

4.2 Survey instrument and measures

In the first section of the questionnaire, respondents were asked about their socio-demographic profile (see Table 1) while the second section included questions for measuring latent variables in the study. The survey participants expressed their attitude towards different statements using a five-point Likert scale similarly to previous studies [45], [46], [57], [58] which simplifies and quickens the completion of the survey [59]. A new variable - good teaching scale was also included in the analyses. In the behavioral sciences, Common Method Bias (also known as Common Method Variance) is one of the essential threats to the validity of analysis [60]. It was assessed by using Harman's single factor test in SPSS [60]. The result was lower than the recommended threshold which is 50%.

4.3 Analytical procedures

The questionnaire was prepared in English, and later it was translated to Hungarian by a native speaker and checked by several researchers who were able to make corrections on it. The survey was conducted from the 15th of January to the 15th of March 2021 which was the period of the rise of the pandemic's 3rd wave. During this period, the number of people infected by COVID-19 was high [61] and students were participating in online education. The respondents were students all over Hungary, who were enrolled in different levels (i.e., bachelor, master, Ph.D.) of education and attendance structure (i.e., full-time, correspondence, evening).

The results of the questionnaire survey were analyzed using the Partial Least Squares estimation technique of Structural Equation Modeling (PLS-SEM) through SmartPLS 3.3.3 software. Chin [62] illustrated that a latent variable might be reflective (direction of causality from latent variable to item), or formative (direction of causality from item to latent variable). Considering applications of TAM [63] as well as recommendations towards using reflective/formative indicators, the proposed model is considered as a reflective measurement model.

5 Results

5.1 Descriptive statistics

Within the framework of the survey, a total of 453 respondents answered the questionnaire, representing 28 different Hungarian higher education institutions. It was a filter condition of completing the questionnaire to participate in online university education in the autumn semester of the 2020-2021 academic year, so 451 valid responses could be used for further analysis.

Table 1. Descriptive statistics: Demographic profile

Category	Grouping variable	Number of respondents	% of respondents
Gender	Female	255	56,54
	Male	196	43,46
Current level of training	Higher-level vocational training	21	4,66
	BA/BSc	331	73,39
	MA/MSc	83	18,40
	Undivided university programme	10	2,22
	Undivided teacher training	4	0,89
	Doctoral (PhD/DLA) programme	8	1,77
Age group	18-21	35	7,76
	22-24	148	32,82
	25-29	101	22,39
	30-39	80	17,74
	40-49	74	16,41
	50-	13	2,88

Source: own editing based on the demographic profile of respondents

5.2 Measurement model

The authors have begun the results section with the examination of the reflective measurement model. The validity of reflective constructs combines convergent validity and discriminant validity [64]. In order to achieve convergent validity, items' outer loadings, as well as average variance extracted (AVE), are expected to be in the accepted range [65, p. 137]. All item loadings above 0.70 were satisfactory. Considering that AVE was exceeding the required threshold of 0.50 convergent validity was achieved [66]. The second step in evaluating reflective indicators was illustrating results for discriminant validity. The discriminant validity illustrates how well the construct performs itself among the other latent variables [64]. Fornell-Larcker criterion is a tool for assessing discriminant validity [64, p. 139]; the items must explain the greater variance of the latent variable to which items belong than other variables [64]. For achieving this requirement, "the square root of each construct's AVE should be greater than its highest correlation with any other construct" [64, p. 139].

In order to be confident about Composite Reliability, firstly Cronbach's alpha (i.e., CA or α) – measure for internal consistency was calculated [64]. The literature on statistics recommends using CA for latent variables with three or more items [67]; the results for CA were greater than 0.70 [68]. So, there is no issue regarding internal consistency. For being able to proceed, the scores of Composite Reliability (CR) for the latent variables are to be greater than 0.70 [64]. Based on the output, the values of CR were in the accepted range (see Table 2). The reliability indicators can also be considered as proof of convergent validity [64], so, greater scores of AVE indicate a stable outcome.

Table 2. Cronbach's alpha, composite reliability, average variance extracted, rho_A, and Fornell-Larcker criterion

	Α	**rho_A**	**CR**	**AVE**	**AU***	**BI***	**PEoU***	**GTS***	**PU***
AU	0.885	0.899	0.929	0.813	0.902				
BI	0.794	0.818	0.880	0.710	0.475	0.843			
PEoU	0.877	0.883	0.924	0.803	0.424	0.629	0.896		
GTS	0.931	0.943	0.948	0.784	0.425	0.584	0.537	0.885	
PU	0.908	0.908	0.942	0.845	0.339	0.771	0.648	0.589	0.919

Note 1: α - Cronbach's alpha; CR - Construct/Composite Reliability; AVE – Average Variance Extracted; Note 2: AU – Actual Usage; BI - Behavioral Intention; PEoU – Ease of Use; GTS – Good Teaching Scale; PU – Perceived Usefulness; Note 3: * - sign used for results of Fornell-Larcker criterion.

5.3 Structural model

Following the requirements for analyzing pathways using Partial Least Squares estimation technique, this part of the study captures attention to t-statistics (t), p-values (p) of the pathways that allow to figure out acceptance or rejection of the above-illustrated hypotheses. Moreover, results for the coefficient of determination (R^2) and effect size (f^2) were also assessed. The coefficient of determination is used for specifying the predictive power of the model and calculated for dependent/exogenous variables [65]. The effect size determines the contribution of an independent (or exogenous construct) on a dependent (or endogenous) construct [65]. The values of effect size show level of influence - low (≤ 0.15) medium (0.15 – 0.35) and high (≥ 0.35) effect on a dependent variable [65, p. 216]. The results of the effect sizes for direct relationships are illustrated in Table 3. Apart from PEoU (R^2(PEoU)= 0.047), the results for R^2 in the overall sample were relatively high. The values for AU, BI, and PU were 0.257, 0.655, and 0.485 respectively.

Table 3. The Summary of direct relationships

Direct Relationships	**t-statistics**	**p-values**	f^2	**Effect**
H1: PEoU → PU***	11.213	p < 0.001	0.233	Medium
H2: PEoU → BI	1.327	p > 0.1	-	-
H3: PU → BI***	7.631	p < 0.001	0.215	Medium
H4: BI → AU***	4.864	p < 0.001	0.107	Low
H5: GTS → BI***	2.964	0.003	0.025	Low
H6: GTS → AU***	3.592	p < 0.001	0.041	Low

Note 1: *p < 0.10; **p < 0.05; ***p < 0.01. Note 2: AU – Actual Usage; BI - Behavioral Intention; PEoU – Perceived Ease of Use; GTS – Good Teaching Scale; PU – Perceived Usefulness; Source: own editing

6 Discussion

6.1 Direct relationships

Firstly, the relationships between modified TAM variables (PEoU, PU, BI, and AU) as well as good teaching scale were examined (Hypothesis 1-6). The results regarding direct relationships between TAM variables illustrate that PEoU of e-learning technologies increases PU. Moreover, the effect size of the relationship is at a medium level (i.e., $f^2(\text{PEoU} \rightarrow \text{PU}) = 0.233$). Some of the previous studies regarding e-learning reported similar results during the COVID-19 pandemic in the case of PEoU and behavioral intention [2] or attitude [69] relationship. So, ease of use in terms of e-learning tools increases its usefulness among questioned Hungarian students.

The results for Hypothesis 2 illustrate that PEoU has no impact on BI in the case of questioned students during the COVID-19 pandemic. The outcome is also consistent with some studies regarding online education conducted before COVID-19 [70], [71]. However, none of the above illustrated two studies considered the moderating effect of gender. Considering compulsory characteristics of online education, ease of use does not have any impact on surveyed students' attitudes towards adopting and using e-learning tools during the COVID-19 pandemic.

In the case of PU → BI pathway (Hypothesis 3) analysis proved the significance of the result. The effect size of the pathway is $f^2(\text{PU} \rightarrow \text{BI}) = 0.215$. Previous studies analyzing the adoption of e-learning tools during COVID-19 also reported a positive relationship [2], [3], [15], [72] between variables. Usage of e-learning tools allowed the continuance of education during pandemics without putting any more pressure on the healthcare system [23]. It helped to keep the number of infected people under control which is considered as the usefulness of e-learning tools during the pandemic [23], [24].

As it was expected, BI influences AU (Hypothesis 4) of surveyed students during COVID-19 in Hungary. The effect size of the relationship is considered to be at a low level ($f^2(\text{BI} \rightarrow \text{AU}) = 0.107$). Unfortunately, there was no evidence regarding previous studies that might be compared with actual findings. It is related to the rare use of AU in the models focusing on an e-learning/online education [16], [35], [42], [54]. However, some studies reported the same outcome before [15], [41] and during [3], [47] pandemic.

Good Teaching Scale was involved in the study for illustrating how e-learning tools are influenced by the quality of teaching (H5-6: GTS → BI/AU). The results illustrate that Good Teaching Scale positively influences behavioral intention and actual use of e-learning tools during the COVID-19 pandemic. Both mentioned hypotheses are accepted. Compared to previously mentioned pathways, the effect sizes of GTS on BI and AU (Hypothesis 5 and 6) are relatively small ($f^2(\text{GTS}\rightarrow\text{BI}) = 0.025$ and $f^2(\text{GTS}\rightarrow\text{AU}) = 0.041$). Unfortunately, previously reviewed works have not studied GTS within the e-learning context. So, it is impossible to compare mentioned results with the available body of knowledge.

6.2 Moderating effects

The authors were also interested in defining whether the age and gender of respondents influence the relationship between mentioned variables. There is a piece of scientific evidence [51] regarding the influence of gender on the variables of TAM which states: males are more influenced by PU (i.e., PU → BI) while females value PEoU (i.e., PEoU → BI). This was the main reason for the authors to measure the influence of moderating effects of gender and age (see Table 4) on the usage of e-learning tools. Also, Venkatesh et al. [38], [40] included age as a significant moderator of human behavior in the model aimed to explain buyers' behavior towards technological products. Based on these notions authors of the current study were interested in the influence of age and gender on the formulation of behavioral intention towards e-learning tools in Hungary during the COVID-19 pandemic. Also, they extended TAM by adding a new construct called a good teaching scale.

6.3 Influence of gender

Hypothesis 7A identifies the influence of gender on Perceived Ease of Use and Perceived Usefulness pathway. The outcome illustrated unsatisfactory results ($p \geq 0.1$). So, the gender of respondents does not moderate the relationship between the above-mentioned variables (i.e., PEoU → PU). Unfortunately, there was no evidence regarding previous studies that might be compared with actual findings. It is related to the rare use of moderators in the case of e-learning/online education [16], [35], [42], [54].

The results for Hypothesis 7B illustrate that gender of respondents had no impact on the relationship between PEoU and BI. Even if the influence of gender was also previously reported for the mentioned pathway in the context of e-learning acceptance [54], [73], the outcome of the current study illustrates an insignificant result (PEoU → Gender → BI). It is important to mention that the previously referenced study conducted by Tarhini [54] used students'attitudes towards e-learning before the COVID pandemic. It might be the main reason for differences in the outcomes. Considering online education being mandatory for university students, ease of use does not have any impact on surveyed students' attitudes towards adopting and using e-learning tools during the COVID-19 pandemic since use for them seemed not to be a choice but a compulsion.

Table 4. The moderating effects: Influence of gender

Relationships	t-statistics	p-values	Results
H7A: PEoU → Gender → PU	1.458	0.145	Not supported
H7B: PEoU → Gender → BI	0.875	0.382	Not supported
H7C: PU → Gender → BI*	1.744	0.081	Supported

Note 1: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Note 2: AU – Actual Usage; BI - Behavioral Intention; PEoU – Perceived Ease of Use; GTS – Good Teaching Scale; PU – Perceived Usefulness; Source: own editing

There is a statistically significant influence of gender on PU → BI (Hypothesis 7C) pathway. The impact of gender on the relationship is considered to be correct with the 90% confidence interval. However, none of the reviewed studies illustrated the significant influence of gender on PU → BI pathway. Moreover, the main outcome of using e-learning tools during the pandemic was to keep continuance of education. The numbers confirm that change in the usefulness level influences behavioral intention of surveyed men more than women. This result differs from the outcome of the study conducted before the COVID outbreak [54], however, it complies with the notion regarding moderating effect of gender in the case of TAM [51].

6.4 Influence of age

Hypothesis 8A focuses on the influence of age on Perceived Ease of Use and Perceived Usefulness pathway. Based on the results of the analysis, age is the moderator of the relationship between ease of use and perceived usefulness with the 99% confidence interval. Unfortunately, there was no evidence regarding previous studies that might be compared with actual findings. It is related to the rare use of moderators in the case of e-learning/online education [16], [35], [42], [54]. The result of the current study complies with the previous scientific achievements regarding the influence of age on technology adoption [38], [40].

Table 5. The moderating effects: Influence of age

Relationships	t-statistics	p-values	Results
H8A:PEoU → Age → PU***	3.020	0.003	Supported
H8B:PEoU → Age → BI	0.826	0.409	Not supported
H8C:PU → Age → BI*	1.653	0.098	Supported

Note 1: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Note 2: AU – Actual Usage; BI - Behavioral Intention; PEoU – Perceived Ease of Use; GTS – Good Teaching Scale; PU – Perceived Usefulness; Source: own editing

The result for Hypothesis 8B illustrates that the age of respondents has also no impact on the relationship between PEoU and BI. Even if the influence of age was also previously reported for the mentioned pathway in the context of e-learning acceptance [54], the outcome of the current study illustrates an insignificant result (PEoU → Gender → BI). It is important to mention that the previous studies [35], [54] used data reported by students'before the COVID pandemic. It might be the main reason for differences. Considering compulsory characteristics of online education, the impact of ease of use on behavioral intention was not moderated by age of the respondents using e-learning tools during the COVID-19 pandemic.

Apart from mentioned age-related hypotheses, there is a statistically significant influence of age on PU → BI (Hypothesis 8C) pathway. There is scientific evidence regarding the influence of age on the relationship between Performance Expectancy (the equivalent of Perceived Usefulness) and Behavioral Intention [38]. In the current study, the impact of age on the mentioned relationship is considered to be correct with the 90% confidence interval. Some of the previous studies also illustrated the significant influence of age on PU → BI pathway [54] however others reported the opposite [35]. Moreover, the main outcome of using e-learning tools during the pandemic was to keep continuance of education. This result differs from the outcome of the study conducted before the COVID outbreak [54], however, it complies with the notion regarding moderating effect of gender in the case of TAM [51].

7 Conclusions

This study extended the TAM by including a new exogenous variable - good teaching scale as well as measured influence of gender and age on students' willingness to use e-learning tools during the pandemic. Apart from the relationship between Perceived Ease of Use and Behavioral Intention all other pathways illustrated meaningful results. Based on the outcomes, the authors assume that PEoU was not a determinant of behavior towards e-learning tools during the COVID-19 pandemic.

The findings partially support the ideas of information system scholars [38], [51] regarding gender and age differences. There is a statistically significant influence of gender on the relationship between PU and BI (Hypothesis 7C) with the 90% confidence interval. However, the age of respondents has an impact on PEoU → PU (90% confidence interval) and PU → BI (95% confidence interval).

This survey has also some limitations. Firstly, the authors measured the moderation effect of only one variable – gender, while age, level of education, and culture might also influence attitude towards e-learning systems. Secondly, the study was conducted during the second and third waves of the COVID-19 pandemic, so it explains the situation only in extraordinary circumstances. Thirdly, the responses gathered using the nonprobability sampling technique, as result, it is not representative so, it limits generalizing potential of findings.

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