What Matters the Most? – Exploratory Analysis of Environmental and Situational Variables Influencing Performance of Students During COVID-19 Pandemic

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Abstract—This study examines the impact of gender and age differences on the performance of students from different Hungarian universities and colleges in online learning during the third wave of COVID-19. The survey responses were assessed using Partial Least Squares estimation technique. The research model attempts to understand the influence of environmental and situational variables (i.e., compatibility, accessibility, perception of online self-efficacy, mobility) on performance and satisfaction with online education. Apart from mobility, other indicators have significant impact on respondents' performance. However, moderating effect of age and gender almost do not influence the performance of surveyed Hungarian students. The results demonstrate that gender impacts the compatibility → performance pathway. The age of respondents has no effect on relationships between environmental and situational variables and performance.

Keywords—e-learning, environmental variables, performance of students, moderating effect of gender, moderating effect of age, COVID-19

1 Introduction

Most recently, one of the most significant global challenges has been the COVID-19 pandemic which broke out in Europe in February 2020. Globally, World Health Organization declared an international public health emergency on 30 January 2020 and a pandemic on 11 March 2020. In many countries, online learning was the only way to keep the education process ongoing during lockdown.

The development of information systems caused the emergence of different approaches from a technological perspective. The terms distance education, online education as well as e-learning emerged in the 1980s [1]. There is confusion in the case of definitions of the mentioned concepts [1]–[3]. Based on the definitions provided by Kovács [4], distance learning is a form of education where the teacher and the student are not in the same place. The learner studies alone, independently for most of the training time, and participates in consultations for a smaller part, deepening the independently acquired knowledge, practicing and developing skills with the help of teachers, i.e. tutors, through personal contact and direct supervision. Referring to Urdan & Weggen [5], the concept of online learning is defined by Keengwe & Kidd [6, p. 1] as follows: “Online learning is a subset of distance education and embraces a wide set of technology applications and learning processes including, computer-based learning, web-based learning, virtual classrooms, and digital collaborations”.

As opposed to the traditional learning environments, which are tied to a location and the presence of the instructor and the student, take place in real time, controlled by the instructor, applying linear teaching methods [7], 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 [6]. After reviewing the stages in the development of distance learning (from correspondence to the digital distance learning), Adermann [8] claims that although technological advances have taken place in the management of distance learning, the use of digital tools and the internet is not enough for successful distance learning. Irrespective of the mediating tools, in addition to professional training, educational theory awareness and educational experience are very important.

In Hungary, prior to the onset of the coronavirus epidemic, higher education was mainly in a traditional, presence-based, full-time schedule. According to the statistical database of the Educational Authority, between the autumn of 2013 and 2019, three-quarters of students participated in full-time and only a quarter in correspondence, much less in evening or distance learning [9]. Incidentally, the data are in line with the international trend, as distance and online education accounted for only 2% of the global $2.2 trillion higher education market before the virus [10]. As Serfőző et al. [11] points out, ‘remote teaching’ is a specific concept born of the pandemic situation. It is not the same as distance learning and not the same as online learning, it combines the features of these two. 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) [11]. The transition to remote teaching caused by the COVID-19 epidemic has taken place in a sudden and unplanned way, as opposed to real distance learning and online learning, so it is safe to use the term ‘emergency remote teaching’ (ERT) [11].

2 Literature review and hypothesis development

The current paper mainly focuses on the influence of environmental and situational variables [12] on the performance of surveyed university students during the pandemic. Previous studies regarding the performance of students during the COVID-19 pandemic mostly use different models such as Technology Acceptance Model – TAM [13]–[15] and Unified Theory of Acceptance and Use of Technology – UTAUT [16]. Some other studies focused on the relationship between performance and study environment [17], psychological impact of COVID-19 [18], difference between face-to-face and online learning [19] and challenges in general [20]. So, there is a big knowledge gap in analysing relationship between environmental and situational factors and performance.

In addition to self-efficacy, accessibility, mobility, and compatibility, Aguilera-Hermida [21] involved facilitating conditions [22] and context of opportunity [23]/trialability [24] in the set of indicators formulating environmental and situational factors [12]. Considering that context of opportunity [23]/trialability [24] and facilitating conditions were not relevant in the context of COVID-19, the authors left them out of the survey (see Table 1). Also, Venkatesh et al. [22, p. 453] claim that facilitating conditions combine some constructs including compatibility. As result, in the mentioned situation the authors find the compatibility of devices to be relevant environmental and situational factors during the pandemic.

Table 1. Definitions and reasons for exclusion of some variables

Tertiary Taxonomy Group*	Definition	The Reason for Exclusion
Context of opportunity [23, p. 156]	"A situation which provides an opportunity for a person to act in a manner consistent with his beliefs about, attitude toward, "subjective norm" and intention with respect to, a specific behavior"	The measurement of the Context of opportunity became impossible because of the urgency of switching to online learning.
Trialability – Innovation Diffusion Theory [24, p. 300]	"The degree to which an innovation may be experimented with on a limited basis."	The application of e-learning was a response to the increasing spread of infection and students mostly had no chance to try/experiment with e-learning tools beforehand.
Facilitating conditions [22]	"The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system."	The fast spread of the virus has not left a chance for implementing any special support using e-learning tools during COVID-19.

Note: *Based on the classification of Kemp [12].
Source: Own editing based on literature review.

2.1 Compatibility

Compatibility (abbr. C) is one of the variables of IDT and it explains "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (i.e., students)" [24, p. 195]. So, in the examined situation compatibility explains how using online education during COVID-19 aligns with the life of university students. It is an essential variable explaining innovation adoption in terms of information systems (abbr. IS) [25]; by including the variable in the model, authors were interested how well students perform using online education tools in the new situation. Moreover, it is known that attitude toward IS is highly influenced by compatibility [26]. Previous studies regarding e-learning illustrated a significant relationship between compatibility and use intention before [27], [28] and during COVID-19 [29]. However, the authors of the current study are interested in identifying the impact of compatibility on the performance of students during the COVID-19 pandemic. Therefore, the authors propose:

H1. Compatibility (C) has a positive influence on the performance (P) of students during the COVID-19 pandemic. (C → P)

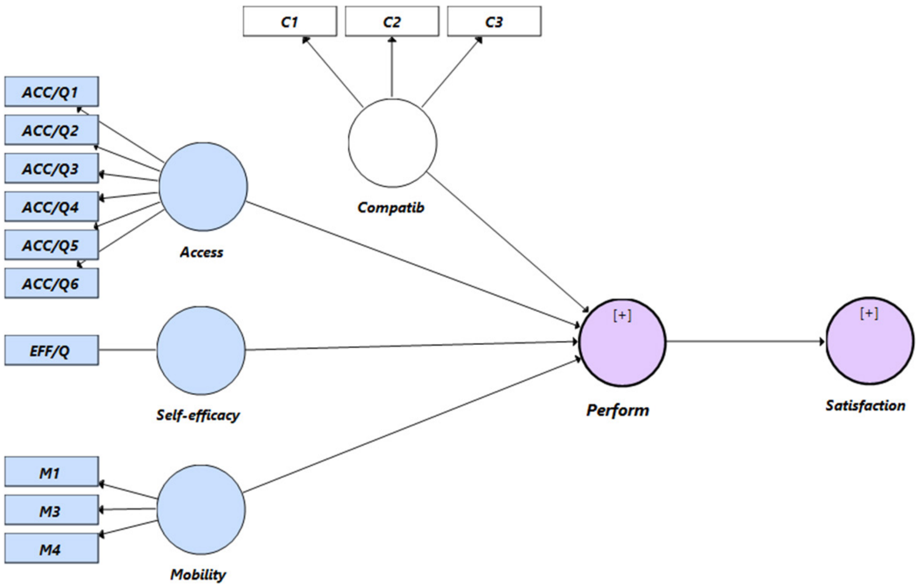

Fig. 1. The proposed model

Source: Own editing.

2.2 Accessibility

Accessibility of e-learning tools can be defined as "the degree of ease with which a university student can access and use a campus e-learning system as an organizational factor" [30, p. 153]. The scholars [21], [30] involving accessibility as a separate variable to the Aguilera-Hermida [21] have not used any specific scale. So, students were asked to answer the following question: "How was the access to the below-mentioned online education tools during COVID-19?" The respondents expressed their attitude regarding online education tools: devices for online education; internet service; teaching materials; communication software/tools (e.g. Skype, Zoom, Teams, Classroom); university online platform (e.g. e-learning); support for solving technical issues. Previous studies examined the relationship between accessibility of e-learning tools and behavioral intention [30] from TAM perspective. However, the current study is focused on identifying the impact of accessibility on the performance of students during the third wave of COVID-19 pandemic. Therefore, the authors propose:

H2. Accessibility (A) has a positive influence on the performance (P) of students during the COVID-19 pandemic. (A → P)

2.3 Perception of online self-efficacy

Self-efficacy defined as "an individual's perceptions of his or her ability to use computers in the accomplishment of a task, rather than reflecting simple component skills" [31, p. 191]. Familiarity with different e-learning tools has high impact on the adoption of e-learning tools [32], however, students might need some support to adapt using e-learning tools if they have never used them before [33]. So, self-efficacy is one of the essential elements of e-learning [32], [34] and classified as one of the environmental/situational factors influencing students' attitude [12] as well as performance. Considering that different higher education institutions use diverse software and e-learning tools, authors addressed only one question for the measurement of self-efficacy.

H3. Self-efficacy (S/E) has a positive influence on the performance (P) of students during the COVID-19 pandemic. (S/E → P)

2.4 Mobility

Mobility (abbr. M) is an opportunity to access online classes using mobile devices without any time or location limitations. Mobility, or in other words mobile education/learning (m-learning) gives students a chance to access, use and share files to increase their knowledge [35]. Previous studies highlighted the importance of mobility in terms of mobile education [36], [37], however, the situation caused by COVID-19 captured special attention to the topic [21], [38]. Some researchers [37], [39] analyzed mobility in the TAM context. The current study is focused on identifying the impact of mobility on the performance of students during the COVID-19 pandemic. Therefore, the authors propose:

H4. Mobility (M) has a positive influence on the performance (P) of students during the COVID-19 pandemic. (M → P)

2.5 Satisfaction

Student satisfaction can be defined as "a crucial measure of how well students are doing in their classes, leading to different outcomes, such as student retention and course quality" [40, p. 4]. During COVID-19, student satisfaction was mainly analyzed in relation to actual use and behavioral intention [40] as well as using exploratory approach [41], [42]. A recent study conducted in Ghana illustrated that students' satisfaction might positively influence students' performance [43]. Therefore, the authors propose:

H5. Performance (P) has a positive influence on the satisfaction (S) of students during the COVID-19 pandemic. (P → S)

2.6 Moderation effect of age and gender on students' performance

The attention of the technology adoption related literature has been drawn to the importance of age and gender only after the 2000s [22], [44], [45]. Previous influential studies and models that focused on understanding behavior towards different IS-related products did not involve any moderators [46]–[48]. However, there is scientific evidence [22], [45] that the involvement of moderators impacts a model's explanatory power in a positive way.

Unfortunately, a limited number of e-learning related studies involve the mentioned moderators. Few studies dealt with the impact of age and/or gender on the formulation of behavioral intention [13], [49]–[51]. There are even less scientific works analysing the relationships between the environmental and situational factors and performance during COVID-19 pandemic.

- H6. Relationships between environmental and situational factors (compatibility, accessibility, self-efficacy, and mobility) and performance are moderated by age.
- H7. Relationships between environmental & situational factors (compatibility, accessibility, self-efficacy, and mobility) and performance are moderated by gender.

3 Methodology

3.1 Sampling, data collection, and analytical procedures

The aim of the study was to determine relationships between environmental and situational factors and performance of students (i.e., undergraduate/graduate) during COVID-19 outbreak in Hungary. The tool of primary data collection was an online questionnaire conducted between the 15th of January and the 15th of March 2021 that interval was considered as the 3rd wave of the pandemic in Hungary which was characterized by high numbers of infected people [59] and the general application of online education [60].

The target population consists of Hungarian students who accessed questionnaire using social media. The used sampling method was therefore the voluntary response sampling: it is a nonprobability sampling method so it "does not need to be representative, or random, but a clear rationale is needed for the inclusion of some cases or individuals rather than others" [52, p. 22], and it is based on the ease of access as participants are not contacted directly but volunteer themselves to respond [53].

The online survey collected 451 completions from respondents who participated in online higher education in the autumn semester of the 2020/2021 academic year. 56.5% of the respondents were female and 43.5% were male. The majority of respondents were aged between 22 and 49 years, with the largest sub-group, 32.8%, aged 22–24 years. Participation in BA/BSc programme accounted for 73.4% of respondents, while 18.4% learnt in MA/MSc programme. Less than 5% each participated in undivided university programme, higher-level vocational training or PhD/DLA.

Complying with previous studies [13] a five-point Likert scale was used for measuring attitude towards different constructs. The scales were translated into Hungarian by a native speaker and several scholars made corrections before spreading it out. The responses were analyzed using Partial Least Squares estimation technique of Structural Equation Modeling (PLS-SEM). Reflective and/or formative indicators were determined following literature recommendation [54], [55].

3.2 Measurement model

The model illustrated in Figure 1 consists of six latent constructs. Based on the recommendation of Hair el al. and other previous literatures, some of the constructs are considered to be reflective (compatibility and mobility) while others are formative (access, performance, and satisfaction). At first, the authors would like to examine reliability/validity of reflective constructs. For this purpose, outer loadings (> 0.7), average variance extracted (AVE > 0.5) and Fornell-Larcker criterion should be measured [56, p. 137]. The authors calculated internal consistency (i.e., Cronbach's alpha/α) and Composite Reliability of reflective latent variables as well. The numbers are greater than 0.7 which considered to be in line with statistical literature [57]. The results for reflective indicators are illustrated in Table 2.

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

	α	CR	AVE	A*	C*	M*	P*	S*	S/E*
A									
C	0.884	0.928	0.810	0.434	0.900				
M	0.882	0.927	0.809	0.435	0.571	0.899			
P				0.501	0.648	0.476			
S				0.627	0.599	0.442	0.661		
S/E	1.000	1.000	1.000	0.442	0.472	0.368	0.560	0.551	1.000

Notes: α – Cronbach's alpha; CR – Construct/Composite Reliability; AVE – Average Variance Extracted; A – Accessibility; C – Compatibility; M – Mobility; P – Performance; S – Satisfaction; S/E – Self Efficacy. *Sign used for results of Fornell-Larcker criterion.

Collinearity was measured for assessing reliability and validity of formative constructs, by using Variance Inflation Factor (VIF) for this purpose. The literature suggests that VIF value should be lower than 5 [56, p. 164]. However, some sources suggest a more conservative approach for the value of VIF which is equal to 3. Considering that VIF values are not very high, the authors decided to keep all the items. (See Table 3)

Table 3. Collinearity: variance inflation factor

Indicator/Item	VIF	Indicator/Item	VIF
ACC/Q1	1.777	SAT/Q4	2.503
ACC/Q2	1.985	SAT/Q5	2.093
ACC/Q3	1.756	SAT/Q6	2.179
ACC/Q4	1.901	SAT/Q7	2.437
ACC/Q5	1.869	SLFPER/Q1	**3.098**
ACC/Q6	1.798	SLFPER/Q2	2.576
EFF/Q	1.000	SLFPER/Q3	**3.421**
SAT/Q1	1.663	SLFPER/Q4	1.983
SAT/Q2	2.573	SLFPER/Q5	2.050
SAT/Q3	**3.108**	SLFPER/Q6	1.453

Note: VIF – Variance Inflation Factor.
Sources: Own editing; Own calculations.

3.3 Structural model

The structural model was used for finding answers to the hypotheses. Hence, authors illustrated t-statistics and p values for each of the discussed relationships [57]. Effect size of each relationship was also calculated [57]. According to statistical literature, the external variable might have a low, medium or high level of impact on the internal variable. The accepted range for each level was determined based on the classification of Hair et al. [56, p. 216]. The summary of the above discussed relationships can be seen in Table 4.

Table 4. The summary of direct relationships

Direct Relationships	t-Statistics	p-Values	F^2	Effect Size
H1: C → P	5.504	$p < 0.001$	0.205	Medium
H2: A → P	1.816	$p = 0.069$	0.048	Low
H3: S/E → P	7.887	$p < 0.001$	0.105	Low
H4: M → P	1.282	$p > 0.1$	–	–
H5: P → S	21.946	$p < 0.001$	0.776	High

Note: A – Accessibility; C – Compatibility; M – Mobility; P – Performance; S – Satisfaction; S/E – Self Efficacy.
Source: Own editing.

4 Results and discussion

Based on the results of the survey conducted, compatibility of the e-learning tools directly influenced the performance (H1: C → P) of surveyed Hungarian students during COVID-19 pandemic. The effect of exogenous variable (i.e., compatibility) on performance is at medium level (F^2 (C→P)=0.205). It emphasizes the importance of compatibility in the case of e-learning. The gender of respondents moderates the relationship (i.e., H6A: C → gender → P) with 90% confidence interval (see Table 5). However, the age of respondents does not have any impact on the above-mentioned relationship (i.e., H7A: C → age → P) (see Table 6). Previous studies also showed that the relationship between facilitating conditions/compatibility and actual use might be moderated by age [22] while moderating effect of gender was not examined.

Table 5. The moderating effects: influence of gender

Relationships	t-Statistics	p-Values	Results
H6A: C → Gender → P	0.079	0.937	Supported
H6B: A → Gender → P	0.547	0.584	Not supported
H6C: S/E → Gender → P	1.353	0.176	Not supported
H6D: M → Gender → P	0.174	0.862	Not supported

Note: A – Accessibility; C – Compatibility; M – Mobility; P – Performance; S – Satisfaction; S/E – Self Efficacy.
Source: Own editing.

The results are different for A → P relationship (Hypothesis 2) and the effect of accessibility on the performance of the students is relatively low (F^2 (A→P)=0.048). It shows that accessibility of e-leaning tools is not as essential as compatibility. The outcome might be strongly connected with the situation during pandemic which caused obligatory characteristics in the application of e-learning tools and systems. Moreover, the age and gender of respondents (i.e., H6B/H7B) do not have any impact on the above-mentioned relationship (i.e., A → age/gender → P).

Results illustrate that there is significant impact of self-efficacy on performance (Hypothesis 3) with 99% confidence interval. Even if the effect of self-efficacy on performance is comparatively low (F^2 (S/E→P)=0.105), it is higher than the value for accessibility. Moreover, the age and gender of respondents (i.e., H6C/H7C) do not have any impact on the above-mentioned relationship (i.e., S/E → age/gender → P). It means that the adaptation to the use of e-learning tools is not connected with age or gender of respondents as moderating variables.

Based on the results of calculations, mobility of e-learning tools does not influence the performance of the students during the third wave of COVID-19 pandemic (H4). The results of the survey are in line with the aforementioned circumstances related to the impact of lockdown as well as limited access to cafés, libraries and other (public) places where students might prepare for and/or participate in classes. Moreover, the age and gender of respondents (i.e., H6D, H7D) do not have any impact on the mobility-performance relationship (i.e., M → age/gender → P).

The authors assumed that in the current model performance might also impact the satisfaction of students with adopting e-learning tools. There is significantly strong relationship between these variables. Also, performance of students has strong effect on their satisfaction (F^2 (P→S)=0.776). Other scholars analyzing e-learning during the pandemic also confirmed that mostly students have undesirable satisfaction [58] with using e-learning tools.

Table 6. The moderating effects: influence of age

Relationships	t-Statistics	p-Values	Results
H7A: C → Age → P	1.346	0.178	Not supported
H7B: A → Age → P	1.095	0.274	Not supported
H7C: S/E → Age → P	1.468	0.142	Not supported
H7D: M → Age → P	1.174	0.240	Not supported

Note: A – Accessibility; C – Compatibility; M – Mobility; P – Performance; S – Satisfaction; S/E – Self Efficacy.
Source: Own editing.

5 Conclusion

The research introduced in this study investigated the impact of situational/environmental variables on the performance of students during the COVID-19 pandemic in Hungary. Results illustrate that mobility of e-learning tools has no impact on the performance of surveyed Hungarian students, while other factors have effect on the mentioned dependent variable. The effect of performance on satisfaction was reinforced by the results. One of the main purposes of the study was to assess the impact of moderators like age and gender on the previously explained pathways. Age and gender of respondents mostly have no moderating effect on the relationships between environmental/situational variables and performance. The only pathway affected by moderating effect of gender was the relationship between compatibility and performance of students during the pandemic. The above illustrated results might be strongly linked with the global situation around COVID-19. Considering that people were locked in their flats, mobility of e-learning tools became insignificant. This explains the Mobility → Performance relationship.

6 References

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