Exploring the Impact of Digital Infrastructure Challenges on Learning Outcomes and Student Satisfaction

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Abstract. *The present study explores the validity of two key dimensions proposed by the Framework for the Assessment of Challenges to Virtual Education (FACVE) in supporting the effective delivery of virtual instruction. Specifically, it examines: (1) C2 — Challenges to Digital Technical Infrastructure (i.e., Connectivity and Equipment), and (2) C5 — Challenges to Digital Learning Infrastructure (i.e., Learning Platforms and Access to Resources). Findings from this exploratory study indicate that C2 is negatively associated with Student Satisfaction (SS), while C5 exhibits a negative relationship with Learning Outcomes (LOs), which, in turn, significantly predicts SS. LOs themselves emerged as a strong predictor of higher levels of SS. Although both C2 and C5 were statistically significant predictors of SS and LOs, the effect sizes were very small. This study represents an initial step toward linking challenges identified by the FACVE framework with well-established constructs in educational research, such as LOs and SS.*

Keywords. FACVE, challenges to virtual education, connectivity and equipment, learning platform, access to resources, learning outcomes, student satisfaction, digital infrastructure, structural equation modelling.

1 Introduction

The framework for the assessment of challenges to virtual education (FACVE) is a new framework developed during the emergency remote teaching (ERT) context of the COVID-19 pandemic (Mu et al., 2022). During this period, most institutions worldwide had to switch their education practices to a virtual education model, which refers to a broad approach to education that uses digital environments for learning and instruction, primarily or entirely online (Allen et al., 2016). FACVE was developed to assess the extent of challenges faced by students and instructors to carry on the new approach in a successful way.

While still a novel technique, FACVE has started to become recognized as a valuable tool to assess virtual education challenges, in particular in developing countries; given that it encompasses aspects such as determined home facilities, difficulties in learning virtual platforms and financial problems as significant factors that challenge virtual instruction (Vargas-Hernández et al., 2024). Also, FACVE highlighted that the pandemic had negative consequences on student life, associated with their subjective well-being and allowed some extent of quantification (Vargas-Hernández et al., 2024). Overall, FACVE is a powerful tool to assess challenges to virtual education in ERT contexts (Mu et al., 2022).

As shown in Fig. 1, FACVE consists of the following dimensions C1 - Quality of Teaching Instruction, C2 - Connectivity and Equipment, C3 - Personal Issues (student), C4 - Home Infrastructure and Study Environment, C5 - Learning Platform and Access to Resources, C6 - Financial Issues (student), and C7 - University Administration and Costs. This framework was developed from the bottom up; that is, it was developed from the challenges expressed by the students struggling to adapt to a sudden switch from physical instruction to a virtual education format. Also, the assessed challenges include some that are particularly suitable for the ERT situation in which the framework was originally developed. While the challenge dimensions reflect the practical reality of the students and have even been used to compare situations in different international settings (Gonzalez-Urango et al., 2025), these variables have not been formalized or tested within the context of normal virtual instruction (non-ERT) or connected to the virtual instruction research stream. This constitutes the research gap to be addressed in the present study.

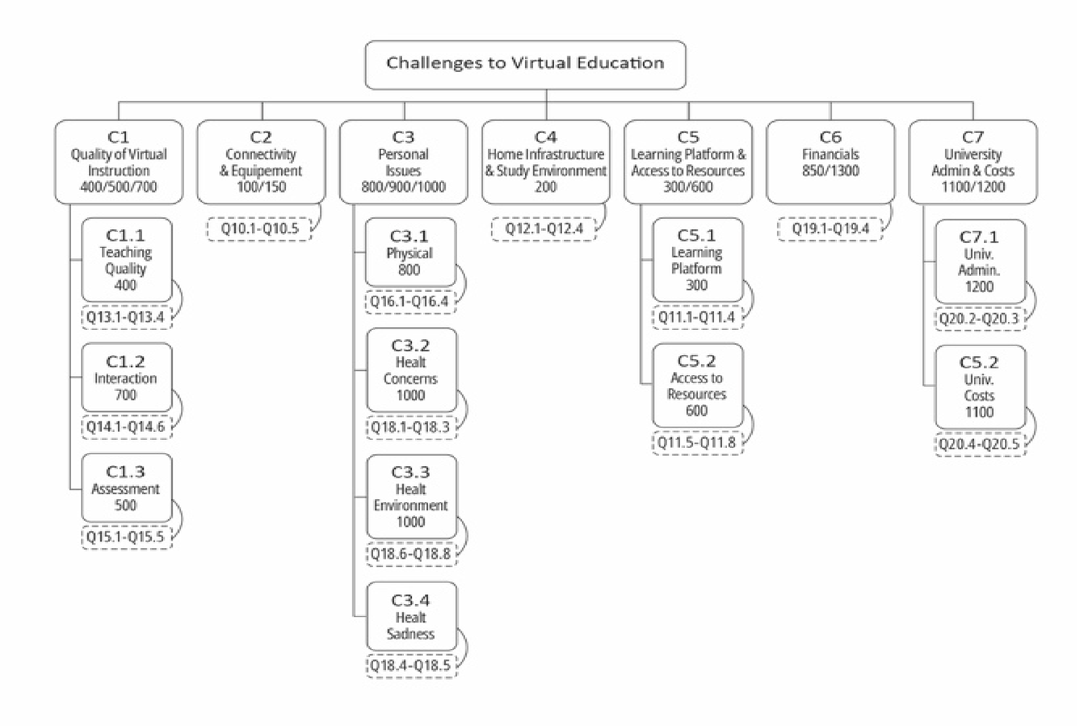

Figure 1. FACVE: Challenges to virtual education
Source: (Mu et al., 2022)

The above rationale suggests the following research objectives:

1. To determine the feasibility of using FACVE in a normal (beyond ERT) virtual instruction context.
2. To determine if FACVE challenge variables have an effect on well-known dependent outcomes of virtual instruction research.

To address the first objective, the focus should be on testing only FACVE dimensions more commonly related to normal (non-emergency) virtual instruction operations. To address the second objective, FACVE dimensions (variables) expected to have an effect on well-known virtual instruction variables should be selected.

For these reasons, this study has chosen to explore if the following FACVE variables: C2 — Connectivity and Equipment and C5 — Learning Platform and Access to Resources have an effect on the extent of Learning Outcomes (LO) and Student Satisfaction (SS), two well-known dependent variables in extant virtual education research (Eom & Ashill, 2016; Kuo et al., 2014).

Also, the present study posits that variables C2 and C5 constitute challenges to the virtual education digital infrastructure. Digital infrastructure includes everything that makes digital systems work (technical infrastructure) such as the internet, devices, and software (e.g., learning management systems). However, this doesn’t just include technology, but also how people use these resources (learning infrastructure) (Bygstad et al., 2022; MagicEdTech, 2025). Based on this, we posit that variable C2 of FACVE constitutes challenges to the digital “technical” infrastructure while variable C5 of FACVE constitutes challenges to the digital “learning” infrastructure. For this reason, this study is proposed as an exploratory impact of digital infrastructure challenges on virtual education outcomes (Goodhue & Thompson, 1995; McGill & Klobas, 2008).

2 Literature Review

FACVE was proposed as a way to assess students’ main challenges in switching to virtual instruction during the COVID-19 pandemic (Mu et al., 2022) as shown in Fig. 1.

Exploring the relation of the digital infrastructure with the proposed outcome variables requires the variables to be defined and the rationale for their expected effects to be explained.

Dependent Variables

SS is widely recognized in the educational literature as a key measure of academic quality, often reflecting the degree of instructional effectiveness and learner engagement (Eom & Ashill, 2016; Kuo et al., 2014). Higher satisfaction levels frequently correlate with stronger academic outcomes, including increased retention and performance. Likewise, LOs—defined as the cumulative knowledge, skills, and competencies developed by students—are essential benchmarks for evaluating educational success (Alqurashi, 2019).

SS is defined as the learner's perception of value and contentment with the educational experience, including its instructional, social, and technological aspects (Martin & Bolliger, 2022).

LOs are defined as the extent to which learners gain new knowledge and skills, and is often aligned with clear and measurable instructional goals. In summary, the success of the online learning depends on whether it has achieved the desired outcomes (Panigrahi et al., 2018).

Independent FACVE variables

The two target FACVE variables for the present study are: C2 — Connectivity and Equipment and C5 — Learning Platform and Access to Resources (Fig. 1).

Connectivity and Equipment (C2) challenges can be defined as the challenges related to the suitable availability of the proper *technical* digital infrastructure, in terms of connectivity (e.g. proper internet access) and the availability of suitable equipment for both the students and the educational institution participating in the virtual instruction.

Learning Platform and Access to Resources (C5) challenges is constituted by the challenges related to the *learning* digital infrastructure along two sub-dimensions: availability and usability of the learning platform (C5.1) and the challenges related to access to educational resources (C5.2); that is the learning digital material itself.

While the above variables refer to challenges related to the "technical" and "learning" digital infrastructure, the analysis will be conducted referring to the original FACVE names to maintain simplicity and consonance with the specific assessment tool used in this study. The purpose of the present research is to assess whether these two challenge variables (C2 and C5) also have an impact on the well-known LOs and SS from the extant virtual education research literature.

The rationale is grounded, theoretically, on the Technology-Task mediated theory which has shown that Task–Technology fit is one factor that has been shown to influence both the use of the digital infrastructure and its learning impact (Goodhue & Thompson, 1995; McGill & Klobas, 2008).

Based on the above, our research question will be as follows:

Research question: Do FACVE challenges C2 - Connectivity and Equipment and C5 - Learning Platform and Access to Resources on Learning Outcomes (LO) and Student Satisfaction (SS)?

This research question can be illustrated in the conceptual model proposed in Fig.2.

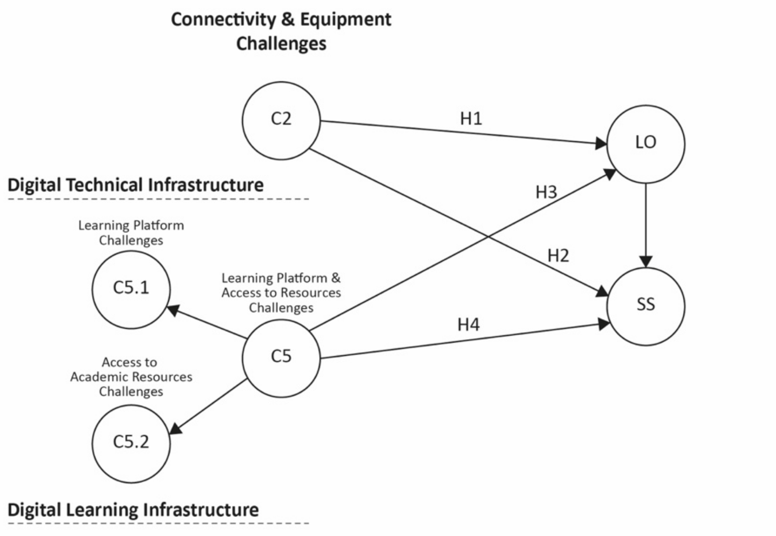

Figure 2. Conceptual model

Consistent with the research question and conceptual model (Fig. 2), the following hypotheses are proposed:

H1: C2 is negatively associated with LO.
H2: C2 is negatively associated with SS.
H3: C5 is negatively associated with LO.
H4: C5 is negatively associated with SS.
H5: LOs are positively associated with student SS.

3 Methodology

A FACVE survey was administered to graduate students enrolled in various Master of Business Administration (MBA) courses at a prominent private university in Peru. It was conducted through the university's online platform, during the period September-December, 2021.

3.1. Demographics

Participants were students enrolled in different synchronous online courses of the evening professional Master of Business Administration (MBA) study program. The survey was conducted by one of the authors, and the digital infrastructure consisted of Canvas as the learning platform system and Zoom as the video conferencing tool (Instructure, 2025; Zoom, 2025). Also, MBA students access to academic resources consisted fundamentally of access to the class presentations and assigned readings.

Participation was entirely voluntary and anonymous, aligning with ethical research standards requested by the home institution. Out of 177 initially submitted responses, 162 were deemed valid for analysis. The demographic data shows that 98.31% of respondents were pursuing graduate-level studies. The gender distribution was predominantly male (59.89%), followed by female participants (29.94%) and a smaller group who chose not to disclose their gender (10.17%). In terms of age, a significant portion of respondents were experienced professionals: 45.20% were between 30 and 34 years old, and 36.16% were older than 34. With respect to instructional formats, the majority (54.80%) attended synchronous online classes, while 28.81% were enrolled in hybrid modalities. A minority participated in asynchronous virtual (2.26%) or traditional face-to-face classes (1.69%). Furthermore, 79.10% of respondents reported active enrollment in at least one virtual course, highlighting the strong relevance of online education within this academic cohort.

3.2. Measures

Testing the nomological validity of the proposed research model (Fig. 1) involves the development of reliable scales. For this purpose, all the measurement items used in the present study were taken from previous studies, to ensure their validity and reliability (Eom & Ashill, 2016; Mu et al., 2022)

3.3. Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the proposed research model, PLS-SEM is particularly useful when the goal is to predict either key determinant (C2 & C5) or target (LO & SS) constructs (Hair et al., 2017). The analysis followed the recommended steps for models that include reflective-reflective HOC constructs, using the disjointed two-stage approach (Chua, 2024; Hair Jr. et al., 2018; Sarstedt et al., 2019).[1]. The analysis consisted of the following steps:

Step 1. Validity and reliability of reflective first-order constructs. The validity and reliability of the reflective first-order model constructs (C2, C5.1, C5.2, LO, and SS) were analyzed (Fig. 1). Because of high Variance Inflation Factors (VIF) values, two items were removed from SS. All indicators included in the model demonstrated loadings above 0.7 ($p < 0.005$), with the exception of the indicator Q10-3 for C2 (0.50) thus it was removed from the model. Average Variance Extracted (AVE) values for all constructs were above the threshold of 0.5, thus satisfying convergent validity for all constructs.

To meet the construct reliability acceptable threshold (>0.70), item Q11-1 was removed from C5.1. All latent constructs then exhibited both Cronbach's α and composite reliability (rho_c) values above the 0.70 threshold. Although the SS construct's rho_c just exceeds the 0.95 ceiling recommended by some authors, treating rho_c as the upper-bound and α as the lower-bound estimate suggests that its true reliability still remain within acceptable limits (Hair et al., 2017).

An initial HTMT assessment revealed discriminant-validity concerns between LOs and SS. For this reason, one indicator from LOs was removed to meet discriminant validity requirements according to best practices for this type of analysis (Hair et al., 2017). VIF values were below the upper threshold of 5, suggesting that, while possible, collinearity issues

[1] C5 is a Higher Order Construct (HOC) in the model, composed of C.5.1 and C.5.2. The software used for this study was SmartPLS 4 Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4.* Bönningstedt: SmartPLS. . https://www.smartpls.com

are unlikely (Hair et al., 2019). Table 1 summarizes these results.

Table 1. First stage model validation results

LOC Constructs and Indicators[1]	Loadings	Cronbach's alpha	rho_c	AVE
C.2. Connectivity & Equipment		0.838	0.885	0.660
Q10-1	0.800			
Q10-2	0.841			
Q10-4	0.892			
Q10-5	0.705			
C5.1. Learning Platform		0.746	0.852	0.659
Q11-2	0.731			
Q11-3	0.886			
Q11-4	0.812			
C5.2. Access to Resources		0.828	0.880	0.647
Q11-5	0.752			
Q11-6	0.743			
Q11-7	0.858			
Q11-8	0.858			
Learning Outcomes (LO)		0.870	0.919	0.792
Q8-2	0.874			
Q8-3	0.916			
Q8-4	0.879			
Student Satisfaction (SS)		0.906	0.955	0.914
Q9-1	0.959			
Q9-3	0.954			

[1] These model validations apply only to Low Order Constructs (LOC) constructs.

Step 2: Validity of Formative Higher-Order Construct (C5). In the second stage, following Sarstedt et al. (2019), we assessed the higher-order model. Items C5.1 and C5.2 loaded significantly on the second-order construct C5, with loadings of 0.652 and 0.987 ($p < .01$). The construct attained an AVE of 0.686. It demonstrated acceptable internal consistency—Cronbach's $\alpha = 0.686$ and composite reliability (rho_c) = 0.817.

Step 3: Structural Model Evaluation. The structural model was evaluated to determine if the proposed hypotheses were supported. The results are presented in Fig. 3 and summarized below:

1. C2 negatively predicts SS ($\beta = -0.106$, $p < 0.05$, $f^2 = 0.026$).
2. C5 negatively predicts LO ($\beta = -0.258$, $p < 0.01$, $f^2 = 0.063$).
3. LO positively predicts SS ($\beta = 0.764$, $p < 0.01$, $f^2 = 1.453$).

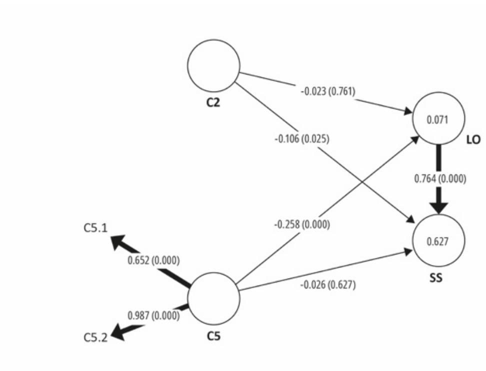

Figure 3. Model PLS-SEM results

The model explains 7.1% ($R^2 = 0.058$) of the variance in LO and 62.7% ($R^2 = 0.627$) of the variance in SS. Regarding the model fit, the standardized root mean square residual (SRMR) of the model was 0.086, which is above the conservative threshold of 0.08 but still within the acceptable level of below 0.1 (Hair, 2017). Positive Q^2 Predict values for both dependent variables further supported predictive power, indicating strong predictive relevance. The overall model predictive power is Q2 = 0.043 for LO and Q2=0.055 for SS.

Although H4 was not supported, the analysis did reveal a significant indirect effect of C5 on SS through LO ($\beta = -0.197$, $p < 0.01$), indicating that C5 might influences SS only via its impact on LOs.

4 Results

The results of the present study are shown in Table 2.

Table 2. PLS-SEM analysis results

H	Beta	f^2	R^2 (LO)	R^2 (SS)
H1	-0.023	0.000	0.071	
H2	-0.106*	0.026		0.627
H3	-0.258**	0.063	0.071	
H4	-0.026	0.001		0.627
H5	0.764**	1.453**		0.627

* $p < 0.05$.
**$p < 0.01$

For greater clarity, the results of hypothesis testing are summarized in Table 3 below.

Table 3. Hypothesis results

Hypothesis	Result
H1: C2 has a negative effect on LO	ns
H2: C2 has a negative effect on SS	**Supported**
H3: C5 has a negative effect on LO	**Supported**
H4: C5 has a negative effect on SS	ns*
H5: LO has a positive effect on SS	**Supported**

*However, it has significant indirect effect on SS through LO

The PLS-SEM results (Tables 2 and 3) show that two dimensions in the FACVE checklist—C2 and C5 have statistically detectable but small links with LO and SS. While only the C2-SS and C5-LO paths reach significance (although with no statistically significant effect sizes), this pattern still helps identify where technology-related issues may start to influence the student experience. In that sense, the framework offers a useful, if preliminary, guide for monitoring online-learning conditions; further work with larger samples will be needed to confirm and extend these findings.

4.1 Validation of FACVE-C2 and FACVE-C5 as Valid Multidimensional Constructs

The FACVE-C2 construct was found to be reliable and showed a statistically significant—but small—negative association with SS. Likewise, FACVE-C5 was validated as a second-order construct with two sub-dimensions (C5.1 learning-platform challenges; C5.2 access-to-resources challenges) and exhibited a statistically significant, though negligible, negative link with LO.

Taken together, these initial findings suggest that the FACVE checklist can flag technology-related issues that may begin to influence LO and SS, even if their direct effects are modest. The direct paths C2 → LO and C5 → SS were not supported; however, a significant indirect effect of C5 on SS via LO indicates full mediation. The findings align with the conceptual foundation of FACVE, which emphasizes a holistic, student-centered approach to addressing virtual education challenge barriers (Mu et al., 2022). Compared to other models aimed at assessing students' perceptions of digital tools and engagement only during emergency learning, the FACVE framework extends the focus to the quality of virtual instructional practices.

Thus, the framework offers a useful early lens for monitoring virtual-learning conditions, while further studies with larger samples are needed to confirm its explanatory power and practical impact.

4.2 Impact on Learning Outcomes

This study shows that C5 shows a statistically significant negative association with LO ($\beta = -0.258$, $p < 0.01$). The corresponding effect size is small ($f^2 = 0.063$), yet the link is robust enough to suggest that shortcomings in the platform or in access to digital resources can dampen students' academic performance. Also, because LO strongly predicts SS (described in the section below), this path also establishes an indirect route by which C5 affects satisfaction.

4.3 Impact on Student Satisfaction

This study shows that C2 has a small but significant negative effect on SS ($\beta = -0.106$, $p < 0.05$, $f^2 = 0.026$). This result suggests that the FACVE checklist can help draw attention to basic connectivity issues, making it worth monitoring the C2 dimension to ensure SS and, in turn, LO.

4.4 Relationship between Learning Outcomes and Student Satisfaction

LOs display a large, positive impact on SS ($\beta = 0.764$, $p < 0.01$, $f^2 = 1.453$). This sizeable effect underscores the centrality of academic achievement in shaping students' overall course evaluations. This finding aligns with the research conducted by Baber (2020) and Eom and Ashill (2016), which identifies academic achievement as a key driver of student satisfaction. This interconnected process contributes to overall virtual instruction success.

4.5 Contextual Implications

The study's findings contribute to the growing literature on virtual education by demonstrating FACVE's applicability beyond emergency remote teaching contexts. While frameworks like Rubtsova et al. (2023) and Kasperski et al. (2023) focus on crisis-specific environments, FACVE offers an assessment framework that is useful for standard virtual education. Its student-centered, bottom-up approach addresses socio-economic and infrastructural barriers, making it particularly relevant for developing countries.

4.6 Theoretical and Practical Contributions

Theoretically, this study confirms FACVE as a valid and robust virtual instruction construct consistent with the extant virtual instruction education literature. Also, this study shows the strong impact of LO on SS, consistent with the extant literature. It has been argued that when students feel they are acquiring meaningful knowledge and skills, their overall satisfaction with the course increases (Eom & Ashill, 2016; Kuo et al., 2014). However, the positive correlation can also be explained in the other direction, by arguing that satisfaction influences students' motivation to engage and thus achieve better learning outcomes (Alqurashi, 2019). Still, the current research results suggest that the first explanation may be the most plausible.

From a methodological point of view, this study reveals strong collinearity between LO and SS, at least when using the existing measures commonly used in educational research as in the classic study by Eom and Ashill (2016).

From a practical standpoint, it validates FACVE-C2 and FACVE-C5 dimension assessment as a powerful tool to foster better LO and SS. These findings align with and extend the practical implications noted by Baruth et al. (2021), Cleary et al. (2024), and Camacho-Zuñiga et al. (2023), providing a comprehensive lens for future interventions

5 Conclusions and Future Work

The FACVE framework was developed in the context of emergency remote teaching during the COVID-19 pandemic. The present study was conducted during the period September-December, 2021 and the studied FACVE challenges, related to digital infrastructure, were found to still have an impact -with different degrees of intensity- on educational outcome variables (SS and LO). More specifically, for this study the results obtained can be summarized as follows:

For digital *technical* infrastructure,

- Challenges related to digital technical infrastructure (C2) are negatively associated with SS.
- Digital technical infrastructure challenges (C2) consistently show a negative association with SS.

For digital *learning* infrastructure,

- Challenges related to digital learning infrastructure (C5) are negatively associated with LO, although the effect size is negligible.

Also, it was found that LO are positively associated with SS.

Limitations and Future Research: The results shown in this study constitute an exploratory study of the inter-relationship of the research variables. While the relations are meaningful and promising, the overall predictive power of the model is small (Q2 = 0.043 for LO and Q2=0.055 for SS), *suggesting the necessity of further studies with larger samples*. Also, the effect of the access to (academic) resources challenges (C5.2) may have been strongly attenuated by the fact that MBA students' academic resources were constituted mainly of reading material. The needed academic resources in other disciplines (e.g., chemistry or nursing) may be more complicated to have available (e.g., laboratory). *Testing the proposed relations with students in various disciplines* would constitute another logical future research step.

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Appendix

I. DIGITAL TECHNICAL INFRASTRUCTURE

C2 – Connectivity & Equipment (Mu et al., 2022)
Q10.1 I do not have (or have limited) access to the internet where I live.
Q10.2 My internet speed is not adequate for my classes.
Q10.3 I do not have access (or it is rather limited) to a computer at home.
Q10.4 There are many technical problems while accessing classes or study material.
Q10.5 My educational institution does not have the appropriate computer equipment (e.g., servers) for virtual teaching.

II. DIGITAL LEARNING INFRASTRUCTURE

C5 – Learning Platform & Access to Resources (Mu et al., 2022)

C5.1 – Learning Platform

Q11.1 The educational platform in use is not suitable for virtual instruction.
Q11.2 Teachers do not know how to use the platform.
Q11.3 Students do not know how to use the platform.
Q11.4 There is no information about the use of the platform.

C5.2 – Access to (Academic) Resources

Q11.5 Lack of access to library books is a severe limitation
Q11.6 Lack of access to laboratories is a problem.
Q11.7 It is necessary to have access to more study material (e.g., PPTs) in addition to the recordings of the class.
Q11.8 Access to teaching resources is less in virtual instruction.

III. DEPENDENT VARIABLES

LO - Learning Outcomes (Eom & Ashill, 2016)

Q8.1 The academic quality of this online class is on par with the face-to-face classes I've taken.
Q8.2 I have learned as much from this online class as I might have from a face-to-face version of the course.
Q8.3 I learn more in online classes than in face-to-face classes.
Q8.4 The quality of the learning experience in online classes is better than in face-to-face classes.

SS – Student Satisfaction (Eom & Ashill, 2016)

Q9.1 I would recommend this instructor to other students.
Q9.2 I would recommend this online class to other students.
Q9.3 I would take an online class at this university again in the future.
Q9.4 I was very satisfied with this online class.