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Uncertainty Avoidance, Perceptions of Emergency Remote Education, and University Commitment: A Cross-Country Analysis

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ABSTRACT

Worldwide, there were significant changes in university courses due to COVID-19. One was a rapid transition to online courses, described as emergency remote education. The purpose of this research was to examine how students' uncertainty avoidance (UA) affected their university commitment (UC) and whether their perceptions of emergency remote education (PERE) mediated this relationship. The *b* path of the mediation analysis (from PERE to commitment) was expected to be moderated by two variables: income and perceived quality of instruction. Students from universities in three countries (i.e., the United States (US), Pakistan, and South Africa (SA)) were assessed. The findings revealed that there were direct and indirect effects for this relationship for students from Pakistan, with a partial moderated mediation effect of perceived quality of instruction for students from Pakistan. Positive main effects of UA on UC were found for students from the United States, Pakistan, and South Africa. Potential explanations and implications for these results were explored.

KEYWORDS

Uncertainty avoidance; emergency remote education; university commitment

COVID-19 affected higher education globally, with only 2% of 109 surveyed countries reporting no changes to teaching and learning (Marinoni et al., 2020). Universities, being close-knit communities, were particularly vulnerable to the virus's spread (Weeden & Cornwell, 2020). To comply with social distancing, many rapidly shifted to emergency remote education (ERE)—an unplanned move to online instruction (Marinoni et al., 2020). Unlike planned online or hybrid courses, ERE was an immediate response to the pandemic, with 87% of students in a multi-country study indicating that their classes moved online (Aristovnik et al., 2020). Post-pandemic, many institutions extended their online offerings. While remote education offered benefits (Peimani & Kamalipour, 2021), technological and emotional barriers impeded some students (Tanhan et al., 2023). Positive perceptions of online learning were linked to better experiences and higher GPAs (Yang, 2023). The impact of this transition on students' university commitment (UC) remains unclear.

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This study explored whether the cultural value of uncertainty avoidance—defined as societal stress, anxiety about the unknown, and risk-taking (Hofstede et al., 2010)—influenced students' UC. It also examined if perceptions of emergency remote education (PERE) mediated this relationship. UC is defined as loyalty, satisfaction, sense of belonging, and the desire to re-enroll (Alshebami & Alamri, 2020).

Perceptions of Emergency Remote Education (PERE)

Students often have ambivalent feelings about online courses. For those with work, family duties, transportation difficulties, or residence in rural areas, online classes offer greater accessibility and sometimes lower tuition costs (Murphy, 2020). Younger students, familiar with technology, also find online learning comfortable (Kamarianos et al., 2020). However, many students value the hands-on nature of in-person courses (Brockman et al., 2020) and face difficulties with online learning, often struggling with course content. Research shows that online students tend to underperform in mandatory exit exams compared to those in onsite courses, particularly in English, reading, writing, and mathematics (Cellini & Grueso, 2021). Online courses also see higher withdrawal rates (Altindag et al., 2021). Historically, students view online classes as easier than onsite ones – a fact which can be seen as a positive or negative, depending on the context (Osborne et al., 2009).

Online classes can create equity issues in communities lacking reliable access to technology. In Pakistan, access to affordable, fast internet is a significant barrier to online learning (Zamir & Wang, 2023). South Africa (SA) faces similar challenges due to the digital divide, i.e., the disparity in access to computers and the internet (Mpungose, 2020). In the United States (US), lower socioeconomic areas also experience this divide (Bacher-Hicks et al., 2020). The shift to remote learning during the pandemic likely exacerbated the achievement gap for students in these communities (Van Lancker & Parolin, 2020).

Research shows that students see online classes as offering both opportunities and challenges (Oliveira et al., 2021). Pre-pandemic, students could choose their learning modality, but COVID-19 forced a rapid shift to ERE, regardless of preference. Many faculty had to quickly adapt to ERE with minimal training, which affected the perceived quality of their courses (Villa-Castaño & Durán León, 2022).

Instruction quality significantly impacts students' academic outcomes and motivation (Sogunro, 2017). Student ratings are a valid measure of teaching effectiveness (Onan, 2020). A large US survey found that student satisfaction with courses dropped from 87% to 59% after moving online, with 31% dissatisfied with instruction quality (Means & Neisler, 2020). Challenges in online classes include accessibility, technology, and quality (Villa-Castaño & Durán León, 2022). The impact of this transition on UC remains unclear.

University Commitment

Challenges with online classes have raised concerns about students' persistence toward their degrees. Persistence in university is crucial for benefits like job security, higher

earnings, and better health (Ma et al., 2016; Womack et al., 2018). A key factor in persistence is UC, which includes loyalty, satisfaction, sense of belonging, and the desire to re-enroll (Alshebami & Alamri, 2020).

Davidson et al. (2009) identified nine predictors of UC: academic and social integration, financial strain, degree commitment, scholastic conscientiousness, academic stress, learning motivation, advising efficacy, and academic efficacy. COVID-19 affected many of these factors, and cultural influences impacted societal pandemic responses (Marinoni et al., 2020).

Uncertainty Avoidance

Culture encompasses shared beliefs and values passed through generations, influencing perceptions and actions toward goals like university graduation (Triandis, 1996). Hofstede's Cultural Dimensions Theory (Hofstede et al., 2010) explains societal cultural differences. This study focused on uncertainty avoidance (UA), one of Hofstede's dimensions, which measures societal stress, anxiety about the unknown, and risk tolerance (Hofstede et al., 2010; Yang et al., 2022). UA thus captures the degree to which a society perceives itself as intimidated or uncomfortable by any unknown and unclear circumstance and the attempts to avoid such circumstances (Yang et al., 2022). In other words, what is the acceptable level of "risk" that can be tolerated? UA may have shaped responses to COVID-19 uncertainties.

UA explains educational differences among countries. Countries with lower UA values (e.g., Nordic nations) show higher reading, math, and science scores (Fang et al., 2013). It has also been related to teaching style preferences: Students from high UA countries (e.g., Germany) prefer structured, teacher-led instruction, while students from lower UA countries favor broad learning objectives and discussion (Hofstede et al., 2010).

In addition, UA influences technology adoption, with mixed results. A meta-analysis of 95 studies found that high UA countries generally adopted new technology more readily, though some exceptions existed (Cardon & Marshall, 2008). High UA societies often prefer technology for its predictability and structure but may also delay adoption to observe initial outcomes from using new technology (Cardon & Marshall, 2008). The influence of UA on attitudes toward online courses remains unclear.

Purpose

Cultural values influence students' perceptions of experiences and may be an important predictor of how students coped during COVID-19. This research explored whether UA influenced students' UC and whether their PERE mediated this relationship. UA was the cultural value chosen because it potentially related to societal responses to the COVID-19 pandemic and has previously been used to explain cross-country differences in educational and technology-related contexts. UA was hypothesized to have a positive effect on UC and a positive influence on PERE, i.e., the *b* path of the mediation analysis (from PERE to commitment) was expected to be moderated by two variables: income and perceived quality of instruction. This partial moderated mediation analysis

quantifies the association between one moderator and the magnitude of UA's indirect effect on UC through PERE when the second moderator is controlled for (Hayes, 2018).

University students in three countries (i.e., US, Pakistan, SA) were assessed according to four hypotheses:

- H1: UA will have a direct effect on UC, where students with higher UA will have more commitment in the US (H1a), Pakistan (H1b), and SA (H1c).
- H2: There will be indirect effects between UA and UC through the mediating variable of PERE, where students in the US (H2a), Pakistan (H2b), and SA (H2c) with higher UA will have higher PERE, which leads to higher commitment.
- H3: The indirect relationship between UA and UC will depend on students' income, where those with low income and low PERE will have the lowest commitment in the US (H3a), Pakistan (H3b), and SA (H3c).
- H4: The indirect relationship between UA and UC will depend on students' perceptions of the overall quality of instruction since COVID-19, where those with perceptions of high-quality instruction and high PERE will have the highest commitment in the US (H4a), Pakistan (H4b), and SA (H4c).

Method

Participants

Participants are described below according to their recruitment countries.

In the US, data were collected from 1,054 undergraduate psychology students at two public universities in the southwestern US through an online study. Participants, aged 17–56 ($M = 19.11$, $SD = 2.63$), included 16.8% males, 81.8% females, 1% transgender or other, and 0.2% undisclosed. Regarding family income, 37.8% reported earning $50,000 USD or less, while 62.2% earned above $50,000 USD, with a median income around $55,000 USD.

In Pakistan, data were collected from 510 undergraduate students at a public university in central Punjab. The university's Directorate of Student Affairs facilitated recruitment through announcements on social media and student portals. Participants, aged 17–46 ($M = 21.71$, $SD = 3.56$), reported their gender as 19.7% males, 79.2% females, and 1% transgender or undisclosed. Regarding family income, 68.9% earned below PKR 500,000 (about $3,000 USD), while 31.1% earned above this amount, with a median income of approximately PKR 300,000 ($1,700 USD)

In South Africa, data were collected from 385 students at a public university in the Gauteng province, with cooperation from the registrars and deans of five faculties. Department heads distributed the survey link via the online student portal. Participant ages ranged from 18 to 42 ($M = 21.74$, $SD = 3.53$). Gender distribution was 23.6% males, 74.2% females, 0.5% transgender, and 1.6% other. Regarding family income, 56% earned R705,500 (about $50,000 USD) or less, while 44% earned above this, with a median income of approximately R500,000 (around $35,000 USD).

Materials

Three published scales were used for data collection, along with questions on perceived instruction quality and annual income.

The Perceptions of Internet Courses Scale (Osborne et al., 2009), adapted from MacKnight (2000), comprised a 12-item survey using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree") as detailed in the Appendix A. All items were reverse-scored except for Items 4 and 10, so higher scores indicated more positive perceptions of online courses. The commonly accepted minimum for Cronbach's alpha (α) is 0.70, though recent studies suggest 0.60 may be acceptable (Daud et al., 2018; Zhan et al., 2021). Alpha reliability coefficients were run and found unacceptably low at $\alpha = 0.458$ for the US but acceptable for Pakistan ($\alpha = 0.600$) and SA ($\alpha = 0.630$). The items that lowered reliability for the US were examined and found to be items 1 and 10. After removing these items, the scale reliability improved to $\alpha = 0.671$ for the US, $\alpha = 0.737$ for Pakistan, and $\alpha = 0.772$ for SA. Thus, on the Perceptions of Internet Courses scale (Osborne et al., 2009), all items were retained for analysis, except items 1 and 10.

The CVScale (Yoo et al., 2011) was developed as a measure of Hofstede's Cultural Value Theory (Hofstede et al., 2010) on the level of the individual (rather than the societal level). This study used the five items of the UA-subscale (e.g., "It is important to have instructions spelled out in detail so that I always know what I'm expected to do") on a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"). Higher scores indicated more uncertainty (Donohue & Bornman, 2021). For the UA-subscale, the alpha coefficients were $\alpha = 0.847$ for the US, $\alpha = 0.726$ for Pakistan, and $\alpha = 0.825$ for SA; hence all five items on this subscale were retained for analyses.

The Institutional Commitment Scale (McEwan, 2013) is a 5-item measure. Questions are related to commitment to a particular university (e.g., "It is important for me to graduate from this university") with a 7-point Likert scale (1 = "strongly disagree" to 7 = "strongly agree"). For the Institutional Commitment scale, the alpha coefficients were $\alpha = 0.847$ for the US, $\alpha = 0.838$ for Pakistan, and $\alpha = 0.763$ for SA; hence all items were retained for analysis.

Perceptions of the quality of instruction were measured with one item, namely "How would you rate the overall quality of instruction in your classes since COVID-19?" and measured on a 7-point Likert scale (1 = "extremely low" to 7 = "extremely high").

All participants were asked to report their annual household income, or parental income if dependent. Nine income categories were included, ranging from 1 (lowest income) to 9 (highest income). In the US, categories ranged from 1 = ≤$30,000 USD to 9 = ≥$100,000 USD. In Pakistan, they ranged from 1 = ≤PKR500,000 (≈ $3,000 USD) to 9 = ≥PKR3,950,001 (≈ $26,000 USD). In SA, they ranged from 1 = ≤R423,300 (≈ $50,000 USD) to 9 = ≥R1,410,001 (≈ $100,000 USD). A method of providing income context is Burgernomics (Ong, 1997), which uses the Big Mac Index to compare Big Mac prices globally, indicating purchasing power parity. This index, updated by The Economist, shows affordability differences. For example, in the US a Big Mac costs $5.15, in Pakistan $3.16 (−38.71%), and in SA $2.34 (−54.53%), reflecting undervalued currencies and potential impacts on living standards such as education, travel, and purchasing power.

Procedure

IRB approval was obtained from the principal investigator's university as well as ethics board approval from other participating universities. Data collection took place from May to December 2020 via Qualtrics. Participants accessed an anonymous survey with informed consent that stressed voluntary participation and the option to withdraw at any time without penalty.

Results

Data were analyzed using SPSS and Amos Version 28, with a significance level set at 5% ($p < 0.05$). The dataset contained missing values, including missing completely random (MCAR), missing at random (MAR), and not missing at random (NMAR) (Van Ginkel et al., 2020). We used multiple imputation to handle missing values. Contrary views in the literature exist. Sterne et al. (2009) cautioned that multiple imputation might lead to misleading results if the data is NMAR. However, Van Ginkel et al. (2020) advocated for multiple imputation over listwise deletion, arguing its effectiveness irrespective of the missingness mechanism.

The questionnaires were analyzed for measurement invariance using multi-group confirmatory factor analyses. This process ensures that constructs are comparable across different contexts (e.g., "apples to apples" in Lee, 2018). Common model fit indices include the chi-square statistic and its corresponding degrees of freedom (df), the RMSEA (Root Mean Square Error of Approximation), the CFI (Comparative Fit Index), and the TLI (Tucker-Lewis Index). The chi-square test was excluded due to its sensitivity to sample size and reduced reliability (Schermelleh-Engel et al., 2003; Vandenberg, 2006).

Model fit recommendations in Table 1 differ from traditional guidelines. While a CFI of $\geq$0.9 is conventionally seen as good fit (Hu & Bentler, 1999), Ajayi and Oyedele (2018) suggest that CFI values range from zero ("no fit") to one ("perfect fit"), with higher values indicating better fit. Debate exists over conventional cutoffs, with Xia and Yang (2019) advocating for smaller RMSEA and larger CFI and TLI values for better fit.

Table 1 provides evidence of configural, metric, scalar, and strict invariance for all three sub-scales, suggesting that the measurement properties remain consistent across

Table 1. Fit indices for models of measurement invariance.

	RMSEA <0.10 (Preferably < 0.08)	CFI 0 (No Fit) – 1 (Perfect)	TLI 0 (No Fit) – 1 (Perfect)
PERE Scale			
Configural invariance	0.061	0.808	0.753
Metric invariance	0.059	0.786	0.766
Scalar invariance	0.059	0.783	0.766
Strict invariance	0.061	0.729	0.747
UA Subscale			
Configural invariance	0.061	0.969	0.937
Metric invariance	0.053	0.964	0.952
Scalar invariance	0.060	0.950	0.940
Strict invariance	0.065	0.917	0.929
UC Scale			
Configural invariance	0.068	0.983	0.948
Metric invariance	0.057	0.976	0.963
Scalar invariance	0.065	0.963	0.952
Strict invariance	0.118	0.808	0.843

Table 2. Mean, standard deviation, and range for summary scores between countries.

Variable	Country	Mean	SD	Range
PERE Summary Score	US	2.411	0.535	1–5
	Pakistan	2.349	0.527	1–5
	SA	2.495	0.612	1–4.6
UA Summary Score	US	4.083	0.657	1–5
	Pakistan	3.774	0.513	1–5
	SA	4.100	0.619	1–5
UC Summary Score	US	5.927	0.864	1–7
	Pakistan	5.279	0.775	1–7
	SA	5.974	0.567	1.8–7
Quality of Classes Score	US	3.680	1.353	1–7
	Pakistan	3.620	1.142	1–7
	SA	3.370	1.103	1–7
Income	US	5.010	2.822	1–9
	Pakistan	2.030	1.202	1–9
	SA	3.530	1.768	1–9

different groups. It is worth noting that the RMSEA value for the UC scale in the strict invariance test is slightly high (0.118). However, establishing configural, metric, and scalar invariance is generally easier than achieving strict invariance, which is less commonly observed.

After establishing measurement invariance, statistical tests were performed to examine each of the four hypotheses. To test H1, path analysis was conducted, and for H2, mediation analysis was conducted. To test H3 and H4, moderated mediation analysis was conducted, followed by partial moderated mediation analysis. For the latter, the PROCESS macro model 16 in SPSS was used, where the *b* path has two moderating variables, each controlling for the effect of the other (Hayes, 2017, 2018). Statistical significance between the independent variable and the moderator tests moderation, while indices of partial moderated mediation analyze partial moderated mediation and conditional effects among moderators (Goodboy et al., 2018). A partial moderated mediation analysis determines whether one variable (i.e., either income or quality of instruction) moderated the indirect effect of UA on UC while controlling for the other moderator (Hayes, 2018). Assessment involves using indices of partial moderated mediation. A confidence interval including zero suggests that, when the other moderator is controlled for, the indirect effect is not influenced by the magnitude of the first moderator (Hayes, 2018).

To estimate the 95% confidence interval, a bootstrap estimation approach was used with 5,000 samples. On the three questionnaires with multiple items, the items were averaged to create summary scores. See Table 2 for means and standard deviations of the summary scores between countries. Refer to Figure 1 for the hypothesized partial moderated mediation models for testing the hypotheses.

United States

UA evidenced a direct positive effect on commitment, $B = 0.359$, $SE = 0.039$, 95%CI [0.282, 0.436], $p < 0.001$. However, UA did not have a significant indirect effect on commitment when PERE was used as mediator ($B = -0.001$, $SE = 0.003$, 95%CI [−0.009, 0.007], $p = 0.740$). Neither income ($B = 0.000$, $SE = 0.001$, 95%CI [−0.002, 0.002], $p = 0.710$) nor perceptions of quality of instruction ($B = -0.002$, $SE = 0.007$, 95%CI [−0.016, 0.011], $p = 0.768$) was found to moderate the effect of PERE on commitment.

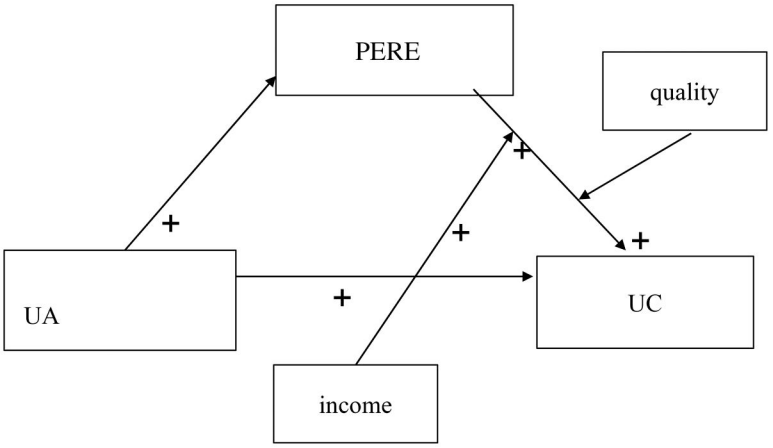

Figure 1. Hypothesized partial moderated mediation model.

The indices of partial moderated mediation indicated no significant effect for income (95%CI [−0.006, 0.001]) and none for quality of instruction (95%CI [−0.001, 0.013]). Approximately 34% of the variance in commitment was accounted for by the predictors ($R^2 = 0.338$).

Pakistan

There was a direct positive effect of UA on commitment ($B = 0.444$, $SE = 0.041$, 95% CI [0.317, 0.569], $p < 0.001$). It was also found that UA had a significant indirect effect on commitment when PERE was used as mediator ($B = 0.073$, $SE = 0.035$, 95% CI [0.020, 0.161], $p = 0.002$). Perceptions of quality of instruction were found to moderate the effect of PERE on commitment ($B = 0.025$, $SE = 0.011$, 95% CI [0.008, 0.056], $p = 0.002$), but income did not ($B = -0.003$, $SE = 0.007$, 95% CI [−0.021, 0.009], $p = 0.478$). Although there was a statistically significant interaction of perceptions of quality of instruction, the CI for the indices of partial moderated mediation contained a score of 0 for both perceptions of quality of instruction (95% CI [−0.058, 0.034]) and income (95% CI [−0.073, 0.007]), which indicated there was not enough evidence to support a conclusion of partial moderated mediation in this analysis. These results can be interpreted as Pakistani students evidencing a relationship between PERE and commitment, dependent on perceptions of quality of instruction. It was where students had *higher* PERE that commitment levels diverged: Students with *low* perceptions about quality of instruction had the *lowest* level of commitment (Figure 2). Approximately 41% of the variance in commitment was accounted for by the predictors ($R^2 = 0.407$).

The interaction effect was probed, but because in tests of partial moderated mediation the indirect effect is a function of two moderators, it is necessary to choose values for each moderator, even though the second moderator is controlled for (Hayes, 2018). The PROCESS default of the 16th, 50th, and 84th percentiles of the moderators was used (Table 3 and Figure 2). The effect of UA on commitment (through PERE) was strongest when income was low and perceived quality of instruction was low ($B = 0.108$, $SE = 0.045$, 95% CI [0.031, 0.207]).

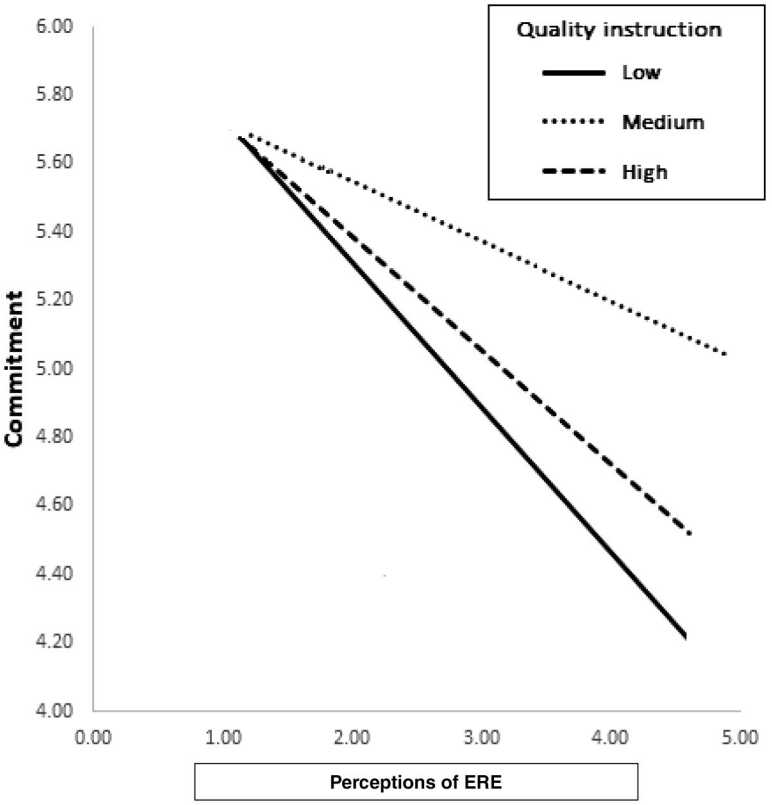

Figure 2. Partial moderated mediation for students in Pakistan of perceptions of quality instruction on the indirect effect between PERE and UC. *Note:* Moderator is plotted at values of low (3), medium (4), and high (5) values of perceived quality of instruction.

Table 3. Partial moderated mediation analyses for students in Pakistan: conditional effects of the focal predictor at values of the moderators.

		Pakistan			
Income	Quality instruction	*B*	*SE*	Llci	Ulci
Low (Score of 1)	3	0.108	0.045	0.031	0.207
	4	0.104	0.043	0.028	0.197
	5	0.102	0.044	0.020	0.192
Medium (Score of 2)	3	0.075	0.035	0.016	0.153
	4	0.072	0.034	0.013	0.144
	5	0.069	0.037	0.003	0.145
High (Score of 3)	3	0.073	0.035	0.015	0.150
	4	0.070	0.034	0.011	0.142
	5	0.067	0.036	0.002	0.143

Note: Values in tables at 16th, 50th, and 84th percentiles of moderators. LLci and Ulci represent the lower limit and the upper limit of the 95% CI, respectively.

South Africa

The results indicated that UA exerted a direct positive effect on commitment ($B = 0.347$, $SE = 0.043$, 95% CI [0.262, 0.432], $p < 0.001$). However, UA did not have a significant indirect effect on commitment when PERE was used as mediator ($B = 0.003$, $SE = 0.006$, 95% CI [−0.007, 0.015], $p = 0.253$). Neither income ($B = -0.001$, $SE = 0.002$,

95% CI [−0.011, 0.001], $p = 0.253$) nor perceptions of quality of instruction ($B = 0.010$, $SE = 0.015$, 95% CI [−0.013, 0.048], $p = 0.401$) were found to moderate the effect of PERE on commitment. There was no evidence of partial moderated mediation for income (95% CI [-0.005, 0.005]) or for the quality of instruction (95% CI [−0.005, 0.020]). Just over 40% of the variance in commitment was accounted for by the predictors ($R^2 = 0.415$).

Discussion

Sapp and Simon (2005) coined the term "thrive or dive" to describe the bimodal distribution of grades in online courses, where some students excel while others struggle. The pandemic heightened concerns about student attrition in online education (Shaikh & Asif, 2022; Xavier & Meneses, 2020). The current study aimed to explore how students' UA influenced their UC and if their PERE mediated this relationship. The impact of PERE on commitment was expected to vary based on income and perceived instruction quality. To test the model's validity, students from diverse regions were included in the sample. Below, each of the four hypotheses is delineated.

- H1: UA will have a direct effect on UC, where students with higher UA will have more commitment in the US (H1a), Pakistan (H1b), and SA (H1c).

The results indicated that H1a, H1b and H1c were supported, where students from all three countries with higher UA scores also reported higher UC. This aligns with previous research that indicated societies high in UA preferred order and structure in their lives (Cardon & Marshall, 2008). High levels of UA could drive greater commitment among students toward achieving their end goals, such as graduating from university. Despite potential dissatisfaction with university, students with high UA scores might prefer committing to completing their degrees rather than facing the uncertainty of dropping out and deciding on alternative paths.

- H2: There will be indirect effects between UA and UC through the mediating variable of PERE, where students in the US (H2a), Pakistan (H2b), and SA (H2c) with higher UA will have higher PERE, which leads to higher commitment.

Building on prior research indicating that societies high in UA prioritize science and technology-based solutions (Cardon & Marshall, 2008), it was hypothesized that individuals with high UA would report greater PERE, resulting in increased commitment. Only for Pakistan did UA show an indirect positive impact on commitment when mediated by PERE (H2b). However, for the US and SA, the results were not statistically significant, thus refuting H2a and H2c.

This finding seems to suggest that, for students from the US and SA, PERE holds more significance for commitment than UA. While UA may play a role in UC, cultural values seem to have less impact compared to perceptions of the learning format required for coursework engagement and success.

Bronfenbrenner's ecological systems theory (2000) could be used as a framework: The immediate environmental setting (i.e., the microsystem, which, in this case, was PERE) has more of an impact on students' commitment than the chronosystem (i.e., cultural values, which, in this study, equates to UA).

As noted previously, the effects of UA on technology have been inconsistent. While many studies reported that those high in UA are quick to adopt technological solutions, others noted the opposite effect (Png et al., 2001; Sundqvist et al., 2005). Furthermore, preferences for technology-based solutions may not extend to positive PERE since there is also a human element to them (e.g., people create online courses and grade assignments).

- H3: The indirect relationship between UA and UC will depend on students' income, where those with low income and low PERE will have the lowest commitment in the US (H3a), Pakistan (H3b), and SA (H3c).

For the moderator of income, it was found that income did not significantly moderate the effect of PERE on commitment across all three countries. Previous research stated that students from low-income backgrounds are the most likely to drop out (Leibowitz & Bozalek, 2014). Despite that finding, in the current study no group showed evidence of a moderating effect of income on the relationship between PERE and commitment independently nor in the context of an indirect effect, thus refuting H3. Unexpectedly, this finding may be attributed to the widespread practice of offering scholarships or bursaries to low-income students globally. Consequently, income may not significantly influence students' UC.

- H4: The indirect relationship between UA and UC will depend on students' perceptions of the overall quality of instruction since COVID-19, where those with perceptions of high-quality instruction and high PERE will have the highest commitment in the US (H4a), Pakistan (H4b), and SA (H4c).

Partial moderated mediation effect was found for perceptions of quality of instruction for students from Pakistan but not for students from the US or SA. When this relationship for Pakistan was graphed (Figure 2), it became apparent that students in the bracket for the lowest perceptions of quality instruction, with low PERE, had levels of commitment roughly equivalent to students from the other brackets for perceptions of quality instruction, thus refuting H4b. It was when students had *higher* PERE that commitment levels diverged: Students with low perceptions about quality of instruction had the lowest level of commitment, which was unsurprising. What was surprising was that students with high perceptions about quality of instruction did not have the highest commitment; those with medium perceptions about quality of instruction had the highest commitment. This was surprising because previous research claimed that students' perceptions of the quality of their instruction were one of their primary motivators in higher education (Sogunro, 2017), and one study found that students reported precipitous drops in the quality of instruction since COVID-19 (Means & Neisler, 2020). One potential reason could be the "middle of the road" scores found on this variable for

Pakistan (mean = 3.620, SD = 1.142, median = 3.520, IQR = 0.000 on a 7-point Likert scale). Pakistan students' opinions of the quality of their instruction since the transition to online courses was neutral. Surprisingly, those with medium perceptions of instruction quality and high PERE demonstrated the highest commitment, contrary to expectations that those with the highest perceived instruction quality would show the highest commitment.

Limitations and Future Directions

This research had several limitations. Firstly, while UC was studied, it was unclear if it led to re-enrollment or graduation. Secondly, the study's sample size and composition may not represent all higher education students. Additionally, differences in online course quality between universities could have affected results, although perceived instruction quality scores were similar across countries. Moreover, the predominantly female sample may have influenced outcomes, warranting future research with more gender diversity. Future studies could address these limitations by tracking students' progress over time, sampling more universities, and ensuring greater gender diversity.

Conclusions

The findings of this research highlight several important points. First, students' commitment is influenced by both cultural values and their course modality. To retain students until graduation, universities should consider these factors and provide support to those at risk of dropping out. This is crucial, especially given the widespread shift to online learning during the COVID-19 pandemic, since many students may opt to continue online courses despite potential impacts on their commitment.

Secondly, results from one country or region may not apply universally. Context and culture differ, impacting how educational experiences translate across students. Therefore, measuring cultural values at the individual level is crucial, rather than assuming that societal scores apply uniformly within a country. Hofstede's country-level scores for UA are as follows: US = 46, Pakistan = 70, and SA = 49 (Hofstede Insights Oy, 2020). When the summary scores for UA in this study were examined, SA students had the highest and Pakistani students had the lowest scores. Applying societal scores to individual students could have led to erroneous interpretations.

In conclusion, this research highlighted both similarities and differences in factors influencing UC among higher education students. It underscores the need for universities to foster commitment, especially among those taking online classes, given the significance of a degree in future career prospects, earning potential, and overall well-being.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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