The Impact of COVID-19 on Students' Perceived Justice, University Support, Professor Support, and Intentions to Drop Out

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Postsecondary education significantly contributes to individuals' career opportunities, lifetime earnings, and social mobility; therefore, understanding the factors that contribute to student retention in higher education has positive economic and societal implications. In this study, with the purpose of contributing to student retention with actionable findings, we focus on factors over which universities exercise reasonable control. We collected data from 430 students in the college of business of a southwestern public university in the U.S. before and during the remote instruction period of the COVID-19 pandemic. We exploit the natural experiment created by COVID-19 to examine group differences in the relationships of perceived organizational support, professor support, fairness of treatment, fairness of outcome, and intentions to drop out. After conducting measurement invariance tests, both samples were fitted to a multi-group structural equation model. Our data revealed that in contrast to the before-COVID sample, during COVID-19, students' perceptions of professor support uniquely and strongly influenced their intentions of dropping out of their studies. Our findings have important implications for student retention.

Keywords: student retention, POS, professor support, student attrition, COVID-19

INTRODUCTION

The emergence of the COVID-19 worldwide pandemic impacted public health and many other aspects of life. On March 13, 2020, the President of the United States issued an emergency declaration, which triggered at the state-level numerous stay-at-home and shelter-in-place orders that inevitably resulted in business closures (Gostin & Wiley, 2020) and the unprecedented shift to remote instruction due to campus closures (Zimmerman, 2020). According to the World Bank (2020), the COVID-19 pandemic was a shock to education systems worldwide, and a major stressor for university students. Universities have struggled with both short-term (e.g., students' mental health) and long-term effects (e.g., overall decline in student enrollment) of the pandemic (Krishnamurthy 2020). While the decreasing number of COVID-19 infections has led to the re-opening of campuses for face-to-face instruction, university enrollment continues to decline. Overall, graduate and undergraduate enrollment has declined 7.4 percent (1.3 million students) since before the pandemic, representing the largest two-year decrease in more than 50 years (NSC, 2020). These statistics are concerning because: (a) they suggest that the skills gap that existed in business graduates prior to the pandemic will widen (AACSB, 2018), (b) they imply a potential long-term economic impact due to dropouts' decrease in lifetime earnings and labor outcomes (Belfield & Bailey, 2017), and (c) they could potentially exacerbate social inequity—college education has the most significant benefits on earnings and opportunities for women, low-income students and students of color (Giani et al., 2020). The importance of understanding the factors that contributed to business students dropping out of college during the pandemic lies in its potential implications.

Although the existing student attrition frameworks have increased our understanding of multiple factors that influence student retention and attrition (Burke, 2019), this phenomenon is not yet fully understood. We lack a comprehensive understanding of how a student's decision to drop out might differ in the context of a major stressor, such as COVID-19, which disrupted education due to school closures. The unprecedent shift from face-to-face to remote instruction seen during COVID-19 (Zimmerman, 2020) was stressful and challenging for students who had to adapt to new technologies while meeting academic requirements (Govindarajan & Srivastava, 2020). Existing research suggests that university students are particularly vulnerable to stressors such as concerns about the future (Tosevski et al., 2010), academic and environmental pressures (Yikealo et al., 2018), and financial difficulties (Heckman et al., 2014), which can influence their academic performance and persistence in their studies (Samuel & Burger, 2020).

Some scholars have argued that the reliance on online instruction during COVID-19 increased the importance of the quality of student-faculty interactions (Govindarajan & Srivastava, 2020), which requires faculty to excel at delivering online instruction (Beech & Anseel, 2020). Recent research suggested that students are hesitant about the value of online learning, and question if a degree is worth their time and money (Edge Research, 2022). COVID-19 caused uncertainty in career prospects for many students (Krishnamurthy, 2020). The potential reduction in quality stemming from the shift to remote instruction may discourage students from persisting in their studies at a time of economic uncertainty due to a perceived diminished return on their investment (Beech & Anseel, 2020). Some have suggested that in these conditions, students require different types of support in order to complete their studies (Edge Research, 2022). Some sources of support that were found to mitigate some of the negative effects of COVID-19 and promote student retention are peer and social support (Kohls et al., 2021), as well as university and faculty support (Noman et al., 2021; Zeng et al., 2021). However, the extent to which university support and faculty support may influence students' decision to persist in their studies post COVID-19 has not been addressed yet.

In this study, we seek to address those gaps and provide initial evidence of the effect of COVID-19 on students' perceptions of university support and intentions to drop out. We draw upon organizational support theory (Eisenberger et al., 1986) and apply it to business students survey data collected pre-COVID and after the President's emergency declaration on March 13, 2020, to examine group differences in the relationships of perceived organizational support (POS); its antecedents, professor support, fairness of treatment, and fairness of outcome; and intention to drop out. We exploit the natural experiment created by COVID-19 to estimate the effect this major stressor has had by applying propensity score matching and fitting the matched sample to structural equation models to identify group differences.

LITERATURE REVIEW

Scholars have argued that student attrition is comparable to employee turnover (Bean, 1980; Mashburn, 2000). One of the most influential models of student attrition, Bean's (1980, 1983) Student Attrition Model, was the first to adopt a turnover framework. A significant contribution of this model was the inclusion of organizational variables that shape key attitudes (i.e., satisfaction) that influence behavioral intentions that, in turn, lead to withdrawal behaviors (cf. Fishbein & Ajzen, 1975). In the organizational literature, another theory that has provided the framework for predicting turnover is organizational support theory (OST, Eisenberger et al., 1986). Although OST was conceptualized to explain an employee-organization relationship, the underlying processes (i.e., attribution, social-exchange, self-enhancement, reciprocation) that explain the links among employees' perceptions of fairness, perceptions of support and intention to quit their organizations, also hold true for students in institutions of higher education (Dufner et al., 2015; O'Mara et al., 2012). The OST framework is particularly relevant for the context of our study because it is grounded on social exchange theory, which has been validated in educational contexts (Fan et al., 2019); to explain the student-faculty relationship (Griffin, 2012; Lillis, 2011), and to predict student retention (Fisher & Baird, 2005).

According to OST, individuals who perceive favorable treatment by their organization and its agents, attribute this to their organization, which leads them to believe that their organization values them and cares about their well-being. Through social exchange processes, POS fulfills socio-emotional needs and elicits a felt obligation to reciprocate favorable treatment with effort and loyalty leading to long-term employee-organization obligations. Three general categories of favorable treatment contribute to POS: supervisor support, fairness of treatment, and fairness of outcome (Rhoades & Eisenberger, 2002). As the organizational agents, supervisors' actions influence POS to the extent that their actions are perceived as being carried out on behalf of the organization (Kurtessis et al., 2017; Maertz et al., 2007). In turn, POS influences turnover cognitions, fully mediating (Eisenberger et al., 2002) or partially mediating (Maertz et al., 2007) the relationship of supervisor support and turnover cognitions.

There is some evidence that suggests that some support may be attributed to supervisors rather than the organization, which may lead to the formation of distinct attachments to supervisors (Maertz et al., 2007). Similar findings in educational research have suggested that students may form expectations and obligations to faculty distinctly to those they form with the university (Fan et al., 2019; Knapp & Masterson, 2018). The heightened role of professors during COVID-19 lends the opportunity to test how the expectations and obligations students form with their professors differed in the context of COVID-19 and to what extent students' evaluation of their professors influenced their evaluation of the university and their intentions to drop out.

Several studies have examined measures of fairness in instructional settings and found that students' perceptions of injustice can influence their perceptions of their instructors (Chory et al., 2014) and indirectly influence drop out behaviors (Bean, 1980; Horan et al., 2010). The literature distinguishes three types of justice: procedural, distributive, and interactional. Procedural justice consists of fairness in policies and procedures; research suggests that it is the strongest predictor of POS (Kurtessis et al., 2017). Distributive justice relates to the fair allocation of rewards and has been found to directly influence both supervisor support and professor support. In the education literature, scholars have argued that grades (Bean, 1980), grading systems (Burleigh & Meegan, 2013; Deutsch, 1979) and access to internships (Hora et al., 2020; Swan, 2015) are forms of distributive justice; thus, distributive justice is expected to be attributed to professor and university support. Interactional justice refers to the perceptions of the way one is treated during the enactment of organization-related decisions by organizational agents, and encompasses interpersonal and informational (e.g., feedback) fairness. Interactional justice has been directly linked to the organizational agent (DeConinck, 2010), which in our study is the professor. Therefore, interactional justice is expected to have a direct effect on professor support.

Perceived support is expected to fulfill socioemotional needs, such as respect, esteem, and approval (Eisenberger, 1986). In turn, the fulfillment of socioemotional needs activates a felt need to reciprocate, which can result in attachment to the organization, and decreased withdrawal intentions (Bean, 1980; Kurtessis et al., 2017). In the management literature, studies have found that the felt obligation to reciprocate increases in relation to the strength of the socioemotional needs (Armeli et al., 1998). Therefore, stressors are expected to strengthen the effects of support on intention to drop out. Findings of empirical research suggest that university and professor support impact students' dropout intentions (Samuel & Burger, 2020). Professor support is one of the most salient sources of support to students, and instrumental to their persistence in their courses and programs (Dachner & Saxton, 2015). The quality of student-faculty interactions has been found to be essential for retaining students who perceive that support is required for their success (Ferrer De Valero, 2001; Hunter & Devine, 2016; Ivankova & Stick, 2007). During COVID-

19, research has found that students' perceptions of support influence their educational decisions (Edge Research, 2022).

Stressors and Their Effects on Students' Attitudes and Behavioral Intentions

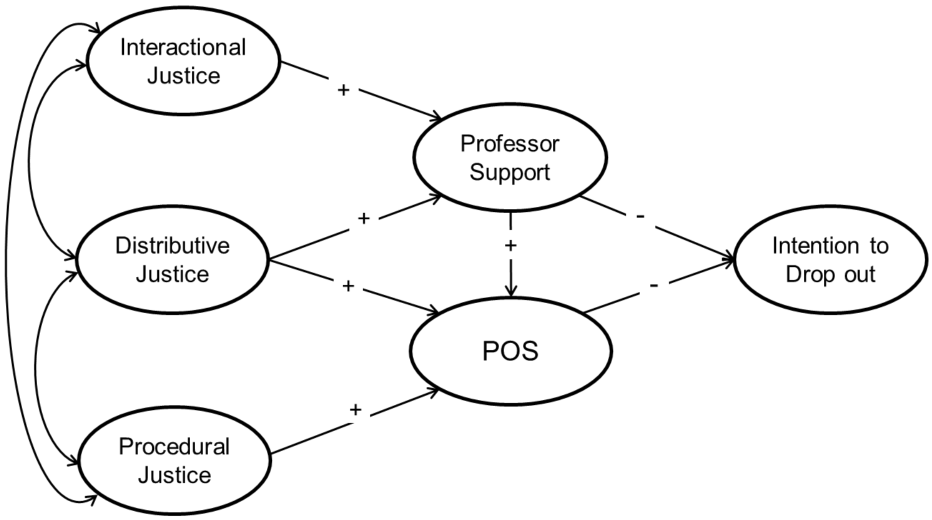
COVID-19's impact on student populations is of particular interest for researchers, due to their vulnerability to stressors (Tosevski et al., 2010; Yikealo et al., 2018). Demographic-based effects during the pandemic have also been identified; students of color from low-income households experienced more challenges during COVID-19 than their high-income white counterparts (Means & Neisler, 2021). Elmer and colleagues (2020) found that controlling for other stressors, the negative effect of COVID-19 on female students was more pronounced than for male students. Also, financial aid recipients were more likely to drop out to protect their GPA (Rodríguez-Planas, 2022). Recent research (Edge Research, 2022) that aimed to identify the drivers of the "exodus from higher education" found that students are evaluating their return on investment when it comes to their education; some students may see a diminished value in online education (Beech & Anseel, 2020).

Research suggests that students need multiple types of support that go beyond financial support, and range from guidance in their courses, to support managing stress, to assistance with job placement upon graduation (Edge Research, 2022). There is significant support in the literature for the role of universities and faculty in helping students cope with stressors and their effects (Swani et al., 2021). Scholars have argued that during COVID-19, university and faculty support decreased the effect of stressors on students' dropout intentions and dropout behaviors (Blankenberger & Williams, 2020; Noman et al., 2021; Zeng et al., 2021). However, before COVID-19, the link between stressors and their influence on student dropout behaviors had been well-documented (Samuel & Burger, 2020; Suhlmann et al., 2018), which suggests that research findings of studies conducted during COVID-19 cannot be fully ascribed to COVID-19 unless the effect of COVID-19 is isolated.

Aims of the Present Study

Given the extant research and the strong support for the relationships among perceptions of justice, professor support, organizational support, and dropout intentions, the aim of our study is twofold. First, we apply OST (Eisenberger et al., 1986) to test a hypothesized model (Figure 1) that predicts that students' perceptions of university support will stem from professor support, fairness of treatment, and fairness of outcome, are reciprocated with decreased intentions to drop out. Specifically, we predict positive direct effects of professor support, procedural justice and distributive justice on POS (Kurtessis et al., 2017), and indirect effects of interactional justice and procedural justice through professor support (Camerman et al., 2007); in turn, POS (Villanueva & Djurkovic, 2009) and professor support (Ferrer De Valero, 2001; Ivankova & Stick, 2007) fulfill students' socioemotional needs eliciting the need to reciprocate by decreasing intentions to drop out. Second, we aim to identify the extent to which remote instruction during COVID-19 impacted the relationships of perceived professor and university support on student intentions to drop out. Considering that the felt need to reciprocate favorable treatment increases with the strength of the socioemotional need (Armeli et al., 1998), we predict that professor support and POS will have stronger negative effects on intentions to drop out during COVID-19.

FIGURE 1
HYPOTHESIZED STRUCTURAL MODEL



RESEARCH DESIGN AND METHODS

Data and Sample

The sample of this study was collected from students in the college of business at a southwestern public university in the United States. After the study was approved by the human subjects committee, a survey instrument was utilized to collect data through the Qualtrics® online survey platform and administered to students through the university's student research participation system. Business students in graduate and undergraduate courses were given the choice to participate in one or more research studies, including this study, for extra-credit as determined by their instructor. A total of 430 surveys were collected. Data were analyzed using R, version 4.2.0 (R Core Team, 2020), the packages MVN, version 4.9 (Korkmaz et al., 2014), MatchIt, version 4.4.0 (Ho et al., 2011), and laavan, version 0.6-11 (Rosseel, 2012). A comprehensive data cleaning process was undertaken where data were evaluated for retention on the basis of completeness, passed attention checks, and no straight lining. After eliminating responses that did not meet retention criteria, the unmatched pooled sample consisted of 351 observations, 145 collected pre-COVID, and 206 collected after the start of the pandemic. The cutoff threshold for group assignment was March 13, 2020, the national emergency declaration. Data for the pre-COVID sample were collected prior to the cutoff. The during COVID sample was collected after the cutoff date; to capture the effect of COVID-19 instructional continuity on the variables of the study, we limited observations of the during-COVID sample to April 2021, which was prior to campus reopening.

The external validity of the sample was assessed by comparing demographic characteristics of the study's pooled sample to the post-secondary public 4-year population profile obtained from the National Center for Education statistics (NCES, 2021). The sample was representative of the general public 4-year university population based on race/ethnicity ($\chi 2$= 2.857 (4), p =.58), financial aid for undergraduate ($\chi 2$= 1.23 (1), p =.27), graduate students ($\chi 2$= 0.08 (1), p =.78), and parental education ($\chi 2$= 1.55 (2), p =.47); however, 72.9 percent of study participants in our pooled sample identified as female, which was significantly higher than the 56.9 percent NCES public 4-year population, ($\chi 2$ (1) = 5.69 (2), p =.02).

TABLE 1
DESCRIPTIVE STATISTICS FOR THE MATCHED SAMPLES

	Pre-COVID		During COVID				
Variable	Mean	SD	Mean	SD	*t* statistic	*p*-value	Cohen *d*
Intention to drop out	1.47	0.75	1.32	0.57	1.88	0.06	0.22
POS	3.81	0.67	3.60	0.84	2.28	0.02	0.27
Professor support	3.61	0.85	3.57	0.85	0.43	0.67	0.05
Interactional justice	3.98	0.77	3.94	0.74	0.43	0.67	0.05
Distributive justice	4.12	0.74	4.08	0.83	0.45	0.65	0.05
Procedural justice	3.92	0.68	3.83	0.82	1.09	0.28	0.13
Gender	1.76	0.49	1.76	0.45	0.13	0.90	0.01
Age	3.49	1.49	3.33	1.46	0.92	0.36	0.11
Educational Level	1.66	0.47	1.63	0.48	0.62	0.54	0.07
GPA	3.09	0.85	3.02	0.79	0.72	0.47	0.09
Credit Hours	2.85	1.21	3.01	1.24	-1.11	0.26	0.13
Financial Aid	1.37	0.48	1.29	0.46	1.38	0.17	0.16
Parent Education	2.32	1.13	2.31	1.10	0.11	0.92	0.01
Race	2.21	1.34	2.29	1.37	-0.48	0.63	0.06

Notes. n=286 [pre-COVID=143, during COVID=143). Educational level=dummy variable [1=undergraduate, 2=graduate]. Gender [1=male, 2=female, 3=non-binary/other]. Race/ethnicity [1=white, non-Hispanic white, 2=Hispanic or Latino, 3=black or African American, 4=Asian, 5=Multiracial or other]. Age [1=under 20, 2=20-25, 3=26-30, 4=31-35, 5=36-40, 6=40 or older]. Parent education [1=up to high school, 2=some college, 3=bachelor's degree or higher]. Financial aid is a dummy variable that indicates if the student receives financial aid [1=no, 2=yes], GPA [4= over 3.5, 3=3.00-3.5, 2=2.5-2.99, 1= less than 2.5].

Propensity Score Matching

The changes created by the COVID-19 pandemic offered a natural experiment to test hypotheses before and during school closures (Tomasik et al., 2021). Quasi-experimental designs are generally imposed with natural experiments, and similar to experimental designs, test causal hypotheses (Dunning, 2009). However, unlike experimental designs where group assignment is random, quasi-experimental designs identify a comparison group that is as similar as possible to the treatment group in terms of baseline (pre-treatment) characteristics. One of the techniques for creating a valid comparison group is propensity score matching (PSM: Rubin, 1997), which we used in this study to account for any treatment selection bias in estimating group differences attributed to COVID-19. All demographic and control variables were input into the propensity score matching algorithm to generate values for the probability of exposure to treatment to match the sets of untreated (pre-COVID) and treated (during COVID) observations using the nearest neighbor matching method with the caliper set to .20 (Caliendo & Kopeinig, 2008, p. 9). The resulting final matched dataset consisted of 143 observations in each group (See Appendix A). Table 1 reports the means, standard deviations, and t-statistics for the matched datasets. Table 2 reports the correlations among variables for each sample.

TABLE 2
CORRELATIONS FOR THE PRE-COVID AND DURING COVID MATCHED SAMPLES

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Intention to drop out	.84	-.30*	-.35*	-.32*	-.42*	-.28*	.03	-.16	-.14	-.08	.07	.02	-.10	.02
2. POS	-.24*	.87	.70*	.62*	.34*	.72*	.00	-.07	-.16	-.16	.00	-.09	.00	.03
3. Professor support	-.24*	.61*	.86	.69*	.49*	.65*	.01	-.06	-.08	-.02	-.04	-.01	.05	-.05
4. Interactional justice	-.20*	.49*	.72*	.90	.46*	.64*	.04	.07	.06	-.05	-.12	-.01	.11	.05
5. Distributive justice	-.29*	.45*	.54*	.53*	.89	.38*	-.03	.02	.01	.15	-.10	-.07	-.05	-.07
6. Procedural justice	-.28*	.72*	.59*	.52*	.38*	.85	.00	-.05	-.11	-.16*	-.10	-.02	.06	.01
7. Gender	.09	.00	-.10	-.05	-.14	.01	—	-.07	-.03	-.14	-.07	-.13	.00	.01
8. Age	.00	-.07	-.09	-.13	-.01	-.01	.05	—	.32*	.04	-.23*	.11	-.11	.03
9. Educational level	-.15	-.16	-.10	-.12	.02	-.10	-.04	.22*	—	.37*	-.53*	.15	.25*	-.01
10. GPA	-.14	-.09	.02	-.02	.07	-.05	-.15	.24*	.41*	—	-.22*	-.02	.09	.14
11. Credit hours	-.03	-.06	-.02	.06	-.04	-.05	.07	-.16	-.29*	-.11	—	-.09	-.02	-.01
12. Fin. aid	.00	-.03	.04	.11	.11	-.03	-.16	-.04	.18*	-.01	-.23*	—	.10	.00
13. Parent education	-.21*	-.02	.05	-.01	.13	-.02	.00	.01	.24*	.28*	-.04	.08	—	-.01
14. Race	.13	-.01	-.04	.05	-.03	.12	.07	-.04	-.01	-.09	.17*	.00	-.09	—

Notes. *p < .05, two tailed, n=286 [pre-COVID=143, during COVID=143). Alpha reliabilities for the scales in the diagonal. Top diagonal=during COVID, bottom diagonal=pre-COVID.

Measures

To test our hypotheses, a survey instrument was developed using items from validated scales. All items were measured using scales ranging from (1) “strongly disagree” to (5) “strongly agree.” Given that the scales were originally conceptualized to measure attitudes in the workplace, items were adapted by inserting the words “university” or “teacher” in place of “organization” or “supervisor.”

Intention to drop out was measured with four items that asked about students’ thoughts of quitting, their plans to leave, and their intention to drop out of the university, which is similar to studies that have examined employees’ intention to quit (Hom et al., 1984; Meyer et al., 1993). A sample item is “I plan to drop out of the university” (α=.78). One item was negatively worded; after using this item to identify straight lining in the data cleaning process, this item was recoded. Perceived organizational support (POS) measured students’ views of favorable treatment by their university, with six items adapted from the POS scale (Eisenberger et al., 1986), a sample item being “My university cares about my well-being” (α=.89). Perceived professor support consisted of four items from the POS scale (Eisenberger et al., 1986), a sample item being “My teachers would forgive an honest mistake on my part” (α=.88). Procedural justice used five items from Moorman’s (1991) Organizational Justice Scale (α=.89). Distributive justice consisted of three items from the Organizational Justice Scale (Colquitt, 2001), and two items from the Distributive Justice Index (Price & Mueller, 1986), a sample item is “My outcomes are justified given my performance” (α=.91). Interactional justice used four items from Moorman’s (1991), which encompass interpersonal and informational justice; sample items are “My teachers treat with kindness and consideration” and “My teachers provide me with timely feedback” (α=.88). Control variables were selected based on their potential impact on the outcome variables of our study, specifically, parental education (Allen, 1999), student’s GPA (Cabrera et al., 1993), and whether a student received financial aid or assistance (Rodríguez-Planas, 2022). Demographic measures included gender, age, race, and graduate or undergraduate status.

Common Method Variance (CMV)

We followed recommendations in Podsakoff et al. (2003) for strengthening the design of the survey to mitigate the risk of method biases. Procedural remedies included mitigation for bias from evaluation apprehension; the survey indicated that there were no right or wrong answers and that responses would remain anonymous (Rogelberg et al., 2006). To avoid item priming effects, the survey presented criterion variables before the predictor variables. Some scale randomization and counterbalancing was implemented to mitigate potential bias from context-induced mood that could occur if the first set of questions induces a mood for responding to the survey and the potential bias from indiscriminate randomization, which could disrupt the respondents' thought process and decrease the quality of the data. An attention check was included in the survey (e.g., "Please click on the little blue circle at the bottom of the screen. Do not click on the scale items that are labeled from 1 to 9" [Oppenheimer et al., 2009, p. 871]) to identify responses that could potentially decrease the quality of the data. Nonetheless, the predictor and criterion variables were measured in a single context and obtained from a single source. Therefore, we used the unmeasured common latent factor technique (UCLF; Podsakoff et al., 2003). Results revealed an estimated variance from method bias of 9%, which is well below the 26% threshold found in Williams et al. (1989), suggesting that CMV is not a major concern in our data.

RESULTS

Multigroup invariance testing assumes that data are normally distributed. An evaluation of the pooled sample showed evidence of multivariate kurtosis; this pattern was observed in the original sample (Mardia=61.47) as well as the matched sample (Mardia=49.67), which can lead to severely inflated fit statistics in SEM models (Moshagen, 2012). Thus, instead of uncorrected chi-square statistic, all CFA and SEM analyses in this study estimate and report the Satorra–Bentler robust statistic (SBχ2; Satorra & Bentler, 1994), which incorporates a scaling correction for the chi-square statistic when normality assumptions are violated. CFA and SEM models were examined for goodness of fit based on the cut-off criteria of comparative fit index (CFI) $\geq .95$, standardized root mean square residuals (SRMRs) $\leq .08$, and the root mean squared error of approximation (RMSEA) $\leq .10$) (Vandenberg & Lance, 2000). For invariance testing, in addition to robust chi-squared difference tests, we used recommended thresholds for changes in fit indices, including CFI $\leq -.005$, RMSEA $\geq .010$, or SRMR $\geq .025$ for factor loadings or $\geq .005$ for intercepts and residuals (Chen, 2007). To determine practical significance, we used guidelines for educational research (Keith, 2006), where effect sizes of $\leq .05$ $\beta < .10$ are considered small, $\leq .10$ $\beta < .25$ are considered moderate, and $\beta \geq .25$ are considered large.

Following guidelines in Nimon and Reio (2011), prior to measurement invariance testing, a confirmatory factor analysis (CFA) assessed the proposed dimensionality through the fit of the survey items to their respective scales for the pooled sample. Fit indices indicated that the six-factor correlated model was a good fit for the data, (CFI =.983, TLI=.981, RMSEA=.031, SRMR=.046). Factor loadings were above the minimum threshold of .5; most were above the more stringent threshold of .7 (Bagozzi & Yi, 1988). Structure coefficients of each manifest variable correlated most highly with its respective factor. Composite reliability (CR) ranged from .80 to .94 and average variance extracted (AVE) ranged from .65 to 81, which exceeded the recommended thresholds of .60 for CR and .50 for AVE (Bagozzi & Yi, 1988), providing evidence of adequate reliability of the scales and convergent validity among the constructs. Discriminant validity was established as the square root of the AVE of each latent variable was greater than its absolute correlation with other variables, and all factor correlations were below the .85 conventional cutoff criteria that would suggest the existence construct overlap (Hinkin, 1998).

Measurement Invariance

Before fitting the sample to the a priori structural model, we conducted measurement invariance tests, as they are a pre-requisite for group comparisons (Chen, 2007). The pre-COVID and during COVID samples were fitted to the CFA measurement model specified for the pooled sample, and a series of nested models that progressively constrained parameters (see Table 3). The configural model (CFA1) estimated all parameters freely for both samples. Robust fit statistics suggested a good fit for the data (SBχ2 [pre-COVID = 435.33 (332); during COVID = 331.94 (332)], CFI=.975, RMSEA=.037, SRMR=.057). Appendix B shows that the pre-COVID sample's pattern and structure coefficients of individual items loaded to their theoretical constructs, CR ranged from 73 to 93, AVE ranged from .69 to .79, and the square root of the AVE for each factor was greater than the absolute correlations with other factors. Pattern and structure coefficients of individual items for the during COVID sample loaded to their theoretical constructs; composite reliability ranged from .77 to .94, AVE ranged from .62 to .82, and the square root of the AVE for each factor was greater than the absolute correlations with other factors. Therefore, the configural model (CFA1) was retained.

Table 3 reports results of the measurement invariance tests. Metric invariance “tests whether respondents under study attribute the same meaning to the latent construct” (van de Schoot et al., 2012, p. 489). The metric invariance model (CFA2) that constrained all factor loadings to be the same for like items across groups was supported. Scalar invariance (CFA3) tests whether “the meaning of the construct and the levels of the underlying items are equal in both groups” (van de Schoot et al., 2012). Scalar invariance (CFA3) that constrained all intercepts to be equal across groups was not supported due to a statistically significant chi-squared difference test. Critical ratios were used to identify noninvariant items as recommended by Byrne and colleagues (1989). We unconstrained two noninvariant intercepts (POS1, procedural justice1); partial scalar invariance (CFA4) was supported. Although many researchers believe that strict—residual— invariance is not necessary to establish measurement invariance, Wu and colleagues (2007) argued that “unless residual variances of the measured variables can be clearly shown to be only a reflection of random errors, as a prudent step, equality in the residual terms should always be tested.” Since measurement error is present in our cross-sectional data, we tested strict invariance (CFA5) to establish measurement invariance. Strict invariance was supported, and the model was retained.

TABLE 3
SUMMARY OF MEASUREMENT AND STRUCTURAL INVARIANCE FOR THE PRE-COVID AND DURING-COVID MATCHED SAMPLES

Model (M)		SBχ2	df	p of Δ	s	ΔCFI	RMSEA	SRMR	Compared to	Rule Accepted
Measurement Invariance										
CFA1	Configural invariance	767.26	664		.975		.037	.057		
CFA2	Metric	801.10	686	.082	.972	-.003	.038	.069	CFA1	Yes
CFA3	Scalar	838.16	708	.002	.968	-.004	.040	.070	CFA2	No
CFA4	Partial scalar (free POS_1, Proc. $justice_1$)	823.08	706	.384	.971	-.001	.038	.070	CFA2	Yes
CFA5	Strict	859.08	734	.182	.969	-.002	.039	.072	CFA4	Yes
Structural Invariance										
SEM1	Baseline model	892.70	744		.963		.042	.080		
SEM2	Factor means	905.27	750	.007	.961	-.002	.043	.082	SEM1	No
SEM3	Factor covariance	895.49	747	.446	.963	.000	.042	.087	SEM1	Yes
SEM4	Partial structural path invariance	894.99	750	.953	.964	.001	.042	.086	SEM3	Yes

Notes. *p* of Δ is the *p* value of the corrected Satorra-Bentler chi-squared difference between models. Invariance was accepted based on *p* of Δ >.05, Δ CFI ≤ .005, Δ RMSEA ≥ .010, and Δ SRMR ≥ .025 for factor loadings and variances or ≥ .005 for intercepts and residuals.

TABLE 4
SUMMARY OF DIRECT AND INDIRECT EFFECTS FOR THE PARTIAL STRUCTURAL INVARIANCE CONSTRAINTS MODEL (SEM4)

	Pre-COVID-19 (n=143)				COVID-19 (n=143)			
	B		β		B		β	
Relationships	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
Professor Support								
←Distributive justice	0.22*		0.16*		0.22*		0.18*	
←Interactional justice	1.08***		0.77***		1.08***		0.71***	
POS								
←Professor support	0.19**		0.25**		0.48***		0.49***	
←Procedural justice	0.66***		0.61***		0.66***		0.52***	
←Distributive justice	0.11	0.04*	0.10	0.04*	-0.12	0.11*	-0.11	0.09*
Intention to drop out								
←POS	-0.35*		-0.28*		-0.02		-0.03	
←Professor support	0.02	-0.07	0.02	-0.07	-0.27*	-0.01	-0.39*	-0.02

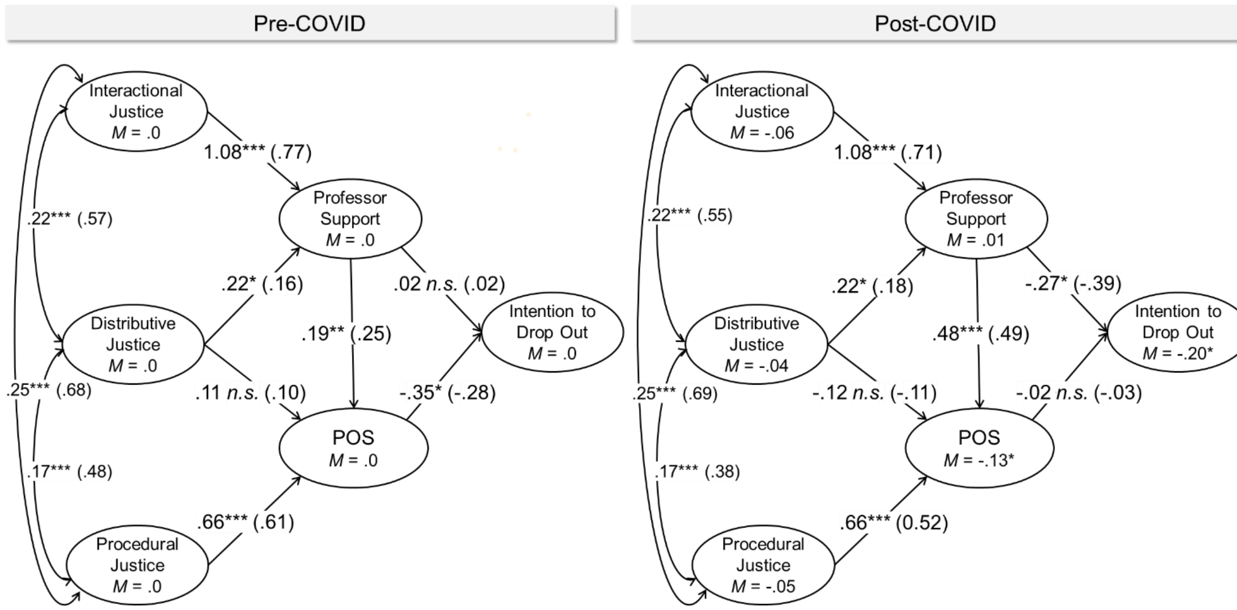
Notes. **p* < .05, ****p* < .01, ****p* < .001. B=unstandardized coefficients. B=standardized coefficients.

Hypotheses Tests

We tested a hypothesized, a priori, structural model with seven structural paths added to the strict invariance constraints model. Fit statistics for the structural model (SEM1) provided evidence of good fit for both samples (SBχ2 [pre-COVID = 495.34 (372); during COVID = 397.36 (372)], CFI=.963, RMSEA=.042, SRMR=.080). We added a direct path from interactional justice to POS to confirm our prediction that they were not directly related. As predicted, the path was not significant for the pre-COVID (p=.391) or during COVID (p=.931) samples, and fit indices suggested that the additional path did not improve model fit (ΔSBχ2(2) = 1.15, p of Δ =.562, RMSEA=.000, SRMR=.001); therefore, for parsimony, the path was eliminated, and the hypothesized (SEM1) model was retained.

We predicted a difference in the structural relationship between perceptions of support and intention to drop out due to a stronger path coefficient for perceived professor support and university support on intention to drop out during COVID. To test the structural invariance of the model across groups, we constrained latent factor means (SEM2), which significantly worsened fit for the data (ΔSBχ2(6) =17.58, p of Δ =.001). Therefore, we followed procedures used in Crombie et al. (2005) for testing group differences by constraining covariances (SEM3) and structural paths. Factor covariances did not significantly worsen fit, (ΔSBχ2(3) = 2.67, p of Δ = .446). Invariance of structural paths was tested using Lagrange multiplier chi-squared fit statistics, which revealed four noninvariant paths (χ2=11.264 (4), p=.02); therefore, they were estimated freely in the final model (SEM4). Figure 2 shows the regression coefficients for the final model. As predicted, interactional justice and distributive justice were positively related to professor support; the effects were invariant across groups. Procedural justice was positively related to POS; the effect was invariant across groups. Also supporting our prediction, a large positive effect from professor support to POS was found in both groups; however, the effect was significantly larger for during COVID (β=.49, p < .01) than pre-COVID (β=.25, p < .01). Our prediction of a positive effect of distributive justice on POS was not supported. The path was significantly different across groups; although the paths were not statistically significant, the finding was noteworthy due to the differences in the direction of the relationship. Before COVID, the effect was positive, β=.11, and negative during COVID, β = -.12. The effect of POS on intention to drop out during COVID was negligible and not significant (β=-.03, p=.85), compared to a large effect before COVID (β=-.28, p=.03). Our prediction of a stronger effect of professor support on intention to drop out during COVID was supported. Before COVID, the path was negligible and not significant (β=.02, p=.85), and during COVID, a large significant effect was found (β=-.39, p=.23). Table 4 reports a summary of direct and indirect effects for the final model.

FIGURE 2
DIFFERENTIAL UNSTANDARDIZED AND (STANDARDIZED) EFFECTS OF PERCEIVED JUSTICE ON PERCEIVED SUPPORT, AND INTENTION TO DROP OUT



Note: *p < .05, ***p < .01, ***p < .001, n.s. p >.05. Factor loadings, intercepts (except POS1 and Procedural justice1), residuals, covariances, and three structural paths (interactional justice→ professor support, distributive justice→ professor support, procedural justice→ POS) constrained to be equal across groups (SEM4). Estimates for the matched sample n [pre-COVID=143; during-COVID=143].

DISCUSSION AND IMPLICATIONS

A growing number of research studies have begun to examine both the psychological and behavioral impact that COVID-19 has had on university students (e.g., Dhar et al., 2020). This recent phenomenon has provided a rare opportunity to study how students are impacted and which students are most vulnerable to difficulties with continuing pursuit of their educational goals. There are numerous reasons why students may have dropped out of their studies during COVID; however, our focus was to examine how students' decision to drop out may have been influenced by their evaluation of treatment received by the university and its agents. These are specific factors over which universities and faculty have some degree of control. Our study contributes to understanding the extent to which perceptions of justice, professor support, and university support influence students' intentions to drop out under normal non-pandemic circumstances (pre-COVID), and during a pandemic event (during COVID).

The results of our study suggest similarities between the pre-COVID and during COVID samples in three hypothesized relationships. First, we found that procedural justice had the strongest positive influence on POS. This was aligned with previous studies that suggested that individuals attribute the fairness of policies and procedures to the organization, as they are generally under the overall organization's control (Kurtessis et al., 2017). Second, we found that interactional justice directly influenced professor support, but did not have a significant direct effect on POS. Our results differ from those found in Camerman et al. (2007), but they were similar to those found in Campbell et al., (2013). This is consistent with the claim that interactional justice directly influences perceptions of the organizational agent rather than the organization itself (Campbell et al., 2013; Colquitt, 2001; Masterson et al., 2000). Third, we found that distributive justice positively influenced professor support in both samples. This result was consistent with findings that suggested that fairness in the distribution of rewards influences perceptions of the organizational agent (Campbell et al., 2013; DeConinck, 2010). As students evaluate the fairness of their outcomes and treatment, they are likely to recall their interactions with their professors and they credit their professors' support. We believe that this emphasizes the importance of professors as a salient source of students' perceptions of justice.

Differences on Attributions of Favorable Treatment

We expected that distributive justice would positively influence, both, professor support and POS. However, while we found support for the influence of distributive justice on professor support, the path from distributive justice to POS was significantly different between samples due to a positive effect pre-COVID, and a negative effect during COVID. This finding is noteworthy as it suggests changes in the attributional processes; the move to remote instruction during COVID, and the "we are all in this together" message shaped the situational antecedent for relational attributions (Eberly et al., 2011), making it more likely for students to see joint responsibility for their outcomes. This also supports the notion that students form expectations and commitments for their instructors and institutions separately (Koskina, 2013).

Although the transition to remote instruction entailed significant work for universities, their staff, and faculty, students perceived a burden due to the significant increase in time and effort required by remote learning (Govindarajan & Srivastava, 2020; Krishnamurthy, 2020). As their inputs increased, so did their needs and expectations (Beech & Anseel, 2020; Ezarik, 2021). Students who observed that their professors responded with supportive behaviors (e.g., extending deadlines, offering larger exam testing windows) felt that the fairness of their outcomes was related to their supportive professors. However, when evaluating the outputs received from the university, their expectations were likely not met. Campus closures resulted in the interruption of multiple services and programs for students, which led students to demand lower tuition fees during remote learning (Lederman, 2021); similarly, COVID impacted the availability of internships for students (Aucejo et al., 2020; Krishnamurthy, 2020), which can significantly affect students' work opportunities upon graduation (Silva et al., 2018). This finding implies that during campus closures that disrupt university services, students are more likely to form negative attitudes about their institutions.

Among the most notable group differences in the model was the relationship of professor support and POS. Consistent with the findings that favorable treatment received from organizational agents should increase POS to the extent that their behaviors can be attributable to the organization (Eisenberger et al., 1986; Kurtessis et al., 2017), the direct path coefficient from professor support to POS was positive and significant for both samples. However, during COVID, the effect was significantly larger than before COVID. Students viewed many of their professors' behaviors towards them as an indication of support by the university. Campus closures during COVID-19 greatly diminished social contact between students and university staff (e.g., library, computer labs, wellness center); however, instructional continuity required that the professor-student relationship be maintained. Thus, the heightened salience of professors as organizational agents increased their influence on students' attitudes about the university.

Many universities in the U.S., including the university where we conducted our study, devoted significant efforts and financial resources to ensure instructional continuity (Krishnamurthy, 2020). However, the actions carried out by universities may have been "behind the scenes" and not easily observable for students. In the forefront were professors, adjusting their courses, creating content suitable for online instruction, and communicating with students. In other words, students did not see the investment on improving learning management systems, but instead they observed the content prepared by their professors; their evaluation of its utility for their academic success shaped their attitudes about their professors and university. Conversely, students who perceived that their professors were not using technology adequately when teaching online blamed the university for not ensuring that professors were prepared (Ezarik, 2021). Our results represent the first direct demonstration of the positive effect of professor support on POS, contributing to the overwhelming support for the relationship of support received by organizational agents and POS, which had primarily focused on supervisors (Kurtessis et al., 2017; Rhoades et al., 2001; Shanock & Eisenberger, 2006). This finding implies that students' perceptions of the university will be influenced by the quality of their interactions with professors to a greater degree when professors' salience increases (e.g., remote learning).

Differences on Reciprocation of Perceived Support

Results of the latent mean analysis revealed that compared to the pre-COVID sample, during COVID students perceived less support from the university, suggesting that students' unmet needs for support increased during the pandemic (Means & Neisler, 2021). Interestingly, despite students' significantly lower POS during COVID, their intentions to drop out were also significantly lower. We expected that POS would decrease students' intention to drop out. This pattern was only observed in the pre-COVID sample. Before COVID, the effect of professor support on intention to quit was fully mediated by POS, which suggests that professors' behaviors that were key influences on students' intentions to drop out may have been perceived as being carried out on behalf of the university or indicative of the university's ethos rather than being representative of professors' individual motivations. This is consistent with findings in the management literature where the effect of supervisor support–as the organizational agent– on turnover intentions was fully mediated by POS (Dawley et al., 2010; Eisenberger et al., 2002).

Unexpectedly, POS had no effect on intention to drop out during COVID. Students' intentions to drop out were strongly influenced by their perceptions of professor support. While students were dealing with the COVID crisis, the support received from professors is what really made the difference. This is not to suggest that the university's responsiveness and support initiatives that were enacted due to COVID were unimportant. Note, we are also not suggesting that professor support is not important during normal operational times, but that in situations of high professor salience, it uniquely influences students' decisions. Simply put, when their success depends on the student-professor dyad, students are more likely to form distinct attachments to their professors than those they form towards the university; students who perceive that their professors value them and care about them are more likely to persist in their studies despite their perceptions about the university. These findings are aligned with previous research of doctoral student retention, where faculty support was found to influence students' persistence in their studies (Ferrer De Valero, 2001; Ivankova & Stick, 2007).

Our findings imply that in times of turbulence, students who perceive that their professors are not supportive are at higher risk of abandoning their studies. Universities should encourage their professors to be more active in supporting students and communicating the different services made available to them by the university. Professors can positively influence a student's social connection by increasing the frequency of their course communications, having live video-conferencing sessions, including opportunities for students to meet virtually with their peers in study groups or assigned teams, and when appropriate putting students in contact with counseling services that the university offers. Our findings also suggest that professor support may be detrimental for student retention in situations in which highly supportive professors leave the university. Therefore, universities should consider rewarding and retaining professors who are supportive to students, as a means to promoting student retention.

Limitations and Directions for Future Research

Despite the novel theoretical contribution of this study and the application of the organizational support framework to an educational context, there are limitations that should be considered and can guide future research. For practical reasons we measured dropout intentions, rather than actually identifying students that dropped out of their studies. The theory of planned behavior (Fishbein & Ajzen, 1975) posits that attitudes lead to intentions, which in turn lead to behavior. Previous studies in the management (Hom et al., 1992; Price, 1997) and education literature (Bean, 1983; Mashburn, 2000) found that intention to quit is a strong predictor of quitting (Thomas & Allen, 2021). Measuring actual attrition by identifying students that dropped out would offer an even more robust test of OST. Although our hypotheses were postulated a priori based on well-established temporal relationships (Eisenberger et al., 2002), our cross-sectional data poses a limitation, which should be addressed in future research.

Our study is also limited in its generalizability—our sample included only students attending a college of business whose academic socialization may influence their attributional processes (cf. Guimond et al., 1989). Future studies with larger and more diverse student samples should be conducted to determine if our findings concerning the importance of university and professor support during times of stress and remote instruction generalize to students pursuing other disciplines. Additionally, our data was collected from a single university that had a highly student-centered and facilitative response to the COVID-19 pandemic. Sampling multiple universities with varying types of response to the pandemic would be able to further evaluate and compare the relative effects of university and professor support.

CONCLUDING COMMENTS

Our study contributes to the existing student retention and attrition research by using perceived organizational support as a framework and highlighting the importance that the actions taken by professors have on students' perceptions of being supported and the impact this has on their intentions to continue with their studies, particularly in times of turbulence.

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APPENDIX 1

TABLE A1
DISTRIBUTION OF DEMOGRAPHICS FOR THE STUDY SAMPLES

	Initial Sample (n=351)					Final Matched Sample (n=286)				
Characteristic	Pre-COVID	During COVID	χ2(df)	*p*	*V*	Pre-COVID	During COVID	χ2 (df)	*p*	*V*
Age			1.94 (5)	.86	.08			1.62 (5)	.90	.08
(1) 20 or younger	4.8%	4.4%				4.9%	4.9%			
(2) 21-25	28.3%	33.0%				32.2%	28.0%			
(3) 26-30	20.7%	21.8%				23.8%	21.0%			
(4) 31-35	20.0%	15.0%				16.1%	20.3%			
(5) 36-40	11.7%	11.7%				10.5%	11.2%			
(6) 40 or older	14.5%	14.1%				12.6%	14.7%			
Gender			3.24 (2)	.20	.09			1.98 (2)	.37	.08
(1) Male	26.2%	25.2%				25.2%	26.6%			
(2) Female	71.0%	74.3%				74.1%	70.6%			
(4) Prefers not to say	2.8%	0.5%				0.7%	2.8%			
Graduate/undergraduate			0.21 (1)	.65	.03			0.25 (1)	.62	.03
(1) Undergraduate	33.8%	37.9%				36.4%	33.6%			
(2) Graduate	66.2%	62.1%				62.9%	66.4%			
Race/Ethnicity			0.20 (4)	.99	.02			0.27 (4)	.99	.03
(1) White	41.6%	43.2%				39.9%	42.0%			
(2) Hispanic or Latino	24.2%	23.0%				24.5%	25.2%			
(3) Black or African American	12.8%	11.7%				12.6%	11.9%			
(4) Asian	12.1%	12.2%				13.3%	11.9%			
(5) Other	9.4%	9.9%				9.8%	9.1%			
GPA			1.12 (3)	.77	.06			1.85 (3)	.60	.09
(1) Over 3.5	35.4%	34.1%				28.0%	35.7%			
(2) 3.0 - 3.5	43.1%	47.8%				51.7%	42.7%			
(3) 2.5 - 2.99	16.7%	14.6%				15.4%	16.8%			
(4) Less than 2.5	4.9%	3.4%				4.9%	4.9%			
Financial aid			2.20 (1)	.14	.08			1.58 (1)	.21	.07
(1) Yes	62.8%	70.9%				70.6%	62.9%			
(2) No	37.2%	29.1%				29.4%	37.1%			
Parent education			0.99 (3)	.80	.05			0.31 (3)	.95	.03
(1) Up to high school	32.9%	33.5%				32.2%	32.9%			
(2) Some college up to 2-year degree	23.8%	24.3%				22.4%	21.7%			
(3) Bachelor's degree	26.6%	29.1%				28.0%	25.9%			
(4) Graduate degree	16.8%	13.1%				17.5%	19.6%			
n	145	206				143	143			

Notes. df = degrees of freedom; V = Cramer's V effect size. The demographic variables in the table were input into the propensity score matching algorithm to match the samples using nearest neighbor matching method with the caliper set to .20.

APPENDIX 2

TABLE B1
PATTERN (P) AND STRUCTURE (S)COEFFICIENTS FOR THE MEASUREMENT MODEL: PRE-COVID SAMPLE

	Intention to Drop Out		POS		Professor Support		Procedural Justice		Interactional Justice		Distributive Justice	
Variable	P	S	P	S	P	S	P	S	P	S	P	S
Intention to drop out$_1$	0.63	0.63		-0.15		-0.09		-0.17		-0.13		-0.19
Intention to drop out$_2$	0.83	0.83		-0.20		-0.12		-0.22		-0.17		-0.25
Intention to drop out$_3$	0.88	0.88		-0.21		-0.13		-0.23		-0.18		-0.26
Intention to drop out$_4$	0.96	0.96		-0.23		-0.14		-0.25		-0.20		-0.29
POS$_1$		-0.19	0.76	0.76		0.51		0.62		0.45		0.38
POS$_2$		-0.20	0.82	0.82		0.55		0.67		0.49		0.41
POS$_3$		-0.18	0.72	0.72		0.48		0.59		0.43		0.36
POS$_4$		-0.16	0.67	0.67		0.45		0.54		0.40		0.33
POS$_5$		-0.17	0.68	0.68		0.45		0.55		0.40		0.34
POS$_6$		-0.14	0.56	0.56		0.38		0.46		0.34		0.28
Professor support$_1$		-0.13		0.57	0.84	0.84		0.54		0.69		0.50
Professor support$_2$		-0.15		0.66	0.97	0.97		0.62		0.80		0.58
Professor support$_3$		-0.12		0.52	0.77	0.77		0.49		0.63		0.46
Professor support$_4$		-0.08		0.38	0.56	0.56		0.36		0.46		0.33
Procedural justice$_1$		-0.18		0.55		0.42	0.67	0.67		0.40		0.28
Procedural justice$_2$		-0.19		0.59		0.46	0.72	0.72		0.43		0.30
Procedural justice$_3$		-0.19		0.58		0.45	0.70	0.70		0.42		0.29
Procedural justice$_4$		-0.23		0.71		0.55	0.87	0.87		0.52		0.36
Procedural justice$_5$		-0.21		0.64		0.50	0.78	0.78		0.47		0.32
Interactional justice$_1$		-0.12		0.35		0.48		0.35	0.59	0.59		0.34
Interactional justice$_2$		-0.17		0.48		0.66		0.48	0.80	0.80		0.46
Interactional justice$_3$		-0.19		0.55		0.75		0.55	0.92	0.92		0.53
Interactional justice$_4$		-0.17		0.49		0.67		0.49	0.82	0.82		0.47
Distributive justice$_1$		-0.22		0.37		0.44		0.31		0.43	0.74	0.74
Distributive justice$_2$		-0.24		0.39		0.47		0.32		0.45	0.78	0.78
Distributive justice$_3$		-0.21		0.34		0.41		0.29		0.40	0.69	0.69
Distributive justice$_4$		-0.26		0.42		0.51		0.35		0.49	0.85	0.85
Distributive justice$_5$		-0.26		0.43		0.51		0.35		0.50	0.86	0.86
Factor Correlations												
Intention to drop out		0.83										
POS		-0.24		0.84								
Professor Support		-0.15		0.67		0.89						
Procedural Justice		-0.26		0.82		0.64		0.87				
Interactional Justice		-0.21		0.60		0.82		0.60		0.88		
Distributive Justice		-0.30		0.50		0.60		0.41		0.58		0.89
CR		0.90		0.85		0.93		0.80		0.87		0.73
AVE		0.69		0.70		0.79		0.75		0.78		0.78

Notes. CR= Composite Reliability. AVE=Average Variance Extracted. Square root of AVE along the diagonal. Matched sample (n=143).

TABLE B2
PATTERN (P) AND STRUCTURE (S)COEFFICIENTS FOR THE MEASUREMENT MODEL: DURING COVID SAMPLE

	Intention to		POS		Professor		Procedural		Interactional		Distributive	
Variable	P	S	P	S	P	S	P	S	P	S	P	S
Intention to drop out$_1$	0.63	0.63		-0.21		-0.25		-0.19		-0.24		-0.28
Intention to drop out$_2$	0.87	0.87		-0.29		-0.34		-0.27		-0.34		-0.39
Intention to drop out$_3$	0.68	0.68		-0.23		-0.27		-0.21		-0.26		-0.30
Intention to drop out$_4$	0.93	0.93		-0.31		-0.37		-0.28		-0.36		-0.41
POS$_1$		-0.28	0.84	0.84		0.67		0.67		0.59		0.32
POS$_2$		-0.29	0.85	0.85		0.68		0.68		0.60		0.33
POS$_3$		-0.29	0.87	0.87		0.69		0.69		0.61		0.34
POS$_4$		-0.26	0.77	0.77		0.61		0.61		0.54		0.30
POS$_5$		-0.25	0.74	0.74		0.59		0.58		0.51		0.28
POS$_6$		-0.16	0.50	0.48		0.38		0.38		0.34		0.19
Professor support$_1$		-0.33		0.66	0.83	0.83		0.59		0.65		0.46
Professor support$_2$		-0.33		0.67	0.85	0.85		0.61		0.67		0.47
Professor support$_3$		-0.35		0.70	0.88	0.88		0.63		0.69		0.49
Professor support$_4$		-0.23		0.46	0.58	0.58		0.41		0.45		0.32
Procedural justice$_1$		-0.25		0.65		0.59	0.83	0.83		0.60		0.35
Procedural justice$_2$		-0.24		0.61		0.55	0.77	0.77		0.56		0.33
Procedural justice$_3$		-0.25		0.65		0.59	0.83	0.83		0.60		0.35
Procedural justice$_4$		-0.27		0.70		0.63	0.88	0.88		0.64		0.38
Procedural justice$_5$		-0.24		0.61		0.55	0.77	0.77		0.56		0.33
Interactional justice$_1$		-0.22		0.39		0.44		0.41	0.57	0.57		0.31
Interactional justice$_2$		-0.32		0.57		0.64		0.59	0.81	0.81		0.44
Interactional justice$_3$		-0.34		0.60		0.68		0.62	0.86	0.86		0.47
Interactional justice$_4$		-0.31		0.56		0.63		0.58	0.80	0.80		0.44
Distributive justice$_1$		-0.34		0.29		0.42		0.32		0.42	0.76	0.76
Distributive justice$_2$		-0.38		0.33		0.48		0.36		0.47	0.85	0.85
Distributive justice$_3$		-0.37		0.32		0.47		0.36		0.46	0.83	0.83
Distributive justice$_4$		-0.37		0.32		0.47		0.36		0.46	0.83	0.83
Distributive justice$_5$		-0.36		0.31		0.45		0.35		0.44	0.81	0.81
Factor Correlations												
Intention to drop out		0.79										
POS		-0.33		0.87								
Professor Support		-0.39		0.79		0.89						
Procedural Justice		-0.31		0.79		0.71		0.90				
Interactional Justice		-0.39		0.70		0.79		0.72		0.87		
Distributive Justice		-0.44		0.38		0.56		0.43		0.55		0.90
CR		0.86		0.90		0.94		0.85		0.85		0.77
AVE		0.62		0.76		0.78		0.82		0.76		0.82

Notes. CR= Composite Reliability. AVE=Average Variance Extracted. Square root of AVE along the diagonal. Matched sample (n=143). SBχ2 = 331.94, df=332, CFI=, RMSEA=.037, SRMR=.057.