Lecturers’ turnover intention and intention to remain with the organization: a dynamic cross-lagged panel model estimation using the PLSe2 method

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Abstract

Purpose – Although numerous studies have been conducted to explore the impact of various factors on employees’ turnover intention and intention to remain with the organization, the relationship between these two constructs remains largely unexplored. Considering the significance of these constructs, particularly in the context of the COVID-19 pandemic, the authors aimed to investigate their association within an academic environment using a dynamic modeling approach.

Design/methodology/approach – This study follows a quantitative approach and utilizes a longitudinal survey design. The authors utilized a cross-lagged panel model (CLPM) and employed the parametric efficient partial least squares (PLSe2) methodology to estimate the dynamic model using data gathered from lecturers associated with both public and private universities in Malaysia. In order to offer methodological insights to applied higher education researchers, the authors also compared the results with maximum likelihood (ML) estimation.

Findings – The findings of the authors’ study indicate a reciprocal relationship between turnover intention and intention to remain with the organization, with intention to remain with the organization being a stronger predictor. Moreover, situational factors were found to have a greater influence on eliciting turnover intention within academic settings. As anticipated, the use of the PLSe2 methodology resulted in higher R² values compared to ML estimation, thereby reinforcing the effectiveness of PLS-based methods in explanatory-predictive modeling in applied studies.

Practical implications – The authors’ findings suggest prioritizing policies that enhance training and consultation sessions to foster positive attitudes among lecturers. Positive attitudes significantly impact judgment-driven behaviors like turnover intention and intention to remain with the organization. Additionally, improving working environments, which indirectly influence judgment-driven behaviors through factors like affective work events, affect and attitudes, should also be considered.

Originality/value – This study pioneers the examination of the causal relationship between turnover intention and intention to remain with the organization, their stability over time and the association of changes in these variables using a dynamic CLPM in higher education. It introduces the novel application of the cutting-edge methodologies in applied studies.
edge-PLSe2 methodology in estimating a CLPM, providing valuable insights for researchers in explanatory-predictive modeling.

Keywords: Turnover intention, Intention to remain with the organization, COVID-19 lockdown, Cross-lagged panel model (CLPM), PLSe2

Paper type: Research paper

Introduction
Within the last few years, many industries and businesses have been adversely affected by the COVID-19 pandemic. Governments introduced lockdowns and quarantines to control the spread of the coronavirus (Vazirani and Bhattacharjee, 2022). As a result, the closure of non-essential businesses, border restrictions and the adoption of remote work led to a profoundly stressful scenario that significantly reshaped numerous aspects of our lives. This remains pertinent considering the empirical evidence linking fear of COVID-19 to feelings of job insecurity and turnover intentions among lecturers (Kakar et al., 2023). This unprecedented situation led to a substantial increase in mental health challenges (Moron et al., 2023).

Within the higher education domain, the landscape of scientific collaborations underwent a significant shift, particularly in the wake of COVID-19. Interestingly, countries heavily affected by the pandemic and those with relatively lower gross domestic products (GDPs) exhibited a greater propensity for engaging in scientific globalism compared to their counterparts with higher GDPs (Lee and Haupt, 2021). In addition, contact learning shifted to online learning to curtail learning losses (Flores et al., 2022), creating completely new conditions alongside numerous challenges for university education and university community across the globe (Eli-Chukwu et al., 2023).

While online course delivery has indeed been acknowledged as a significant source of satisfaction for lecturers (Marasi et al., 2022), it’s important to recognize that its impact isn’t universally perceived as entirely positive, given its potential to disrupt both pedagogical roles and personal lives (Watermeyer et al., 2021). This holds importance as existing studies highlight how lecturers’ job satisfaction plays a role in reducing their turnover intention (Otache and Inekwe, 2022). Furthermore, research indicates a causal link between maintaining work–life balance and decreased turnover intentions among lecturers (Kakar et al., 2021).

Therefore, providing support to public sector employees to ensure their effective operation during the COVID-19 pandemic is crucial (Schuster et al., 2020). Indeed, maintaining lecturers’ motivation and satisfaction is vital, as evidence suggests that perceived organizational support boosts lecturers’ affective commitment and reduces turnover intentions (Esop and Timms, 2019). Specifically, research suggests that motivation plays a pivotal role in reducing turnover intention during this challenging period (Demirovic Bajrami et al., 2021). Additionally, studies have consistently shown a strong negative correlation between job satisfaction and physical withdrawal behaviors like absenteeism and turnover (Schemerhorn et al., 2020).

Despite the implementation of various supportive measures, turnover intention can still be observed among lecturers, mirroring trends seen in other educational contexts (e.g. Ding and Lyu, 2023). Although previous studies, guided by the affective events theory (AET) (Weiss and Beal, 2005), have examined the influence of attitudes (e.g. job satisfaction and motivation) on judgment-driven behaviors (e.g. turnover intention and intention to remain with the organization), the direction of causality between turnover intention and intention to remain with the organization, as well as the stability of these constructs and the extent to which their changes are interrelated over time, have received limited exploration in previous research. Given that new COVID-19 variants have been reported and may become pandemic again anytime in the near future and considering the critical importance of turnover intention and intention to remain with the organization in the context of the COVID-19 pandemic (Demirovic Bajrami et al., 2021), we conducted a study using a cross-lagged design (Newsom, 2015). Our aim was to explore the nature of the relationship between these two constructs and prospectively examine their
The primary research questions addressed in this study are: (1) what is the nature of the relationship between lecturers' turnover intention and their intention to remain with the organization during and after the COVID-19 lockdown? (2) To what degree are changes in turnover intention associated with changes in intention to remain with the organization at the end and two months after the COVID-19 lockdown? And (3) to what extent are lecturers' turnover intention and intention to remain with the organization stable across time during the pandemic? To address our research questions, we employed a cross-lagged panel model (CLPM) to analyze the relationship between turnover intention and intention to remain with the organization, utilizing its ability to identify potential causal directions (Biesanz, 2012). As a methodological advancement in our study, we utilized the parametric efficient partial least squares (PLSc2) estimator (Bentler and Huang, 2014; Ghasemy et al., 2021b; Ghasemy, 2022) for CLPM estimation, and we compared the results with maximum likelihood (ML) estimation to offer insights to applied higher education researchers regarding this cutting-edge model specification, estimation and evaluation methodology. Subsequently, we interpreted the findings, discussed their implications, provided concluding remarks and proposed potential avenues for future research.

Theoretical background

Turnover is defined as employees voluntarily and involuntarily leaving an organization (Coomber and Louise Barriball, 2007) and turnover intention is its immediate precursor and best predictor (Tett and Meyer, 1993) though it might not necessarily result in actual turnover (Ma and Trigo, 2012). In contrast, intention to remain with the organization is seen as the stated probability of an individual staying in his or her present position (Cowden et al., 2011) and is more likely to be expressed by organizational members with high levels of affective commitment than those who are viewed as less affectively committed employees (Kehoe and Wright, 2013). These two constructs are conceptually linked and often considered as opposite ends of a continuum though the direction of causality between these two variables has not been investigated.

Both turnover intention and intention to remain with the organization are judgment-driven behaviors (Weiss and Beal, 2005) and, therefore, are correlated. Notably, affect and emotions play a vital role in this regard to the extent that employees stay in their organizations based on their feelings about their jobs (Tett and Meyer, 1993). This is consistent with AET (Weiss and Beal, 2005), which explains how affective responses cause attitudes (e.g. satisfaction, engagement and motivation) that, in turn, influence judgment-driven behaviors that are pursued through a long and deliberate process of cognitive evaluations of affective work events (e.g. role and interpersonal conflicts (Ghasemy et al., 2021a)).

Focusing on job satisfaction as one of the main attitudes influencing judgment-driven behaviors, Guenter et al. (2014) suggested that the negative affective states, caused by delay in information exchange, lead to a decrease in job satisfaction and ultimately increase withdrawal behavior among the coworkers; The findings of Padilla-González and Galaz-Fontes (2015) indicated a significant relationship between faculty members’ intention to leave their institutions and factors such as job satisfaction, mediated by job stability and the presence of adequate working conditions; Otache and Inekwe (2022) and Samad et al. (2022) showed that job satisfaction is a cause of lower levels of turnover; and Strahan and Credé (2015) found evidence for the moderate to strong relationships between satisfaction with college and retention intentions.

With respect to the impact of other attitudes on judgment-driven behaviors, Gambino (2010) found evidence for the impact of commitment on intention to remain with the organization among nurses; Tourangeau et al. (2010), through their qualitative inquiry, proposed a model for determinants of nurses’ intention to remain employed and motivation-
related factors, such as organizational support, work environment condition and rewards; Esop and Timms (2019) presented evidence showcasing the negative influence of continuing commitment on lecturers’ turnover intention; Shareef and Atan (2019) and Kim (2018) showed that motivation negatively influences turnover intention; finally, Mak and Sockel (2001) found evidence for motivation’s impact on intention to remain with the organization.

Despite the literature review on the AET (Weiss and Beal (2005) identifies many empirical studies testing the attitude → judgment-driven behavior proposition, the nature of the expected relationship between turnover intention and intention to remain with the organization – as two judgment-driven behaviors – is under-explored. In essence, there is a dearth of longitudinal studies examining the stability and causal direction between these two constructs, both in a general context and specifically in relation to the global COVID-19 pandemic. Therefore, in order to study the stability of these theoretical constructs over time and determine the causality direction in the relationship between them, we build a CLPM (Newsom, 2015), which is displayed in Figure 1. Given the characteristics of these constructs, it becomes apparent that the stability or autoregressive coefficients exhibit positive values, whereas the crucial cross-lagged coefficients, which help determine the direction of causality, demonstrate negative relationships. Furthermore, when examining the significant effects between the constructs over time using the CLPM methodology and in accordance with current practice and established conventions, we refrain from formulating and testing specific hypotheses, instead relying on the analysis results to reveal the evolving nature of the relationship between the two constructs over time.

### Method

**Research design and analytic procedure**

Our study follows a quantitative approach and employs a longitudinal survey design. We estimated a CLPM (Newsom, 2015; Biesanz, 2012) to prospectively investigate the nature of the relationship between two judgment-driven behaviors, namely, turnover intention and intention to remain with the organization. Importantly, these two variables influence each other across time, thus functioning as both independent and dependent variables according to the time intervals within our CLPM. We leveraged the cutting-edge PLSe2 methodology (Bentler and Huang, 2014; Huang, 2013; Ghasemy et al., 2021b, 2023; Ghasemy, 2022; Ghasemy and Frömling, 2023) in estimating our CLPM. Notably, the main advantages of the PLSe2 methodology in applied
research might be summarized as: (1) It is the only PLS-based method capable of estimating longitudinal models in explanatory-predictive studies (Ghasemy, 2023; Ghasemy and Frömbling, 2023); (2) It enables testing of non-recursive models (Bentler and Huang, 2014; Ghasemy et al., 2023); (3) It accommodates both multivariate normal and non-normal data (Ghasemy, 2022; Ghasemy et al., 2021b), leveraging the robust Satorra-Bentler (S-B) method (Satorra and Bentler, 1994); (4) It demonstrates better performance in terms of effect size and power (Deng and Yuan, 2023; Rigdon et al., 2017); and (5) It provides well-established fit indices and convenient standard errors (Bentler and Huang, 2014; Ghasemy, 2022; Ghasemy et al., 2021b). Furthermore, we presented the ML estimation results of our model for researchers interested in comparing the outcomes of the PLSe2 and ML methodologies. To specify and estimate the model, we used the EQS 6.4 statistical package (Bentler, 2006; Bentler and Wu, 2018).

Measures
We measured turnover intention using the three-item turnover intention scale developed by Tillman et al. (2018). With respect to intention to remain with the organization, we used the four-item scale developed by Kehoe and Wright (2013). To rate the items, we provided the respondents with a five-point Likert scale anchored by 1 (strongly disagree) to 5 (strongly agree), which was symmetric and equidistant (Ghasemy et al., 2020). All the items with their descriptive statistics appear in online Appendix A1.

Population and sample
For our study, we focused on lecturers affiliated with Malaysian public and private universities. We began by compiling a database of email addresses from 23,050 lecturers using the contact information available on institutional websites. This database served as the input for the SurveyMonkey platform, where we conducted a digital survey to gather data from 20 public and 26 private institutions. In April 2020 (Time 1: at the start of the lockdown), we obtained 707 surveys, equating to a response rate of 3%. Among these, 698 surveys met the criteria for analysis due to their completeness. We then conducted subsequent surveys in June 2020 (Time 2: at the end of the lockdown) and in August 2020 (Time 3: two months after the lockdown). These surveys were directed at the same cohort of 698 lecturers. During Time 2 and Time 3, we garnered 326 and 298 completed surveys, respectively. Nevertheless, due to attrition among our subjects, we relied on data collected from 220 random lecturers who had successfully completed the survey during all three time points.

Among our sample, 98 participants (44.5%) were male and 122 (55.5%) were female. In terms of academic ranks, 55 participants (25%) were lecturers, 89 (40.5%) were senior lecturers, 43 (19.5%) were associate professors and 33 (15%) were professors. Regarding work experience, 146 participants (66.4%) had previous higher education work experience, while 74 (33.6%) did not have relevant experience. Additionally, 46 participants (20.9%) held official leadership positions, such as dean or head of department, while 174 (79.1%) did not have formal leadership roles in their universities. Lastly, the average age of the participants was 46.38 (SD = 8.92).

Results
Our initial emphasis was on predicting and replacing missing values. Given that the maximum number of missing values per indicator was 2 (equating to less than 1%), we chose to replace missing values with the median of the observed indicators. We based this choice on the guidance of Tabachnick and Fidell (2013), who posited that when only a minor fraction of data points (5% or lower) are randomly missing in a large dataset, the issues are less severe, and most methods for managing missing values produce comparable outcomes. Next, we assessed latent variables' measurement invariance across time. In line with the discussion
made by Biesanz (2012), since we were not interested in assessing the indicator intercepts, we only focused on establishing three types of measurement invariance, namely configural, weak (metric) and strict (residual) in our study.

In so doing, we specified and estimated a six-factor longitudinal confirmatory factor analysis (CFA) model to identify multivariate outliers, assess multivariate normality of our data and, ultimately, achieve configural invariance. The PLSe2 estimation results revealed that the normalized estimate of multivariate kurtosis (Yuan et al., 2004) was 54.81 and three cases had large contributions to this statistic. We removed these three multivariate outliers and re-estimated the model. Removing these cases reduced the normalized estimate of multivariate kurtosis to 45.59. Although all factor loadings were statistically significant, we noticed that Item 1 of the turnover intention scale as well as Items 3 and 4 of the intention to remain with the organization scale were not contributing items at the three measurement occasions. Therefore, we removed these three items and re-estimated the model. Through this run of the analysis, the normalized estimate of multivariate kurtosis was reduced to 31.94, a value greater than 3 and thus, in line with the discussions made by Bentler (2006), suggestive of the multivariate nonnormal nature of our data. Consequently, we considered the robust Satorra–Bentler (S–B) methodology (Satorra and Bentler, 1994) through which corrected standard errors and fit indices are generated in the face of multivariate non-normality. Online Appendix A2 displays items’ factor loadings, the average variance extracted (AVE) values and the composite reliability (CR) estimates based on the PLSe2 method for the final configural invariance model (Model 1), implying the fulfillment of all quality criteria. In addition, for the sake of comparison, we provided the same statistics based on the ML methodology. Consistent with the simulation results of Bentler and Huang (2014) and Ghasemy et al. (2021b), we observed that the results were comparable. Moreover, Model 1 exhibited an incredibly good fit to the data (CFI = 0.995 and RMSEA = 0.037, see Table 1).

Next, we used the configural invariance model (Model 1) as the baseline model to evaluate the extent to which other levels of factorial invariance are supported by our data. Given that for weak factorial invariance, the loadings are not allowed to vary across measurements’ occasions, we specified equality constraints on the corresponding loadings across the three measurement occasions (Model 2) and estimated the model using the PLSe2 estimator. The results revealed an incredibly good fit of the model to the data (CFI = 0.996 and RMSEA = 0.030, see Table 1). Thereafter, we focused on the third level of invariance (i.e., strict factorial invariance) and added an additional equality constraint to the model to keep the corresponding indicators’ residual variances the same across measurement occasions (Model 3). The PLSe2 estimation of Model 3 showed that the model fits the data well too (CFI = 0.993 and RMSEA = 0.038, see Table 1). As elaborated by Newsom (2015), since the change in model fit from the lower level of invariance (configural invariance – Model 1) to the higher level of invariance (strict invariance – Model 3) was negligible in our study, as evidenced by the non-significant Δ S-B $\chi^2$ statistics (see Table 1), we concluded that different levels of factorial invariance hold for our model, and thus, we favored the more parsimonious constrained model (Model 3) in our subsequent analyses.

Using our parsimonious strict model (Model 3), we built and evaluated the fit of five structural cross-lagged panel models. Regarding the first cross-lagged model (Model 4), we estimated all structural coefficients. Model fits were good (CFI = 0.972, RMSEA = 0.072, see Table 1). In the second cross-lagged model (Model 5), we constrained the stability autoregressive coefficients to be equal across the time intervals. The difference in fit between Models 4 and 5 was negligible as evidenced by the Δ S-B $\chi^2$ = 0.812 and $p = 0.666$. In the third cross-lagged model (Model 6), we additionally constrained all cross-lagged coefficients to be equal across time. The difference in fit between Models 5 and 6 was negligible (Δ S-B $\chi^2$ = 2.442 and $p = 0.295$). Regarding the fourth cross-lagged model, we imposed another equality constraint to Model 6 and constrained items’ residual covariances across time (Model 7). Again, the difference in fit between Models 6 and 7 was negligible as evidenced by the Δ
<table>
<thead>
<tr>
<th>Model</th>
<th>Method</th>
<th>S-B $\chi^2$</th>
<th>df</th>
<th>$\Delta$ df</th>
<th>$\Delta$ S-B $\chi^2$, p-value</th>
<th>NFI</th>
<th>TLI</th>
<th>CFI</th>
<th>IFI</th>
<th>RMSEA</th>
<th>90% CI for RMSEA</th>
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<td>Model 1</td>
<td>Configural invariance model</td>
<td>PLSe2</td>
<td>40.191</td>
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<td>N/A</td>
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<td>ML</td>
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<td>N/A</td>
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<td>Model 2</td>
<td>Weak (metric) invariance model</td>
<td>PLSe2</td>
<td>46.361</td>
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<td>5.548, 0.235</td>
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<td>0.987</td>
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<td></td>
<td>ML</td>
<td>55.673</td>
<td>35</td>
<td>4</td>
<td>8.546, 0.074</td>
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<td>Strict (residual) invariance model</td>
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<td>56.399</td>
<td>43</td>
<td>8</td>
<td>9.954, 0.268</td>
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<td>0.987</td>
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<td></td>
<td>ML</td>
<td>73.689</td>
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<td>15.464, 0.061</td>
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<td>Model 4</td>
<td>Structural model—all regression coefficients estimated</td>
<td>PLSe2</td>
<td>98.923</td>
<td>47</td>
<td>N/A</td>
<td>N/A</td>
<td>0.948</td>
<td>0.955</td>
<td>0.972</td>
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<td>Structural model—autoregressive coefficients constrained</td>
<td>PLSe2</td>
<td>98.067</td>
<td>49</td>
<td>2</td>
<td>0.812, 0.666</td>
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<td>Model 6</td>
<td>Structural model—cross-lagged coefficients constrained</td>
<td>PLSe2</td>
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<td>51</td>
<td>2</td>
<td>2.442, 0.285</td>
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<td></td>
<td>ML</td>
<td>94.884</td>
<td>51</td>
<td>2</td>
<td>0.862, 0.650</td>
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<td>Model 7</td>
<td>Structural model—items’ residual covariances constrained</td>
<td>PLSe2</td>
<td>97.366</td>
<td>55</td>
<td>4</td>
<td>1.825, 0.768</td>
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<td>ML</td>
<td>96.512</td>
<td>55</td>
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<td>0.965, 0.915</td>
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<td>Model 8</td>
<td>Structural model—disturbance variances across time and covariances within time constrained</td>
<td>PLSe2</td>
<td>93.108</td>
<td>58</td>
<td>3</td>
<td>3.401, 0.339</td>
<td>0.951</td>
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<td>ML</td>
<td>104.482</td>
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</table>

**Note(s):** $\Delta$ S-B $\chi^2$ is not $\chi^2$-distributed and to compute this statistic, we followed the guidelines by Bentler (2006, p. 158)

All reported fit indices are robust indices based on the Satorra-Bentler methodology (Satorra and Bentler, 1994)

The ML-based statistics and fit indices in italics are merely provided for the purpose of fit indices’ comparison

**Source(s):** Authors’ own work
S-B $\chi^2 (4) = 1.825$ and $p = 0.768$. Next, we constrained the disturbance variances across wave 2 and 3 and also disturbance covariances within each wave – that capture the degree to which changes on one construct are associated with changes on the other construct at the same time point (Biesanz, 2012) – to build and estimate Model 8. We observed that the difference in fit between Models 7 and 8 was negligible ($\Delta$ S-B $\chi^2 (2) = 3.401$ and $p = 0.339$). Consequently, we favored the parsimonious Model 8 and retained the longitudinal constraints on the structural parameter coefficients, residual variances, residual covariances, disturbance variances and disturbance covariances. All the detailed fit indices based on the PLSe2 method for Model 1 to Model 8 appear in Table 1. In addition, for the sake of comparison, we have provided the fit indices based on the ML estimation in this table.

Figure 2 presents the final CLPM (Model 8). In line with the recommendation made by Newsom (2015) with respect to the wisest way of inspecting and reporting the results, while we have reported both unstandardized and standardized estimates, we resort to the standardized estimates for the interpretation since they are connected to common definitions of variance accounted for by a predictor.

As displayed in Figure 2, intention to remain with the organization is a more stable construct across time as evidenced by the size of the standardized path coefficients ($\beta = 0.776$ in the first interval and $\beta = 0.768$ in the second). Also, we observed that the cross-lagged effects of intention to remain with the organization on turnover intention ($\beta = -0.207$ and $\beta = -0.202$) are slightly stronger than the effects of turnover intention on intention to remain with the organization ($\beta = -0.120$ and $\beta = -0.121$). Nevertheless, given that all cross-lagged effects were statistically significant, practically relevant and relatively equivalent, our best conclusion was that the relationship between these two constructs was reciprocal. With respect to the nondirectional associations displayed in Figure 2, our results uncovered that the relationship between the two constructs at the first assessment time (the beginning of the COVID-19 lockdown in April 2020) was large ($r = -0.603$). Also, the relationships between

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**Figure 2.** Model 8 with unstandardized and standardized (italicized) estimates based on PLSe2

**Note(s):** The figure omits indicators, residual variances, and cross-time residual covariances. All parameters are statistically significant. The ML-based $R^2$ statistics are $R^2_{(F2)} = 0.557$, $R^2_{(F3)} = 0.559$, $R^2_{(F5)} = 0.622$, and $R^2_{(F6)} = 0.622$

**Source(s):** Authors’ own work
other factors that would influence these constructs over time – the variables/constructs that have not been assessed in our study but have been summarized as disturbance terms in our model – were meaningful over time ($\psi = -0.287$). Last, we observed that the $R^2$ values of turnover intention at the end ($R^2 = 0.628$) and two months after the COVID-19 lockdown ($R^2 = 0.633$) were slightly smaller than the $R^2$ values of intention to remain with the organization at the end ($R^2 = 0.728$) and two months after the lockdown ($R^2 = 0.726$), indicating that situational factors (e.g. COVID-19 pandemic circumstances) were more influential in affecting academic's turnover intention than intention to remain with the organization.

The detailed estimation results (factor loadings and path coefficients) based on the PLSe2 and ML methodologies – for the sake of comparison – appear in online appendices A2 and A3. Also, all factor variances/covariances, disturbance variances/covariances, and residual variances were found to be statistically significant through the PLSe2 method, although detailed reporting of these findings is not provided in this paper. Moreover, it should be highlighted that while the fit indices of the specified and estimated models based on the PLSe2 and ML methodologies (see Table 1) were comparable and communicated the same message in terms of the fit of the models to the data, the obtained $R^2$ values based on the PLSe2 were larger than the $R^2$ values based on the ML method in our final model (see Figure 1), which, of course, was expected due to the characteristics of the PLS-based methods (Ghasemy et al., 2020) and hence confirming the strength of PLS-based methods in explanatory-predictive studies.

Discussion of the findings

Theoretical implication

While the relationship between turnover intention and intention to remain with the organization, as two judgment-driven behaviors (Weiss and Beal, 2005), may be intuitively understood, our study goes beyond common sense by providing robust empirical evidence for the reciprocal nature of this relationship. Our findings are in alignment with the attitude → judgment-driven behavior proposition of the AET. More specifically, we observed covariances between turnover intention and intention to remain with the organization at each assessment point, and as highlighted by Newsom (2015), these covariances “may be due to synchronous causal effects at either time point or any extraneous variable responsible for the association between the variables.” Therefore, in our case and in line with the AET, it might be that attitudes are responsible for the covariances between the two constructs.

Despite our results revealed that the nature of the relationship between turnover intention and intention to remain with the organization during the period of assessment is likely to be reciprocal with intention to remain with the organization being slightly better predictor of turnover intention in both time intervals ($\beta = -0.207$ versus $\beta = -0.120$ in the first time interval and $\beta = -0.202$ versus $\beta = -0.121$ in the second), this finding might be generalized to other time intervals due to the support for the stationarity assumption (Biesanz, 2012). We also observed a significant and relevant association ($\psi = -0.287$) between changes on turnover intention and changes on intention to remain with the organization at the end and two months after the COVID-19 lockdown that, again, might be generalizable to other time intervals. Furthermore, we observed that while both constructs were stable across time, intention to remain with the organization was more stable than turnover intention as evidenced by the size of the autoregressive parameters. Additionally, the comparison of disturbance variances showed that the situational factors (e.g. COVID-19 circumstances) were stronger in influencing turnover intention than intention to remain with the organization, suggesting that turnover intention is more situationally elicited while intention to remain with the organization is more internally elicited.
Practical implications

Our results suggest that policies to enhance lecturers’ attitudes such as job satisfaction, commitment and motivation should be focused since, as elaborated by Weiss and Beal (2005), attitudes triggered by affective states influence judgment-driven behaviors (e.g. turnover intention and intention to remain with the organization). In relation to this, initiatives such as establishing mentorship opportunities for new lecturers, allowing lecturers a degree of autonomy in their teaching methods and research pursuits, establishing effective communication of expectations, feedback and organizational updates, involving lecturers in relevant decision-making processes and fostering a culture of collaboration and support among lecturers and administration can contribute to a positive atmosphere. This, in turn, fosters positive affectivity and ultimately enhances lecturers’ job satisfaction, commitment and motivation. As we exhibited in our theoretical backgrounds section (e.g. Otache and Inekwe (2022), Samad et al. (2022) and Mak and Sockel (2001)), these attitudes considerably reduce turnover intention and increase intention to remain with the organization.

In line with the AET propositions, improvements in working environments that indirectly influence judgment-driven behaviors through attitudes (Weiss and Beal, 2005) should be considered. For example, a sense of work–life balance, both independently and in conjunction with person-job fit as demonstrated by Kakar et al. (2021), diminishes lecturers’ inclination to leave their roles. As another example, lecturers’ wellbeing has been shown to be a strong predictor of lecturers’ job satisfaction which, in turn, considerably reduces their turnover intention (Samad et al., 2022). Relatedly, universities should incorporate policies that address job crafting to effectively manage workload and enhance lecturers’ job satisfaction and commitment. This is a crucial point because problems such as absenteeism, turnover, errors, accidents, dissatisfaction, reduced performance, unethical behavior and even illness are the consequences of extremely stressful working places (Schermerhorn et al., 2020). Additional efforts aimed at enhancing the work environment could involve enhancing the less-favorable physical conditions, introducing wellness initiatives like fitness programs and mental health support resources and implementing a system to recognize and incentivize the contributions of lecturers.

Universities should also identify the key factors that influence lecturers’ decisions to stay or leave. This knowledge can inform talent management strategies (Mohammed et al., 2020), such as recruitment, selection, onboarding, training and career-development programs. Moreover, understanding these factors can help universities attract and retain top talent, improve lecturers’ engagement and foster a positive university brand.

Given the documented relationship between succession planning and reduced turnover intentions (Ali and Mehreen, 2019), it is evident that understanding lecturers’ turnover intention and intention to remain with the organization can play a vital role in facilitating succession planning and knowledge transfer within educational institutions. By identifying potential gaps in faculty positions, universities can take proactive steps to recruit and retain talented lecturers.

Lastly, considering the impact of personality traits on turnover (Zimmerman, 2008), lecturers’ selection and retention policies should be adjusted in ways that can account for a careful assessment of the personality traits of lecturers during the recruitment process (Ghasemy, 2023).

Concluding remarks and recommendations

In this study, we observed that the relationship between turnover intention and intention to remain with the organization is reciprocal in nature, with intention to remain with the organization being a stronger predictor (see Table 1 for fit indices and online appendices A2
and A3 for factor loadings and path coefficients). Moreover, situational factors were found to have a greater influence on eliciting turnover intention within academic settings. Furthermore, we observed that while both constructs were stable across time, the intention to remain with the organization was more stable than turnover intention. Notably, in concordance with previous simulation studies (Ghasemy, 2022; Ghasemy et al., 2021b; Bentler and Huang, 2014), our comparison showed that while the parameters estimated through both the PLSe2 and ML estimators were comparable, the $R^2$ values based on the PLSe2 method were larger (see Figure 2). This latter expected finding – which is consistent with the PLS methodology foundations (Ghasemy et al., 2020) – suggests that higher education researchers can enjoy the advantages of ML and PLS methods via estimating their longitudinal models using the PLSe2 estimator.

Finally, we would like to recommend two methodological suggestions for future research. First, since we only focused on the longitudinal association of turnover intention and intention to remain with the organization, researchers are recommended to replicate our study and consider covariates to explain the variability in turnover intention and intention to remain with the organization in their models. This can be done based on the methodological suggestions made by Ghasemy (2022). Second, while we considered chi-square difference tests in assessing measurement invariance in our study, we would like to suggest researchers to apply other advanced and recommended methods of invariance assessment such as equivalence testing (Jiang et al., 2017; Yuan and Chan, 2016) and the projection-based approach (Jiang et al., 2017) in future research.

References


**Online appendix**

The supplementary material for this article can be found online.

**About the authors**

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