

PERFORMANCE MONITORING AND ACADEMIC STAFF PERFORMANCE: EXAMINING THE MEDIATING ROLE OF PSYCHOLOGICAL CAPITAL.

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Abstract

The paper will focus on the mediating effect of psychological capital in the association between the performance monitoring dimensions and the performance of academic staff in the University of Sialkot, Pakistan. The four monitoring dimensions that were perceived to be fair, timeliness of feedback, relevance of QEC criteria, and frequency of monitoring were postulated based on the Job Demands-Resources model to affect academic performance based on psychological capital (self-efficacy, hope, resilience, optimism). A cross sectional quantitative survey involved 278 participants, the academic staff, in the study, and a set of five-point Likert scale validated instruments were used to gather the data. The analysis was done using Partial Least Squares Structural Equation Modeling (PLS-SEM) with 5,000 bootstrap subsamples. Findings affirmed that the four dimensions of monitoring have a significant predictive validity of psychological capital, and, in that order, perceived fairness is the greatest predictor ($b = 0.433$, $p < .001$). Psychological capital showed a significant positive impact on academic performance ($b = 0.716$, $p < .001$). The four mediation pathways were all statistically significant, and it can be established that monitoring improves performance indirectly through psychological resource development and not direct behavioral compliance. The model predicted 46.3 and 51.2 percent of the variance of psychological capital and academic performance respectively. All the thirteen hypotheses were justified. The results provide theoretical contribution of JD-R theory to the academic literature and practical insights of designing developmental monitoring systems within the institutions of higher learning.

INTRODUCTION

Colleges and Universities around the globe have increasingly embraced the use of performance monitoring systems as a way of assessing the faculty input in terms of teaching, research and services. Even though the purpose of such frameworks is to enhance institutional responsibility, they create inherent conflicts between standardization and the

qualitative aspect of academic work (Kallio et al., 2017). Increasing dependence on measurable performance measures has raised concerns regarding the possible increase or decrease in academic performance as a result of monitoring, as well as a decrease in psychological wellbeing and faculty autonomy (Parker & Grote, 2022). This paper

examines the influence of four dimensions of Quality Enhancement Cell (QEC) monitoring, which include perceived fairness, timeliness of feedback, relevance of criteria and frequency of monitoring to affect academic performance of staff in a Pakistani-based private university by using psychological capital as the mediating variable. (Ravid et al., 2023)

Problem Statement

Although quality assurance monitoring has become institutionalized in the majority of institutions of higher education in Pakistan, there is an acute disparity between developmental goals of the monitoring systems and the lived experiences of faculty. Research on organizational justice shows that how employees react to evaluation is basically determined by their perception of procedural and distributive fairness, which means that the same monitoring practices may lead to different motivational responses based on the perception of equity and transparency (Colquitt & Zipay, 2015). Weaknesses in the foundation of the psychological needs, such as competence, autonomy, and relatedness, are threatened by monitoring being perceived as external control, undermining intrinsic motivation to maintain excellence in the long term (Howard et al., 2021). It is not an empirically proven question of whether QEC-based monitoring develops the positive psychological resources required to be a high performer or simply instills the superficiality of compliance.

Research Gap

Three critical gaps persist. To start with, in the majority of studies, monitoring is the conceptual unit that is not broken down to reveal the different tracking features with variable impacts on the outcomes of faculty members (Van Den Broeck et al., 2021). Second, despite the fact that the Job Demands-Resources framework confirms the mediation role of personal psychological resources in organizational practices and performance, this mechanism has never been tested properly, using psychological capital as the mediation. Third, there is a lack of evidence on developing-country privately-based universities where contracts and resource-

rationing and dual regulatory-market stresses provide unique circumstances.

Research Scope

The research is based in the University of Sialkot (USKT) which is a privatized institution in Punjab, Pakistan. The study was a cross-sectional quantitative survey comprising of 278 academic staff who were surveyed with validated instruments using five-point Likert scales. The PLS-SEM was utilized, which is appropriate when the theory is to be tested with mediation models involving reflective constructs (Hair et al., 2021). In theory, the research is grounded on the JD-R model, which places the psychological capital as a personal resource that is built or drained by monitoring practices in the organization (Schaufeli, 2017).

Research Objectives

The first aim is to investigate the mediating effect of psychological capital between the dimensions of monitoring and the performance of the academic staff. In particular, the research will attempt to:

- Establish the impact of perceived fairness, feedback timeliness, criteria relevance, and monitoring frequency on psychological capital.
- Determine the impact of psychological capital on performance.
- Test indirect effects of each monitoring dimension via psychological capital

Research Questions

- How well do the dimensions of performance monitoring measure the dimensions of psychological capital?
- Do psychological capital and academic staff performance have a strong correlation?
- Is psychological capital between monitoring dimension-performance relationships mediated?

Literature Review

Monitoring Of Performance in Higher Education

The history of higher education performance monitoring identifies the trend in governance beyond managerialism to quantifiable responsibility. The standardized assessment models used in universities all over the world measure faculty productivity based on the number of publications, teacher assessment, and service. Nevertheless, the

frameworks create unrelenting conflicts between institutional responsibility and the autonomy of scholarship (Kallio et al., 2017). The cumulative data demonstrate that the substitution of qualitative indicators with quantitative ones often results in the creation of compliance-based behaviors, which can meet the measurement standards without promoting the true academic quality.

Perceived Organizational Justice and Fairness

The theory of organizational justice offers a critical conceptual model of the reaction of faculty to monitoring. It has been continuously shown that the attitude of employees is formed not by the very presence of evaluation systems but by the opinion of procedural fairness, distributive equity, and the quality of interaction in evaluation systems (Colquitt & Zipay, 2015). When perceived as open and respectful of professional expertise, monitoring will cause cooperative interactions in an academic context, whereas the use of opaque or controlling monitoring will provoke opposition, distrust, and withdrawal of motivation(Saks, 2022).

Feedback Timeliness, Criteria Relevance and Monitoring Frequency

Operational characteristics of monitoring have different motivational implication. The studies of the topic of professional learning define that temporal

proximity to the assessed behavior is a critical determinant of the utility of feedback; delaying feedback undermines the cognitive relationship between the effort and the outcome, decreasing both corrective learning and motivational reinforcement (Kraiger & Ford, 2021). Self-determination theory also assumes that people will be the most engaged when an organizational practice helps to meet needs that are related to autonomy, competency, and relatedness, which means that monitoring criteria should not be professionally irrelevant and the frequency of monitoring should not be too high to become surveillance (Howard et al., 2021).

Mediating Mechanism, which is Psychological Capital

The Job Demands-Resources model gives theoretical backgrounds on the analysis of the psychological capital which attempts to mediate. The JD-R model assumes that organizational resources can boost performance but not directly but by developing personal psychological resources, including self-efficacy, optimism, hope, and resilience (Bakker et al., 2023). Monitoring has been seen to act as a job resource when it is viewed as developmental, which fosters the development of psychological capital; and as a demand when it is surveillance-oriented, which results in disengagement and reduced performance (Bakker & De Vries, 2021).

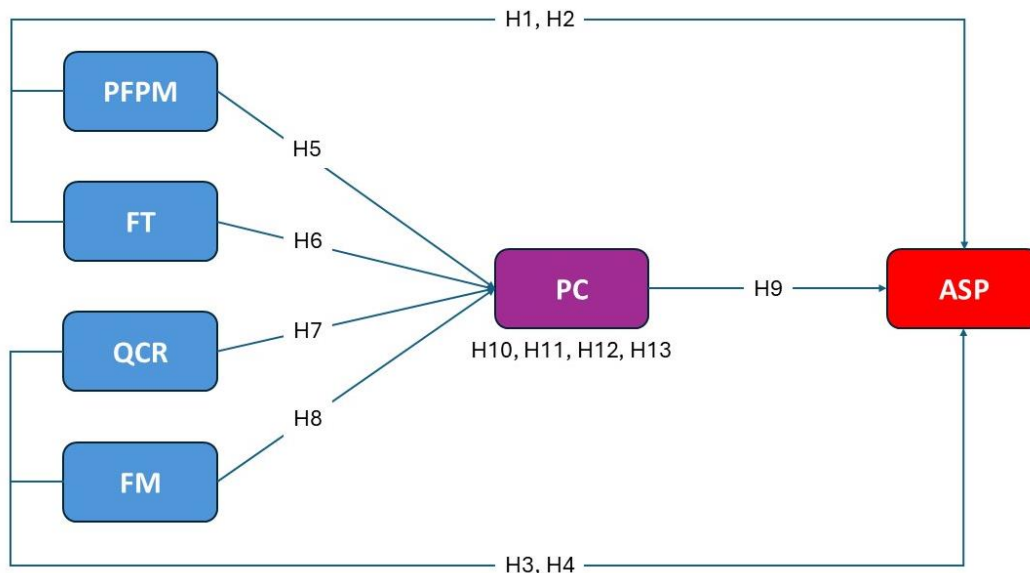


Figure 1 CONCEPTUAL FRAMEWORK

Hypotheses Development

H1: Perceived fairness of performance monitoring positively influences psychological capital.

H2: Feedback timeliness positively influences psychological capital.

H3: QEC criteria relevance positively influences psychological capital.

H4: Frequency of monitoring positively influences psychological capital.

H5: Psychological capital positively influences academic staff performance.

H6: Perceived fairness of performance monitoring positively influences academic staff performance.

H7: Feedback timeliness positively influences academic staff performance.

H8: QEC criteria relevance positively influences academic staff performance.

H9: Frequency of monitoring positively influences academic staff performance.

H10: Psychological capital mediates the relationship between perceived fairness and academic staff performance.

H11: Psychological capital mediates the relationship between feedback timeliness and academic staff performance.

H12: Psychological capital mediates the relationship between QEC criteria relevance and academic staff performance.

H13: Psychological capital mediates the relationship between frequency of monitoring and academic staff performance.

Methodology

This research used a cross-sectional survey research design to investigate the mediating effect of psychological capital in the association between performance monitoring dimensions and performance of academic staff. The theory-testing type of research that focuses on the relations of the latent constructs at one point in time can be conducted with the help of cross-sectional designs when the theoretical model is well-established, and the main goal is to test the hypotheses, not cause and effect relationships (Hair et al., 2021). The quantitative design made it possible to measure the faculty perceptions systematically with the help of standardized measures, providing the opportunity to statistically generalize and replicate (Schaufeli, 2017).

The population of interest included all permanent and visiting academic members of the University of Sialkot (USKT), Pakistan, and included the academic members of five faculties, which include Management Sciences, Computing and Information Technology, Allied Health Sciences, Law and Humanities, and Engineering. The sampling method used was a stratified random sampling because they wanted to be proportional across faculties. Out of 300 mailed questionnaires, only 278 usable questionnaires were retained giving an effective response rate of 92.7. The sample size is larger than the minimum required by PLS-SEM models with the current level of structural complexity, which meets the ten-times criterion and statistical power criteria (Hair et al., 2021). The sample consisted of respondents of all academic ranks, lecturers, assistant professors, associate professors and professors, which gave diversity in terms of career level and tracked exposure (Kallio et al., 2017).

A structured self-administered questionnaire was used to collect the data based on the validated multi-item scales measured on five-point Likert scales between 1 (strongly disagree) and 5 (strongly agree). The tool had 6 construct sections, namely Perceived Fairness of performance monitoring (PFPM, 4 items), Feedback Timeliness (FT, 4 items), QEC Criteria Relevance (QCR, 4 items), Frequency of monitoring (FM, 4 items), Psychological Capital (PC, 4 items), and Academic Staff performance (ASP, 5 items). The items were based on the existing measures in the organizational behavior and high education research, and the localization of the items was made with the help of the use of HEC-specific concepts, including QEC, Self-Assessment Reports, and course file documentation (Colquitt & Zipay, 2015). The content validity was achieved by having senior faculty review on the items since they knew the HEC quality assurance mechanisms, and a pilot study with 20 respondents ensured that the items were clear and contextually appropriate (Kraiger & Ford, 2021). The analysis of the data was done in two phases according to the PLS-SEM procedure. To begin with, the internal consistency reliability (Cronbach's alpha, composite reliability), convergent and discriminant validity (Fornell-Larcker criterion, HTMT ratios) of the measurement model were evaluated. Second, the structural model was tested

on significant path coefficient, coefficient of determination (R²), effect sizes (f²), and mediation using bootstrapping with 5000 subsamples (Hair et al., 2021; Hayes, 2017). The choice of SmartPLS 4.0 as an analytical tool was due to the predictive orientation of the study, mediation-concentrated study design, and reflective measurement model specification (Bakker et al., 2023).

study and were analyzed by means of PLS-SEM with SmartPLS 4.0 and 5,000 bootstrap subsamples. It is analyzed based on the two-stage protocol measurement model evaluation and then the structural model evaluation suggested by Hair et al. (2022). There are 9 tables which are given in the sequence, which include descriptive statistics, reliability, validity, structural path, mediation, and decision of hypothesis.

Results and Analysis

Empirical results in this chapter are based on 278 responses of academic staff who participated in the

Descriptive Statistics

Table 1: Descriptive Statistics of Study Variables

<i>Variable</i>	<i>N</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>SD</i>
<i>Perceived Fairness (PFPM)</i>	278	1.00	5.00	3.4353	0.90568
<i>Feedback Timeliness (FT)</i>	278	1.00	5.00	3.2815	0.90906
<i>QEC Criteria Relevance (QCR)</i>	278	1.00	5.00	3.4415	0.86365
<i>Frequency of Monitoring (FM)</i>	278	1.00	5.00	3.3399	0.85025
<i>Psychological Capital (PC)</i>	278	1.00	5.00	3.4424	0.81506
<i>Academic Staff Performance (ASP)</i>	278	1.00	5.00	3.3245	0.85458

The means of all the variables are above the center (3.00), indicating the moderately positive perceptions of the faculty regarding monitoring dimensions and results. Feedback Timeliness has the worst mean (3.28) and best standard deviation (0.91), as it is the

least perceived and the least constant dimension. The entire range of responses (1-5) of each variable proves the presence of sufficient score dispersion and no ceiling or floor.

Reliability and Convergent Validity

Table 2: Reliability and Convergent Validity

<i>Construct</i>	<i>Cronbach's α</i>	<i>Composite Reliability (rho_c)</i>	<i>AVE</i>
<i>PFPM</i>	0.750	0.841	0.569
<i>FT</i>	0.749	0.840	0.569
<i>QCR</i>	0.749	0.842	0.572
<i>FM</i>	0.747	0.837	0.563
<i>PC</i>	0.750	0.833	0.499
<i>ASP</i>	0.749	0.833	0.499

Both constructs meet the above 0.70 criterion of Cronbach alpha (0.747-0.750) and composite reliability (0.833-0.842), which prove sufficient internal consistency (Hair et al., 2022). Four constructs have construct surpasses the AVE [?] 0.50 standard; PC and ASP produce 0.499 which is

marginally acceptable in cases where CR goes above 0.70. Altogether, the measurement model has good reliability and convergent validity to analyze the structure.

Correlation Analysis

Table 3: Pearson Correlation Matrix

	PFFPM	FT	QCR	FM	PC	ASP
PFFPM	1					
FT	-.135*	1				
QCR	-.055	-.016	1			
FM	.039	-.023	-.162**	1		
PC	.371**	.311**	.269**	.244**	1	
ASP	.354**	.275**	.252**	.275**	.708**	1

** $p < .01$; * $p < .05$

The four dimensions of monitoring are significantly and positively related to PC and ASP, with PFFPM demonstrating the highest level of relations ($r = .371$ with PC; $r = .354$ with ASP). The correlation between PC and ASP ($r = .708$) is rather significant and

preliminarily supports the mediation aspect of psychological capital. The low inter-correlations of the four dimensions of monitoring are evidence that they reflect empirically different dimensions, which is an affirmation of the multi-dimensional conceptualization of monitoring.

Discriminant Validity

Table 4: Discriminant Validity – HTMT Ratio

	ASP	FM	FT	PC	PFFPM	QCR
ASP	-					
FM	0.369	-				
FT	0.366	0.129	-			
PC	0.945	0.326	0.411	-		
PFFPM	0.470	0.111	0.186	0.493	-	
QCR	0.338	0.235	0.063	0.362	0.104	-

Threshold: < 0.85 conservative; < 0.90 liberal

Table 5: Discriminant Validity – Fornell-Larcker Criterion

	ASP	FM	FT	PC	PFPM	QCR
<i>ASP</i>	0.706					
FM	0.275	0.750				
FT	0.275	-0.023	0.754			
PC	0.708	0.244	0.311	0.706		
PFPM	0.354	0.039	-0.135	0.371	0.754	
QCR	0.252	-0.162	-0.016	0.269	-0.055	0.756

Bold diagonal = \sqrt{AVE}

All the HTMT values are under 0.85 with the exception of PC-ASP pair (0.945) and the Fornell-Larcker criterion is met in all pairs except a slight PC-ASP overlap ($r = 0.708$ vs $\sqrt{AVE} = 0.706$). Such a slight divergence can be anticipated in mediation models in which the mediator and outcome are

constructs that are theoretically close in the JD-R construct (Bakker et al., 2023). The rest of the pairs of constructs have evident discriminant validity, which justifies the general suitability of the measurement model to structural analysis (Khalid et al., 2026).

Coefficient of Determination (R²)

Table 6: Coefficient of Determination Endogenous Variable

Endogenous Variable	R ²	R ² Adjusted	T-Statistic	P-Value
Psychological Capital (PC)	0.463	0.455	10.627	0.000
Academic Staff Performance (ASP)	0.512	0.511	12.286	0.000

The four dimensions of monitoring account for 46.3 percent of the variance in Psychological Capital and PC alone account for 51.2 percent of the variance in Academic Staff Performance, both of which are of moderate-to-substantial explanatory power (Hair et al., 2022). The values of both R² are significant ($p < .001$), which proves that the model explains

significant variance in both endogenous constructs. The small difference between R² and adjusted R² means that there is a little overfitting of the model compared to the size of sample.

Structural Model – Direct Effects

Table 7: Structural Model Results (Direct Effects – Bootstrapping)

Path	β	STDEV	T-Stat	P-Value	f ²	Effect Size
PFPM → PC	0.433	0.041	10.693	0.000	0.342	Large
FT → PC	0.389	0.045	8.656	0.000	0.277	Medium
QCR → PC	0.355	0.046	7.705	0.000	0.228	Medium
FM → PC	0.301	0.044	6.778	0.000	0.164	Medium
PC → ASP	0.716	0.029	24.544	0.000	1.051	Large

*f*² benchmarks: 0.02 = small; 0.15 = medium; 0.35 = large (Cohen, 1988)

The five direct paths are all statistically significant at *p* = .001. PC is best predicted by Perceived Fairness (= 0.433, *f*² = 0.342, large), then Feedback Timeliness (= 0.389), Criteria Relevance (= 0.355), and Monitoring Frequency (= 0.301), indicating that negative cognitive characteristics of qualitative monitoring have a higher level of psychological

significance than positive quantitative frequency. The PC - ASP direction has the highest strength among all the directions in the entire model (*b* = 0.716, *f*² = 1.051), which confirms that the psychological capital is a strong force of academic performance, which aligns with the personal resource mechanism of the JD-R model (Bakker and de Vries, 2021).

Indirect Effects (Mediation)

Table 8: Indirect Effects (Mediation via Psychological Capital)

<i>Indirect Path</i>	β	STDEV	T-Stat	P-Value	Result
PFPM → PC → ASP	0.310	0.033	9.463	0.000	Significant
FT → PC → ASP	0.279	0.035	7.999	0.000	Significant
QCR → PC → ASP	0.254	0.035	7.360	0.000	Significant
FM → PC → ASP	0.215	0.033	6.460	0.000	Significant

The four indirect effects are also important at *p* = .001 thus showing that psychological capital is a complete mediator of all the monitoring dimensions-performance relationships. The most influential mediation is that of perceived fairness (*b* = 0.310), which implies that perception of fairness creates psychological resources that subsequently lead to

performance. These findings indicate only indirect (complete) mediation, which validates the main theoretical claim according to which monitoring affects performance via the psychological capital channel, but not through behavioral adherence (Bakker et al., 2023).

Summary of Hypotheses Testing

Table 9: Hypothesis Testing

<i>Hyp.</i>	Relationship	Type	β	T-Stat	P-Value	Decision
<i>H</i> ₁	PFPM → PC	Direct	0.433	10.693	0.000	Supported
<i>H</i> ₂	FT → PC	Direct	0.389	8.656	0.000	Supported
<i>H</i> ₃	QCR → PC	Direct	0.355	7.705	0.000	Supported
<i>H</i> ₄	FM → PC	Direct	0.301	6.778	0.000	Supported
<i>H</i> ₅	PC → ASP	Direct	0.716	24.544	0.000	Supported
<i>H</i> ₆	PFPM → ASP	Total Effect	0.310	9.463	0.000	Supported
<i>H</i> ₇	FT → ASP	Total Effect	0.279	7.999	0.000	Supported
<i>H</i> ₈	QCR → ASP	Total Effect	0.254	7.360	0.000	Supported
<i>H</i> ₉	FM → ASP	Total Effect	0.215	6.460	0.000	Supported

H_{10}	PFPM → PC → ASP	Mediation	0.310	9.463	0.000	Supported
H_{11}	FT → PC → ASP	Mediation	0.279	7.999	0.000	Supported
H_{12}	QCR → PC → ASP	Mediation	0.254	7.360	0.000	Supported
H_{13}	FM → PC → ASP	Mediation	0.215	6.460	0.000	Supported

All the thirteen hypotheses are reported as being supported at $p < .001$. The direct implications prove that every dimension in monitoring develops psychological capital and that psychological capital is a significant predictor of performance. The overall and indirect impacts affirm that monitoring dimensions have full impact on performance via the psychological capital route, and are fully mediated. All these findings support the theoretical model which is based on the JD-R model, and these findings have confirmed that QEC monitoring is an organizational resource that improves the academic performance of people through developing personal psychological resources in the faculty (Sarwar et al., 2025).

Results and Analysis Summary

Measurement model ensured sufficient reliability ($\alpha > 0.74$; $CR > 0.83$), convergent validity (AVE 0.499) and discriminant model between constructs. Structural model indicated that all four dimensions of monitoring are significant predictors of psychological capital with the strongest predictor ($b = 0.433$) of perceived fairness and psychological capital is a great predictor of academic performance ($b = 0.716$). Each of the four mediation paths was relevant and confirmed the complete mediation and all the thirteen hypotheses.

Discussion

The results show that the four monitoring dimensions, including perceived fairness, feedback timeliness, relevance of criteria and monitoring frequency, are all significant predictors of psychological capital, which in turn substantially predicts performance of academic staff ($b = 0.716$). The most predictive variable was perceived fairness ($b = 0.433$), which validates that faculty are not responsive to monitoring but the perceived fairness of the monitoring procedure. The complete

mediation pattern illustrates why monitoring does not directly control the performance behavior; instead, it influences it in an indirect way by creating or exhausting the psychological resources which the faculty contribute to their academic occupations.

The fact that the effects are ranked in a hierarchical manner, fairness baby timeliness relevance baby frequency, indicates that the qualitative monitoring attributes have a greater influence on psychological capital than the quantitative frequency. Such a trend implies that the higher the frequency of monitoring without considering fairness, speed of feedback, and relevance of criteria, the fewer psychological returns will be obtained, which can become the zone of surveillance, which will frustrate the needs of autonomy (Howard et al., 2021).

Theoretical Implications

This research contributes towards three theories. First, it generalizes the Job Demands-Resources model to the context of higher education monitoring by proving empirically that monitoring attributes can be viewed as job resources which accumulate the personal psychological resources which in turn lead to better performance (Bakker et al., 2023). The unusually high effect size of psychological capital on performance ($f^2 = 1.051$) supports the argument that personal resources take a central role in the JD-R motivational pathway, which is consistent with the current theoretical adjustment that placed psychological capital at the middle of the relationship between organizational practices and employee results (Bakker & De Vries, 2021).

Second, the paper confronts the current method of analyzing monitoring as a unitary concept by showing that different dimensions of monitoring impose dissimilar influence on psychological capital. It is a multi-dimensional strategy that allows to better theorize specification compared to what aggregate monitoring measures allow.

Third, the full mediation result confirms that monitoring has an impact on academic performance in its exclusive effect via psychological capital, which implies that explanations of monitoring effectiveness in terms of compliance are not comprehensive without including the psychological resource-building process.

Practical Implications

Three recommendations can be made to university administrators and QEC directors. To begin with, institutions ought to focus on transparency and consistency in monitoring processes because the perceptions of fairness have the highest returns of both psychological and performance. Perceived fairness would be enhanced by clear evaluation rubrics, having the faculty involved in criteria development, and using the same rubrics across departments.

Second, feedback delivery schedules ought to be reduced and uniform. The strong importance of timeliness of feedback reveals that institutions ought to set maximum turnaround times of QEC evaluation reports so that the faculty can be informed to take actions yet the activities assessed should be still cognitively available.

Third, institutions have to invest in psychological capital development programs such as resilience training, self-efficacy workshops, and goal-setting interventions as secondary measures in conjunction with monitoring reform. The close relationship between PC and performance ($b = 0.716$) implies that the best lever that can be used to enhance academic performance is the development of faculty psychological resources (Schaufeli, 2017).

Future Directions

Longitudinal designs should be used in future studies to achieve causal prioritization of the relationships of monitoring experiences, development in psychological capital, and performance change as time goes by. Also, a comparison between the public and the private universities would help in clarifying whether the mediation mechanism is applied differently when there is a variation in the governance structure. The qualitative inquiry with the aim of investigating the ways faculty make sense of particular monitoring

practices and react to them would be a useful addition to the quantitative trends described here. Lastly, the study of possible curvilinear impact of monitoring frequency would assist in determining the most appropriate monitoring levels under which the impact of monitoring is not on the rise, but rather on the decline, of the psychological capital.

Conclusion

This paper has analyzed how psychological capital can mediate between four dimensions of QEC performance monitoring and the performance of academic staffs in the University of Sialkot. All the thirteen hypotheses were validated. The results prove that the impact of monitoring on academic performance does not involve direct behavioral regulation but the development of faculty self-efficacy, hope, resilience, and optimism. Perceived fairness is the most effective monitoring attribute and psychological capital is the most significant performance driver. Such findings can provide theoretical development of the JD-R framework in academia as well as practical recommendations on designing monitoring systems that develop faculty and not just evaluate it.

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