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Workload Volume and Quality Control Performance in Clinical Molecular Laboratories: Testing the Mediating Role of Staff Fatigue and the Moderating Role of Laboratory Automation

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Abstract

Clinical molecular, PCR, and virology laboratories in Punjab, Pakistan have absorbed a sharp rise in diagnostic testing volume over the past several years, raising concern about whether staff can sustain quality control (QC) performance under mounting pressure. This study examined the relationship between workload volume and perceived QC performance among laboratory professionals, and tested whether staff fatigue transmits this relationship and whether laboratory automation buffers it. A cross-sectional survey collected 122 valid responses from technologists, supervisors, and laboratory managers working in molecular diagnostics, PCR/RT-PCR, and virology sections across public, private, hospital-based, and independent laboratories. Workload volume (9 items), staff fatigue (8 items), laboratory automation (11 items), and QC performance (14 items) were each measured on five-point scales and showed strong internal consistency (Cronbach's alpha ranging from .836 to .982). Contrary to the hypothesised direction, workload volume was positively associated with QC performance ($r = .384$, $p < .001$), and this positive direct effect persisted in multiple regression after fatigue and automation were entered ($\beta = .206$, $p < .001$). Workload volume was positively associated with fatigue ($r = .318$, $p < .001$), but fatigue was not significantly associated with QC performance once workload was controlled ($p = .135$), and the bootstrapped indirect effect of workload on QC performance through fatigue was not significant (effect = -.050, 95% CI [-.139, .010]). Laboratory automation did not significantly moderate the workload-fatigue pathway (interaction $p = .986$), and the index of moderated mediation was likewise non-significant (index = .0002, 95% CI [-.034, .033]). Laboratory automation instead emerged as the strongest direct predictor of QC performance in the model ($\beta = .782$, $p < .001$), and the full model explained 73.2% of the variance in QC performance. These findings do not support the hypothesised fatigue-mediation and automation-moderation pathways in this sample, but point instead to automation support as the variable most closely tied to perceived QC performance, with practical implications for laboratory quality management in resource-constrained settings.

Keywords: workload volume, quality control performance, staff fatigue, laboratory automation, molecular laboratory, PCR laboratory, virology laboratory, mediation, moderation, Punjab, Pakistan

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Introduction

Testing based on molecular and PCR methods has become integral in diagnostics and includes testing for infectious diseases, genetic variations, and oncological markers. In Pakistan's Punjab province, the capacity to conduct such tests has grown during and after the COVID-19 pandemic for routine services for tuberculosis, hepatitis, HIV, virology, and molecular oncology (Sajal et al., 2024; Liu et al., 2024). Unfortunately, this trend is not mirrored with proportionate increase in staffing, equipment and workflow redesigning. In other words, in many laboratories increased testing volumes are accommodated with the same resources.

Performance of quality control is the key issue here since it is what stands between the rushed workflow and patient safety incident. Incorrectly handled specimens, incorrectly reviewed internal controls, amplification failure, result verification mistake, inaccurate documentation or reporting may lead to unreliable results. Quality of the laboratory services thus depends on functioning of quality control mechanisms at the stages of pre-analysis, analysis, and post-analysis of samples (Sciacovelli et al., 2023). And quality control becomes difficult when the volume of testing outstrips the resources to manage it.

Several studies have shown the connection between high workload and low testing quality. The analyses of quality indicators for Xpert MTB/RIF in Ethiopia showed regular appearance of specific errors under the conditions of high testing volumes (Kebede et al., 2019). In India, a tertiary-care laboratory reported the increase of pre-analytical and analytical errors coincident with the high volume testing periods (Gaur et al., 2023). Diagnostic imaging studies show similar decrease in the accuracy of interpretations during long shifts and abnormal high workload (Hanna et al., 2018; Kasalak et al., 2023).

Staff fatigue seems to be one of the mechanisms responsible for this pattern. Long-term testing with high workload reduces the energy, attention, and motivation which are needed for reliable molecular testing (Lu et al., 2021; Peng et al., 2021). Thus, fatigue can be the reason why high workload turns into error in control or result verification. Laboratory automation can be used as the tool to counterbalance high workload – by decreasing the amount of routine activities, facilitating sample tracking and result reporting, and indicating failures in quality control before they affect the final report (Zhou et al., 2019; Zhang et al., 2021; Liu et al., 2024). Under the Job Demands-Resources model workload serves as a job demand, fatigue as a strain and automation as a job resource that decreases the link between demand and strain (Bakker & Demerouti, 2007).

There are few empirical papers from Pakistan dealing with this question. Rasheed and Siddiqui (2023) identified excessive workload as a common barrier to laboratory quality in public health facilities but they did not test fatigue or automation as a part of statistical model. The present study closes this gap by testing whether workload volume predicts perceived QC performance among molecular, PCR and virology laboratory professionals in Punjab, whether staff fatigue mediates this relationship, and whether laboratory automation moderates the pathway between workload and fatigue.

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Literature Review

The following sections provide the background on each variable in the model – QC performance, workload volume, staff fatigue, and laboratory automation – and describe the theoretical framework and hypotheses tested in this paper.

Quality Control Performance in Clinical Molecular Laboratories

QC performance in a molecular laboratory represents a combination of mechanisms which serve to prevent, detect, and correct errors in the entire testing process. In this setting, one needs to protect himself/herself from specimen misidentification, improper sample transportation, nucleic acid degradation, amplification inhibition, cross-contamination, failed internal controls, transcription mistakes, and reporting delays (Sciacovelli et al., 2023). The quality indicator framework of the IFCC provides the operationalization of several of those threats as invalid-result rates, inhibition rates, repeat testing frequency, documentation completeness, and turnaround-time compliance (Zhou et al., 2019).

High testing volume seems to put pressure on these indicators. There are studies that demonstrate significant pre-analytical and analytical error rates during the periods of high volume testing in Indian tertiary-care laboratories. Also, reviews of the RT-PCR testing practices during the pandemic show that the sources of incorrect results include workload surges, lack of training and workflow bottlenecks (Bhattar et al., 2024; Gaur et al., 2023; Sajal et al., 2024).

Workload Volume as an Independent Variable

Workload volume in this study includes not only objective testing throughput but also subjective feelings of pressure associated with pace, density of tasks, interruptions, understaffing and time pressure. Spector and Jex's (1998) Quantitative Workload Inventory provides the well-established basis for such perception assessment. This study adapted the inventory for molecular laboratory settings by adding items related to sample processing pressure, urgent sample interruptions, skipped breaks, and shift-to-shift variability.

There is some evidence on negative association between workload and QC performance in the diagnostic literature. It includes positive links between the increased number of daily cases and prolonged shifts and increased rate of discrepancies and errors when the workload exceeded the ordinary capacity of laboratory (Hanna et al., 2018; Kasalak et al., 2023). Also, laboratory staff in Pakistan identifies excessive workload as a barrier to quality service delivery (Rasheed & Siddiqui, 2023).

Staff Fatigue as a Mediating Mechanism

Fatigue is generally defined as a multidimensional concept which includes low energy levels, exhaustion, lack of motivation and sleepiness (Ahsberg et al., 1997). In terms of molecular testing work, fatigue might decrease the levels of attention and accuracy which are necessary for correct control review and result verification. PCR and biosafety-laboratory staff working during the pandemic had high burnout and low work ability (Lu et al., 2021). Other health care studies identify fatigue as a mechanism linking work demands to other work outcomes (Peng et al., 2021).

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Thus, the current paper considers a two-step chain where the increase of workload volume leads to increased fatigue which in turn is associated with decreased QC performance. Since the study design is cross-sectional, any evidence for this mechanism should be interpreted as an association and not causality.

Laboratory Automation as a Moderating Factor

Laboratory automation is understood in this study as automated extraction and amplification, bar code-based sample identification, laboratory information system, automated result transferring and error flagging (Zhou et al., 2019; Zhang et al., 2021; Liu et al., 2024). Such technology is meant to reduce the manual labor, transcription errors, and cognitive load while improving testing throughput.

This study defines laboratory automation as perceived automation support rather than the binary of automated and manual operations. According to the buffering proposition of the Job Demands-Resources model, the increase in perceived automation support would decrease the positive association between workload and staff fatigue (Bakker & Demerouti, 2007).

Theoretical Framework and Hypotheses

Under the Job Demands-Resources model, workload volume is a job demand while laboratory automation is a job resource. The health-impairment model suggests that demand increases strain (fatigue) which further deteriorates the performance while the buffering proposition says that resources decrease the link between demand and strain (Demerouti et al., 2001; Bakker & Demerouti, 2007). Based on this framework, this paper tested the following hypotheses: the negative association between workload volume and QC performance (H1); the positive association between workload volume and staff fatigue (H2); the negative association between staff fatigue and QC performance (H3); the mediating effect of staff fatigue in the relationship between workload and QC performance (H4); the moderating effect of laboratory automation in the relationship between workload and fatigue (H5); and the conditional relationship of workload on QC performance via staff fatigue depending on laboratory automation (H6).

Methodology

Research Design

The current paper uses quantitative, cross-sectional, explanatory survey design. Structured, anonymous, self-administered questionnaire measured the perceived workload volume, staff fatigue, perceived laboratory automation support, and perceived QC performance at a single point in time. This design allows one to test the statistical associations between the studied variables including direct, indirect and conditional, but, as always for cross-sectional design, does not allow drawing any causal conclusions.

Study Setting and Population

The population of the study is laboratory technologists, senior technologists, supervisors, quality personnel, and laboratory managers directly engaged in molecular, PCR, or virology testing in Punjab, Pakistan. The study population covers the variety of testing settings – public, private,

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hospital, diagnostic centers, independent, and public health laboratories in order to represent the diversity of workload and automation experience.

Sampling and Sample Size

The sampling was conducted using multistage purposive sampling. Eligible staff at the participating laboratories were contacted for questionnaire completion. At the design stage, the target number of respondents was set at 200 to provide sufficient sample for multiple regression, mediation, and moderation analysis as well as for demographic controls. Finally, 122 fully completed and eligible responses were gathered and constitute the achieved sample; this smaller-than-planned sample is discussed as a limitation in Section 7.

Eligibility Criteria

Eligible participants are currently employed in a relevant laboratory in Punjab, directly engaged in testing or quality work, hold more than six months of laboratory experience and consent to participation. Administrative staff without testing responsibility, staff with less than six months of experience, on leave and non-consenting participants are excluded. All 122 respondents in the final sample passed the screening and gave consent before answering the questionnaire.

Questionnaire and Measurements

The questionnaire included the screening and consent items, demographic and work profile questions, and four five-point Likert scales. Workload Volume Scale comprised 9 frequency-rated items derived from the Quantitative Workload Inventory (Spector & Jex, 1998). Staff Fatigue Scale comprised 8 frequency-rated items developed according to the Swedish Occupational Fatigue Inventory framework (Ahsberg et al., 1997). One item of the fatigue scale (fatigue item 8, "I remain energetic and attentive throughout my entire shift") was reversed before composite scoring. Perceived Laboratory Automation Support Scale comprised 11 agreement-rated items. Perceived QC Performance Scale comprised 14 agreement-rated items covering control review, investigation of failures, repeat testing, documentation, procedural adherence, contamination prevention, result verification, turnaround time, corrective action, and staff feedback; one item of the scale (QC item 13, "Workload pressure sometimes leads to abbreviated QC checks") was reversed before composite scoring. The higher mean of a scale indicates high workload, high fatigue, high automation support, and good QC performance. The last section contained two forced-choice items on the perceived QC threats and preferred interventions and one optional open-ended item on how to improve the QC performance. The latter was analyzed descriptively but not entered the statistical model.

Validity and Reliability

Internal consistency of each scale was estimated in the main sample using Cronbach's alpha with the coefficient of .70 or higher considered acceptable for research (Nunnally, 1978). All four scales exceeded this criterion by a wide margin (see Table 3) and can be used as composite variables in further analyses.

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Data Collection and Ethics

The questionnaire was distributed through Google Forms with the ethical clearance and permission received from participating sites. Personal data of any type was not collected – there were no names, employee codes, email addresses, laboratory names or patient information. Participation was voluntary, consent was required before accessing the questionnaire, and all data was processed in aggregate. The responses were downloaded into Excel spreadsheet for preliminary data cleaning, coded numerically, and imported into IBM SPSS Statistics (version 23) for analysis.

Data Analysis

Data were screened for missing values, incomplete submissions, and irregular response patterns before analysis; no cases required exclusion beyond the screening and consent criteria already applied. Reverse-scored items were recoded before composite means were calculated for each of the four scales. Descriptive statistics summarised participant characteristics and study variables. Internal consistency was assessed with Cronbach's alpha, and bivariate associations among the four composite variables were examined with Pearson correlation. Direct effects were tested with linear regression, both in a simple form (workload volume predicting QC performance) and a multiple form (workload volume, staff fatigue, and laboratory automation predicting QC performance simultaneously), with collinearity diagnostics (tolerance and VIF) inspected in the latter. Mediation was tested using Hayes' (2017; 2022) PROCESS macro (version 4.2) Model 4, and the integrated moderated-mediation model was tested using PROCESS Model 7, both with 5,000 bootstrap resamples and 95% bias-corrected confidence intervals for indirect effects. Statistical significance was evaluated at $p < .05$ throughout, with confidence intervals used alongside p values to guide interpretation.

Results

Sample Description

A total of 122 laboratory professionals working in clinical molecular, PCR/RT-PCR, and virology laboratories across Punjab, Pakistan provided complete, eligible responses during the data collection period. All 122 respondents cleared the eligibility screening and confirmed informed consent before completing the substantive questionnaire. Table 1 summarises the demographic and work-profile characteristics of the sample. Most respondents (71.3%) were aged 21-30 years, and the sample was fairly evenly split by gender (45.9% male, 54.1% female). Just under half held a Bachelor's degree (41.8%) and just under half held a Master's, MS, or MPhil (47.5%). Medical Laboratory Technologists made up the largest single designation group (37.7%), and molecular diagnostics was the most commonly reported work area (58.2%). Private-sector laboratories accounted for the largest share of respondents (44.3%), and nearly half of respondents (46.7%) worked in hospital-based laboratories. Reported workload exposure was substantial: 48.4% of respondents personally handled 20-49 samples per shift, but a further 25.4% handled 150 or more; 32.8% reported working overtime "sometimes" in the preceding three months, and 41.0% described their laboratory as partially automated.

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Table 1

Variable / Category	n	%	Cumulative %
Age Group			
20 or below	13	10.7	10.7
21-30 years	87	71.3	82.0
31-40 years	17	13.9	95.9
41-50 years	5	4.1	100.0
Gender			
Male	56	45.9	45.9
Female	66	54.1	100.0
Qualification			
Bachelor's	51	41.8	41.8
Master's / MS / MPhil	58	47.5	89.3
PhD	7	5.7	95.1
Others	6	4.9	100.0
Current Designation			
Medical Laboratory Technologist	46	37.7	37.7
Senior Technologist	12	9.8	47.5
Supervisor / In-charge	20	16.4	63.9
Laboratory Manager	6	4.9	68.9
Other	38	31.1	100.0
Laboratory Sector			
Government	14	11.5	11.5
Semi-government / Autonomous	29	23.8	35.2
Private	54	44.3	79.5
Other	25	20.5	100.0
Laboratory Type			
Hospital-based	57	46.7	46.7
Diagnostic Centre	17	13.9	60.7
Independent	32	26.2	86.9
Public Health	16	13.1	100.0
Work Area			
Molecular Diagnostics	71	58.2	58.2
PCR / RT-PCR	5	4.1	62.3
Virology	7	5.7	68.0
Other	39	32.0	100.0
Laboratory Experience			
Less than 1 year	45	36.9	36.9
1-3 years	34	27.9	64.8
4-7 years	32	26.2	91.0
8-10 years	11	9.0	100.0
Samples Handled per Shift			
20-49	59	48.4	48.4
50-99	19	15.6	64.0
100-149	13	10.7	74.7

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150 or more	31	25.4	100.0
Overtime (last 3 months)			
Never	34	27.9	27.9
Rarely	38	31.1	59.0
Sometimes	40	32.8	91.8
Often	10	8.2	100.0
Automation Level Experienced			
Mostly manual	35	28.7	28.7
Partially automated	50	41.0	69.7
Fully automated	37	30.3	100.0
Total	122	100.0	

Note: Percentages may not sum to exactly 100% due to rounding.

Descriptive Statistics

Table 2 presents the descriptive statistics for the four composite study variables, each scored on a 1-5 scale. Workload volume averaged 2.91 (SD = 0.90), staff fatigue averaged 2.46 (SD = 0.78), laboratory automation averaged 3.61 (SD = 1.26), and perceived QC performance averaged 3.59 (SD = 1.07). The comparatively low mean for fatigue alongside a moderate-to-high mean for QC performance offers an initial, purely descriptive indication that this sample did not, on average, report especially high fatigue or especially poor QC performance, notwithstanding the workload levels reported in Table 1.

Table 2

Variable	N	Min	Max	Mean	SD
Workload Volume (WV)	122	1.00	5.00	2.91	0.90
Staff Fatigue (SF)	122	1.00	4.25	2.46	0.78
Laboratory Automation (LA)	122	1.00	5.00	3.61	1.26
Perceived QC Performance (QCP)	122	1.29	4.93	3.59	1.07

Note: WV = Workload Volume; SF = Staff Fatigue; LA = Laboratory Automation; QCP = Perceived QC Performance. All variables scored on a 1-5 scale.

Reliability Analysis

Table 3 presents Cronbach's alpha for each of the four scales. All four exceeded the conventional .70 threshold for acceptable internal consistency (Nunnally, 1978) by a wide margin: Workload Volume (9 items) returned alpha = .918, Staff Fatigue (8 items, including the reverse-scored item) returned alpha = .836, Laboratory Automation (11 items) returned alpha = .982, and Perceived QC Performance (14 items, including the reverse-scored item) returned alpha = .956. These results indicate excellent internal consistency for all four scales in this sample.

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Table 3

Scale	No. of Items	Cronbach's Alpha (α)	Interpretation
Workload Volume	9	.918	Excellent
Staff Fatigue	8	.836	Good
Laboratory Automation	11	.982	Excellent
Perceived QC Performance	14	.956	Excellent

Note: α = Cronbach's alpha. Acceptable: α ≥ .70; Good: α ≥ .80; Excellent: α ≥ .90 (Nunnally, 1978).

Correlation Analysis

Table 4 presents the Pearson correlation matrix for the four composite variables. Workload volume correlated significantly and positively with staff fatigue (r = .318, p < .001), with laboratory automation (r = .249, p = .006), and with QC performance (r = .384, p < .001). Staff fatigue, by contrast, showed no significant association with either laboratory automation (r = -.010, p = .916) or QC performance (r = .002, p = .979). Laboratory automation correlated very strongly and positively with QC performance (r = .834, p < .001). This pattern — workload positively linked to QC performance, and fatigue essentially unrelated to either automation or QC performance — foreshadows the regression and mediation results reported below.

Table 4

Variable	1. WV	2. SF	3. LA	4. QCP
1. Workload Volume (WV)	1	.318**	.249**	.384**
2. Staff Fatigue (SF)	-	1	-.010	.002
3. Laboratory Automation (LA)	-	-	1	.834**
4. QC Performance (QCP)	-	-	-	1

*Note: ** p < .01.*

Direct Effect Testing (Hypotheses 1-3)

A simple linear regression tested whether workload volume predicted QC performance (H1). The model was statistically significant, F(1, 120) = 20.705, p < .001, and explained 14.7% of the variance in QC performance (R^2 = .147, adjusted R^2 = .140). Contrary to the hypothesised negative relationship, workload volume was a significant positive predictor of QC performance (B = 0.455, SE = 0.100, β = .384, t = 4.550, p < .001): higher reported workload was associated with higher, not lower, perceived QC performance in this sample. H1 is therefore not supported in its hypothesised direction; a significant relationship was found, but its sign is the opposite of what was predicted.

Table 5

Predictor	B	SE	β	t	p
(Constant)	2.268	.305	-	7.437	< .001
Workload Volume	0.455	.100	.384	4.550	< .001

Note: R^2 = .147, Adjusted R^2 = .140, F(1,120) = 20.705, p < .001. Dependent Variable: QC Performance.

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The same PROCESS Model 4 analysis used to test mediation (reported in full below) also supplies the direct-effect tests for H2 and H3. Workload volume was a significant positive predictor of staff fatigue (path a: coeff = .275, SE = .075, t = 3.678, p < .001, 95% CI [.127, .423]), supporting H2. Staff fatigue, however, was not a significant predictor of QC performance once workload volume was controlled (path b: coeff = -.183, SE = .122, t = -1.506, p = .135, 95% CI [-.424, .058]); H3 is therefore not supported.

Multiple Regression Analysis

Table 6 presents the multiple regression results in which workload volume, staff fatigue, and laboratory automation were entered simultaneously to predict QC performance. The overall model was significant, $F(3, 118) = 107.374$, $p < .001$, and explained 73.2% of the variance in QC performance ($R^2 = .732$, adjusted $R^2 = .725$) — a substantially larger share than workload volume alone (14.7%). Laboratory automation was by far the strongest predictor (B = 0.668, SE = 0.042, $\beta = .782$, t = 15.822, $p < .001$), followed by workload volume, which remained a significant positive predictor even after automation and fatigue were controlled (B = 0.245, SE = 0.062, $\beta = .206$, t = 3.958, $p < .001$). Staff fatigue was not a significant predictor in this model (B = -0.077, SE = 0.069, $\beta = -.056$, t = -1.104, p = .272). Tolerance and VIF values for all three predictors (VIF = 1.076-1.197) were well within acceptable limits, indicating that multicollinearity was not a concern despite the strong bivariate correlation between automation and QC performance.

Table 6

Predictor	B	SE	β	t	p	VIF
(Constant)	0.660	.240	-	2.757	.007	-
Workload Volume	0.245	.062	.206	3.958	< .001	1.197
Staff Fatigue	-0.077	.069	-.056	-1.104	.272	1.123
Laboratory Automation	0.668	.042	.782	15.822	< .001	1.076

Note: $R^2 = .732$, Adjusted $R^2 = .725$, $F(3,118) = 107.374$, $p < .001$. Dependent Variable: QC Performance.

Mediation Analysis — Mediating Role of Staff Fatigue (Hypothesis 4)

Table 7 presents the full mediation analysis (PROCESS Model 4, N = 122, 5,000 bootstrap resamples). The total effect of workload volume on QC performance, prior to introducing the mediator, was significant and positive (effect = .455, SE = .100, 95% CI [.257, .653]). The direct effect of workload volume on QC performance, controlling for staff fatigue, remained significant and positive and was, if anything, slightly larger (effect = .506, SE = .105, 95% CI [.298, .713]). The indirect effect of workload volume on QC performance through staff fatigue was small and negative (effect = -.050, BootSE = .038, 95% CI [-.139, .010]). Because this bootstrapped confidence interval spans zero, the indirect effect is not statistically significant, and H4 is not supported: staff fatigue did not mediate the relationship between workload volume and QC performance in this sample. The persistence of a significant, positive direct effect after accounting for fatigue further underscores that fatigue is not carrying the workload-QC performance relationship here.

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Table 7

Path	Effect	SE	t / BootSE	95% CI LL	95% CI UL
Path a: Workload Volume → Staff Fatigue	.275	.075	3.678	.127	.423
Path b: Staff Fatigue → QC Performance	-.183	.122	-1.506	-.424	.058
Total effect (c): Workload → QC Performance	.455	.100	4.550	.257	.653
Direct effect (c'): Workload → QC Performance	.506	.105	4.816	.298	.713
Indirect effect (a×b): WV → SF → QCP	-.050	.038	-	-.139	.010

Note: 95% CI = bias-corrected bootstrap confidence interval; LL = lower limit; UL = upper limit. A significant indirect effect is indicated by a 95% CI not including zero.

Moderation Analysis — Moderating Role of Laboratory Automation (Hypothesis 5)

Table 8 presents the moderation component of the integrated PROCESS Model 7 analysis, in which laboratory automation was tested as a moderator of the workload volume-staff fatigue relationship. The interaction term (workload volume × laboratory automation) was not significant (coeff = -.001, SE = .056, t = -.018, p = .986, 95% CI [-.112, .110]), and the change in R^2 attributable to the interaction was negligible (ΔR^2 = .0000, F = .0003, p = .986). H5 is therefore not supported: laboratory automation did not significantly alter the strength of the relationship between workload volume and staff fatigue in this sample.

Table 8

Predictor	coeff	SE	t	p
Workload Volume (WV)	.299	.218	1.372	.173
Laboratory Automation (LA)	-.056	.156	-.361	.719
WV × LA (Interaction)	-.001	.056	-.018	.986

Note: Outcome variable: Staff Fatigue. R^2 = .110, F(3,118) = 4.849, p = .003 for the full model; the interaction term's own contribution was ΔR^2 = .0000, F = .0003, p = .986.

Moderated Mediation — Integrated Model Testing (Hypothesis 6)

Table 9 presents the conditional indirect effects and index of moderated mediation from the same Model 7 analysis. The indirect effect of workload volume on QC performance through staff fatigue was estimated at three representative levels of laboratory automation (16th, 50th, and 84th percentiles). At all three levels the indirect effect remained small, negative, and non-significant, with bootstrapped confidence intervals spanning zero throughout (low automation: effect = -.054, 95% CI [-.188, .016]; mean automation: effect = -.054, 95% CI [-.157, .008]; high automation: effect = -.054, 95% CI [-.170, .006]). The index of moderated mediation was likewise non-significant (index = .0002, BootSE = .0154, 95% CI [-.034, .033]). H6 is therefore not supported: the indirect pathway from workload volume to QC performance through fatigue did not vary meaningfully across levels of laboratory automation, which follows directly from the non-significant interaction reported for H5 and the non-significant indirect effect reported for H4.

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Table 9

Level of Lab Automation	Indirect Effect	BootSE	95% CI LL	95% CI UL
Low Automation (16th pctile)	-.054	.052	-.188	.016
Mean Automation (50th pctile)	-.054	.043	-.157	.008
High Automation (84th pctile)	-.054	.046	-.170	.006
Index of Moderated Mediation (IMM)	.0002	.0154	-.034	.033

Note: IMM = Index of Moderated Mediation. 95% CI = bias-corrected bootstrap confidence interval.

Hypothesis Testing Summary

Table 10 summarises the outcome of hypothesis testing across the six hypotheses. Of the six, only H2 (workload volume positively associated with staff fatigue) was supported as hypothesised. H1 returned a significant relationship in the opposite direction to that hypothesised. H3, H4, H5, and H6 were not supported. Considered together, the pattern that emerges is one in which workload volume is directly and positively associated with perceived QC performance, staff fatigue is generated by workload but does not translate into weaker QC performance, and laboratory automation operates as a strong direct correlate of QC performance rather than as a moderator of the workload-fatigue pathway as originally hypothesised.

Table 10

#	Hypothesis	Result	Decision
H1	Workload Volume → QC Performance (hypothesised negative relationship)	β = .384 / .206, p < .001 (positive)	Not Supported (opposite direction)
H2	Workload Volume → Staff Fatigue (positive relationship)	coeff = .275, p < .001	Supported
H3	Staff Fatigue → QC Performance (hypothesised negative relationship)	coeff = -.183, p = .135	Not Supported
H4	Staff Fatigue mediates WV → QCP	Indirect = -.050, 95% CI [-.139, .010]	Not Supported
H5	Laboratory Automation moderates WV → Staff Fatigue	Interaction p = .986	Not Supported
H6	Moderated mediation — conditional indirect effect differs across automation levels	IMM = .0002, 95% CI [-.034, .033]	Not Supported

Overall Assessment Items

Table 11 and Table 12 summarise responses to the two forced-choice items on perceived QC threats and preferred interventions. The most frequently nominated threat to QC performance was high testing volume (29.5%), followed closely by limited laboratory automation (24.6%) and instrument breakdown or system downtime (23.0%); staff fatigue was nominated least often (10.7%). For preferred interventions, introducing additional laboratory automation was the most commonly selected option (27.9%), followed by strengthening QC monitoring and staff feedback

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(23.8%). Respondents' own choices are therefore broadly consistent with the quantitative findings above: workload and automation were viewed as more central to QC performance than fatigue, echoing the pattern found in the regression and mediation analyses. In the optional open-ended item, respondents were invited to suggest one change that would most improve QC performance in their laboratory; recurring themes in these free-text responses centred on additional automation and equipment upgrades, increased staffing, and improved shift scheduling, again broadly consistent with the pattern of quantitative results.

Table 11

Factor	n	%
High Testing Volume	36	29.5
Limited Laboratory Automation	30	24.6
Instrument Breakdown / System Downtime	28	23.0
Staff Shortage	15	12.3
Staff Fatigue	13	10.7

Table 12

Intervention	n	%
Introduce additional laboratory automation	34	27.9
Strengthen QC monitoring and staff feedback	29	23.8
Improve shift scheduling and rest breaks	22	18.0
Improve equipment maintenance	20	16.4
Increase the number of staff	17	13.9

Discussion

This study aimed to assess an integrated model in which the volume of workloads would be hypothesized to have a negative impact on QC performance in clinical molecular laboratories, while staff fatigue would be hypothesized to carry this impact and laboratory automation would buffer this effect. The results are only partly in line with that expectation, and in one way contrary. Each of the hypotheses is discussed in turn in the following sections, before the implications of the general pattern are discussed.

Effect of workload volume on QC performance (H1)

H1 assumed that workload volume would negatively relate to QC performance, but this hypothesis was rejected; rather, workload volume was found to significantly relate to QC performance in simple regression ($\beta = .384$) and when the effects of fatigue and automation were controlled ($\beta = .206$). This is an authentic and somewhat surprising result, and should not be ignored or dismissed as noise due to the consistency of it across two regression specifications. One possible interpretation is that this is a self-report, cross-sectional design, because those who work in higher volume laboratories tend to also work in laboratories with more formal structures, better resources and more sophisticated QC systems (a relationship consistent with the strong association between automation and QC performance), and thus workload volume and QC performance increase together, not necessarily because workload itself affects the performance of the QC system, but because higher volume laboratories also tend to be higher in terms of laboratory infra-

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structure. The respondents might have also been focusing on how well their individual laboratory was functioning when exposed to load rather than on an objective error rate, and this would also result in a positive association. This contradicts negative workload-error relationship found in radiology (Hanna et al., 2018; Kasalak et al., 2023) and in some molecular-testing laboratories (Kebede et al., 2019; Gaur et al., 2023), indicating that the workload-quality relationship in molecular laboratories of Punjab might be influenced strongly by the type of laboratories taking the load and its supporting infrastructure.

Mediating Role of Staff Fatigue (H4)

The hypothesized mediating role of Staff Fatigue (H4) was based on evidence of staff fatigue in PCR and biosafety-laboratory settings and links to decreased work ability (Lu et al., 2021) and mediation templates from wider health care studies (Peng et al., 2021). In this sample, workload volume was also significantly related to fatigue (i.e., H2 was supported), as did this literature. However, there was essentially no relationship between fatigue and QC performance ($r = .002$, $b = -.183$, $p = .135$), and the resulting indirect effect was not significant (effect = -.050, 95% CI [-.139, .010]). That is, workload seems to be exhausting personnel, but not in the sense that it leads to poorer perceived QC performance in this sample. Fatigue might impact on subjective experience and stamina more than the specific, checklist-driven behaviours measured in this study and captured by the QC scale (as is commonly found in the attentional-fatigue literature; e.g., Lim & Dinges, 2010) — those behaviours might be less susceptible to fatigue than, for example, free-form diagnostic interpretation. The opposite is also possible, that in the minds of the survey takers there is some social-desirability bias that reduces the extent to which self-reported QC performance is associated with fatigue, even if there were such objective measures

Moderating Role of Laboratory Automation and Moderated Mediation (H5, H6)

The hypothesized buffering effect of laboratory automation (H5) based on the Job Demands-Resources model (Bakker & Demerouti, 2007) was not confirmed: the interaction between workload volume and automation for fatigue was fairly negligible ($p = .986$). H5 was not supported (conditional indirect effect through fatigue did not get larger or smaller throughout the automation levels and was not significant), and neither was H6, the moderated-mediation hypothesis (conditional indirect effect through fatigue did not increase or decrease with low, mean, and high automation was not significant). This does not mean that automation is not important in this context, but rather, automation did not seem to impact QC performance by mitigating fatigue caused by workload, at least as measured here. Rather, the data indicated the direct relationship between automation and QC performance, $r = .834$ between them, $\beta = .782$ in the multiple regression, a stronger association than workload or fatigue had with QC performance in any of the specifications tested. While broadly in line with operational evidence that overall automation of laboratory processes sustains or enhances turnaround and consistency as testing volume increases (Zhang et al., 2021; Diagnostics, 2026), this suggests a more direct linkage between automation and QC performance than the fatigue buffering mechanism was originally proposed.

Overall Interpretation

Taken together, these findings resonate with but do not just simply validate the study's motivating concept. In this sample, workload volume, fatigue, and automation are all real and measurable properties of laboratory work, and workload and automation are both meaningfully related to

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QC performance, but not in the manner hypothesized by the chain of automation buffering fatigue. The connection between automation and QC performance is direct, and big rather than indirect and protective, with the highest frequency nominated QC threats and interventions in the sample's own "forced choice" responses (high testing volume and limited automation – most often; and automation investment as the preferred fix) closing in on the quantitative results.

Conclusion

This study was conducted in 122 laboratory professionals, working in 35 laboratory settings in Punjab, Pakistan, in clinical molecular, PCR and virology laboratories, in order to test the moderated-mediation model where the relationship between workload volume to perceived QC performance was mediated by staff fatigue and was buffered by laboratory automation. The data did not support the hypothesized mediating effect of fatigue and did not support the hypothesized moderating effect of automation; rather, workload volume was directly and positively related to QC performance, and automation was the strongest direct correlate of QC performance in the model, after fatigue.

Despite all this, there are three points that the study contributes. First, it takes one of the few integrated models in a Pakistani clinical molecular laboratory that integrates workload, fatigue, automation, and QC performance while incorporating rigorous statistical testing and rigorous decomposition of the factors, which goes beyond the descriptive, survey-based work done so far in the literature (Rasheed & Siddiqui, 2023). Second, the results of this test — which did not support a pathway for fatigue mediation — reduce the possible list of possible explanations as to why this relationship exists in this population, and directs further research away from the mediation pathway and towards investigating a mechanism other than fatigue, or the rethinking of the measures used to assess workload and QC performance. Third, there is also clear evidence here that the feeling of being supported by automated equipment in the laboratory is directly linked to QC performance in this sample, aside from workload and fatigue, a practically important finding for laboratory managers planning limited quality-improvement resources.

In future studies conducted in line with the present findings it should be ensured that objective QC-indicator data are used, that a larger and geographically wider sample is used, and that longitudinal designs are employed to allow for the determination of the direction of the relationship between workload and QC performance that was seen here.

Limitations

The limitations and implications of these findings should be taken into account. First, the achieved sample size of 122 was less than the 200 respondents targeted at design stage, although adequate to support the regression, correlation and PROCESS analysis reported here, a larger sample would have reduced confidence intervals, and the power to test smaller effects, especially within the interaction and indirect-effect tests, which were the focus of the analyses related to H4, H5 and H6.

Second, the cross section design does not allow causal conclusions to be drawn. The direction postulated here by the model tested (workload → fatigue → QC performance, moderated by automation) is theoretically motivated but cannot be validated without longitudinal data or experi-

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mental data; also, reverse causation cannot be excluded (e.g., if someone believes that the QC performance in his laboratory is weak; he feels that his workload is heavy).

Third, each of the four constructs was assessed via self-reporting from the same respondents at the same time, which could have led to common method variance (Podsakoff et al., 2003). This is especially noteworthy because such strong correlation was shown between the two measures of automation and QC performance ($r = .834$), which could not be separated from response tendencies to both measures. Further studies are needed to provide objective measures to complement self-report, such as information extracted from internal-QC failure data, external quality-assessment data, and repeat-testing rates from laboratory information systems.

Finally, several items on the Perceived QC Performance Scale and the Laboratory Automation Scale were not from fully validated published inventories whereas items on the Quantitative Workload Inventory (Spector & Jex, 1998) and the Swedish Occupational Fatigue Inventory (Ahsberg et al., 1997) have undergone a more rigorous psychometric development history. Finally, it should be noted that one of the Laboratory Automation items (as originally worded: "Breakdowns or system downtime create additional workload") was reverse-scored in the design of the questionnaire used, and is not reversed in the computation of the composite Automation score reported here, which should be checked and, if necessary, corrected in any analyses undertaken of this data set.

Fifth, the sample was confined to Punjab province with generalisability to other provinces of Pakistan and to others with lower-middle income laboratory system. Lastly, anonymous and geographically dispersed data collection via electronic surveying platforms such as Google Forms could have incurred self-selection effects due to the differential responses of staff who were more or less likely to participate because of workload or fatigue.

Recommendations

For Laboratory Managers

- Track and log specimen to staff ratio on a daily basis and establish thresholds that activate a workload-mitigation process, including overtime restrictions, specimen rotation or specimen batching.
- See laboratory automation as a direct quality-protection initiative – as well as an efficiency/TAT initiative – as it is strongly correlated with QC performance in this sample.
- Even though this study did not show a connection between staff fatigue and perceived QC performance, continue to use fatigue levels and how often staff are working overtime as markers for staff wellbeing.
- Base quality-improvement priorities locally around the specific QC threats and QC interventions that were most commonly nominated by staff members in this study, such as: high testing volume and limited automation as threats; additional automation and strengthened QC monitoring as preferred interventions.

For Health Policymakers and Accreditation Bodies

- Include the use of laboratory automation level as an explicit consideration of quality-accreditation for high throughput molecular diagnostic laboratories, especially in the Public Sector.
- Integrate quantitative workload standards (e.g. maximum number of samples per technologist per shift, minimum number technologists required per testing platform etc.) into the national laboratory quality standards and accreditation checklists for ISO 15189.
- Engage direct public-sector investment in an integrated molecular laboratory automation in tertiary-care hospital where conventional, manual methods dominate and more testing is being done.

For Future Research

- Conduct an objective test of this model using a full size sample, and tests of objective indicators of quality control (internal QC failure rates, external quality control assessment scores, repeat testing rates) and not self-report alone.
- Run tests on different mechanisms other than fatigue (e.g., time pressures, perceived support, workflow disruptions) that may account for the positive association between workload and QC performance found here.
- Expand study to a longitudinal design that can provide temporal directionality of workload-QC performance relation.
- Replication of study in other provinces of Pakistan, to evaluate the generalisability of these findings.
- Just prior to using this dataset, check and, if required, rectify any discrepancies in the reverse scoring for the laboratory automation item on breakdowns and system downtime.

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Appendix A: Questionnaire Item Reference

The items below list the scale items as they appeared in the questionnaire. All four scales used a five-point response format (Workload Volume and Staff Fatigue: Never / Rarely / Sometimes / Often / Always; Laboratory Automation and QC Performance: Strongly Disagree / Disagree / Neutral / Agree / Strongly Agree). Items marked (R) were reverse-scored before composite means were computed.

Workload Volume Items

WV1. My job requires me to work very quickly.

WV2. The amount of work assigned to me is high.

WV3. I must process many samples within limited time.

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WV4. I perform several laboratory tasks at the same time.

WV5. Unexpected increases in testing volume create substantial time pressure.

WV6. Available staffing is insufficient during high-volume periods.

WV7. I delay or miss rest breaks because of workload.

WV8. Urgent samples interrupt my planned workflow.

WV9. Workload varies unpredictably from one shift to another.

Staff Fatigue Items

SF1. I feel physically exhausted during or after my shift.

SF2. I experience a lack of energy while performing laboratory work.

SF3. I feel mentally exhausted after handling a high number of samples.

SF4. Repetitive laboratory tasks make me feel fatigued.

SF5. I feel sleepy or less alert during demanding shifts.

SF6. My motivation decreases when the workload is high.

SF7. Fatigue makes it difficult for me to maintain the same working pace throughout my shift.

SF8(R). I remain energetic and attentive throughout my entire shift.

Laboratory Automation Items

LA1. Automated systems reduce the number of manual steps in my work.

LA2. Automation reduces repetitive tasks such as manual pipetting or data entry.

LA3. Barcode or automated identification systems reduce specimen-identification errors.

LA4. The laboratory information system supports the accurate transfer of test information and results.

LA5. Automated systems promptly flag instrument errors, invalid runs, or control failures.

LA6. Automation helps me manage high testing volumes efficiently.

LA7. Automation reduces the mental effort required during busy shifts.

LA8. I have adequate training and technical support to use automated systems effectively.

LA9. Automation reduces my workload-related fatigue.

LA10(R). Breakdowns or system downtime create additional workload.

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LA11. Automated systems are well integrated with the laboratory workflow.

Perceived QC Performance Items

QC1. Internal quality controls are reviewed before patient results are released.

QC2. QC failures are identified and investigated promptly.

QC3. Testing is repeated whenever QC or internal-control requirements are not met.

QC4. QC activities and corrective actions are documented accurately.

QC5. Staff follow approved procedures even during periods of high workload.

QC6. Invalid, inhibited, or doubtful molecular results are investigated before reporting.

QC7. Contamination-prevention procedures are followed consistently.

QC8. Test results are carefully verified before final authorization.

QC9. Turnaround-time targets are met without compromising QC requirements.

QC10. Corrective actions are implemented and followed up after QC problems are identified.

QC11. QC performance remains consistent when patient testing increases.

QC12. Staff receive timely feedback when QC problems occur.

QC13(R). Workload pressure sometimes leads to abbreviated QC checks.

QC14. Quality indicators are reviewed regularly to identify recurring problems.