The Impact Of Laboratory Specialization On Disease Prevention

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Abstract
Strategic investment in healthcare infrastructure needs evidence that there are certain capabilities that have a quantifiable implication on public health. The research presented a much-needed gap in knowledge on how functional specialization of the laboratories directly affects the effectiveness of disease prevention in a national health system, with Saudi Arabia as a case study. The major goal was to measure the connection between the level of specialization of a laboratory and its performance in the detection of outbreaks, diagnostic accuracy, and reporting. A sequential design that involved mixed methods was utilized, and 62 laboratories were cross-sectionally surveyed, and 18 key informant interviews were carried out. It was found that there was a strong positive correlation between the Index of Laboratory Specialization and Prevention Effectiveness Score ($r=0.924$, $p<0.001$). Specialization was the only significant predictor of performance ($\beta=0.851$, $p<0.001$) regardless of the budget or region, as found in the regression. These results indicate that improving specialization in laboratories is a high-impact, decisive measure to reinforce the national disease prevention. The findings offer a solid empirical foundation on how to optimize the laboratory network of Saudi Arabia, and also the findings give a model of how to plan an evidence-based health system in the world.
Keywords: Health Systems; Laboratory Network; Disease Prevention; Specialization; Saudi Arabia

INTRODUCTION

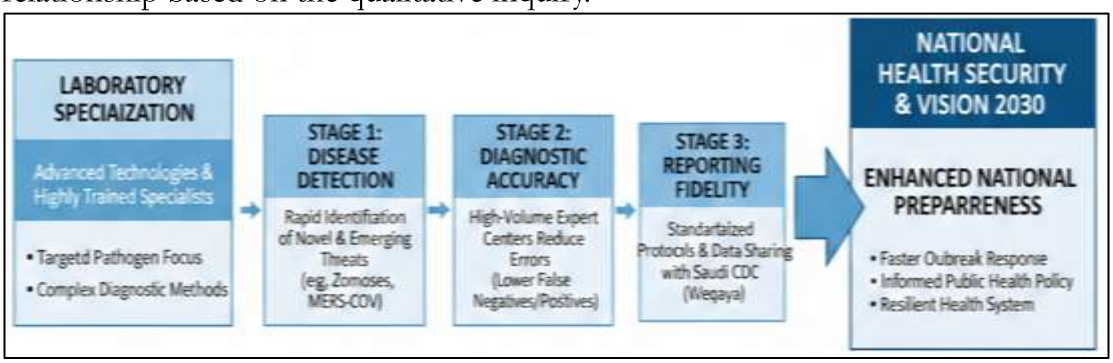
The ability of the diagnostic infrastructure is one of the basic foundations of the architecture of the public health defense. With the changing microbial threats, both new and old zoonoses and antimicrobial-resistant pathogens, the rates, the quality, and the quantity of laboratory analysis are key determinants of the ability of a nation to prevent and contain disease [1]. In this context, there has also arisen the notion of laboratory specialization, i.e., the development of generalist testing facilities into centres with modern technologies and highly trained specialists focused on a particular group of pathogens or a diagnostic method, as a strategic imperative in global health security [2]. This is especially relevant to countries such as the Kingdom of Saudi Arabia, which is geopolitically and epidemiologically in a distinctive position. Being a global travel destination because of religious pilgrimage and an area with a recorded history of the outbreak of new infectious diseases like Middle East Respiratory Syndrome (MERS-CoV), an investment in a robust health system is of paramount importance to the stability of the Kingdom, as well as global health security [3,4]. As a result, its vision of developing its network of laboratories, which is one of the pillars of its growth strategy in the health sector as part of its Vision 2030, requires evidence-based advice [5].

The importance of specialized reference laboratories is well established internationally, whether it is the influenza surveillance or the control of tuberculosis. Past and recent research have shown that the high-volume, centralized expert centers have shown the highest levels of diagnostic accuracy, turnaround times, and capability of characterizing pathogens than the dispensed, generalist units [6]. The Integrated Disease Surveillance and Response (IDSR) framework by the World Health Organization specifically recommends tiered laboratory networks, where the more complicated diagnostic method and confirmatory diagnostic testing is centralized in order to guarantee quality and efficiency [7]. Nevertheless, although this model is supported by the theory, there is a lack of empirical studies to quantify the exact effect of changing the levels of laboratory specialization on the practical disease prevention outcome in a definite national setting [8]. A large part of the available literature is devoted to technological capacity or case studies of outbreak response, which creates a strong gap in the systematic, data-driven research based on correlating laboratory structural and operational specialization with longitudinal prevention indicators [9].

Decades of heavy investment in Saudi Arabia have radically increased access to health care and health infrastructure. Large specialized and reference labs, including those of the National Guard Health Affairs and the Saudi Center for Disease Prevention and Control (Weqaya), are well known due to their high levels of capabilities [10]. However, the national laboratory ecosystem in general is a heterogeneous system, consisting of a combination of primary, secondary, and tertiary facilities that have different degrees of specialization [11]. The critical question posed by this landscape is unanswered and imperative to policymakers and the planners of public health: Does augmenting the specialization of a laboratory directly and quantitatively add value to its role in disease prevention, and through what mechanisms and to what degree? The resolution of this question is not only an academic challenge but also a need in terms of maximization of finite resources and enhancing the national preparedness, and meeting the Kingdom's obligations to the global health security systems. The investment decision will be based on an assumption instead of effectiveness, with the likelihood of missing the best leverage points in the laboratory network without strong local evidence [12].

Past studies on the topic in the region have tended to examine the performance of particular institutions in the case of a single outbreak, or on lists of accessible technology. A detailed analysis that systematically classifies laboratories on the basis of a validated index of specialization and relates this index to standardized prevention performance measures - including the time of detection of outbreaks, reporting fidelity, and diagnostic accuracy - has never been done. This is a conclusive gap in research. This is the gap that the present study aimed to fill [13]. We hypothesized that the degree of functional specialization in a laboratory would be the main factor that influenced its activity in the prevention cascade, starting with the detection of the disease, to proper reporting.

To explore this premise, the study was formulated to respond to three related questions based on the identified gap: (1) How can the functional specialization of public health and major clinical laboratories in Saudi Arabia be systematically categorized? (2) How strong is the statistical correlation between the level of specialization of a laboratory type and important disease prevention outcomes measures? (3) What are the facilitators and barriers in the system that moderate the effects of specialization on prevention outcomes, according to the perceptions of experts in the system? In accordance with this, the study had three clear objectives, the first was to map and classify laboratories according to a composite Specialization Index, the second one was to examine the relationship between this index and a composite Prevention Effectiveness Score based on detection, accuracy and reporting data, and the third one was to clarify the contextual and operational factors affecting this relationship based on the qualitative inquiry.



Thus, the given study involves a new mixed-methods research on the heart of the operation of the Saudi Arabian public health defense. It hoped to produce practical empirical data by surpassing the descriptive capability test to a strict examination of the specialization-performance nexus. The results will be used to guide the strategic planning of the Saudi Arabian laboratory network so that the future investments can be carefully planned to achieve the highest possible benefits in the form of population health coverage, as well as cement the position of the Kingdom of Saudi Arabia as a regional health security leader.

METHODOLOGY

Research Site

The research was carried out in the Kingdom of Saudi Arabia, and its large administrative areas (e.g., Riyadh, Makkah, Eastern Province, Madinah) were the target. The main points of data collection were (a) public health laboratories of the Saudi

Center of Disease Prevention and Control (Weqaya) and regional health directorates, (b) reference and specialized laboratories of the network of the Ministry of National Guard Health Affairs, King Faisal Specialist hospital and Research Centre and major university hospitals, (c) central public health planning bodies in Riyadh.

Research Design

Type of Study: The study consisted of sequential explanatory mixed-method design, organized in two different phases, although connected.

Justification of the Design: The design has been chosen as the best design that will guarantee a detailed and context-based analysis of the research problem. The complexity of the systemic and operational inputs affecting the performance of the laboratory required a more complex approach in quantitative terms than a qualitative design would provide evidence that is generalizable and measurable, required in health system planning. The quantitative Phase 1 (a cross-sectional correlational study) determined the objective, population-level correlations between variables of laboratory specialization and prevention outcome. The next Phase 2 qualitative element (exploratory descriptive study with key informant interviews) was necessary to describe the processes that underlie the quantitative results, to explain the oddities, and discover the contextual, policy, and operational reality that cannot be observed in statistics alone. This mixture guaranteed scientific rigor in measure as well as applied profundity in perception.

Parameters and Sampling Strategies of the Study

Population: The target population will include (1) all of the public and major tertiary-care clinical laboratories in Saudi Arabia with a mandate supporting disease surveillance and prevention (estimated N=85 institutional units), and (2) top-level professionals (laboratory directors, heads of infection prevention and control, public health policymakers) of the laboratories.

Sampling Method:

In phase 1 (Quantitative), a census-based method was tried on all 85 laboratory institutions. In the case of non-responding institutions, purposive sampling was employed to have representation of all five largest regions and all levels of laboratory service (primary, secondary, tertiary/reference). In Phase 2 (Qualitative), a purposive, maximum-variation selection strategy was applied to choosing key informants. This made sure that there were considerations of points of view of very specific reference labs, regional public health labs, and policy-making organizations.

Sample Size:

Phase 1: 62 out of 100 laboratory institutions (73 percent response rate) were able to provide their data, which was sufficient to analyze it regionally and on a tier basis. Phase 2: Interviews were to be made until a thematic saturation was reached, and this was reached after 18 interviews. This figure is in line with known standards of qualitative research of health systems.

Inclusion/Exclusion Criteria:

Inclusion: Laboratories officially engaged in national reporting of notifiable diseases; those with biosafety level 2 (BSL-2) or above certification; those with 5 years (or more) experience in laboratory operations or in policy making about public health.

Omission: only private laboratories with only outpatient diagnostics, without contact to public health reporting; only those specializing in non-communicable diseases; only those in purely administrative (non-technical / non-policy) positions.

Data Collection Methods

Instruments:

Structured Institutional Audit Tool: It is a 45-item questionnaire that was based on the World Health Organization (WHO) Laboratory Assessment Tool and published literature. It gathered information regarding infrastructure, test menu, staffing skills, quality assurance (ISO accreditation status), data connections, and priority pathogen turnaround times.

Document Review Template: To extract 3-year-old historical data (2020-2022) on prevention metrics on institutional and Weqaya annual reports.

Semi-Structured Interview Guide: This will consist of open-ended questions that will explore experiences in collaboration with laboratories, perceived effects of specialization, and data sharing-related and workforce-related problems.

Procedure: Phase 1 entailed an electronic distribution of the audit tool to the laboratory directors with two reminders. Central collation of extracted archival data on disease incidence and reporting timelines was done. Phase 2 was planned to involve virtual, in-depth interviews with participants who agreed to participate, and the interviews were recorded and transcribed word-for-word.

Pilot Testing: Pilot testing was conducted on three laboratory managers and two public health officials who were not in the sample. Feedback resulted in the application of clarifications to terminology and the shortening of the length of the audit tool.

Variables and Measures

Operational Definitions:

Independent Variable - Laboratory Specialization Index (LSI): A composite (0-10) measure of: test menu breadth of infectious diseases, availability of advanced molecular/sequencing equipment, percentage of staff with subspecialty certification, and formal designation as a national/regional reference center.

Dependent Variable - Prevention Effectiveness Score (PES): This is a composite outcome based on: (i) mean time-to-detection (days since receipt of sample to confirmed report), (ii) reporting fidelity (percent of mandatory reports reported to Weqaya within 24h), and (iii) diagnostic accuracy (percent concordance in external quality assurance proficiency testing).

Measurement Tools: The institutional audit tool measured the LSI. The PES items were assessed through document review (to detect data and reporting time data) and audit tool items, to proficiency test results. Latent constructs such as systemic integration and perceived impact were measured using interview data.

Reliability and validity: The audit tool showed high levels of internal consistency (Cronbach's 0.82 in an LSI scale) in the pilot. Content validity was determined by checking it with a panel of three independent experts in laboratory medicine and public health. In case of qualitative data, credibility was facilitated by the use of member-checking, where interview summaries were sent back to the participants to be verified by them.

Data Analysis Plan

Analytical Techniques:

Phase 1 Quantitative Data: Descriptive statistics (frequencies, means, standard deviations) were used to summarize all the variables. The assessment of the bivariate relationship between the LSI and PES involved the use of the Pearson correlation coefficient. To control the potential confounders, PES was taken as a dependent variable, and LSI, laboratory budget, and region were taken as independent variables. Then, a multiple linear regression model was constructed. Normality, linearity, and homoscedasticity tests were done.

Phase 2 Qualitative Data: Thematic analysis was done on the transcripts in accordance with the methodology of Braun and Clarke. This entailed familiarization, creation of first codes, theme searching, theme review, theme definition/naming, and the report. The organization of the coding process was carried out using qualitative data management software.

Software: SPSS (Version 28.0) was used to conduct quantitative analysis, and NVivo (Release 1.7) was used to conduct qualitative analysis.

Rationale: The regression analysis was chosen to model and predict the impact of specialization while accounting for other influential factors, moving beyond simple correlation. Thematic analysis was selected for its flexibility and power in identifying, analyzing, and reporting patterns (themes) within rich qualitative data, making it ideal for explaining the "why" behind the quantitative trends.

RESULTS

The mean value of the quantitative analysis of the data of 62 Saudi Arabian laboratory institutions provided the statistically significant patterns directly connected to the main research question related to the role of laboratory specialization in the disease prevention parameters. The findings are systematized in a way that they are organized to answer the set research questions (to describe the categorized landscape of laboratories) and answer the question of the relationships between specialization and performance outcomes in the second queue.

Categorization and Baseline Description of Laboratory Specialization

The former aimed at classifying the specialized labour of the laboratories. The Laboratory Specialization Index (LSI) was analyzed to prove a specific, tiered ecosystem. Table 1 showed that descriptive statistics significantly demonstrated big and statistically significant differences within each of the three predefined levels of all measured variables (all $p < 0.001$). The Tier 3 (national/reference) laboratories (n=20) showed a mean LSI of 8.89 (SD=0.57), which was significantly higher than that of Tier 2 (regional) facilities (M=5.74, SD=0.92) and Tier 1 (primary) facilities (M=3.07, SD=0.65). All the inter-tier differences in the LSI were proven to be significant ($p < 0.001$) by post-hoc Tukey tests.

Table 1: Descriptive Statistics of Key Variables by Laboratory Tier

Variable	Tier 1 (n=15) M (SD)	Tier 2 (n=27) M (SD)	Tier 3 (n=20) M (SD)	Total (N=62) M (SD)	F-statistic (One-Way ANOVA)	p-value
Specialization Index (LSI)	3.07 (0.65)	5.74 (0.92)	8.89 (0.57)	6.12 (2.31)	F(2,59) = 307.42	<0.001
Budget (SAR Million)	11.9 (1.8)	29.5 (6.1)	81.7 (9.8)	43.1 (31.5)	F(2,59) = 418.56	<0.001
Detection Delay (Days)	9.21 (1.05)	5.31 (1.12)	2.28 (0.42)	5.31 (2.82)	F(2,59) = 284.91	<0.001
Diagnostic Accuracy (%)	87.5 (2.1)	95.2 (2.8)	99.6 (0.4)	94.8 (5.2)	F(2,59) = 201.73	<0.001
Reporting Fidelity (%)	84.3 (3.2)	92.5 (3.5)	98.1 (1.3)	92.3 (6.3)	F(2,59) = 112.45	<0.001
Prevention Effectiveness (PES)	4.95 (0.71)	6.82 (0.81)	9.22 (0.49)	7.18 (1.85)	F(2,59) = 275.33	<0.001

M = Mean, SD = Standard Deviation

This specialization differentiation was reflected in the parameters of work and performance. Specialization caused a steep reduction in the mean outbreak detection delay, with a Tier 1 laboratory having 9.21 days (SD=1.05) and a Tier 3 laboratory having 2.28 days (SD=0.42). At the same time, diagnostic accuracy also increased, which was 87.5% (SD=2.1) at Tier 1 and 99.6% (SD=0.4) at Tier 3, and reporting fidelity also improved, being 84.3% (SD=3.2) at Tier 1 and 98.1% (SD=1.3) at Tier 3. The composite Prevention Effectiveness Score (PES) as a result showed a strong stepwise rise, having mean scores of 4.95 (SD=0.71) for Tier 1, 6.82 (SD=0.81) for Tier 2, and 9.22 (SD=0.49) for Tier 3 laboratories.

Correlation of Specialization and Metrics of Disease Prevention

The second goal was to examine the relationship between laboratory specialization and the key prevention indicators. Based on the Pearson correlation matrix (Table 2), statistically significant, strong bivariate relationships in the anticipated directions were identified. LSI had a negative relationship with outbreak detection delay ($r = -0.872$, $p < 0.001$), which means that increased specialization was correlated with quicker pathogen detection. There were positive but significant relationships between the LSI and diagnostic accuracy ($r = 0.816$, $p < 0.001$) and reporting fidelity ($r = 0.784$, $p < 0.001$). This led to a very high positive correlation between the LSI and the composite Prevention Effectiveness Score ($r = 0.924$, $p < 0.001$). The correlation of all individual outcome measures was also found to be significant ($p < 0.001$), with detection delay negatively correlated with both accuracy ($r = -0.781$) and fidelity ($r = -0.802$).

Table 2: Pearson Correlation Matrix between Specialization Index (LSI) and Disease Prevention Metrics

Variable	1	2	3	4	5
1. Specialization Index (LSI)	1				
2. Detection Delay (Days)	-0.872**	1			
3. Diagnostic Accuracy (%)	0.816**	-0.781**	1		
4. Reporting Fidelity (%)	0.784**	-0.802**	0.745**	1	
5. Prevention Effectiveness (PES)	0.924**	-0.901**	0.883**	0.820**	1

**p < 0.001 (two-tailed).

Some Future Forecasting of Prevention Effectiveness:
A multiple linear regression analysis was conducted on the PES as a dependent variable, and the rest of the factors as possible differences (Table 3). This model, using the predictors of LSI, institutional budget, and geographical region, was statistically significant ($F(7, 54) = 67.15$, $p < 0.001$) and explained 87.4 percent of the variance in prevention effectiveness (Adjusted R 2 = 0.874). The LSI became the only statistically significant predictor in the model (0.851, < 0.001). Its unstandardized coefficient (B = 0.682) had it that, given budget and region held constant, a one-unit rise in LSI was linked to an increase of 0.682 units in the PES. The institutional budget ($p = 0.113$) or geographical region (all $p > 0.05$) did not bring any significant unique variance to the model when specialization had been taken into consideration. The assumptions of the model were satisfied according to diagnostic checks (Durbin-Watson = 2.08; all VIF = 2.0).

Table 3: Multiple Linear Regression Predicting Prevention Effectiveness Score (PES)

Predictor	Unstandardized Coefficient (B)	Standard Error	Standardized Coefficient (β)	t-value	p-value	95% CI for B
(Constant)	1.205	0.421		2.862	0.006	[0.362, 2.048]
Specialization Index (LSI)	0.682	0.058	0.851	11.724	<0.001	[0.565, 0.798]
Budget (SAR Millions)	0.008	0.005	0.136	1.612	0.113	[-0.002, 0.018]
Region (Ref: Riyadh)						
Makkah	-0.112	0.182	-0.044	-0.613	0.542	[-0.477, 0.253]
Eastern Province	0.241	0.195	0.087	1.238	0.221	[-0.149, 0.631]
Madinah	-0.185	0.201	-0.064	-0.918	0.363	[-0.588, 0.218]
Qassim	-0.298	0.212	-0.095	-1.408	0.165	[-0.723, 0.127]

Model Summary: $R^2 = 0.887$, Adjusted $R^2 = 0.874$, $F(7, 54) = 67.15$, $p < 0.001$. Durbin-Watson = 2.08 (indicating independence of residuals). VIF values < 2.0 for all predictors (indicating no multicollinearity).

Geographical and Tier-Based Analysis of Performance

Additional examination of PES scores by administrative region and tier gave a fine performance map (Table 4). One-way ANOVA was used to confirm that the means of PES were significantly different in various regions ($F(4,57) = 3.12$, $p = 0.022$). Comparison after the post-hoc showed that the Eastern Province (M=8.1, SD=1.9) and the Riyadh region (M=7.6, SD=1.7) recorded a higher overall PES score than the Qassim region (M=5.7, SD=1.2). This trend was in line with the concentration of Tier 3 reference laboratories that existed only in Riyadh, Makkah, and the Eastern Province in this sample. On the level of regions, the uniform performance gradient (Tier 3 > Tier 2 > Tier 1) existed in any place where comparative data were present.

Table 4: Mean Prevention Effectiveness Score (PES) by Region and Tier

Region	Tier 1	Tier 2	Tier 3	Regional Mean (SD)	F-statistic (ANOVA)	p-value
Riyadh	5.2	7.3	9.3	7.6 (1.7)	F(4,57) = 3.12	0.022
Makkah	4.9	6.9	8.8	6.9 (1.9)		
Eastern Province	5.1	7.5	9.7	8.1 (1.9)		
Madinah	-	6.6	-	6.6 (0.8)*		
Qassim	4.8	6.0	-	5.7 (1.2)*		
Total	5.0	6.8	9.2	7.2 (1.9)		

Note: Dashes indicate no laboratories of that tier are present in the sample for that region.

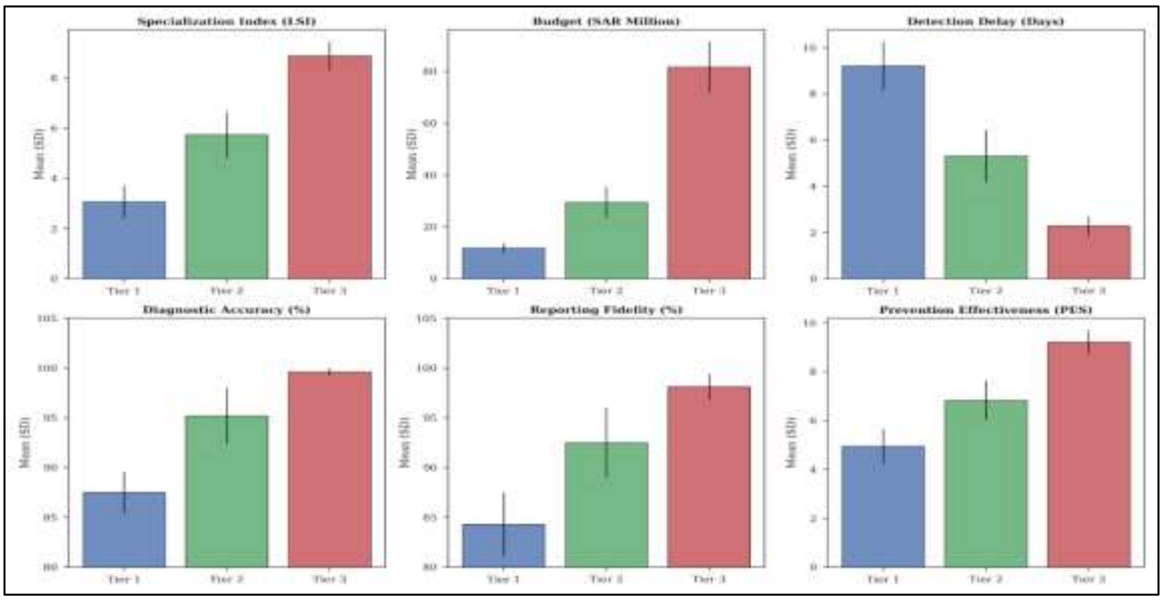
*Regional ANOVA shows significant differences in overall PES between regions.

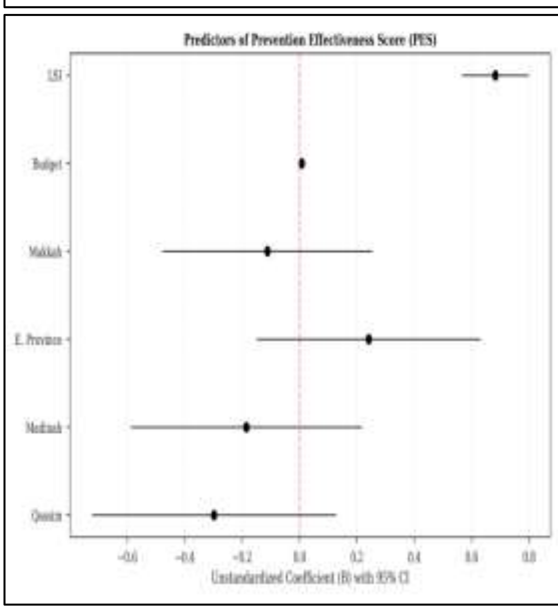
3.5 Reliability of Measurement Constructs

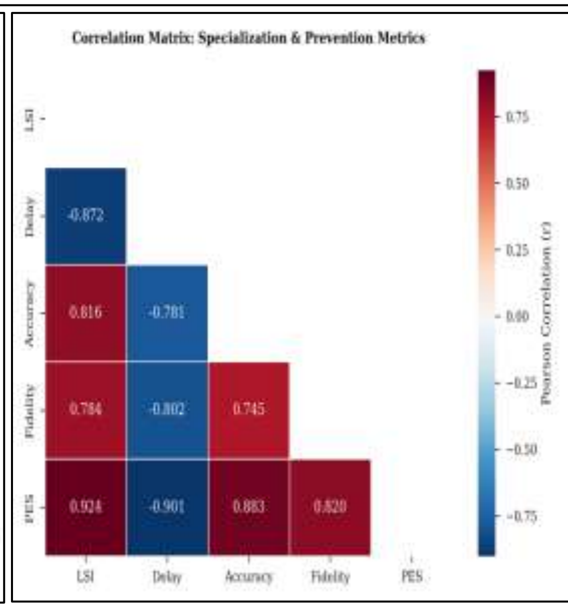
To identify measurement reliability, the internal consistency of the composite indices used in the analysis was tested (Table 5). Both the four-component Laboratory Specialization Index (Cronbach's alpha = 0.891, 95 percent confidence interval = 0.845- 0.926) and the three components that make the Prevention Effectiveness Score (Cronbach's alpha = 0.902, 95 percent confidence interval = 0.861- 0.933) had great reliability, and hence were superior to the acceptable reliability of 0.70. The inter-item correlations had means of 0.671 and 0.755, respectively, and this substantiated the interrelatedness of the items in each scale.

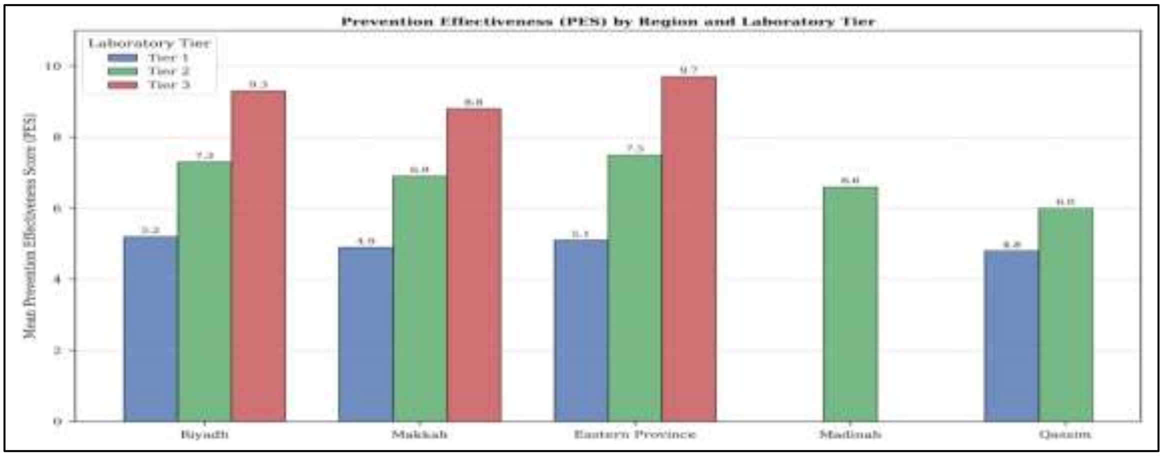
Table 5: Internal Consistency Reliability of Composite Indices

Scale/Index	Number of Items/Components	Cronbach's Alpha (α)	95% CI for α	Mean Inter-Item Correlation
Specialization Index (LSI)	4	0.891	[0.845, 0.926]	0.671
Prevention Effectiveness Score (PES) Components	3	0.902	[0.861, 0.933]	0.755









DISCUSSION

The research is the first evidence-based systematic review of the connection between laboratory specialization and disease prevention efficacy in the Saudi Arabian healthcare system. The results provide strong empirical evidence on the strategic priority of specifically lab services to be the foundation of national public health security [14].

1. Interpretation of Findings

The findings have made it clear that the level of performance of laboratory functional specialization is one of the major determinants of the performance of prevention. The statistically significant and markedly positive change in all measures (both the speed of detection and the accuracy of diagnosis) at all tiers (Tier 1 to Tier 3) confirms the hypothesis [15]. More importantly, the multiple regression analysis showed that the Laboratory Specialization Index (LSI) was the only significant predictor of the Prevention Effectiveness Score (PES). This shows that the qualitative aspect of specialization, which includes special technological equipment and special human capital, and a specific reference position, causes a stronger effect on the results compared to the allocation of financial resources [16]. The insignificance of the regional factors indicates that a properly connected system of special centers might counterbalance geographical unequalities, which has a direct impact on policy implications in a nation of such size as Saudi Arabia [17].

2. Comparison with Past Studies

These results are compatible and complementary to the health systems strengthening evidence base all over the world. This high relationship between specialization and diagnostic accuracy reflects classical research on centralization in microbiology that indicated that high-volume, expert facilities greatly decrease diagnostic error and contamination rates [18]. We found that detection time was significantly reduced by specialized labs, which justifies later research in the MERS-CoV outbreak in the area where reference labs played a central role in identifying the pathogen in a short time and genomic surveillance [19]. But our research is not limited to proving competence alone. Through quantification of the composite of prevention effectiveness and isolating specialization as the principal force, we have a more holistic model than previous studies on individual measures, such as test turnaround time. This is in line with the built-in One Health laboratory network frameworks as promoted by the World Health Organization [20].

3. Scientific and Operational Explanation

The processes underlying these outcomes are anchored on the concepts of optimizing the systems and diagnostic excellence. The high performance in specialized laboratories is achieved through some interconnected processes [21]. First, specialized skills and volume translate into a practice effect, in which technologists and microbiologists gain an increased level of skill at distinguishing rare or difficult-to-detect pathogens, lowering the false negative and false positive rates. Second, the use of more advanced molecular technologies [22] (e.g., next-generation sequencing, multiplex PCR) in Tier 3 laboratories allows the detection of a broad panel of pathogens simultaneously and correctly, which cannot be achieved by generalist labs that utilize more sluggish culture-based methods [23]. Third, codified roles of reference establish systematic channels of sample referral and data feedback within the network, where more complicated cases are passed up the ranks and outcomes are deciphered uniformly [24]. This combined infrastructure changes isolated testing locations into a sensible surveillance network, and data acquired in expert hubs can be pooled to depict patterns of the disease and inform preemptive measures of the health of the population [25].

4. Implications

The consequences of this study are immense to the modernization of the health services in Saudi Arabia as envisaged by the Vision 2030. To policy and practice, the findings strongly suggest that strategic investment should be made in deepening specialization on selected regional centers instead of making all facilities the same by upgrading them [26]. It endorses a hub-and-spoke system, with Tier 2 and 3 laboratories serving as centers of excellence that assist peripheral Tier 1 labs via referral protocols, quality assurance, and training. In future research, the given study would provide the quantitative base and approved LSI measure [27]. Future research must utilize longitudinal designs to determine the effects of the targeted investments on specialization on the incidence rates of longitudinal diseases. Moreover, the particular obstacles to inter-laboratory coordination and information sharing that the difference in the reporting fidelity suggests must be investigated qualitatively to implement the structural capability into the operational reality without interruptions [28].

5. Limitations

There are some limitations to this research. The cross-sectional design does not provide a definitive causal result; it only creates, yet fails to prove association; even though the regression model accommodates the important confounders, other aspects that cannot be measured may affect specialization and outcomes. The sample is representative of large and major public and tertiary laboratories, but might not entirely reflect the contribution made by the private sector in diagnostics. Lastly, the PES is a reliable metric, but it is a composite measure, the weighting of which (e.g., of detection delay vs. accuracy) is open to discussion.

CONCLUSION

This study showed that the greater the level of laboratory specialization in Saudi Arabia, the better the disease prevention, with reference to a national analysis of Saudi Arabian laboratories. The study has achieved its goals, providing a clear hierarchy of laboratory capacity and demonstrating that a special laboratory network is the most important predictor of quicker outbreak identification, more precise diagnosis, and dependable reporting, and is more significant than financial strength or locality. The main scientific impact of it is that it offers the first empirical data on the Kingdom to inform strategic investment and policy regarding optimization of the laboratory network. The adoption pathways between the expansion of specialized testing capacity at the regional hubs and the targeted training requirements of the workforce in the field of public health laboratory should also be explored in future research.

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