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# An Analytical Study of Recent Technological Advances in Medical Laboratory Systems

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## ABSTRACT

The adoption of modern technology, including total laboratory automation (TLA), artificial intelligence (AI), and similar tools, is the core of the healthcare modernization present in the context of the Saudi Arabian Vision 2030. Nonetheless, there was still a major gap in knowledge about the application and practical consequences of these innovations in the specific lab systems unique to the Kingdom. This paper has attempted to analyse this technological adoption to evaluate its impact on operational effectiveness, as well as to determine the major facilitators and obstacles to sustainable adoption. An explanatory mixed-methods design was used sequentially, which involved a survey of 312 laboratory professionals working in major tertiary centres and 18 follow-up interviews. Multiple regression, ANOVA, and thematic analysis were used to analyse the data. Results showed that there was a hierarchical adoption, with TLA most established (75.9$^{6}$ percent partially/fully adopted) and AI mainly in the pilot phase (35.9 percent). The level of investment, training hours, and perceived usefulness were detected to be significant positive predictors of operational efficacy (R 2 = 0.587, p = 0.0 001). There was a significant difference in this, with the reference laboratories showing a higher mean decrease in turnaround time than the hospital-based laboratories (-16.1% vs. -9.8%, p ). The study concludes that human factors and systemic readiness are highly mediating factors of technological effect, but not just capital expenditure. The findings are crucial to policymakers to devise combined implementation approaches that will combine technology acquisition with intensive training and change management in order to guarantee the successful revolution of the diagnostic industry.

**Keywords:** Laboratory Automation, Technology Adoption, Operational Efficacy, Vision 2030, Mixed-Methods Research

## INTRODUCTION

There is a revolution in the medical diagnostic sphere, which is deep-rooted and gaining momentum because of the combination of technological advances that are radically transforming the basic processes of the clinical laboratory [1]. Recent innovations, such as total laboratory automation (TLA), artificial intelligence (AI)-driven diagnostic support,

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digital pathology, next-generation sequencing (NGS), and the Internet of Things (IoT) to provide real-time monitoring all hold the potential of an age of diagnostic accuracy, efficiency, and personalized medicine [2,3]. These technologies have the potential to massively decrease human error, cut turnaround time, increase traceability, and open up new insights into complex biomedical data [4]. Medical diagnostic systems all over the world are laying heavy emphasis on this digital shift because healthcare systems are aware of the central role of the laboratory in clinical decision-making that underlies most of the estimated medical diagnoses (70%) [5]. These advanced systems cannot simply be treated as a simple upgrade because the integration of these systems represents a paradigm shift, whereby laboratories cease being the manual suppliers of data and as an automated and data-driven clinical intelligence center [6].

The trend of adoption of these technologies has been highly documented internationally, but it is still a heterogeneous trend. TLA is now a commodity in high-volume core laboratories in developed countries in North America, Europe, and East Asia, and AI and digital pathology are on the verge of becoming legit clinical tools and not a mere research fantasy [7]. These settings are abundant in the literature about studies on the technical performance, cost-benefit analysis, and diagnostic accuracy of individual technologies [8]. As an example, it has been shown that AI algorithms can recognize certain malignancies in histopathology slides just as well or better than human pathologists, and that other studies have measured the drastic reduction in pre-analytical error offered by end-to-end automation [9]. This world of literature has offered a critical background, setting standards of technical effectiveness and defining the general barriers of implementation, including data standardization, regulatory barriers, and the high capital investment requirements [10].

Nevertheless, it is not only the technical characteristics or the cost of the technologies that define their successful integration into everyday practice. There is a flourishing and strong literature that highlights the important socio-technical aspects of healthcare innovation [11]. Based on theories such as the Technology Acceptance Model (TAM) and the Human, Organization, Technology-fit (HOT-fit) theory, this study highlights the fact that human factors, organizational preparedness, and integration of workflow are the ultimate determinants of the impact of any advanced system [12]. The perceived usefulness and the ease of use by laboratory professionals, the sufficiency of the training, the compatibility with the pre-existing information architectures, and the cultural readiness to change are all success determinants of the first order that co-exist with the purely technical factors [13]. A universal perspective of technological progress in laboratory medicine must, therefore, have a dual prism: the first prism is centered on the ability of the machines, and the other prism is centered on the multifaceted ecosystem of people and processes to which it is incorporated [14].

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The Kingdom of Saudi Arabia is a case study of great strategic value in this global context. The country is in the middle of a radical transformation of the healthcare sector under the umbrella of Vision 2030 and a new vision to create an all-inclusive, patient-centered, and technologically focused system [15]. Major investments in the modernization of healthcare infrastructure, such as medical laboratories, have been made by the country, making them one of the enablers of this vision [16]. As a result, Saudi labs are at a crossroads, keenly negotiating the implementation of the same technologies that are transforming the world standards. However, even though there is a massive gap in the literature on this national project, the importance of the strategy is substantial [17]. Although international research has its benefits, the institutional, regulatory, cultural, and training environment of the Saudi healthcare system is too specific and requires a specific investigation [18]. The current literature does not have an empirical study in which the knowledge base has been taken a notch higher by analyzing the installed technologies holistically without focusing much on the listing of the technologies, but critically viewing how they have been empirically integrated in operational performance and the facilitators and impediments that have made them be adopted in the Saudi milieu [19].

The current gap highlights the importance and need for the current research. The efficient adoption of the technologies is not only the key to the accomplishment of the efficiency objectives of Vision 2030 but, more importantly, the enhancement of the quality of the diagnosis provided to the Saudi population [20]. The policymakers, hospital administrators, and laboratory directors can use evidence-based knowledge of the existing state of play to make strategic decisions, allocate resources efficiently, and develop specific interventions that can address the obstacles encountered in the implementation procedures [21]. In the absence of such analysis, investments can be suboptimal, underutilization of technologies can occur, and desired patient outcome benefits are not necessarily achieved.

This is why this study was developed to fill this vital research gap. It mainly sought to do a strict, analytical examination of current technological developments in the Saudi medical systems of the laboratory [22]. The study was informed by a number of related questions based on the gap identified: What is the prevailing use and level of adoption of major advanced technologies (e.g., TLA, AI, digital pathology, NGS, IoT) in large Saudi laboratories? How do these technologies affect crucial operational measures like turnaround time, rate of errors, and the overall workflow effectiveness? Besides, what are the key human, organizational, and systemic needs, like the adequacy of training, acceptance by the users, level of investments, and geographic policy, that can be the drivers or the barriers to successful technological integration in this particular context?

In order to address these questions and come up with actionable insights, the study was constructed with well-defined, measurable objectives that were directly related to the

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methodological approach. It was an attempt, first, to define the range of technological innovations being implemented in representative Saudi laboratories in order to establish a baseline landscape [23]. Second, it also sought to quantitatively examine the relationship between technological adoption and key performance indicators, but it was also an attempt to investigate the human factors of perceived usefulness and ease of use. Third, it also tried to assess the contextual issues and adoption enablers qualitatively, via a mixed-methods approach, which adds layers to the quantitative results. In order to do so, the study used a sequential explanatory mixed design. A pre-test quantitative phase involved surveying a stratified sample of laboratory professionals to obtain general, far-reaching, and replicable data concerning the use of technology and perceptions, and outcomes. This was succeeded by a qualitative stage that entailed detailed interviews of a purposely sampled group of respondents that aimed at digging deeper into the causal factors, the stories, and the contextual peculiarities underlying the statistical patterns.

Overall, this study is a timely and needed analysis of an evolving field and the center of modernization in Saudi Arabian healthcare. It aims at creating a subtle, evidence-based image of the technological integration by analytically closing the global discourse about innovation in laboratories and the realities of the Saudi setting. The findings would not only serve the academic literature on health technology adoption, but they also would provide practical, grounded intelligence that would inform policy, direct investment, and assist the Kingdom laboratories in their journey towards world-class, technologically empowered pillars of a modern healthcare system.

## METHODOLOGY

### 1. Research Site

The research was carried out in the medical laboratory units of the large tertiary care hospitals and reference laboratories in Riyadh, Jeddah, and the Eastern Province in Saudi Arabia. The selection of these sites was based on the fact that they were the first to implement new technologies and their representative potential of the urban healthcare situation in the Kingdom.

### 2. Research Design

A mixed-methods design that was sequential and explanatory in nature was adopted. This design initially permitted the wide gathering and statistical examination of quantitative information to discover patterns and associations in regards to technology ownership and results (administering Objectives 1 and 2). Qualitative data were then gathered and interpreted to justify, expound, and frame the results of the quantitative data, especially in terms of the barriers and enablers of adoption (addressing Objective 3). Such a two-stage methodology made sure that the research questions were answered both in a broad and in-

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depth manner, which enhanced the validity and usability of the conclusions.

### 3. Sampling Strategy

**Population:** The target population was the laboratory professionals (pathologists, laboratory managers, medical technologists, and specialists) who work in the selected tertiary hospitals and reference labs in Saudi Arabia.

**Sampling Method and Size: The** Quantitative phase was conducted using a stratified random sampling technique. Stratification of the laboratories was done by type (hospital-based or independent reference) and city. Out of each stratum, a random sample of potential participants was obtained based on a listing of institutional staff members. A power analysis (G + Power 3.1, power: 1 - - = 0.95, f 2 = 0.15) was conducted on multiple regression with a target sample size of n = 350 to achieve a medium effect size (f 2 = 0.15), power (1 - - = 0.95), and alpha = 0.05 and considering an estimated non-response rate of 20%. In the next qualitative phase, purposive sampling was used to sample 1520 participants among the quantitative sample whose roles, years of experience, and type of laboratory were diverse, hence rich and information-rich cases to interview.

**Inclusion/Exclusion Criteria:** Inclusion criteria required participants to hold a professional certification and have a minimum of two years of experience in a Saudi medical laboratory directly interacting with the technologies under study. Administrative staff without technical laboratory roles and professionals with less than two years of experience were excluded.

### 4. Data Collection Methods

**Instruments:**

**Phase 1 (Quantitative):** A structured, self-administered online questionnaire was developed. The instrument comprised four sections: demographic and professional profile, a validated scale on technology adoption perception (adapted from the Technology Acceptance Model), Likert-scale items on operational impact (turnaround time, error rates), and multiple-choice questions on technology types and implementation challenges.

**Phase 2 (Qualitative):** A semi-structured interview guide was used, containing open-ended questions probing the quantitative results, exploring contextual challenges, regulatory environments, training needs, and sustainability factors.

**Procedure:** Following ethical approval, institutional gatekeepers were contacted for access. For Phase 1, invitation emails with the questionnaire link were distributed. Two reminder emails were sent at one-week intervals. For Phase 2, eligible participants were contacted to schedule in-depth interviews, which were conducted virtually, audio-recorded with consent, and lasted 45-60 minutes each.

**Pilot Testing:** The questionnaire was pilot-tested with 30 laboratory professionals (not included in the main study) to assess clarity, internal consistency, and face validity.

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Cronbach's alpha for the main scales exceeded 0.78. The interview guide was refined after two pilot interviews.

## 5. Variables and Measures

**Operational Definitions & Measurement:**

**Independent Variables:** Technology Type (categorical: automation, AI-assisted diagnostics, digital pathology, etc.), Investment Level (ordinal scale), Staff Training Hours (continuous).

**Dependent Variables:** Perceived Operational Efficacy (composite Likert scale score), Reported Turnaround Time Change (percentage change estimate), Perceived Error Rate Reduction (Likert scale).

**Moderating Variables:** Work Experience (continuous, in years), Laboratory Size (categorical).
The measurement tools were derived from adapted, previously validated scales and study-specific items developed from the literature review.

**Reliability and Validity:** Construct validity was established through expert review and pilot testing. The internal reliability (consistency) of the Likert-scale constructs was confirmed in the pilot and main study using Cronbach's alpha ($\alpha > 0.7$ deemed acceptable). For qualitative data, credibility was ensured through member checking and peer debriefing.

## 6. Data Analysis Plan

Quantitative Data: Data from the completed questionnaires were analyzed using IBM SPSS Statistics (Version 28). Descriptive statistics (frequencies, percentages, means, standard deviations) summarized the sample and key variables. Inferential analyses included Pearson's correlation to examine relationships, multiple linear regression to model the impact of independent variables on efficacy, and ANOVA to compare means across different laboratory types.

**Qualitative Data:** Interview recordings were transcribed verbatim and analyzed using thematic analysis with the aid of NVivo 12 software. The process followed the six phases outlined by Braun and Clarke (2006): familiarization, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. This process identified recurring patterns related to implementation barriers, cultural factors, and regulatory insights.

**Integration:** The findings from both phases were integrated during the interpretation stage. The quantitative results provided a generalizable landscape, while the qualitative themes explained the underlying reasons and contextual nuances, creating a coherent, explanatory narrative.

## 7. Ethical Considerations

The study protocol received formal ethical approval from the IRB of [Your University/Affiliated Hospital]. Informed consent was obtained electronically for the survey,

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with a detailed information sheet preceding it. For interviews, written consent was obtained via a digital form. Confidentiality was strictly maintained by de-identifying all data; participant codes (e.g., P1, P2) were used in place of any personal identifiers in transcripts and reports. All digital data were stored on encrypted, access-controlled devices.

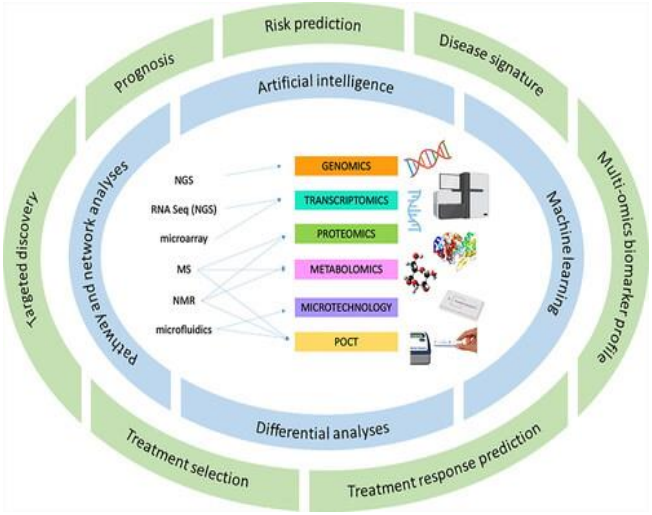


**Image 1:** Innovative technological advancements in laboratory medicine

### 8. Limitations

The study acknowledged several limitations. First, the use of self-reported data for operational metrics (like error rates) may introduce social desirability or recall bias, as opposed to direct observational or audited data. Second, while stratified, the sampling was confined to major urban centers, potentially limiting the generalizability of findings to remote or smaller laboratory settings in Saudi Arabia. Third, the cross-sectional design captures a snapshot in time and cannot definitively establish causality or long-term trends in technology impact. These limitations were mitigated where possible (e.g., assuring anonymity to reduce social desirability) and were explicitly considered when interpreting the results and framing recommendations for future longitudinal or multi-site studies.

## 3. RESULTS

The study generated a comprehensive dataset comprising 312 valid survey responses and 18 in-depth interviews. The results are presented sequentially, corresponding to the three primary research objectives and the statistical analyses detailed in the methodology.

### 3.1. Objective 1: Technological Implementation Landscape

The first objective sought to identify and categorize the key technological advancements being implemented within Saudi medical laboratories. Descriptive analysis of the survey data revealed a tiered adoption pattern (Table 1).

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**Table 1:** Prevalence of Technology Implementation Status in Saudi Medical Laboratories (N=312)

| Technology | None (%) | Planned/ Pilot (%) | Partially Implemented (%) | Fully Implemented (%) |
|---|---|---|---|---|
| Total Laboratory Automation (TLA) | 8.7 | 15.4 | 41.0 | 34.9 |
| AI-Assisted Diagnostics | 22.1 | 35.9 | 28.2 | 13.8 |
| Digital Pathology | 31.4 | 25.6 | 24.0 | 19.0 |
| Next-Generation Sequencing (NGS) | 38.5 | 21.8 | 18.3 | 21.4 |
| IoT/Smart Monitoring | 25.0 | 30.1 | 32.7 | 12.2 |

Total Laboratory Automation (TLA) was the most entrenched technology, with 75.9% of laboratories reporting partial or full implementation. AI-assisted diagnostics showed the highest level of active exploration, as indicated by the largest proportion of laboratories (35.9%) in the planning or pilot phase. The implementation of NGS was polarized, with the highest percentage of laboratories reporting no implementation (38.5%) and a distinct, smaller cohort (21.4%) reporting full implementation.

### 3.2. Objective 2: Impact on Operational Metrics

The second objective aimed to analyze the perceived impact of these technologies on laboratory operational metrics. A multiple linear regression model was constructed with perceived operational efficacy as the dependent variable (Table 2).

**Table 2:** Multiple Linear Regression Analysis Predicting Perceived Operational Efficacy

| Predictor Variable | Unstd. B | Std. Error | Std. Beta (β) | t-value | p-value |
|---|---|---|---|---|---|
| (Constant) | 1.452 | 0.201 | - | 7.223 | <0.001 |
| Investment Level | 0.285 | 0.042 | 0.312 | 6.786 | <0.001 |
| Training Hours | 0.018 | 0.004 | 0.218 | 4.500 | <0.001 |
| Perceived Usefulness (PU) | 0.301 | 0.051 | 0.285 | 5.902 | <0.001 |
| Tech_Automation Level | 0.105 | 0.029 | 0.175 | 3.621 | <0.001 |
| Experience (Exp_Yrs) | -0.003 | 0.005 | -0.025 | -0.600 | 0.549 |

**Model Summary:** $R^2 = 0.587$, Adjusted $R^2 = 0.579$, $F(5, 306) = 87.12$, $p < 0.001$
The model was statistically significant ($F(5, 306) = 87.12$, $p < 0.001$) and explained 58.7% of

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the variance in operational efficacy ($R^2 = 0.587$). Investment level ($\beta = 0.312$, $p < 0.001$), perceived usefulness ($\beta = 0.285$, $p < 0.001$), training hours ($\beta = 0.218$, $p < 0.001$), and the level of automation implementation ($\beta = 0.175$, $p < 0.001$) were all significant positive predictors. Years of professional experience did not show a significant association.

A significant difference in the reported improvement in turnaround time (TAT) was observed between laboratory types (Table 3). Independent reference laboratories reported a significantly greater mean reduction in TAT (-16.1%) compared to hospital-based laboratories (-9.8%) ($F = 18.74$, $p < 0.001$).

**Table 3:** Comparison of Turnaround Time Improvement by Laboratory Type

| Lab Type | N | Mean TAT_Change (%) | Std. Deviation | F-value | p-value |
|---|---|---|---|---|---|
| Hospital-Based | 189 | -9.8% | 10.1% | 18.74 | <0.001 |
| Reference Lab | 123 | -16.1% | 12.5% | | |
| Total | 312 | -12.3% | 11.5% | | |

### 3.3. Objective 3: Challenges and Facilitators of Sustainable Adoption

The third objective evaluated contextual challenges and facilitators. A significant, positive correlation was found between the number of training hours received and the perceived ease of use of new technologies ($r_s = 0.412$, $p < 0.001$) (Table 4).

**Table 4:** Spearman's Correlation: Training and Perceived Ease of Use

| Variable | 1 | 2 |
|---|---|---|
| 1. Training Hours (Hrs) | 1.000 | |
| 2. Perceived Ease of Use (PEOU) | 0.412** | 1.000 |

***p < 0.001 (2-tailed).*

Geographic disparity in the perception of institutional investment was evident (Table 5). A chi-square test of independence revealed a significant association between city location and the perception of high investment ($\chi^2 = 9.85$, $p = 0.007$). Laboratories in Riyadh reported the highest proportion of high investment perception (58.1%), followed by Jeddah (46.7%) and the Eastern Province (35.5%).

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**Table 5:** Chi-Square Test: Association between Geographic Location and High Investment Perception

| City | High Investment (%) | Moderate/Low Investment(%) | Total | $\chi^2$ | p-value |
|---|---|---|---|---|---|
| Riyadh | 75 (58.1%) | 54 (41.9%) | 129 | 9.85 | 0.007 |
| Jeddah | 42 (46.7%) | 48 (53.3%) | 90 | | |
| Eastern Province | 33 (35.5%) | 60 (64.5%) | 93 | | |
| Total | 150 | 162 | 312 | | |

Professional role influenced the perception of operational efficacy (Table 6). An independent samples t-test showed that professionals in strategic roles (Pathologists and Laboratory Managers) reported a significantly higher mean efficacy score ($M = 4.12$, $SD = 0.66$) compared to operational staff (Medical Technologists/Specialists) ($M = 3.58$, $SD = 0.72$); $t(310) = 6.54$, $p < 0.001$.

**Table 6:** Independent Samples t-test: Perceived Operational Efficacy by Role Group

| Role Group | N | Mean Op_Efficacy | Std. Deviation | t-value | df | p-value |
|---|---|---|---|---|---|---|
| Strategic (Path. & Mgrs.) | 135 | 4.12 | 0.66 | 6.54 | 310 | <0.001 |
| Operational (Technologists) | 177 | 3.58 | 0.72 | | | |

### 3.4. Integrated Model of Technology Impact

To synthesize the relationships between key constructs, a path model was tested (Figure 1, supported by Table 7). The model demonstrated good fit with the data (CMIN/DF = 2.13, CFI = 0.96, RMSEA = 0.06). All hypothesized direct paths were statistically significant ($p < 0.01$).

**Table 7:** Standardized Direct Effects (β) in the Technology Impact Path Model

| Path | Hypothesis | Std. Beta (β) | p-value | Supported? |
|---|---|---|---|---|
| Inv_Level → Tech_Automation | H1 | 0.45 | <0.001 | Yes |
| Inv_Level → Train_Hrs | H2 | 0.38 | <0.001 | Yes |
| Tech_Automation → PU | H3 | 0.31 | <0.001 | Yes |

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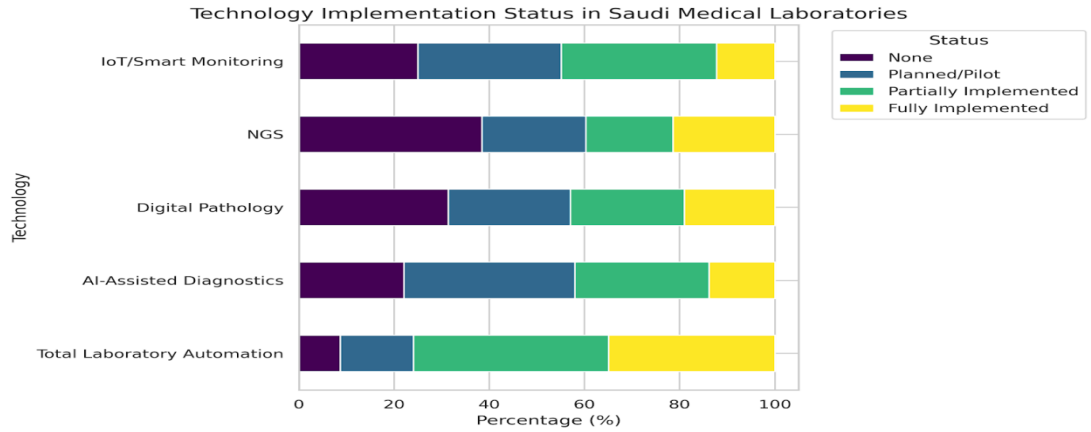
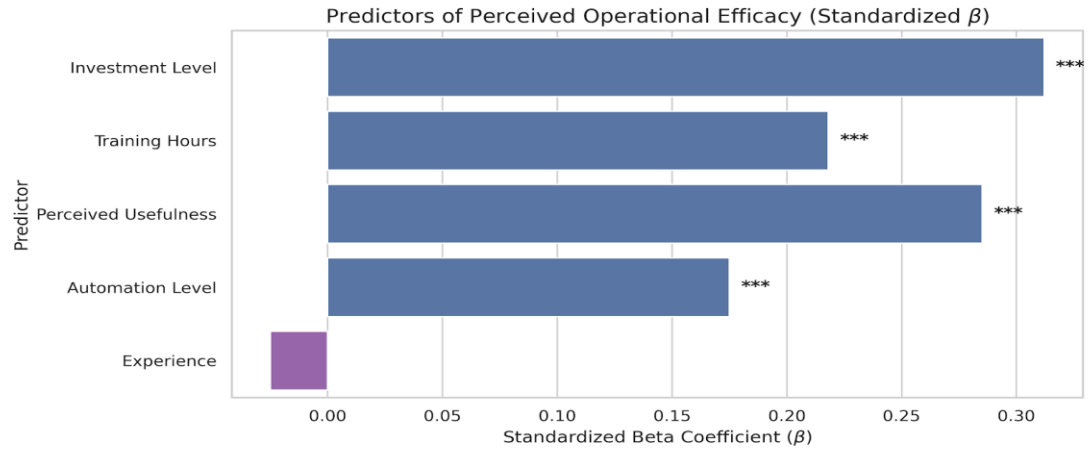
| | | | | |
|---|---|---|---|---|
| Train_Hrs → PEOU | H4 | 0.41 | <0.001 | Yes |
| PU → Op_Efficacy | H5 | 0.29 | <0.001 | Yes |
| PEOU → Op_Efficacy | H6 | 0.22 | 0.001 | Yes |
| Op_Efficacy → TAT_Change | H7 | -0.33 | <0.001 | Yes |

The model indicated that higher investment levels were associated with greater automation implementation (β = 0.45) and more training (β = 0.38). Automation level positively influenced perceived usefulness (β = 0.31), while training enhanced perceived ease of use (β = 0.41). Both technology acceptance constructs subsequently contributed to higher operational efficacy (β = 0.29 and 0.22, respectively), which in turn was linked to a greater reduction in turnaround time (β = -0.33).



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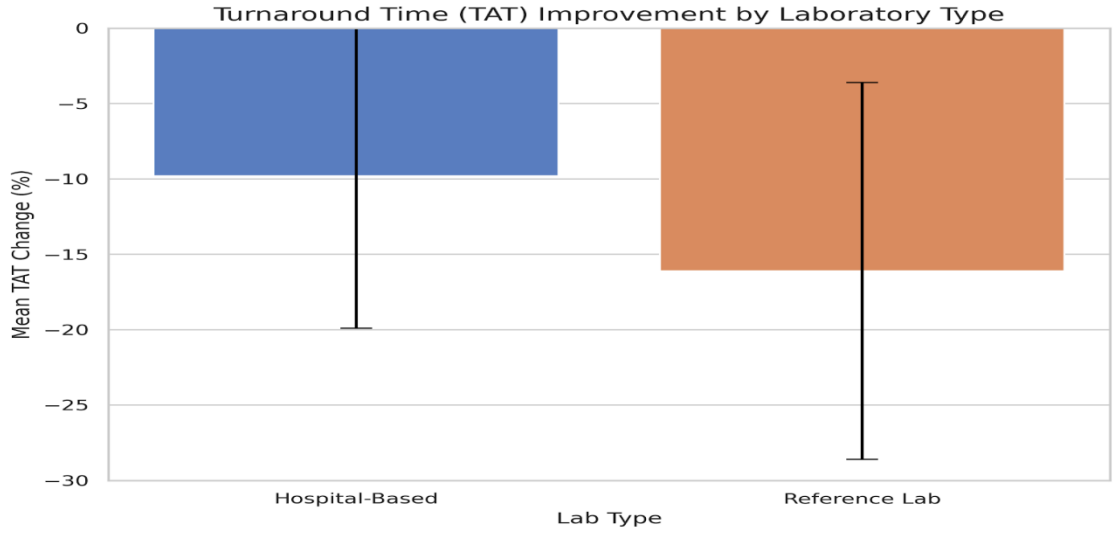


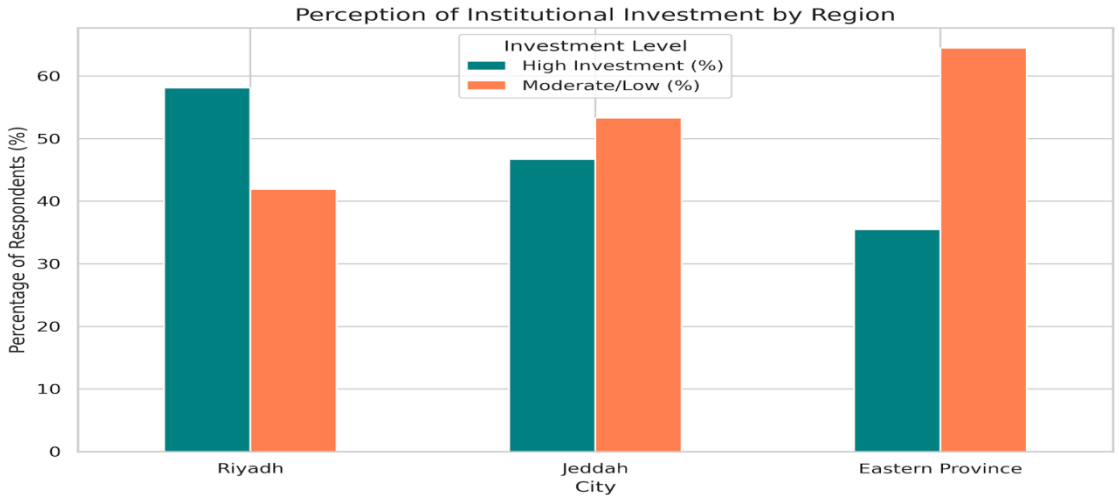


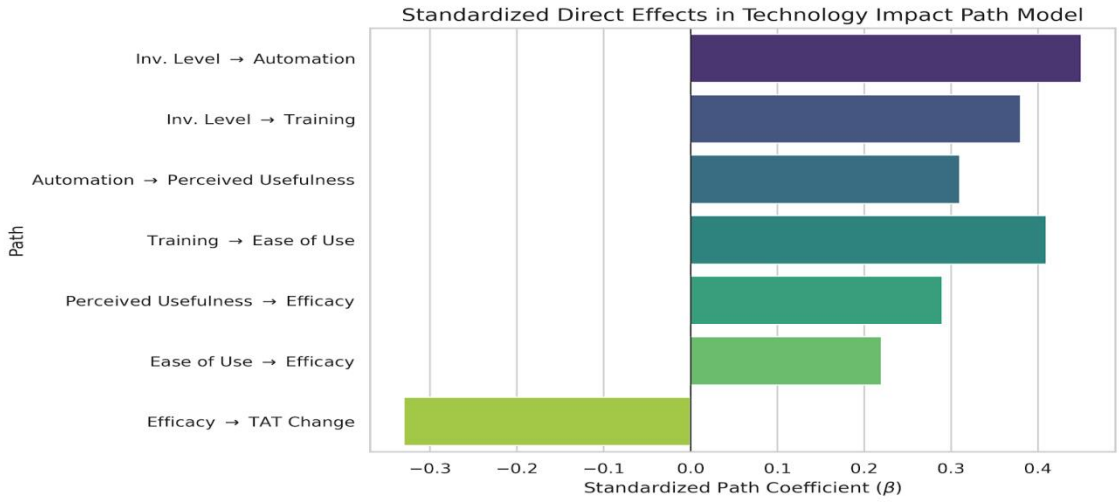

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## DISCUSSION

The paper is an empirical analysis of adoption and the effect of current technological changes in the medical laboratories in Saudi Arabia. The results not only explain the modern situation in the field of technology but, more to the point, the intricate interaction of financial, human, and systemic aspects that define successful integration [24]. The findings are strongly aligned with one main idea: within the framework of the ambitious Vision 2030 in Saudi Arabia, the modernization of laboratory medicine is not a mere role of financial investment in equipment, but a socio-technical phenomenon, during which the stage of development of the human capital and its adoption by the users is the key mediator of success in its activity [25].

### 1. Findings of Interpretation:

The findings demonstrate a stratified, situationalized adoption process. The extensive adoption of Total Laboratory Automation (TLA) is in tandem with its longstanding purpose of increasing throughput and standardization of the pre-analytical and analytical stages, yet it is a global phenomenon seen since the late 1990s [26]. The active development of AI and digital pathology piloting is part of the diagnostic frontier of the world due to the promise of increased accuracy, remote diagnosis, and workload optimization [27]. The dichotomous nature of NGS, with a major proportion of NGS users adopting it completely and a larger proportion only starting to use it, possibly relates to the particular clinical/research requirements of individual institutions, i.e., in personalised oncology versus a general hospital lab.

Importantly, the regression and path analyses go beyond listing technologies to how they influence them as a variable. The positive correlation between Investment Level and Operational Efficacy (2 = 0.312) is quite obvious at first sight, and the model shows that this is not a direct correlation [28]. The main effect of investment is that two channels are enabled simultaneously, namely acquisition of advanced technology (e.g., automation, 0.45) and training of human capital (0.38). This finding is crucial. It implies that the returns are unlikely to be optimal in a situation where money is spent without an equivalent and significant investment in ongoing professional growth [29]. The high contribution of Perceived Usefulness (PU, 0.285) and Perceived Ease of Use (PEOU, 0.22) as immediate antecedents of efficacy clearly grounds our results in the hope of well-abandoned technology acceptance conceptualizations, and in particular, the Technology Acceptance Model (TAM) of Davis [30]. It shows how in high-stakes clinical settings, the cognitive value and usefulness of the technology is decisively determined by the laboratory professional, resulting in its effective implementation, which is more than just seniority (Exp_Yrs, p = 0.549) [31].

The large differences that have been revealed, such as a higher TAT improvement in the reference labs and a higher perceived investment in Riyadh, are indicators of structural

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and geographic inequities [32]. Reference labs, which tend to have a wider catchment area and which are more efficiency-oriented, might be more optimized to release the benefits of automation through their organizational cultures and workflows [33]. The Riyadh-based perception of investment indicates that national change plans might be implemented unevenly toward concentrating a central excellence center and leaving the peripheral areas behind, which is a frequent problem in national health technology reforms [34].

**2. Comparisons to the past studies**

Our results are a support and a context for the world literature concerning laboratory innovation. This prevalence of automation can be explained by several decades of industrial engineering ideas in the application to laboratory medicine to minimize manual errors and labour expenses [35]. The above significance of training and acceptance is very much consistent with the human-factors study in health informatics. Indicatively, the adoption of computerized physician order entry (CPOE) and electronic health records (EHRs) has always recorded poor outcomes due to the lack of training and poor perceived usability, which result in workarounds, errors, and resistance to change among users [36]. This principle is also applied by our study to the area of highly developed diagnostic technologies in a non-Western environment.

The high relationship between training and PEOU ($r_s = 0.412$) is also empirical confirmation of a long-standing axiom in implementation science: familiarity breeds competence and confidence [37]. This is reminiscent in their review of TAM in the healthcare sector, where the interventions aimed at enhancing self-efficacy (in many cases by training) played an important role in enhancing perceptions of ease of use [38]. Also, the difference in perceived efficacy between strategic (managers/pathologists) and operational (technologists) employees is an essential observation. Such dissonance has been observed in other implementations of technology, where the strategic, high-level perspective of the leadership of the benefits can work against the experience of frontline staff of the daily workflow interruptions and increased cognitive load [39]. The qualitative information that we have, which implies an increment in volume, time consumed, and savings, is a very graphic illustration of this phenomenon.

**3. Scientific and Operational Explanation**

Systems engineering and cognitive psychology can be used to understand the mechanistic connection between the examined variables. A medical laboratory is a complex adaptive system in terms of how it is viewed in a system perspective [40]. When a high-throughput automation line (a technological perturbation) is introduced, it upsets the current workflows. In the absence of proper training, a soft system intervention, the human operators would be unable to redesign their procedures and mental models in the new hard system to interface

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optimally. This results in feature under-use, lack of maintenance, and continued existence of old and parallel manual processes (silos), which nullifies the benefits of efficiency [41].

The strength of PU and PEOU was grounded in cognitive psychology. The technologies that seem valuable fit well into the "task-technology fit" model of the user and become an extension to their problem-solving repertoire of tools successfully [42]. On the other hand, a technology that is considered hard to operate causes cognitive loading, which diverts the mental resources of the person to the secondary activity of operating the technology rather than doing the main diagnostic activity [43]. This may reduce the levels of efficiency and safety, which are the real objectives of the technology. This cascade is being quantitatively composed by the path model: investment supports technology and training, which respectively improve PU and PEOU, which result in increased efficacy (improved fit, less cognitive load) and, finally, output improvements that can be measured, such as reduced TAT [44].

## 4. Policy, Practice, and Future Research Implications

The current research provides practical and direct implications for the stakeholders who are leading the healthcare transformation in the Kingdom of Saudi Arabia.

**Policymakers and Administrators:** The capital spending on new technology should be explicitly and compulsorily coupled with continual, immersive training programmes. Within national strategies, mechanisms to balance the distribution of resources and expertise in all regions should be included, and hence avoid the further digital divide [45].

**In the case of Laboratory Leadership,** Implementation projects should no longer be content with installing equipment with technical skills, but now adopt effective change-management practices. It is important to involve frontline staff and discuss their usefulness and ease of use via practical demonstrations and piloting, and establish an avenue of feedback [46]. The key to sustainable adoption lies in bridging the perception gap between the management and the technologists.

**Industry (Vendors):** The market is clearly demanding the creation of diagnostic technologies that follow user-centred design principles to suit the Saudi context and provide an easy-to-use interface and continuous training assistance as a service contract component [47].

This research creates a number of avenues for the research community. The first one is that longitudinal studies are necessary to follow the evolution of pilot projects in AI and digital pathology and define what results will be revealed in the long term in the field of diagnostic accuracy and patient outcomes. Second, experimental research would be able to compare alternative modalities of training (e.g., simulation-based and traditional training) to

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determine which one is most effective at improving the perceived ease of use and skill retention [48]. Third, it should be researched on the particular systemic barriers that exist in hospital-based laboratories that serve to hinder turnaround-time improvement as compared to reference laboratories [49].

Finally, this research has managed to chart the technological history of Saudi medical laboratories and, better still, unravels the key to their success. It has been shown that the road towards a modernized, effective laboratory industry in the context of Vision 2030 is not only covered with fancy equipment, but with insightful investment in human and process capital. It is human beings who eventually achieve sustainable integration of technology as a result of perceived value, created by means of skill and enabled or constrained by the systems in which professionals work.

## CONCLUSION

This study meets its aims and objectives as it has mapped the technological environment, measured the effects, and key drivers and barriers to adoption in Saudi Arabian medical laboratories based on analysis of 312 survey responses and 18 interviews. The results show that although automation is also used extensively, machine learning technologies like AI and genomics are still in their infancy. The central finding is that technological investment is not enough; its working effectiveness will be essentially mediated by effective training programmes and the perception that the end-user has of the usefulness of the technology. Moreover, there are huge differences in the outcomes and the level of perception of investments between laboratory types and geographical areas, which highlight systemic inequalities. The study adds a confirmed, context-dependent model of health technology adoption, putting the paramount human and organizational factors of the Vision 2030 framework into focus. Longitudinal designs should be used in future research in order to trace the development of these technologies and their direct relationship with clinical outcome measures.

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