**ASSESSMENT OF LABORATORY INFORMATION SYSTEM (LIS) SATISFACTION AMONG MEDICAL LABORATORY PROFESSIONALS: A MIXED-METHODS MULTI-SITE STUDY**

**ABSTRACT**

Laboratory Information Systems (LIS) are pivotal in enhancing the efficiency and accuracy of medical laboratory operations, yet satisfaction among medical laboratory professionals (MLPs) remains underexplored. This study assessed LIS satisfaction among MLPs, identified key determinants, and provided recommendations for system optimization. Despite LIS’s critical role in sample tracking, data management, and result reporting, previous research has largely overlooked MLPs’ unique experiences, focusing instead on broader healthcare staff or electronic health records. This gap is significant given the precision-driven, data-centric nature of laboratory work, where dissatisfaction may compromise workflow and diagnostic quality. Using a mixed-methods approach, data were collected via structured surveys and semi-structured interviews from 250 MLPs across hospital laboratories, independent diagnostic centers, and academic facilities in a cross-sectional study conducted in Delta State, Nigeria. The survey assessed satisfaction using validated scales, while interviews explored contextual factors such as usability, technical support, and training adequacy. Findings revealed moderate satisfaction (M = 3.4, SD = 0.8 on a 5-point scale), with system reliability (β = 0.42, p < .001) and ease of use (β = 0.35, p < .01) as significant predictors. Qualitative data highlighted inadequate training and poor technical support as key barriers in resource-limited settings. Satisfaction differed significantly across laboratory types (F(2, 247) = 6.78, p < .01), with hospital-based MLPs reporting lower scores. These results underscore the need for tailored LIS design and improved support structures. This study fills a critical research gap by centering MLPs’ perspectives and offering actionable insights to improve LIS implementation.

**Keywords:** Laboratory Information System, medical laboratory professionals, user satisfaction, health information technology, mixed-methods research

**1.0 Introduction**

The rapid evolution of health information technology has transformed the landscape of medical diagnostics, with Laboratory Information Systems (LIS) emerging as cornerstone tools in modern laboratory practice. These systems, designed to automate and manage laboratory workflows, facilitate critical tasks such as specimen tracking, data entry, result reporting, and quality control (Georgiou *et al.,* 2020). By reducing manual processes and minimizing the risk of human error, LIS have the potential to enhance operational efficiency, improve diagnostic accuracy, and ultimately elevate the standard of patient care (Park *et al.,* 2019). For medical laboratory professionals (MLPs), the Medical Laboratory Scientists, Medical Laboratory Technicians, Laboratory Technologists, Pathologists and Laboratory Assistants who operate these systems daily, LIS represent both a technological advancement and a daily interface that shapes their professional experience. Despite their widespread adoption across hospital-based laboratories, independent diagnostic centers, and research facilities, the satisfaction of MLPs with LIS remains a pivotal yet underexamined factor in determining the success of these systems.

User satisfaction with information systems is a well-established construct in the field of technology adoption, often serving as a proxy for system effectiveness and acceptance (Chen *et al.,* 2020). In healthcare settings, where the stakes of technological integration are exceptionally high, satisfaction influences not only individual performance but also broader organizational outcomes, such as patient safety and service delivery (Nguyen *et al.,* 2014). For MLPs, satisfaction with LIS is particularly consequential because their work demands precision, timeliness, and reliability attributes that depend heavily on the functionality and usability of the systems they employ. A poorly designed or inadequately supported LIS can disrupt workflows, increase stress levels, and contribute to errors that compromise diagnostic integrity (Cohen *et al.,* 2018). Conversely, a system that aligns with user needs can enhance productivity, reduce burnout, and foster a positive working environment (Yusof *et al.,* 2008). Given these implications, understanding the satisfaction of MLPs with LIS is not merely a technical concern but a critical component of healthcare quality improvement.

The adoption of LIS in medical laboratories has been driven by broader trends in healthcare digitization, including the push for interoperability, data standardization, and compliance with regulatory frameworks such as the Health Insurance Portability and Accountability Act (HIPAA) and Clinical Laboratory Improvement Amendments (CLIA) (Blumenthal & Tavenner, 2010). These systems are often marketed as solutions to longstanding challenges in laboratory management, such as turnaround time delays and data mismanagement. However, the transition from manual or legacy systems to advanced LIS platforms is not without its challenges. Studies have documented implementation barriers, including inadequate training, resistance to change, and technical glitches, all of which can erode user confidence and satisfaction (Srivastava *et al.,* 2020; Atemoagbo *et al.,* 2024). For MLPs, whose roles require both technical expertise and adaptability, these challenges are amplified by the need to maintain high standards of accuracy under time-sensitive conditions (Tuthill *et al.,* 2014). As such, the extent to which LIS meet the practical and professional needs of MLPs warrants thorough investigation.

Despite the growing body of literature on health information systems, research specifically addressing LIS satisfaction among MLPs remains sparse. Much of the existing scholarship focuses on broader categories of healthcare professionals, such as physicians and nurses, or examines electronic health records (EHRs) rather than laboratory-specific systems (Ammenwerth *et al.,* 2019). For instance, studies by Topaz *et al.* (2016) and Holden *et al.* (2017) have explored user satisfaction with EHRs, identifying factors such as ease of use, system reliability, and organizational support as key predictors. However, these findings cannot be directly extrapolated to LIS, given the distinct operational context of medical laboratories. Unlike EHRs, which are primarily patient-facing, LIS are specimen- and data-centric, requiring functionalities tailored to laboratory workflows, such as batch processing and instrument integration (Rana *et al.,* 2015; Atemoagbo, 2024). This specificity underscores a critical research gap: the lack of targeted studies examining how MLPs perceive and interact with LIS in their day-to-day practice.

The research gap is further compounded by the limited attention paid to the human factors influencing LIS adoption. While technical performance metrics such as system uptime and processing speed are frequently evaluated, the subjective experiences of users are often overlooked (Wiederhold *et al.,* 2008, Atemoagbo *et al.,* 2024). This omission is significant, as dissatisfaction among MLPs can lead to workarounds, reduced system utilization, and even staff turnover, all of which undermine the intended benefits of LIS implementation (Cohen *et al.,* 2018). Moreover, regional variations in laboratory infrastructure, workforce training, and resource availability suggest that satisfaction levels may differ across settings, yet few studies have explored these differences systematically (Wiederhold *et al.,* 2021). The absence of a comprehensive assessment of LIS satisfaction among MLPs represents a missed opportunity to inform system design, enhance user training programs, and improve laboratory outcomes.

The scope of this study is deliberately broad yet focused, encompassing MLPs working in diverse laboratory environments, including hospital-based laboratories, standalone diagnostic centers, and academic research facilities. This multi-setting approach allows for a nuanced understanding of how contextual factors such as laboratory size, workload, and technological resources shape satisfaction with LIS. The study employs a cross-sectional design, collecting data through surveys and interviews to capture both quantitative satisfaction metrics and qualitative insights into user experiences. Variables of interest include system usability, technical support, training adequacy, and perceived impact on workflow, all of which have been identified as critical in prior technology acceptance models (Davis, 1989; Atemoagbo *et al.,* 2024).

The aims of this research are threefold: first, to quantify the level of satisfaction with LIS among MLPs; second, to identify the key determinants of satisfaction, both positive and negative; and third, to propose evidence-based recommendations for improving LIS implementation and support. The specific objectives are as follows: (a) to assess the overall satisfaction of MLPs with their current LIS platforms using validated satisfaction scales; (b) to examine the relationship between system features (e.g., functionality, reliability, and ease of use) and user satisfaction; (c) to explore the role of organizational factors, such as training and technical assistance, in shaping MLP perceptions; and (d) to compare satisfaction levels across different laboratory settings to identify contextual influences. By addressing these aims and objectives, this study seeks to fill the identified research gap and contribute to the optimization of LIS as vital tools in medical diagnostics.

The satisfaction of MLPs with LIS is a multifaceted issue that intersects technology, workflow, and human experience. As laboratories continue to navigate the complexities of digital transformation, understanding and enhancing user satisfaction will be essential for maximizing the benefits of LIS and ensuring high-quality patient care. This research aims to provide a comprehensive assessment of LIS satisfaction, offering insights that are both theoretically robust and practically actionable for laboratory managers, system developers, and policymakers alike.

**2.0 Materials and Methods**

**2.1 Study Design**

This study employed a mixed-methods, cross-sectional design to evaluate the satisfaction of medical laboratory professionals (MLPs) with Laboratory Information Systems (LIS). The approach integrated quantitative data from structured surveys with qualitative insights from semi-structured interviews, allowing for a comprehensive assessment of satisfaction levels, identification of key determinants, and exploration of contextual factors influencing MLP perceptions across diverse laboratory settings (Creswell & Plano Clark, 2018).

**2.2 Participants and Sampling**

The study population comprised MLPs, including Medical Laboratory Scientists (MLS)—who conduct tests and analyze samples to help diagnose diseases—Medical Laboratory Technicians (MLT), Laboratory Technologists, Pathologists, and Laboratory Assistants, who actively use LIS in their daily workflows. A total of 250 participants were recruited from three laboratory types: hospital-based laboratories, independent diagnostic centers, and academic research facilities within Delta State, Nigeria. Sample size was determined using G\*Power 3.1 software (Faul *et al.,* 2009), with parameters set for a multiple linear regression model: statistical power (1 – β) = 0.80, alpha level (α) = 0.05, and a medium effect size (f² = 0.15), following Cohen’s (1988) guidelines. This yielded a minimum required sample size of 200 participants**.** An additional 25% (50 participants) were recruited to account for potential non-response or incomplete data, resulting in a final sample of 250. Purposive sampling ensured representation across the three laboratory settings, with participants selected based on their direct LIS experience and willingness to participate (Palinkas *et al.,* 2015). Sample size was calculated using G-Power software for multiple regression analysis, targeting a statistical power of 0.80, an alpha of 0.05, and a medium effect size (f² = 0.15), yielding a minimum sample of 200. An additional 25% (50 participants) were recruited to account for potential non-response or incomplete data, resulting in a final sample of 250.

**2.3 Data Collection Instruments**

**2.3.1 Structured Survey**

A self-administered survey was developed to quantitatively measure LIS satisfaction. The instrument was adapted from validated tools, including the System Usability Scale (SUS) (Brooke, 1996) and the DeLone and McLean Information Systems Success Model (Delone & McLean, 2016), customized for the laboratory context. The survey included four sections:

1. Demographic and Professional Information: Age, gender, years of experience, job role, and laboratory type.
2. Satisfaction with LIS: A 10-item scale assessing overall satisfaction, rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Example items included “The LIS meets my daily work needs” and “I am satisfied with the system’s performance.”
3. System Features: A 15-item section evaluating attributes such as reliability, ease of use, and functionality, also on a 5-point Likert scale.
4. Organizational Factors: A 5-item section assessing training adequacy, technical support, and resource availability (e.g., “I received sufficient training to use the LIS effectively”).

The survey was pilot-tested with 20 MLPs to ensure clarity and reliability, achieving a Cronbach’s alpha of 0.87, indicating strong internal consistency (Tavakol & Dennick, 2011) and has also be used by Atemoagbo *et al.,* (2024).

**2.3.2 Semi-Structured Interviews**

Semi-structured interviews were conducted with a subset of 30 participants (10 from each laboratory type) to explore their experiences in depth. An interview guide was developed based on themes from prior literature (Wiederhold *et al.,* 2008), covering system usability, technical support, training, and workflow impact. Open-ended questions included: “How does the LIS support or hinder your daily tasks?” and “What improvements would enhance your satisfaction with the system?” Interviews were audio-recorded with participant consent and lasted approximately 30–45 minutes each.

**2.4 Procedure**

Data collection occurred between January and March 2024. Participants were recruited through professional networks, laboratory associations, and direct outreach to facility administrators. Surveys were distributed electronically via a secure online platform (Qualtrics) and in paper format where internet access was limited. Participants received an information sheet detailing the study’s purpose, confidentiality measures, and voluntary participation. Completed surveys were returned within two weeks.

Interviews were scheduled based on participant availability and conducted either in-person at the workplace or via a secure video conferencing platform (Zoom and Gmeet). A trained research assistant facilitated the interviews, ensuring consistency in question delivery and probing for elaboration as needed. All data were anonymized, with participants assigned unique identifiers to protect privacy.

**2.5 Data Analysis**

**2.5.1 Quantitative Analysis**

Survey data were analyzed using SPSS version 28.0 (IBM Corp., 2021). Descriptive statistics (means, standard deviations) summarized overall satisfaction and demographic characteristics. Inferential analyses included:

Multiple Linear Regression: To identify predictors of satisfaction (e.g., system reliability, ease of use), with satisfaction as the dependent variable and system/organizational factors as independent variables (Cohen *et al.,* 2013).

One-Way Analysis of Variance (ANOVA): To compare satisfaction scores across laboratory types (hospital-based, independent, academic), followed by post-hoc Tukey tests for significant differences (Field, 2018).

Assumptions of normality and homoscedasticity were tested using Shapiro-Wilk and Levene’s tests, respectively. Statistical significance was set at p < .05.

**2.5.2 Qualitative Analysis**

Interview recordings were transcribed verbatim and analyzed using thematic analysis (Braun & Clarke, 2006). Two researchers independently coded the transcripts, identifying recurring themes such as training gaps or technical support issues. Codes were grouped into broader categories, and discrepancies were resolved through discussion until consensus was reached. Qualitative findings were triangulated with survey results to provide a holistic interpretation of MLP satisfaction (Creswell & Plano Clark, 2018).

**2.6 Materials**

Materials included the survey instrument, interview guide, consent forms, and data collection tools (Qualtrics, audio recorders, Zoom and Gmeet). No additional laboratory equipment or reagents were required, as the study focused on user perceptions rather than system performance metrics.

**3.0 Result and discussion**

**3.1 Participant Characteristics**

A total of 250 medical laboratory professionals (MLPs) participated in the study, with a response rate of 92% for surveys and 100% for scheduled interviews. Participants were distributed across hospital-based laboratories (n = 100, 40%), independent diagnostic centers (n = 80, 32%), and academic research facilities (n = 70, 28%). The sample included 55% females (n = 138) and 45% males (n = 112), with a mean age of 38.2 years (SD = 9.1). Years of experience ranged from 1 to 25 years (M = 10.3, SD = 6.2), and job roles comprised technicians (60%), scientists (30%), and pathologists (10%).

**3.2 Quantitative Findings**

**3.2.1 Overall Satisfaction with LIS**

The overall satisfaction with Laboratory Information Systems (LIS) was moderate, with a mean score of 3.4 (SD = 0.8) on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Scores ranged from 1.8 to 4.9, indicating variability in MLP perceptions.

**3.2.2 Predictors of Satisfaction**

Multiple linear regression analysis identified system reliability (β = 0.42, p < .001) and ease of use (β = 0.35, p < .01) as significant predictors of satisfaction, explaining 38% of the variance in satisfaction scores (R² = 0.38, Adjusted R² = 0.36, F(5, 244) = 29.63, p < .001). Other factors, including functionality (β = 0.12, p = .18), technical support (β = 0.09, p = .27), and training adequacy (β = 0.06, p = .32), were not statistically significant.

To assess multicollinearity, **Variance Inflation Factor (VIF)** values were computed for each independent variable. All VIF values ranged from **1.12 to 1.45**, well below the conventional threshold of 5.0, indicating no multicollinearity concerns among predictors. Table 1 summarizes the regression results along with VIF values.

**Table 1: Multiple Linear Regression Analysis of Predictors of LIS Satisfaction**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Predictor** | **β (Standardized)** | **SE** | **t** | **p-value** | **VIF** |
| System Reliability | 0.42 | 0.06 | 7 | < .001 | 1.31 |
| Ease of Use | 0.35 | 0.07 | 5 | < .01 | 1.45 |
| Functionality | 0.12 | 0.08 | 1.5 | 0.18 | 1.23 |
| Technical Support | 0.09 | 0.07 | 1.29 | 0.27 | 1.18 |
| Training Adequacy | 0.06 | 0.06 | 1 | 0.32 | 1.12 |

*Note: R² = 0.38, Adjusted R² = 0.36, F(5, 244) = 29.63, Significance cut-off points: p < .05,* ***p*** *< .01,* ***p*** *< .001..*

**3.2.3 Satisfaction Across Laboratory Types**

One-way ANOVA revealed significant differences in satisfaction across laboratory types (F(2, 247) = 6.78, p < .01, η² = 0.05). Post-hoc Tukey tests indicated that hospital-based MLPs (M = 3.1, SD = 0.7) reported significantly lower satisfaction than those in independent diagnostic centers (M = 3.6, SD = 0.8, p < .01) and academic facilities (M = 3.5, SD = 0.9, p < .05). Table 2 presents these findings.

**Table 2: Satisfaction Scores by Laboratory Type**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Laboratory Type  | N | Mean Satisfaction | SD | 95% CI |
| Hospital-Based  | 100 | 3.1 | 0.7 | [3.0, 3.2] |
| Independent Diagnostic | 80 | 3.6 | 0.8 | [3.4, 3.8]  |
| Academic Research | 70 | 3.5 | 0.9 | [3.3, 3.7] |

Note: F(2, 247) = 6.78, η² = 0.05. *Significance cut-off points: p < .05*, **p** < .01, ***p*** < .001.

**3.3 Qualitative Findings**

Thematic analysis of the 30 semi-structured interviews identified three key themes: (a) inadequate training, (b) poor technical support, and (c) workflow disruptions, particularly in resource-limited settings. The sample size of **30 interviews** was determined based on the principle of **theoretical saturation**, the point at which no new themes emerged from the data (Guest, Bunce, & Johnson, 2006). Saturation was assessed iteratively during data collection and analysis, and was judged to be achieved by the 27th interview, with subsequent interviews confirming but not extending the identified themes.

**i. Inadequate Training**

Participants frequently cited insufficient initial and ongoing training as a barrier to effective LIS use. A hospital-based technician noted, *“We were given a two-hour session and expected to figure out the rest ourselves,”* reflecting a common sentiment across settings.

**ii. Poor Technical Support**

Delays in resolving system issues were a recurring concern, especially in hospital laboratories. One scientist remarked, *“When the system crashes, it takes hours to get help, and that delays everything.”*

**iii. Workflow Disruption**

In resource-limited settings, MLPs reported frequent downtimes and compatibility issues with older equipment, exacerbating dissatisfaction. An academic MLP stated, *“The LIS doesn’t integrate well with our instruments, so we’re constantly double-checking manually.”*

**3.4 Interpretation of Findings**

This study provides the first comprehensive assessment of LIS satisfaction among MLPs, revealing a moderate overall satisfaction level (M = 3.4, SD = 0.8) that aligns with prior research on health information systems (Delone & McLean, 2016). The significant predictors, system reliability and ease of use, underscore their critical role in shaping user perceptions, consistent with technology acceptance models (Davis, 1989). **Moreover**, reliability (β = 0.42, p < .001) emerged as the strongest predictor, reflecting the precision-driven nature of laboratory work where system downtimes or errors can directly impact diagnostic quality (Georgiou *et al.,* 2020). **Similarly**, ease of use (β = 0.35, p < .01) highlights the importance of intuitive interfaces in high-pressure environments, supporting findings from EHR studies (Holden *et al.,* 2017).

**Furthermore**, the variation in satisfaction across laboratory types (F(2, 247) = 6.78, p < .01) is a novel contribution, with hospital-based MLPs reporting the lowest scores (M = 3.1). This may be attributed to higher workloads and resource constraints in hospital settings, where LIS are often integrated into complex, multi-user systems (Pantano *et al.,* 2021). **In contrast**, independent diagnostic centers (M = 3.6) and academic facilities (M = 3.5) likely benefit from more focused workflows or greater institutional support, respectively. These differences suggest that contextual factors beyond system design play a pivotal role in user satisfaction.

**Regarding the qualitative findings**, they enrich this narrative by identifying inadequate training and poor technical support as key barriers. **The emphasis on training** aligns with Kaplan and Harris-Salamone (2009), who noted that insufficient preparation undermines technology adoption in healthcare. **Similarly**, the reported delays in technical support echo Cohen *et al.* (2018), linking unresolved system issues to workflow disruptions and user frustration. **Nevertheless**, in resource-limited settings, these challenges are amplified, as MLPs grapple with outdated infrastructure **a finding that warrants further investigation** into equity in LIS implementation.

**3.5 Implications for Practice and Policy**

The moderate satisfaction level and identified predictors suggest actionable strategies for LIS optimization. First, developers should prioritize reliability and usability in system design, incorporating user-centered approaches to ensure alignment with MLP needs (Yusof *et al.,* 2008). Second, organizations must invest in robust training programs, extending beyond initial onboarding to include ongoing skill development. Third, enhancing technical support infrastructure particularly in hospital settings could mitigate workflow disruptions and boost satisfaction. These recommendations address the human factors often overlooked in LIS implementation, offering a pathway to improve diagnostic efficiency and patient care quality (Nguyen *et al.,* 2014).

Furthermore, these findings carry significant implications for laboratory management and policy formulation. Laboratory administrators should consider leveraging satisfaction data to guide procurement and implementation decisions, tailoring LIS solutions to the specific operational realities of each laboratory type. For instance, hospital-based settings may benefit from policy-driven investments in IT infrastructure and dedicated LIS support teams to address their lower satisfaction levels. At the technological level, system vendors should engage in co-design processes with end-users to ensure that LIS platforms are adaptable to diverse workflows and resource constraints. By integrating user feedback into continuous development cycles, both technological innovation and user acceptance can be enhanced. These practical applications underscore the potential of satisfaction-driven insights to inform both strategic planning and technological advancements within laboratory environments.

**4.0 Conclusion and Recommendation**

**4.1 Conclusion**

This study provides a pioneering evaluation of Laboratory Information System (LIS) satisfaction among medical laboratory professionals (MLPs), addressing a critical yet underexplored dimension of health information technology. The moderate satisfaction level (M = 3.4, SD = 0.8) reflects a nuanced balance between the benefits of LIS in enhancing laboratory efficiency and persistent challenges that hinder optimal use. System reliability (β = 0.42, p < .001) and ease of use (β = 0.35, p < .01) emerged as key drivers of satisfaction, underscoring their centrality to the precision-driven workflows of MLPs (Simonsen *et al.,* 1990). However, significant variation across laboratory types (F(2, 247) = 6.78, p < .01), with hospital-based MLPs reporting lower scores (M = 3.1), highlights the influence of contextual factors such as workload and resource availability (Pantano *et al.,* 2021). Qualitative insights further illuminated barriers, notably inadequate training and poor technical support, which disproportionately affect resource-limited settings. By integrating quantitative and qualitative data, this research fills a vital gap in the literature, shifting the focus from broader healthcare systems to the laboratory-specific experiences of MLPs. These findings affirm that LIS success hinges not only on technical performance but also on human-centered design and organizational support, offering a robust foundation for improving diagnostic quality and patient care outcomes.

**4.2 Recommendations**

Based on the study’s findings, the following evidence-based recommendations are proposed to optimize LIS implementation and enhance MLP satisfaction:

1. Prioritize System Reliability and Usability in Design: LIS developers should adopt user-centered design principles, emphasizing reliability and intuitive interfaces to align with the precision and time-sensitive demands of laboratory work. Regular system updates and stress testing can minimize downtimes, addressing the strongest predictor of satisfaction identified (β = 0.42, p < .001).
2. Implement Comprehensive Training Programs: Healthcare organizations should establish structured, ongoing training initiatives that extend beyond initial onboarding. Tailored programs addressing MLP-specific needs highlighted as a key qualitative barrier can enhance system proficiency and reduce workflow disruptions, particularly in high-pressure settings like hospitals.
3. Strengthen Technical Support Infrastructure: Institutions, especially hospital-based laboratories, must invest in responsive technical support systems to address delays and compatibility issues reported in interviews. Rapid resolution of system failures can mitigate the workflow interruptions that erode satisfaction, ensuring operational continuity.
4. Tailor LIS Implementation to Laboratory Context: Given the significant satisfaction differences across settings (F(2, 247) = 6.78, p < .01), LIS deployment should be customized to account for workload, resource availability, and infrastructure. Hospital laboratories, with lower satisfaction scores (M = 3.1), may require additional resources or modular systems to accommodate complex multi-user environments.
5. Address Equity in Resource-Limited Settings: Policymakers and vendors should prioritize scalable, cost-effective LIS solutions for resource-constrained facilities, where qualitative data revealed heightened challenges with outdated equipment. Bridging this gap can promote equitable access to reliable diagnostic tools, enhancing overall healthcare quality.

These recommendations provide a strategic roadmap for stakeholders’ developers, laboratory managers, and policymakers to maximize the potential of LIS, ensuring they serve as effective tools for MLPs and, ultimately, support high-quality patient care.

**Consent**

As per international standards or university standards, Participants’ written consent has been collected and preserved by the author(s).

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