

An independent third-party autoverification platform iXLAB Verify and its application in a core clinical biochemistry laboratory

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16 **Abstract**

17 **To develop and validate a third-party autoverification system independent of the**
18 **laboratory information system (LIS) and instrument middleware, and to evaluate its**
19 **feasibility in clinical chemistry testing. The autoverification system iXLAB Verify**
20 **was configured following Clinical and Laboratory Standards Institute (CLSI)**
21 **AUTO15 guidelines and the Autoverification of Clinical Laboratory Quantitative**
22 **Test Results (WS/T 616-2018). A retrospective validation using 53,120 samples was**
23 **conducted prior to formal deployment, after which autoverification pass rates and**
24 **turnaround time (TAT) were evaluated over seven months of clinical operation (n =**
25 **135,257). Pre-deployment validation demonstrated 100% sensitivity and 97.28%**
26 **specificity, with a false negative rate of 0%. Following deployment, the overall**
27 **autoverification pass rate was 86.19%, and the 90th percentile TAT was reduced**

from 223 to 120 min (outpatient), 215 to 168 min (inpatient), and 204 to 124 min (health check). The autoverification system reduced turnaround time in a core clinical chemistry laboratory. Independent of laboratory instruments and information systems, the iXLAB Verify platform has the potential to be deployed across different laboratory environments without rule reconfiguration.

Keywords: autoverification, iXLAB, laboratory information system, transferability, validation

Autoverification is a workflow improvement strategy, which can help clinical laboratories reduce unnecessary manual review of test results [1]. To standardize a general framework for the autoverification process, the Clinical and Laboratory Standards Institute (CLSI) published CLSI AUTO10 Autoverification of Clinical Laboratory Test Results in 2006 [2]. In 2019, a new guideline CLSI AUTO15 Autoverification of Medical Laboratory Results for Specific Disciplines was published, providing specific disciplines for different laboratory branches [3]. The sustained growth in clinical laboratory test volumes has reinforced the need for automated verification to maintain turnaround time and manage workload [4]. Autoverification is frequently described in terms of efficiency gains and cost reduction. One recent implementation reported a 97% reduction in manual dilution costs through automated threshold-based reporting [5, 6].

The expert system within the laboratory information system (LIS) can access patient demographics, previous results, and other test orders, offering advantages in data accessibility [7]. The effectiveness of this system has been validated across multiple institutions. Torke et al. demonstrated a 40% reduction in manual verification workload (from 14.0 to 8.5 full-time equivalents) through LIS-based process redesign [8]. A previous study reported that after 13 years of implementing the LIS-based autoverification system, the autoverification rate increased from 40% to 99.5%, accompanied by a 32% improvement in staff productivity [9]. Wang et al. further integrated LIS with hospital information systems (HIS), enabling diagnosis-aware limit adjustments for clinical conditions such as anticoagulation and pregnancy [10]. From a quality assurance perspective, a two-stage validation model incorporating correctness and

completeness verification achieved zero clinical complaints across over 3.5 million automated reports [11]. Middleware-based autoverification operates on an intermediary software layer between analysers and the LIS, independent of the underlying instrument platform. This approach has been implemented in clinical chemistry [12], haematology [13], and coagulation testing [14], achieving up to 95% autoverification across multiple hospital sites [7].

A practical limitation of both LIS-based and middleware-based autoverification lies in platform dependency. LIS-based autoverification rules require reconfiguration when the LIS is migrated or upgraded, whereas middleware-based rules are tied to specific instrument platforms and must be rewritten when analysers are replaced [4, 5]. Gómez-Rioja et al. surveyed 85 Spanish clinical laboratories and found that 36% had not implemented autoverification despite having LIS capability, with configuration complexity cited as a contributing factor [15]. Rimac et al. recognized this barrier in national recommendations and called for implementation architectures that reduce complexity while meeting all testing requirements [16]. More recently, machine learning-based autoverification has been explored as an alternative approach [17], but data-driven models require substantial training data and face interpretability challenges compared with transparent rule-based systems. However, a system intrinsically decoupled from both the LIS and instrument middleware, thereby deployable across platforms without rule reconfiguration, has not been prospectively evaluated in clinical chemistry testing.

In this study, we developed and evaluated a third-party autoverification system independent of the LIS and middleware platform. The system interfaces with existing laboratory systems through data exchange, eliminating the need for rule reconfiguration when the LIS or analysers are replaced. We report the system architecture, implementation outcomes including pass rates and TAT improvements, and an analysis of failure patterns over seven months of clinical operation.

Results

System Validation

The autoverification system achieved a 96.20% (51,100/53,120) pass rate for validation samples, with 3.80% (2,020) requiring manual review, and all autoverified results were

consistent with manual review (Table 2). Of these manually reviewed tests, 590 were confirmed as true positive, while 1,430 were considered acceptable after manual review (Supplementary Table S2). Among the 2,020 intercepted samples, the most common outcome was approval after direct manual review (46.49%), followed by delta check limit violations (24.31%) and values exceeding the autoverification range (20.99%). Sensitivity and specificity were 100% (95% CI: 99.38%–100%) and 97.28% (95% CI: 97.14%–97.41%) respectively, with a false positive rate of 2.72% (95% CI: 2.59%–2.86%) and a false negative rate of 0% (95% CI: 0%–0.62%) (Table 2).

Table 2. Validation performance of the autoverification system

Performance	Value	95% CI
Sensitivity	100.00% (590/590)	99.38%–100.00%
Specificity	97.28% (51,100/52,530)	97.14%–97.41%
Positive predictive value	29.21% (590/2,020)	27.27%–31.23%
Negative predictive value	100.00% (51,100/51,100)	99.99%–100.00%
False positive rate	2.72% (1,430/52,530)	2.59%–2.86%
False negative rate	0.00% (0/590)	0.00%–0.62%

Abbreviation: CI, Confidence interval.

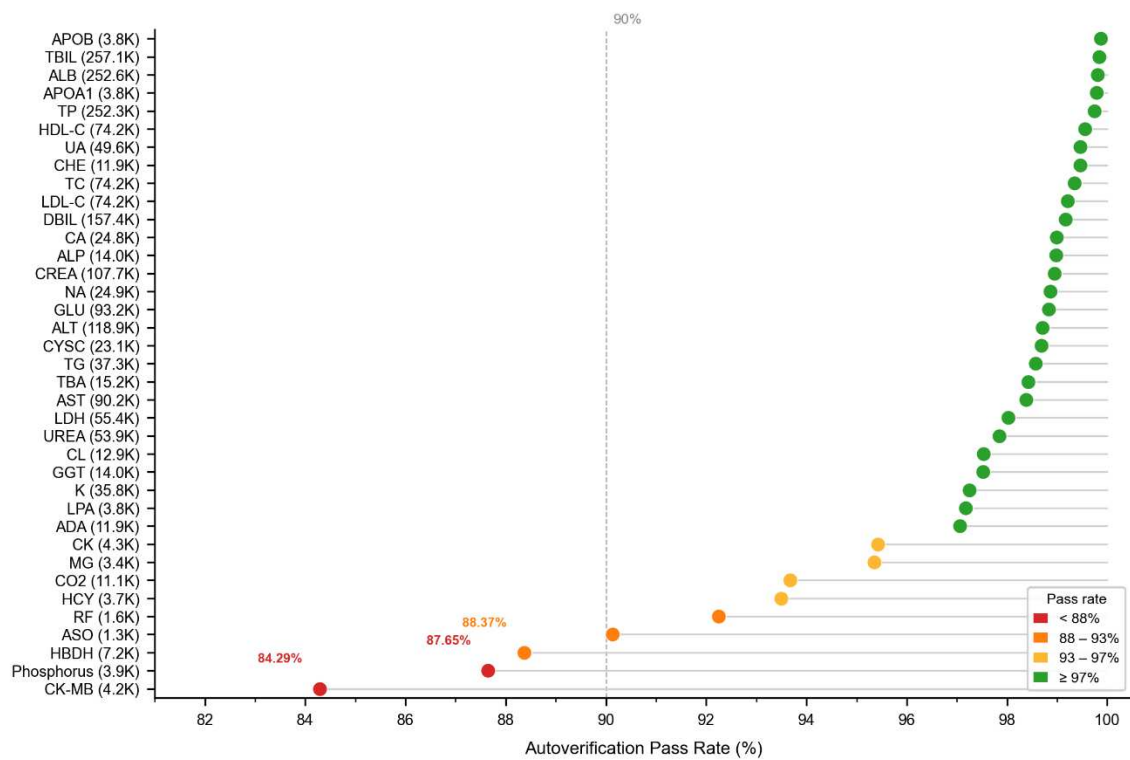
Overall Autoverification Pass Rates

During the seven-month post-implementation period, 116,585 of 135,257 serum samples passed autoverification, yielding an overall pass rate of 86.19% (95% CI: 86.01%–86.37%). Pass rates varied by patient type (Table 3): 96.15% for health check (95% CI: 96.01%–96.28%), 77.57% for outpatient (95% CI: 77.12%–78.02%), and 67.53% for inpatient samples (95% CI: 66.95%–68.10%). Among the 37 analytes, 34 achieved pass rates above 90%, accounting for 91.9% for all analytes, with apolipoprotein B (APOB) showing the highest pass rate at 99.87% (Figure 2). CK-MB had the lowest pass rate at 84.29%, followed by phosphorus at 87.65%, α -hydroxybutyrate dehydrogenase (HBDH) at 88.37%, antistreptolysin O (ASO) at 90.13%, and rheumatoid factor (RF) at 92.25%; the corresponding failure proportions were 15.71%, 12.35%, 11.63%, 9.87%, and 7.75%, respectively.

Table 3. Sample-based autoverification pass rates by patient type.

Patient Type	Total (n)	Autoverification Passed		Pass rate	95% CI
		(n)			
Outpatient	32,944	25,556		77.57%	77.12%–78.02%
Inpatient	25,661	17,328		67.53%	66.95%–68.10%
Physical examination	76,652	73,701		96.15%	96.01%–96.28%
Total	135,257	116,585		86.19%	86.01%–86.37%

111



112

113 **Figure 2. Autoverification pass rates for 37 analytes from October 2024 to April**
114 **2025.** Pass rates are presented as a horizontal lollipop chart in ascending order. The
115 dashed reference line indicates a 90% pass rate. Test volumes are shown in parentheses
116 after each analyte name, where K means thousand. Abbreviations: ADA, Adenosine
117 deaminase; ALB, Albumin; ALP, Alkaline phosphatase; ALT, Alanine aminotransferase;
118 APOA1, Apolipoprotein A1; APOB, Apolipoprotein B; ASO, Antistreptolysin O; AST,
119 Aspartate aminotransferase; CA, Calcium; CHE, Cholinesterase; CK, Creatine kinase;

CK-MB, Creatine kinase-MB isoenzyme; CL, Chloride; CO₂, Carbon dioxide; CREA, Creatinine; CYSC, Cystatin C; DBIL, Direct bilirubin; GGT, Gamma-glutamyl transferase; GLU, Glucose; HBDH, Hydroxybutyrate dehydrogenase; HCY, Homocysteine; HDL-C, High-density lipoprotein cholesterol; LDH, Lactate dehydrogenase; LDL-C, Low-density lipoprotein cholesterol; LPA, Lipoprotein (a); MG, Magnesium; NA, Sodium; P, Phosphorus; RF, Rheumatoid factor; TBA, Total bile acids; TBIL, Total bilirubin; TC, Total cholesterol; TG, Triglycerides; TP, Total protein; UA, Uric acid; UREA, Urea.

Turnaround Time Comparison

Following autoverification implementation, the 90th percentile TAT decreased from 223 to 120 min for outpatients, 215 to 168 min for inpatients, and 204 to 124 min for physical examination samples. Pre- and post-implementation sample sizes were 32,944 and 40,030 for outpatients, 25,661 and 22,990 for inpatients, and 76,652 and 89,670 for physical examination samples, respectively (Figure 3). Median TAT fell from 110 to 78 min for outpatients, 136 to 102 min for inpatients, and 145 to 66 min for physical examination samples.

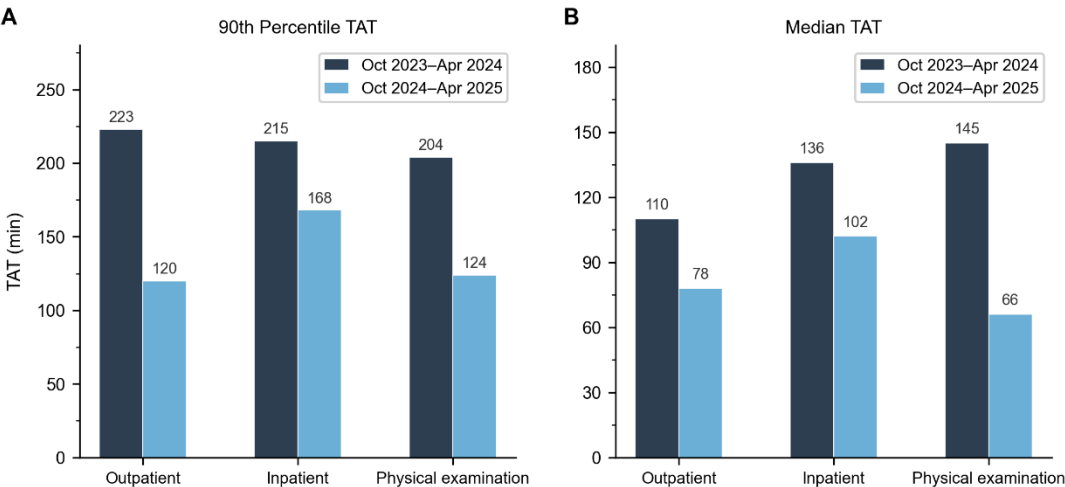


Figure 3. Turnaround time before and after autoverification implementation for the periods October 2023 to April 2024 and October 2024 to April 2025. (A) 90th

percentile TAT; (B) median TAT. Sample sizes were 32,944 and 40,030 for outpatients, 25,661 and 22,990 for inpatients, and 76,652 and 89,670 for physical examinations.

Analysis of Autoverification Failures

In the seven months following implementation, 23,139 of 480,036 tests were intercepted by the autoverification system. The most common cause was results exceeding the autoverification range, accounting for 62.93% of interceptions, followed by delta check limit violations at 31.13%. Smaller proportions were attributable to critical value alerts, instrument alarms, and logical rule violations, at 2.60%, 1.55%, and 1.78% respectively (Table 4).

Among range limit failures, glucose (GLU) was the most frequently affected analyte with 991 of 14,562 interceptions, followed by HBDH with 816, lactate dehydrogenase (LDH) with 693, UREA with 677, and CK-MB with 656. The per-test failure proportion was highest for HBDH at 11.36% (816/7181). For delta check failures, alanine aminotransferase (ALT) and aspartate aminotransferase (AST) were the leading contributors with 1,278 and 1,210 interceptions, followed by direct bilirubin (DBIL), UREA, and potassium. Logical rules accounted for 412 failures, with the lipid fraction check and two transaminase hierarchy rules being the most prevalent triggers. Critical value alerts were issued for 601 tests, mainly for creatinine, glucose, and potassium. Instrument alarms were the least frequent category with 359 events, predominantly due to absorbance limit exceeded.

Table 4. Classification of autoverification failure reasons.

Failure Reason	Top Five Contributing Analytes (tests, n)	Total failures (tests, n)	Failure proportion (%)
Instrument alarm	ALE alarm (337), linearity error (14), insufficient sample (8)	359	1.55%
Exceeds delta check limit	ALT (1,278), AST (1,210), DBIL (947), UREA (481), potassium (455)	7,205	31.13%
Exceeds autoverification	GLU (991), HBDH (816), LDH (693), UREA (677), CK-MB (656)	14,562	62.93%

Failure Reason	Top Five Contributing Analytes (tests, n)	Total failures (tests, n)	Failure proportion (%)
range			
Critical value	CREA (353), GLU (95), potassium (74), CA (53), TBIL (18)	601	2.60%
Logical rule violation	TC > HDL-C + LDL-C (196), ALT > 100 $\Rightarrow$ AST > 40 (118), AST > 100 $\Rightarrow$ ALT > 50 (58), CYSC > 2 $\Rightarrow$ CREA > 100 (14), CREA > 200 $\Rightarrow$ CYSC > 2 (13)	412	1.78%
Total	—	23,139	100.00%

Abbreviations: ALE, absorbance limit exceeded; ALT, alanine aminotransferase; AST, aspartate aminotransferase; CA, calcium; CK-MB, creatine kinase-MB isoenzyme; CREA, creatinine; CYSC, cystatin C; DBIL, direct bilirubin; GLU, glucose; HBDH, hydroxybutyrate dehydrogenase; LDH, lactate dehydrogenase; TBIL, total bilirubin; TC, total cholesterol; UREA, urea.

Discussion

In this study, we developed and validated a platform-independent autoverification system (iXLAB Verify) in a core clinical chemistry laboratory processing 135,257 samples over seven months. The system achieved a 0% false negative rate in pre-deployment validation (n = 53,120) and reduced the 90th percentile TAT by 22-46% across outpatient, inpatient, and physical examination populations after deployment. These TAT improvements are comparable to those reported for LIS-based and middleware-based autoverification [9, 12, 17], supporting the feasibility of a decoupled architecture without compromising safety.

The overall autoverification pass rate of 86.19% was lower than some integrated systems [9, 12], reflecting a conservative initial configuration that prioritized sensitivity over throughput.

Autoverification pass rates varied substantially by patient type, ranging from 96.15% for physical examinations to 77.57% for outpatients and 67.53% for inpatients. Corresponding for TAT reduction were 39%, 46% and 22% respectively. The high pass rate for physical examinations is consistent with Froom and Barak's work, which

181 reported pass rates above 97% for complete blood count in community screening
182 populations [18]. The lower pass rate for inpatients reflects a higher prevalence of
183 abnormal results, critical values, and therapeutic interventions, which resonates with the
184 inverse relationship found by Randell between inpatient proportion and pass rate [4].
185 Despite a moderate pass rate of 77.57%, outpatients showed the largest TAT reduction of
186 46%, indicating that removal of the manual result release can improve turnaround time.
187 In contrast, the smaller TAT gain in inpatients suggests that optimization of
188 autoverification rules may further improve efficiency.

189 Pass rate alone, however, is insufficient to assess the safety of an autoverification system.
190 In the validation across 53,120 samples against parallel manual review, no false negatives
191 were identified. Miler et al. similarly reported a risk priority number (RPN) of zero across
192 all analytes in their failure mode and effects analysis (FMEA)-based verification [19]. Of
193 the failed samples in our study, 70.79% were confirmed clinically acceptable by manual
194 review (Supplementary Table S2).

195 Range limit violations were the most common cause of failure, accounting for 62.93%
196 after implementation versus 20.99% before, which is consistent with previous reports
197 where up to 81% of autoverification holds result from out-of-range values [1]. In our
198 system, autoverification ranges were defined within the linear range, from the lower
199 bound to 80% of the upper bound. The impact of this range varied across analytes.

200 GLU accounted for 991 of 14,562 range limit failures, in part because random glucose $\geq$
201 11.1 mmol/L occurs in 24% ~ 45% of hospitalized patients [20, 21]. HBDH had the third
202 highest per-test failure proportion at 11.36% (816/7,181), attributable to elevated values
203 in suspected cardiac injury [22]. LDH contributed to 693 failures at a 1.25% per-test
204 proportion, primarily due to high test volume (55,365 tests). UREA had 677 failures with
205 1.26% per-test proportion, reflecting high test volume and frequent elevation in
206 hospitalized patients [23, 24].

207 CK-MB had the highest per-test failure proportion at 15.71% (656/4,175) despite low test
208 volume, possibly because it is primarily ordered for suspected cardiac injury and the
209 limitations of the immunoinhibition assay [25]. This method cannot distinguish CK-MB
210 from CK-BB or macro-CK, which occurs in 1–6% of hospitalized patients and falsely

211 elevates results in approximately 0.8% of myocardial infarction cases [26-28]. The
212 autoverification range for CK-MB was therefore restricted to 0–25 U/L, with exceedances
213 retested by chemiluminescence. This conservative strategy further narrowed an already
214 limited verification window.

215 Beyond range limits, delta checks were the second most common source for
216 autoverification failure, with 31.13% after implementation compared with 24.31% before
217 implementation. ALT and AST had the most failures at 1,278 and 1,210 tests, followed
218 by DBIL (947), UREA (481), and potassium (455). Transaminases rise acutely in
219 conditions such as hepatitis, drug-induced liver injury, and sepsis and decline during
220 recovery, frequently exceeding the $\pm 20\%$ delta check threshold within a 7-day window.
221 AST is also present in skeletal muscle and myocardium. Skeletal muscle injury is the
222 leading non-hepatic cause of elevated AST, accounting for 54.2% of cases [29, 30].
223 Potassium, despite lower test volume, had a 1.27% per-test proportion, which may be
224 explained by its narrower $\pm 10\%$ limit. DBIL and UREA, with wider $\pm 30\%$ thresholds,
225 showed lower proportions at 0.60% and 0.89%.

226 These findings point to several directions for optimization. Population-based percentile
227 thresholds rather than fixed analytical ranges have been shown to reduce hold rates
228 substantially from 29.44% to 16.18% while maintaining safety in previous studies [1, 31].
229 Similarly, adjusting delta check thresholds by reference change values, measurement
230 intervals, or analyte panel-level specificity can reduce flagging rates from over 10% to
231 below 5% without compromising error detection [16, 32, 33]. The applicability of these
232 strategies to our system should be evaluated in future investigation.

233 iXLAB Verified was deployed at a single site by interfacing with the existing LIS through
234 standardized data exchange. The system operated continuously for seven months without
235 requiring LIS reconfiguration in contrast to the established burden of LIS-based
236 autoverification [4]. However, several limitations should be acknowledged. The study
237 was performed at a single centre using one analyser platform. In addition, the
238 autoverification rules were developed without a formal risk assessment framework such
239 as FMEA [19] and rule customization may be required to accommodate differences in
240 patient populations and laboratory practice. Validation in multiple centres, analyser

platforms, and patient populations is needed to assess the generalizability of these findings. Despite these limitations, validation across 53,120 samples with parallel manual review demonstrated 100% sensitivity and 0% false negatives. The seven-month deployment across 135,257 samples from outpatient, inpatient, and physical examination populations provided comprehensive failure pattern data.

Future directions include expanding autoverification beyond routine chemistry to tumour markers, endocrine assays, and infectious serology [34, 35]. Machine learning could also be incorporated into autoverification decisions and applied to specific classification tasks such as serum protein electrophoresis pattern interpretation [17, 36, 37]. Systematic frameworks such as Six Sigma DMAIC (Define, Measure, analyse, Improve, Control) and FMEA could be adopted to guide iterative rule optimization and safety assessment [1, 19].

In conclusion, The iXLAB Verify autoverification system reduced the 90th percentile turnaround time by 21–46% across outpatient, inpatient, and physical examination populations, with pre-deployment validation demonstrating 100% sensitivity and a 0% false negative rate. As a platform-independent system, it has the potential to be deployed across different LIS and analyser environments. Overall, iXLAB Verify is a promising platform to automate verification of test reports and improve efficiency of clinical laboratories.

Materials and Methods

Study Design

The study was conducted at Pingshan People's Hospital, a tertiary general hospital performing more than 3 million clinical chemistry annually. Data were collected during three distinct periods. The pre-implementation phase, spanning October 1, 2023, to April 1, 2024, established the baseline TAT. During system validation from March 1 to May 20, 2024, autoverification system and manual review were run independently and compared to assess the autoverification system's accuracy. Following formal implementation, data from October 1, 2024, to April 1, 2025, were analysed to determine pass rates, TAT, and failure patterns. The autoverification system (iXLAB Verify, Version 0.0.0.18) was developed by Shenzhen New Industries Biomedical Engineering Co., Ltd. (Snibe). It

operates as third-party software that interfaces with LIS (Version 8.0.10.2, Guangzhou Hanyu Computer Technology Co., Ltd., Guangzhou, China) through data exchange, independent of the instrument middleware (Figure 1). Clinical chemistry testing was performed on a Hitachi LABOSPECT 008 AS automated biochemistry analyser using Snibe reagents. Only serum specimens were included. Urine and other sample types were excluded from autoverification. This study was approved by the Institutional Ethics Committee of Pingshan People's Hospital (approval number: KY-2023-020-01). All procedures involving human participants were performed in accordance with the ethical standards of the institutional research committee, the Declaration of Helsinki, and relevant guidelines and regulations. All data were anonymized prior to analysis. The requirement for informed consent was waived due to the retrospective design and no collection of patients' information.

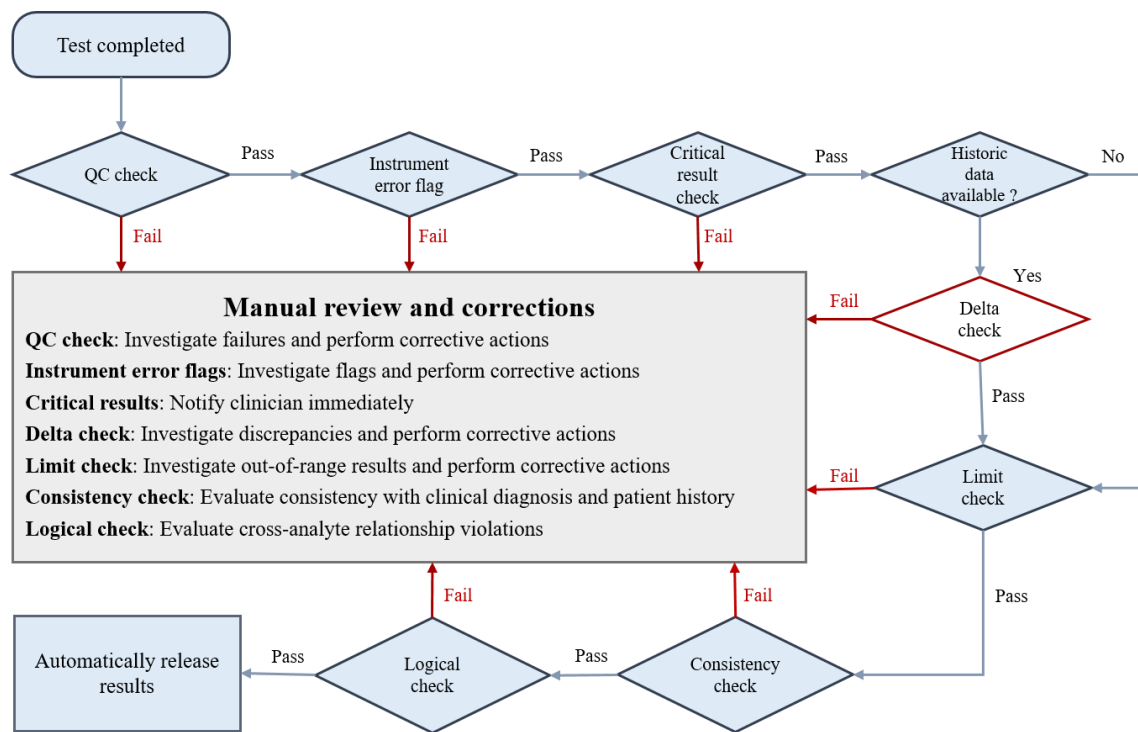


Figure 1. Autoverification system workflow. The iXLAB Verify software receives test results from the laboratory information system, evaluates them against the rule framework, and releases the verified results. QC, quality control.

Rule Development and Validation

We developed the autoverification rules according to the Clinical and Laboratory Standards Institute (CLSI) AUTO15 [3] and the Autoverification of Clinical Laboratory Quantitative Test Results (WS/T 616-2018) issued by the National Health Commission of the People's Republic of China (NHC). Clinical laboratory scientists, senior technologists, and instrument and IT specialists collaborated to define the acceptability criteria. The rule framework included limit check, instrument error flags, QC check, delta check, critical results, consistency check, and logical check. Limit checks were defined based on linear ranges, with the upper limit set to 80% of the upper linear boundary and the lower limit consistent with the lower linear boundary. Targeted adjustments were made for nephrology inpatients and diabetic populations. The urea (UREA) and creatinine (CREA) limits were widened to 1 ~ 30 and 20 ~ 1000 mmol/L for nephrology inpatients. Glucose (GLU) was widened to 3 ~ 24 mmol/L for diabetic patients. Creatine kinase MB (CK-MB) was restricted to 0 ~ 25 U/L. For each patient, the current result was compared with the most recent previous result obtained within the preceding 7 days. Acceptable delta limits were determined for each analyte according to its biological variation and the analytical performance of the corresponding detection reagent. A default threshold of $\pm 30\%$ was applied, whereas a wider threshold of $\pm 50\%$ was used for patients from the nephrology and diabetes departments because of their greater biological variability. Any result exceeding the predefined limit was excluded from autoverification and referred for manual review. The logical checks exploit known physiological and analytical relationships between analytes (e.g., protein and bilirubin fractions, enzyme isoenzyme hierarchies) to detect sample misidentification, analytical errors, and physiologically inconsistent results (Table 1). Instrument alarms and Westgard failures prompted manual review. Critical values overrode all other rules and required immediate clinician notification. The rules were validated using 53,120 residual specimens collected from March 1 to May 20, 2024, in which autoverification decisions were compared against manual review. Analyte-specific parameter ranges are provided in Supplementary Table S1.

Table 1. Logical check rules based on cross-analyte relationships.

Rule	Expression
Protein fraction	$TP > ALB + 10 \text{ g/L}$
Bilirubin fraction	$TBIL > DBIL$
Lactate dehydrogenase isoenzyme	$LDH > HBDH$
Lipid fraction	$TC > HDL-C + LDL-C$
Creatine kinase isoenzyme	$CK > CK-MB$
Hepatorenal (normal UREA)	$UREA \text{ normal} \Rightarrow CREA < 120 \mu\text{mol/L}$
Hepatorenal (normal CREA)	$CREA \text{ normal} \Rightarrow UREA < 12 \text{ mmol/L}$
Hepatic aminotransferase ($ALT > 100 \text{ U/L}$)	$ALT > 100 \text{ U/L} \Rightarrow AST > 40 \text{ U/L}$
Hepatic aminotransferase ($AST > 100 \text{ U/L}$)	$AST > 100 \text{ U/L} \Rightarrow ALT > 50 \text{ U/L}$
Cystatin C–creatinine (CYSC elevated)	$CYSC > 2 \text{ mg/L} \Rightarrow CREA > 100 \mu\text{mol/L}$
Cystatin C–creatinine (CREA elevated)	$CREA > 200 \mu\text{mol/L} \Rightarrow CYSC > 2 \text{ mg/L}$

Abbreviations: TP, total protein; ALB, albumin; TBIL, total bilirubin; DBIL, direct bilirubin; LDH, lactate dehydrogenase; HBDH, hydroxybutyrate dehydrogenase; TC, total cholesterol; HDL-C, high-density lipoprotein cholesterol; LDL-C, low-density lipoprotein cholesterol; CK, creatine kinase; CK-MB, creatine kinase-MB isoenzyme; ALT, alanine aminotransferase; AST, aspartate aminotransferase; UREA, urea; CREA, creatinine; CYSC, cystatin C.

Statistical Analysis

Autoverification performance was assessed by sample-based and analyte-based pass rates. The sample-based pass rate was defined as the proportion of samples that passed all autoverification rules relative to total samples screened, stratified by patient type (outpatient, inpatient, and health check). For each analyte, the analyte-based pass rate was calculated as the proportion of test results that passed autoverification among all results processed.

TAT was defined as the interval from sample receipt in the laboratory to result verification and release. Median and 90th percentile TAT were calculated separately for outpatient, inpatient, and physical examination before and after autoverification implementation. Absolute reductions were derived by comparing the post-implementation period with the same calendar period in the previous year.

Autoverification failures were classified into five categories, including instrument alarms, delta check failures, autoverification range violations, critical value detections, and logical rule violations. The failure proportion for each category was calculated as the percentage of failed tests attributed to that cause relative to the total failed tests.

Descriptive statistics, including counts, percentages, medians, and percentiles, were used for all analyses. Confidence intervals for proportions were calculated using the Wilson score interval for values not at extremes and the Clopper–Pearson exact method for proportions of 0% or 100%. All data processing and statistical analyses were performed using Python 3.12.4 (Python Software Foundation, Wilmington, DE, USA).

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Author contributions

B.Z., L.C. (Li Chen), and C.C. contributed equally to this work. B.Z. and C.C. developed the autoverification rules, performed rule validation, conducted data analysis, and drafted the manuscript. L.C. (Li Chen) performed rule validation and data analysis. Q.L. collected reference materials and participated in discussions on rule configuration. G.Z., R.F., L.C. (Lin Cen), W.F., Y.C., S.Z., and C.S. operated the autoverification software and provided feedback for system improvement. S.Y., L.Z., and Z.F. provided guidance and supervision on rule configuration and study design. J.Z. collected reference materials and participated in discussions on rule configuration. All authors reviewed and approved the final manuscript.

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Data availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Additional information

The authors declare no competing interests.

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