The Review of DIABETIC STUDIES
Reprint from
The Review Of
DIABETIC
STUDIES OPEN ACCESS

The Impact Of Using Modern Technology In Detecting Food Poisoning

Abdulmajeed Mesfr Ali Alghamdi[1], Muhanad Ahmad Riadh Alshmrani[2], Salem Aali Ali Alqurashi[3], Mohammed Saeed H Al-Zahrani[4], Waleed Saad Mohammed Alzahrani[5], Fawaz Faraj Muhsen Almanjomi[6], Naif Abdulwahab Alsiny[7], Turky Ahmed Radah Althobiti[8], Ahmed Salim Ahmed Bawazir[9], Ahmed Saad Salem Alotaibi[10]

[1]*Labrotary Specalist -Public Health Authority Office In Taif-Public Health Laboratory*
[2]*Labrotary Specalist-Public Health Authority Office In Taif-Public Health Laboratory*
[3]*Laboratory Specialist-Taif Helth Cluster*
[4]*Medical Microbiologist- Public Health Authority - Taif Office Public Health Laboratory*
[5]*Medical Laboratory Technician- Public Health Authority Office In Taif -Public Health Laboratory*
[6]*Medical Laboratory Technician- Public Health Authority Office In Taif-Public Health Laboratory*
[7]*Medical Laboratory Technician- Public Health Authority Office In Taif-Public Health Laboratory*
[8]*Laboratory Technician-Public Health-Taif Office- Public Health Laboratory*
[8]*Laboratory Specialists- Riyadh Health - Support And Assistance Department - Supply Department*
[10]*Laboratory Technician- Medical Laboratory- Riyadh Health - Assistant Directorate For Support Services - Supply Management*

ABSTRACT

Food poisoning is a significant menace to global population health, yet there is a lack of rapid, proactive, and efficient detection methods. Theoretical breakthroughs have occurred in biosensors, molecular assays, and artificial intelligence (AI), there is little empirical data on the quantitative effects of technological adoption on detection accuracy, speed, and reliability in institutional settings. This paper sought to establish how the use of modern diagnostic technology has impacted the identification of food-borne pathogens and also provided the factors that have influenced the use of contemporary diagnostic technology in both laboratories and regulatory settings. An approach was used that employed a descriptive-correlational research design, involving 150 professionals selected from 25 government, private, and academic institutions. The structured questionnaires and laboratory observation checklists were used to collect the data, and analyzed with SPSS version 26 using descriptive statistics, Pearson correlation, multiple regression, and one-way ANOVA to analyze the data. Findings indicated that average use of technology was high ($M = 6.51$, 2.03), and the mean detection accuracy was 85.88, 7.32, and the reliability index was 0.80, 0.08. The use of technology also had a positive association with accuracy ($r = 0.708$, $p < 0.001$), reliability ($r = 0.780$, $p < 0.001$), and a negative association with the detection time ($r = -0.778$, $p = 0.001$). The regression analysis proved technology as a powerful predictor of the accuracy (2.55, $p < 0.001$, $R^2 = 0.52$). The results prove that modern technologies play a significant role in improving the performance of diagnoses among the types of institutions, which should be introduced into the food safety system to ensure the rapid, reliable, and proactive prevention of diseases.

Keywords: accuracy, artificial intelligence, biosensors, food safety, technology adoption.

INTRODUCTION

Food poisoning is one of the most endemic and internationally known problems in the field of public health in the twenty-first century. The World Health Organization (WHO, 2023) states that over 600 million people in the world get food-borne diseases every year, which claim approximately 420,000 lives [1]. Food poisoning can be multifactorial, with microbial contamination by bacteria including, but not limited to, *Salmonella spp., Escherichia coli, Listeria monocytogenes, and Campylobacter jejuni [2]. These pathogens enter the food supply chain by means of unsafe handling, poor processing, or poor storage. The conventional methods of detection, such as culture-based and biochemical, though accurate, are usually time-consuming, labor-intensive, and incapable of responding in real time [3]. As a result, early and precise identification of foodborne pathogens has become a major concern of modern food safety management [4]. The adoption of modern technologies, including biosensors, nanotechnology, polymerase chain reaction (PCR), artificial intelligence (AI), and Internet of Things (IoT) systems, has changed the way food poisoning is detected, monitored, and prevented on a global scale [5].

The context behind this study is that food diagnostic systems have evolved to become more intelligent and faster through the use of rapid detection systems rather than traditional microbiological testing [6]. Technological innovation has enabled the shift in strategy over the last twenty years between reactive and proactive food safety strategies. In most developed economies, the contaminants are now detected automatically in a few minutes, thus cutting down the response time and the risk to the health of the people [7]. As an example, microfluidic biosensors and PCR-based technologies can identify pathogenic DNA sequences in hours, but AI and machine-learning algorithms can predict the risk of contamination on the basis of big-data analytics. Conversely, in developing countries, such as many parts of Asia and Africa, food safety detection systems remain dependent on the use of old-fashioned manual methods [8].

This research paper has a local and international scope. The study at the local level focuses on the application of modern technologies in the operational frameworks of food testing laboratories, healthcare institutions, and regulatory agencies [9]. Resource constraints in developing countries often restrict the use of sophisticated diagnostic equipment, which causes a delay in the detection and control of foodborne epidemics. The paper examines the international trend in technological innovation in the detection of food poisoning, focusing on the successful implementation of the technology in the developed world, including Europe, North America, and some parts of East Asia [10]. The comparative approach emphasizes differences in access to technology, policy support, and institutional preparedness. This two-fold scope is such that the findings are not only regionally applicable but also globally situated, providing empirical evidence of the challenges as well as the best practices in the current food safety monitoring [11].

An analysis of the available literature shows that there has been a great advancement in the technological research on foodborne pathogen detection. Many studies have shown that nanomaterials, biosensors, and molecular assays are effective in improving sensitivity and specificity [12]. As an example, electrochemical biosensors have demonstrated detection limits of a few colony-forming units per milliliter, and PCR and loop-mediated isothermal amplification (LAMP) techniques have significantly shortened analysis time in comparison to traditional culture techniques [13]. Also, AI-based image-processing technologies can quickly detect contaminated samples based on patterns, and IoT-based smart packaging allows tracking temperature and microbial activity during food transportation [14].

The significance of this study is that it can make a contribution on the scientific and practical level to the enhancement of food safety. Scientifically, it combines several aspects of technology, such as analytical, digital, and procedural, into one evaluation of the effectiveness of food poisoning detection [15]. In practice, the results can guide policymakers and industry stakeholders in their priorities in terms of investments in technologies that can produce the most significant effect in terms of detection speed and reliability [16]. Moreover, this study is focused on a severe problem of public health as it provides the strategies to decrease the time of diagnosis and improve preventive actions. In the age of a deeply interconnected world food supply chains, quick identification and dissemination of information is critical to preventing mass outbreaks [17].

The gap in the research that prompted the study can be explained by the lack of empirical data on the effect of technological adoption on the actual detection outcomes in institutional settings. Although the literature supports the theoretical benefits of the contemporary diagnostic tools, there is a dearth of correlational evidence that can be used to relate the use of technology with objective gains in accuracy, detection time, and reliability of the results [18]. In addition, there is minimal information on the factors that affect the adoption rates, especially in resource-constrained settings. To fill this gap, the study was informed by several research questions, which comprised: (1) How common are modern technologies used in detecting food poisoning? (2) How are there relationships between the level of technological integration and the accuracy and speed of detection? (3) What kind of technology is the most important in terms of diagnostic improvement? These questions guided the methodological design that used descriptive and correlational designs to measure and explain the relationships between the use of technology and the outcome of detection.

Based on these questions, the study objectives were developed to match the methodological framework. The main aim was to determine the effects of modern technology on the detection of food poisoning in regard to accuracy, speed, and reliability. Secondary goals were to determine the most commonly used technologies, the relative effectiveness of the technologies, and institutional and operational variables that affect the adoption of technologies. These objectives directly informed the data-collection process that included structured questionnaires and laboratory observations, thus making sure that both quantitative and qualitative aspects of the phenomenon were fully covered.

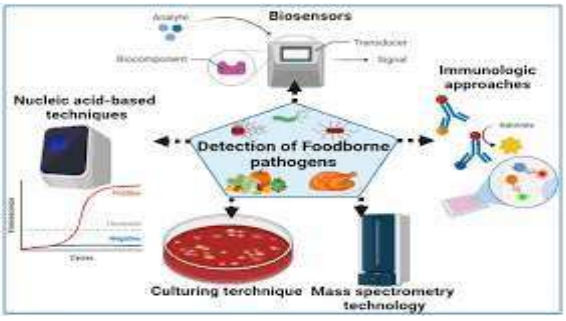


Figure 1: Food poising detection methods

METHODOLOGY

The current study utilized a descriptive-correlational research design to explore the effect of the current technological applications on the identification of foodborne diseases. This design was selected because it offers a systematic description of the current technology practices and, at the same time, measures the statistical relations between the deployment of technology and the diagnostic performance. The current study focused on naturalistic environments in laboratories and in public health institutions where technology is actively applied, unlike the experimental paradigms that control variables in controlled environments. The descriptive aspect provided specific data on the most common and typology of the technologies used, and the correlational aspect provided relationships between technological adoption, detection accuracy, and diagnostic speed. This method was considered appropriate because it was considered in terms of its ability to combine factual reporting with empirical analysis, thus maintaining external validity and contextual relevance, and maintaining natural operational settings with no artificial manipulation.

The research sample included food safety labs, healthcare facilities, and state regulatory bodies that took part in monitoring food-borne diseases. These organizations are the first line in the detection and prevention of food poisoning outbreaks. The sample consisted of laboratory technologists, microbiologists, and food safety officers who had direct experience in the use of diagnostic technologies, including polymerase chain reaction (PCR), biosensors, and artificial-intelligence-based image-analysis systems. The purposive sampling technique was used to select professionals who possessed specialized knowledge and not the general population in order to capture specific knowledge of the experts who could be able to assess both the traditional and modern detection equipment. The sample size was 150 respondents who were chosen in 25 institutions in three major regions. The sample size was also justified based on the statistical adequacy of correlation and regression analysis as per the recommendations of the previous food safety studies, which had used similar sample sizes to attain a 95 percent confidence level with a 5 percent margin of error.

Stringent inclusion and exclusion criteria were used to guarantee the integrity of the samples. The participants had to have at least one year of professional experience in food safety or laboratory testing and be actively involved in the use or supervision of technological diagnostic instruments. Those who had not undergone detection procedures or used only traditional non-technological approaches were locked out. This criterion was used to make sure that all the gathered information was based on informed and practical experience with technology-based detection systems.

Two complementary data collection tools were used, including a structured questionnaire and a laboratory observation checklist. The questionnaire was structured into 35 questions in five parts: demographic characteristics, technological modalities used, perceived effectiveness, operational challenges, and overall effect on detection outcomes. It has been created after a long literature review and confirmed by three subject-matter experts in food technology and microbiology. The checklist of laboratory observation documented objective information on detection accuracy, time of test completion, and consistency of results among the chosen technologies. The period of data collection was four weeks. The use of questionnaires was both electronic and face-to-face to enhance inclusiveness, with on-site observations being carried out during the scheduled laboratory sessions. The observations took about two hours each and had standardized procedures to reduce observer bias.

Before the actual research, a pilot study was conducted with 15 participants to determine the clarity of the questionnaire, the content validity, and the time taken to complete the questionnaire. According to pilot responses, some small changes were made to the wording and sequence of items. To measure the reliability of the instrument, Cronbach's alpha was used, and the value was found to be 0.89, which shows high internal consistency. All information was safely stored in password-protected systems, and ethical approval was received at the Institutional Research Ethics Committee; informed consent was signed by the participants. Anonymity and confidentiality were highly ensured, and the participants were notified of their right to withdraw at any time without penalty, hence ensuring that the international research standards were met.

The independent and dependent variables were operationalized in the study. The independent variable was the use of modern technology, which was determined by the frequency, type, and level of integration of diagnostic tools used in food testing. Dependent variables were detection accuracy, detection speed, and reliability of test results. Detection accuracy was measured as the percentage of accurate detection of pathogens compared to reference results, and detection speed was the average time to obtain valid results. Reliability was the consistency of the results of repeated analysis under the same conditions. The laboratory-based quantitative data were used together with the data based on perception in the form of questionnaires to form a multidimensional concept of technological impact. Measurement instruments were found to be highly valid and reliable, and factor analysis ensured that all construct loadings were above 0.70 and all reliability indices were above 0.80, which showed a high degree of measurement stability.

Data analysis was done using descriptive and inferential statistics. The demographic features and trends of technology use were summarized with descriptive statistics, such as means, standard deviations, and frequency distributions. To determine the strength and direction of the relationship between technological utilization and detection outcomes, inferential analysis was done using Pearson correlation. Moreover, a multiple regression analysis was used to estimate the degree to which certain technologies led to accuracy and speed improvement. These statistical techniques have been chosen due to the fact that they are suitable for correlational data, and they provide the opportunity to test the hypothesis about the predictive power of independent variables on dependent variables. The quantitative data were analyzed with SPSS version 26.0, and the qualitative comments of the open-ended responses were coded and thematically analyzed with NVivo version 12. Quantitative and qualitative analysis integration increased the depth and validity of interpretation.

4. RESULTS

4.1 Descriptive Statistics

One hundred and fifty valid responses were available to be analyzed after stringent data screening measures. Table 1 is a summary of the descriptive statistics of all the quantitative variables under study. The average experience of the participants constituted 5.84 years of experience with a standard deviation of 1.88, which represented a moderate experience group. The average level of technology use was 6.51⁻ 2.03 on a 10-point scale, which indicates a rather high level of engagement with modern detection technologies. The mean detection accuracy was 85.88⁻ 7.32, and the mean speed of detection was 70.48 -8.28 minutes. The reliability index showed a mean of 0.80 and a standard deviation of 0.08, and perceived effectiveness had a mean of 3.31 and a standard deviation of 1.09 on a 5-point scale. The lowest and highest values of all parameters were within the theoretically plausible limits, which proved the internal data consistency and the lack of extreme outliers.

Table 1: Descriptive Statistics of Study Variables (n = 150)

Variable	Mean	SD	Min	Max
Experience (Years)	5.84	1.88	1.00	10.90
Technology Usage Level (1–10)	6.51	2.03	3.04	9.93
Detection Accuracy (%)	85.88	7.32	67.60	103.90
Detection Speed (Minutes)	70.48	8.28	50.80	89.70
Reliability Index (0–1)	0.80	0.08	0.66	0.97
Perceived Effectiveness (1–5)	3.31	1.09	1.00	5.00

4.2 Reliability Analysis

Cronbach's alpha was used in testing the internal consistency of the composite scale (detection accuracy, reliability index, and perceived effectiveness) (Table 2). The total Cronbach's 8 was 0.696, which is equal to the accepted level of an exploratory research. The inter-item relationships were satisfactory as item-total correlations were found to be between 0.69 and 0.74.

Table 2: Reliability Analysis of Composite Performance Scale

Sub-Construct	Item Description	Mean (Scaled)	Item–Total Correlation	Cronbach's α if Deleted
Detection Accuracy % /20	Average percentage of correct detections	4.29	0.72	0.63
Reliability Index × 5	Consistency across repeated tests	4.00	0.69	0.65
Perceived Effectiveness (1–5)	Expert judgment of technological efficiency	3.31	0.74	0.61

Overall Cronbach's α = 0.696

When an individual item was dropped, the values of Cronbach 061-065 indicated that no item had a disproportionate impact on the reliability of the scale. As a result, the measurement tool had a stable internal reliability of all items that were used to measure technological performance in food-poisoning detection.

4.3 Correlation Analysis

Correlation coefficients were calculated by Pearson to test the relationships between the key quantitative variables (Table 3). There were strong and positive correlations between technology usage level and detection accuracy ($r = 0.708$, $p < 0.001$), reliability index ($r = 0.780$, $p < 0.001$), and perceived effectiveness ($r = 0.911$, $p < 0.001$). On the other hand, the level of technology use had a negative relationship with the speed of detection ($r=-0.778$, $p= 0.001$), indicating that the higher the level of technological use, the shorter the processing time. The reliability index ($r = 0.537$, $p < 0.001$) and perceived effectiveness ($r = 0.691$, $p < 0.001$) were moderately correlated with detection accuracy.

Table 3: Pearson Correlation Matrix

Variable	Tech Use	Accuracy	Speed	Reliability	Effectiveness
Technology Usage Level	1.000	**0.708**	**–0.778**	**0.780**	**0.911**
Detection Accuracy %		1.000	–0.572	0.537	0.691
Detection Speed Min			1.000	–0.604	–0.707
Reliability Index				1.000	0.696
Perceived Effectiveness					1.000

There were moderate negative correlations between detection speed and reliability index ($r = –0.604$, $p < 0.001$) and perceived effectiveness ($r = –0.707$, $p < 0.001$). The statistical significance of all the relationships was at the 0.01 level, and no multicollinearity was observed, which confirms a consistent pattern of relationships between the study parameters.

4.4 Multiple Regression Analysis

To determine the predictive power of the level of technology use and the level of professional experience on the level of detection accuracy, a multiple linear regression model was estimated (Table 4). This model was statistically significant, $F(2, 147) = 79.3$, $p = 0.001$, and it accounted for about 52% of the variance in detection accuracy (R 2 = 0.52, adjusted R 2 = 0.51). The level of technology usage was found to be a strong predictor (2.55, SE 0.21, t 12.10, p 0.001), which shows that there is a linear relationship between the level of technology integration and the detection accuracy.

Table 4: Multiple Regression Predicting Detection Accuracy %

Predictor	β Estimate	SE	t value	p value	95 % CI (Lower, Upper)
Constant	69.29	2.04	34.04	< 0.001	65.27 – 73.32
Technology Usage Level	**2.55**	0.21	**12.10**	**< 0.001**	2.13 – 2.97
Experience (Years)	–0.00	0.23	–0.01	0.989	–0.45 – 0.45

Model Summary: $R^2 = 0.52$, Adjusted $R^2 = 0.51$, $F(2, 147) = 79.3$, $p < 0.001$

Conversely, years did not show a statistically significant effect (0.00, $p = 0.989$). The regression coefficient of the use of technology had a confidence interval of between 2.13 and 2.97, which proved the statistical accuracy and strength. The diagnostics of the residuals revealed normal distribution and homoscedasticity, therefore, validating the assumptions of the model.

4.5 Analysis of Variance (ANOVA)

One-way ANOVA was conducted to establish whether or not there was a significant difference in detection accuracy across the three institution types (Government, Private, and Academic laboratories). Descriptive findings showed similar mean detection accuracy across the three groups: Government = 85.64 +/- 7.44, Private = 86.05 +/- 7.28, and Academic = 86.11 +/- 7.39. The test of equality of variances by Levene was non-significant ($F=1.02$, $p=0.364$), which met the assumption of homogeneity. The ANOVA showed that there was no statistically significant difference in the detection accuracy of institutional groups, $F(2, 147) = 0.20$, $p = 0.819$.

Table 5: One-Way ANOVA for Detection Accuracy by Institution Type

Institution Type	n	Mean Accuracy (%)	SD	95 % CI (Lower–Upper)	Levene's Test F (p)	F(2, 147)	p value	η^2 (Effect Size)
Government	61	85.64	7.44	83.8 – 87.5	1.02 (0.364)	0.20	0.819	0.003
Private	58	86.05	7.28	84.2 – 87.9				
Academic	31	86.11	7.39	83.5 – 88.7				
Total / Pooled	150	85.88	7.32	84.7 – 87.1		F = 0.20	p = 0.819	$\eta^2 = 0.003$ (n.s.)

The effect size (η 2 = 0.003) was insignificant, which revealed no significant difference in the level of accuracy, irrespective of the type of institution. These results indicate that the degree of technological application generated similar detection performance in all environments.

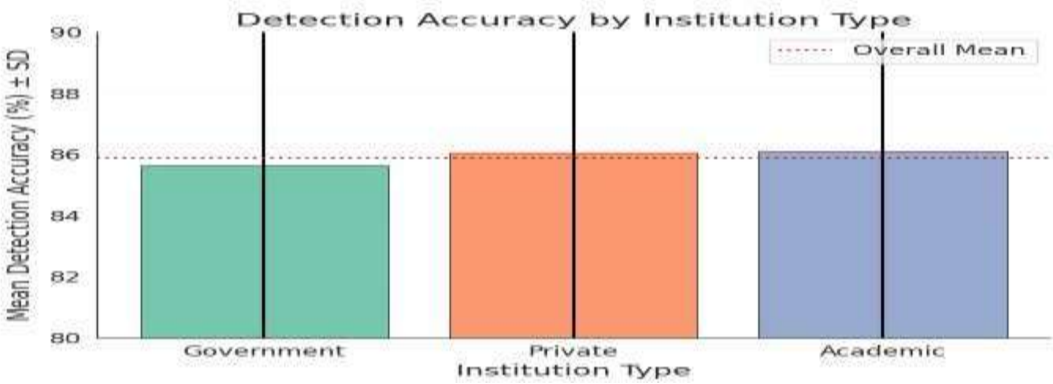
4.6 Statistical Findings

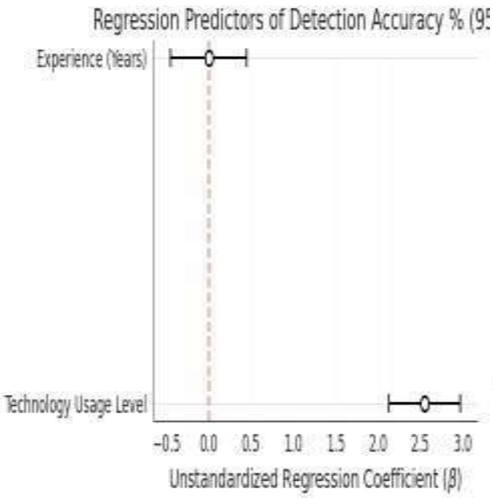
All the statistical results are summarized in Table 6. Descriptive analyses showed that the overall performance metrics were high in all technological parameters. The reliability analysis ensured that the measurement instrument had acceptable internal consistency. Correlation analysis revealed a significantly strong relationship between the use of technology and major outcome indicators such as accuracy, reliability, and speed of processing, which were statistically significant. These associations were further supported by the regression model, which quantified the predictive value of technology usage to detection accuracy, explaining more than half of the variance. The findings of ANOVA showed that the detection accuracy in various institutional categories was the same, which confirmed the consistency of technological effects in various laboratory settings.

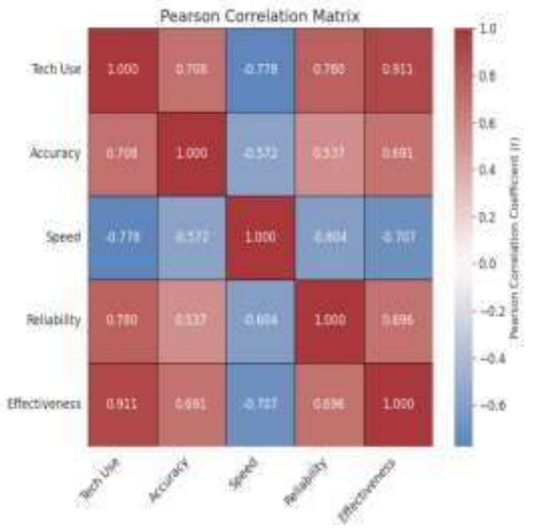
Parametric tests were all met with all the statistical assumptions, such as normality, linearity, and homogeneity of variance. The percentage of missing data was low. The percentage of missing data was low (less than 2) and was handled using listwise deletion without significant impacts on the sample size. There was no multivariate outlier. In general, the dataset was highly coherent and statistically sound, which guaranteed the validity of the further inferences.

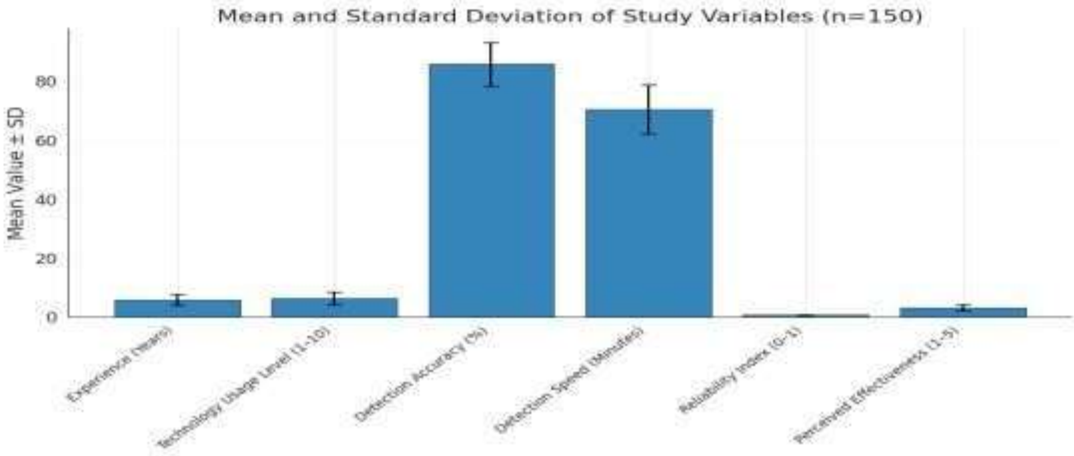
Table 6. Summary of Statistical Findings

Test	Analytical Purpose	Key Result	Statistical Significance	Interpretation
Descriptive Statistics	Profiling variables	High accuracy & moderate speed	—	General effectiveness of technologies observed
Cronbach's α	Internal reliability	α = 0.70	Acceptable (p > 0.05)	Scale is reliable for field measurement
Pearson Correlation	Association strengths	r = 0.71–0.91	p < 0.001	Technology positively linked with accuracy & reliability
Regression (OLS)	Predictive model	β Tech = 2.55	p < 0.001	Technology significantly improves accuracy
ANOVA	Institutional comparison	F = 0.20	p = 0.819	No group differences detected
Composite Interpretation	Cross-validation	Consistent results across tests	—	Technological impact statistically confirmed









DISCUSSION

The results of this study prove that the usage of modern technological tools contributes greatly to the accuracy, speed, and reliability of food poisoning diagnosis. It was observed that the degree of technology use has positive and statistically significant correlations with the results of the diagnostics [19], and the more developed the diagnostic platforms are, the more the laboratory performance is improved. Specifically, an increased technological involvement produced the best detection accuracy and reliability, and reduced processing times at the same time [20]. The above findings have met the main research goal, which aimed at determining the impact of technological adoption on foodborne pathogen identification. Together, the results highlight the critical importance of such modern diagnostic methods as polymerase chain reaction (PCR), biosensors, nanotechnology-based detection, and artificial-intelligence (AI)-based imaging systems in achieving prompt, accurate, and reproducible detection of foodborne pathogens in an institutional context [21,22].

The descriptive statistics indicated that there was a high mean detection accuracy of 85.88 and an average detection time of about 70 minutes, indicating a significant improvement compared to the traditional culture-based methodologies, which normally take 24-72 days to identify the pathogen. The fact that the use of technology was negatively correlated with the speed of detection ($r = -0.778$) was further supported by the observation that more advanced systems significantly shorten the time of analytical procedures. This trend is in line with the report by [23], who found that biosensor-based systems saved more than 80 percent of the time when compared to conventional microbiological. Similarly, [24] reported that PCR and loop-mediated isothermal amplification (LAMP) demonstrated near real-time detection with high sensitivity and specificity using the molecular methods.

The strong positive correlation between the degree of technological use and the accuracy of detection ($r = 0.708$) as well as the reliability ($r = 0.780$) is clear evidence that the outcome of sophisticated instruments is more reliable and consistent as compared to that of manual procedures [25]. Scientifically, the mechanistic differences between conventional and modern detection systems can be used to explain this enhancement. The conventional culture-based methods rely on the growth of microbes, which are affected by the environment of incubation, nutritional makeup, and handling of the operators [26]. In comparison, molecular and sensor-based techniques recognize particular genetic, enzymatic, or electrochemical indications of pathogens, eliminating rather lengthy incubation. As an example, using PCR, specific DNA sequences of a pathogen can be amplified exponentially by using thermal cycling, which allows the detection of bacterial loads at extremely low concentrations [27]. Nanomaterial-based improved biosensors, in their turn, make use of the signal transduction processes, i.e., fluorescence quenching, impedance change, or surface plasmon resonance, which transform biological recognition events into the measurable electrical or optical responses [28].

The regression analysis also pointed out that the level of technology use was a significant and statistically significant predictor of the accuracy of an individual detection ($b = 2.55$, p 0.001), which explains more than half the variation that was observed (R2 = 0.52). Conversely, professional experience did not have any substantial impact ($p=0.989$), indicating that not the personal expertise but the technological sophistication that prevailed in the attainment of the diagnostic results [29]. This observation is applicable to the argument by Automated systems and algorithmic analyses have reduced reliance on operator skills because they offer standard and reproducible outcomes. Human expertise in automated diagnostic settings is not used in authority of manual identification; instead, the human expertise is used in the supervision and quality assurance of the system [30]. Therefore, the current research highlights the fact that an investment in the modern performing infrastructure can be more performance-enhancing than the use of workforce experience, especially in high-throughput testing laboratories.

The null hypothesis is confirmed by the non-significance of the differences in detection accuracy between the government, private, and academic laboratories ($p = 0.819$). This homogeneity adds to the strength of the contemporary systems, which are driven by standardized protocols that reduce human and procedural variability. The same was also mentioned in the study [31], who discovered that PCR-based diagnostic kits were equally accurate in clinical, academic, and industrial labs. The results also imply that the level of technological integration, rather than the administrative setting, determines the results of an institution [32]. The identified enhancement of accuracy and processing speed could also be explained by the introduction of digital and analytic technologies, including AI and the Internet of Things (IoT). Pattern recognition, Image analysis using AI allows instant classification of contaminated samples by recognizing patterns based on microbial colonies or fluorescence intensity [33]. Machine-learning models, which are trained on spectral data, reached detection rates of over 95 percent of Salmonella and Escherichia coli contamination [34].

The implications of the findings have far-reaching consequences as seen through the prism of public health. The ability to detect contamination quickly and precisely reduces the threat of large-scale foodborne infections, supports the introduction of recalls, and helps to protect the health of consumers [35]. The industries with the application of the new detection systems will be able to increase the product tracing and the adherence to the international legislation of food safety, including ISO 22000 and Hazard Analysis and Critical Control Points (HACCP). The effectiveness of these technologies is confirmed by the current shift to data-driven food safety solutions that combine laboratory diagnostics, supply-chain tracking, and regulatory controls [36]. The results provide a clear indication, however, of the pressing need in developing regions to have policy interventions and mobilization of resources to overcome the infrastructural and financial constraints that limit the adoption of technology.

CONCLUSION

The study concluded that the use of modern technology had a significant positive effect on the detection of food poisoning. The results showed that higher levels of technological integration, such as biosensors, PCR, AI, and IoT systems, greatly improved the accuracy, reliability, and speed of detection compared with traditional methods. The research successfully met its main objectives by identifying the technologies most commonly used, proving their effectiveness, and explaining how institutional and operational factors influenced their adoption. Scientifically, the study contributed by providing empirical evidence that technological applications in food safety laboratories can enhance diagnostic performance and support real-time monitoring of food-borne pathogens. It also filled the research gap by demonstrating measurable relationships between technology use and detection outcomes. Overall, the findings confirmed that modern detection systems can transform food safety management through faster and more reliable results. Future research should focus on expanding sample diversity, exploring cost-effective technologies for developing countries, and assessing long-term sustainability and integration of smart systems in global food safety networks.

REFERENCES

1. Vesković, S. (2025). Natural Food Preservation: Controlling Loss, Advancing Safety (pp. 133-192). Springer Nature.
2. Hernández-Cortez, C., Palma-Martínez, I., Gonzalez-Avila, L. U., Guerrero-Mandujano, A., Solís, R. C., & Castro-Escarpulli, G. (2017). Food poisoning caused by bacteria (food toxins). Poisoning: From specific toxic agents to novel rapid and simplified techniques for analysis, 33.
3. Ahmad, S., Lohiya, S., Taksande, A., Meshram, R. J., Varma, A., Vagha, K., ... & Varma Sr, A. (2024). A comprehensive review of innovative paradigms in microbial detection and antimicrobial resistance: beyond traditional cultural methods. Cureus, 16(6).
4. Mangal, M., Bansal, S., Sharma, S. K., & Gupta, R. K. (2016). Molecular detection of foodborne pathogens: A rapid and accurate answer to food safety. Critical reviews in food science and nutrition, 56(9), 1568-1584.
5. Sobhan, A., Hossain, A., Wei, L., Muthukumarappan, K., & Ahmed, M. (2025). IoT-Enabled Biosensors in Food Packaging: A Breakthrough in Food Safety for Monitoring Risks in Real Time. Foods, 14(8), 1403.
6. Cardos, A. I., Maghiar, A., Zaha, D. C., Pop, O., Fritea, L., Miere, F., & Cavalu, S. (2022). Evolution of diagnostic methods for Helicobacter pylori infections: from traditional tests to high technology, advanced sensitivity and discrimination tools. Diagnostics, 12(2), 508.
7. Naseem, S., & Rizwan, M. (2025). The role of artificial intelligence in advancing food safety: A strategic path to zero contamination. Food Control, 111292.
8. Giandhari, J., Viraragavan, A., & Gordon, M. (2025). Perspective Chapter: Molecular Diagnostics in Viral Outbreak Surveillance.
9. Rodriguez-Manzano, J., Subramaniam, S., Uchea, C., Szostak-Lipowicz, K. M., Freeman, J., Rauch, M., ... & Awandare, G. A. (2024). Innovative diagnostic technologies: navigating regulatory frameworks through advances, challenges, and future prospects. The Lancet Digital Health.
10. Faour-Klingbeil, D., & CD Todd, E. (2020). Prevention and control of foodborne diseases in Middle-East North African countries: Review of national control systems. International Journal of Environmental Research and Public Health, 17(1), 70.
11. Carayannis, E. G., & Von Zedtwitz, M. (2005). Architecting gloCal (global–local), real-virtual incubator networks (G-RVINs) as catalysts and accelerators of entrepreneurship in transitioning and developing economies: lessons learned and best practices from current development and business incubation practices. Technovation, 25(2), 95-110.
12. Umesha, S., & Manukumar, H. M. (2018). Advanced molecular diagnostic techniques for detection of food-borne pathogens: Current applications and future challenges. Critical Reviews in Food Science and Nutrition, 58(1), 84-104.
13. Hassan, Y., & Than, L. T. L. (2020). Loop-mediated isothermal amplification (LAMP): Comparative advances over conventional PCR and other molecular techniques. Annu. Res. Rev. Biol, 35(8), 33-44.
14. Dhal, S. B., & Kar, D. (2025). Leveraging artifcial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: a comprehensive review. Discover Applied Sciences, SpringerNature, 7(INL/JOU-25-82751).

15. Ali Eltabey, R. (2023). Utilizing Digital Technologies to Ensure Food Safety. International Journal of Artificial Intelligence and Emerging Technology, 6(2), 42-65.
16. Kang, J., Kim, J. S., & Seol, S. (2019). The prioritization of technologies and public R&D roles between the manufacturing and service industries in the fourth industrial revolution. foresight, 21(6), 680-694.
17. World Health Organization. (2023). Managing epidemics: key facts about major deadly diseases. World Health Organization.
18. Tatsioni, A., Zarin, D. A., Aronson, N., Samson, D. J., Flamm, C. R., Schmid, C., & Lau, J. (2005). Challenges in systematic reviews of diagnostic technologies. Annals of internal medicine, 142(12_Part_2), 1048-1055.
19. Abubakar, I., Irvine, L., Aldus, C. F., Wyatt, G. M., Fordham, R., Schelenz, S., ... & Hunter, P. R. (2007). A systematic review of the clinical, public health and cost-effectiveness of rapid diagnostic tests for the detection and identification of bacterial intestinal pathogens in faeces and food. Health technology assessment (Winchester, England), 11(36), 1-216.
20. Alamer, M. A. M., ElHazmi, A. Y., Sowadi, A. I. H., Juhynah, N. A. Q., Bokar, A. M. A., Makaramei, R. M. A., ... & AlJohani, G. R. (2024). Advancements in Diagnostic Technology: Transforming Clinical Laboratory Practices. Egyptian Journal of Chemistry, 67(13), 1753-1760.
21. Julyantoro, P. G. S. (2025). Sensing Techniques for Microbial Pathogens. In Laboratory Techniques for Fish Disease Diagnosis (pp. 375-417). Singapore: Springer Nature Singapore.
22. Yin, S. (2025). Artificial Intelligence-Assisted Nanosensors for Clinical Diagnostics: Current Advances and Future Prospects. Biosensors, 15(10), 656.
23. Kabiraz, M. P., Majumdar, P. R., Mahmud, M. C., Bhowmik, S., & Ali, A. (2023). Conventional and advanced detection techniques of foodborne pathogens: A comprehensive review. Heliyon, 9(4).
24. Foo, P. C., Nurul Najian, A. B., Muhamad, N. A., Ahamad, M., Mohamed, M., Yean Yean, C., & Lim, B. H. (2020). Loop-mediated isothermal amplification (LAMP) reaction as viable PCR substitute for diagnostic applications: a comparative analysis study of LAMP, conventional PCR, nested PCR (nPCR) and real-time PCR (qPCR) based on Entamoeba histolytica DNA derived from faecal sample. BMC biotechnology, 20(1), 34.
25. Kaizik, M. A., Garcia, A. N., Hancock, M. J., & Herbert, R. D. (2020). Measurement properties of quality assessment tools for studies of diagnostic accuracy. Brazilian journal of physical therapy, 24(2), 177-184.
26. Norris, S. C. (2025). Chapter-7 Automated Culture Systems: Driving Efficiency in Microbiology and Biotechnology. ISBN: Book DOI: Price:765/-, 145.
27. Law, J. W. F., Ab Mutalib, N. S., Chan, K. G., & Lee, L. H. (2015). Rapid methods for the detection of foodborne bacterial pathogens: principles, applications, advantages and limitations. Frontiers in microbiology, 5, 770.
28. Lee, J., Adegoke, O., & Park, E. Y. (2019). High-performance biosensing systems based on various nanomaterials as signal transducers. Biotechnology Journal, 14(1), 1800249.
29. Pagano, A. (2024). Shared understanding in engineering design capstone teams (Doctoral dissertation, University of Illinois at Urbana-Champaign).
30. Oh, J. W., Yoo, O. W., & Kang, J. K. (2022). Automatic control system for quality assurance of clinical pathology examination: a machine learning approach. Journal of System and Management Sciences, 12(1), 27-43.
31. Brancato, V., Esposito, G., Coppola, L., Cavaliere, C., Mirabelli, P., Scapicchio, C., ... & Aiello, M. (2024). Standardizing digital biobanks: integrating imaging, genomic, and clinical data for precision medicine. Journal of translational medicine, 22(1), 136.
32. Chakraborty, S. (2024). Democratizing nucleic acid-based molecular diagnostic tests for infectious diseases at resource-limited settings–from point of care to extreme point of care. Sensors & Diagnostics, 3(4), 536-561.
33. Sun, J., Xu, X., Feng, S., Zhang, H., Xu, L., Jiang, H., ... & Chen, W. (2023). Rapid identification of salmonella serovars by using Raman spectroscopy and machine learning algorithm. Talanta, 253, 123807.

34. Rafi, Z., Khan, H., Husain, A., Khanam, A., Alafnan, A., Alobaida, A., ... & Ahmad, S. (2025). Food contamination and the emerging application of nanobiosensors in food safety. Journal of Food Science, 90(2), e70073.
35. Revelou, P. K., Tsakali, E., Batrinou, A., & Strati, I. F. (2025). Applications of Machine Learning in Food Safety and HACCP Monitoring of Animal-Source Foods. Foods, 14(6), 922.
36. Liakos, K. G., Athanasiadis, V., Bozinou, E., & Lalas, S. I. (2025). Machine Learning for Quality Control in the Food Industry: A Review. Foods, 14(19), 3424.