



Knowledge and Application of Differential Equations in Medical Laboratory Research among Laboratory Professionals in Kenema District, Sierra Leone: An analytical cross-sectional study

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ABSTRACT

Background: Differential equations support mathematical modelling in biomedical research, disease surveillance, and laboratory decision-making. This study assessed knowledge and application among laboratory professionals in Kenema District, Sierra Leone.

Methods: An analytical cross-sectional study included 500 laboratory professionals selected using stratified sampling and simple random sampling within strata. Data were collected using a structured questionnaire and analysed using descriptive statistics, correlation, and multivariable linear regression with institution-clustered standard errors.

Results: Moderate knowledge was observed in 48% of participants, while 23% demonstrated high knowledge. Knowledge correlated positively with application ($r = 0.58$, $p < 0.001$). Training, software access, data availability, and technical support were significant predictors. Limited training was the most common barrier (73%).

Conclusion: Strengthening training and workplace resources may improve mathematical modelling capacity.

Keywords: Differential equations; Laboratory professionals; Mathematical modelling; Research capacity; Sierra Leone.

INTRODUCTION

Mathematical modelling plays an important role in biomedical and public health research by providing a systematic approach to understanding biological processes and changes over time. Ordinary differential equations (ODEs) describe how biological variables change in response to interactions among different components of a system. They are widely used in infectious disease epidemiology, pharmacokinetics, pharmacodynamics, systems biology, and other areas of biomedical research. Compartmental models based on differential equations provide a mathematical framework for investigating disease transmission, evaluating potential interventions, and predicting epidemiological trends under specified assumptions [1,2]. Medical and public health laboratories generate diagnostic, experimental, and surveillance data that can contribute to mathematical modelling. Differential equation-based models can help researchers investigate biomarker kinetics, drug concentration profiles, treatment responses, and biological signalling pathways. Bardini et al. discussed multilevel and hybrid modelling approaches for representing complex biological systems, demonstrating the potential of mathematical models to integrate biological information across different levels [2]. Such approaches may support the interpretation of laboratory findings, the generation of research hypotheses, and the investigation of mechanisms underlying disease progression. However, model predictions depend on data quality, appropriate parameter estimation, transparent assumptions, and careful interpretation. Differential equations are therefore most useful when the research question involves a dynamic process that can be meaningfully represented mathematically.

Differential equation-based susceptible–infectious–recovered (SIR) and susceptible–exposed–infectious–recovered (SEIR) models are widely used to investigate infectious disease transmission. These models represent the movement of individuals between epidemiological states and allow researchers to explore the effects of transmission rates, recovery rates, and public health interventions [1]. Mathematical modelling has become particularly important in epidemic preparedness, disease surveillance, and public health decision-making because it can provide insights into possible disease trajectories and intervention outcomes. The COVID-19 pandemic further demonstrated the contribution of mathematical modelling to understanding disease transmission and assessing infection prevention and control strategies.

Grant et al. discussed opportunities to expand the use of mathematical modelling in healthcare epidemiology, while Smith et al. reviewed its contribution to understanding the transmission and control of SARS-CoV-2 in healthcare settings [3,4]. These applications demonstrate the value of collaboration among laboratory professionals, epidemiologists, clinicians, statisticians, and mathematical modellers. Differential equations are also used in pharmacokinetic and pharmacodynamic modelling to describe drug absorption, distribution, metabolism, elimination, and biological effects. Truong et al. compared ordinary differential equation and agent-based approaches to pharmacokinetic–pharmacodynamic modelling, illustrating how different mathematical frameworks can be used to investigate drug behaviour and treatment responses [5]. In systems biology, mathematical models are used to represent interactions among genes, proteins, metabolites, and cellular signalling pathways. Bardini et al. described multilevel and hybrid approaches to systems biology modelling, while Rachel et al. examined dynamic modelling of signalling pathways in situations where conventional ODE approaches may not be feasible [2,6]. These studies illustrate that the selection of a modelling approach should be guided by the biological question, available data, and characteristics of the system under investigation. For laboratory professionals, mathematical modelling may support the interpretation of longitudinal laboratory measurements, investigation of diagnostic trends, analysis of treatment responses, and evaluation of quality improvement strategies. Nevertheless, direct application of differential equations is not necessary for every laboratory task; their practical value depends on the research problem and the availability of suitable data and technical expertise. The development of mathematical modelling skills requires appropriate education, practical training, analytical resources, and opportunities for collaboration. These requirements may be challenging to meet in resource-limited settings where access to specialist expertise, computing facilities, research funding, and advanced analytical training is unevenly distributed. Kaduru et al. described the implementation of a malaria modelling fellowship in Nigeria and reported lessons relevant to developing local mathematical modelling capacity [7]. Ofori et al. examined an infectious disease modelling training programme for policymakers in East Africa that emphasised practical learning and the use of modelling in decision-making [8]. Similarly, Ntshebe et al. evaluated a quantitative methods capacity-building programme in sub-Saharan Africa, highlighting the importance of training and research networks [9].

These initiatives demonstrate the potential value of structured training, mentorship, and collaborative research. However, much of the capacity-building literature focuses on mathematical modellers, public health professionals, policymakers, or academic researchers. The specific knowledge and application of differential equations among medical laboratory professionals have received comparatively limited attention. Laboratory professionals are essential to diagnostic services, disease surveillance, outbreak investigation, and biomedical research. The World Health Organization's Laboratory Leadership Competency Framework identifies research, surveillance, and outbreak investigation as important areas of laboratory leadership development [10]. The Global Competency and Outcomes Framework for the Essential Public Health Functions also identifies competencies needed to support effective public health services [11]. In addition, the WHO Strategic Framework for Strengthening Health Laboratory Services emphasises the contribution of laboratory systems to surveillance and public health responses [12]. The application of mathematical methods depends not only on individual knowledge but also on the workplace environment. Previous modelling or statistics training may improve familiarity with quantitative approaches, while access to computers, suitable software, reliable data, and technical support may facilitate practical application. Research funding, protected time for research, institutional encouragement, and collaboration with mathematicians, statisticians, and epidemiologists may also be relevant. Professionals may understand differential equations but lack the resources or opportunities to use them in their work. Conversely, access to software and technical assistance may be of limited benefit when the necessary conceptual knowledge is absent. Evaluating knowledge alongside professional and institutional factors can therefore provide a more comprehensive understanding of mathematical modelling practices within the laboratory workforce.

In Sierra Leone, district-level evidence concerning laboratory professionals' knowledge of differential equations, their reported use in research and decision-making, and the workplace factors associated with application remains limited. Previous research has established the relevance of differential equations in infectious disease modelling, pharmacokinetics, systems biology, and biomedical research [1–6]. Capacity-building initiatives in Africa have also demonstrated the importance of training, mentorship, and research networks in strengthening mathematical modelling skills [7–9].

However, these findings do not establish the level of differential equation knowledge among laboratory professionals in Kenema District or the extent to which they report applying this knowledge in research and decision-making. Furthermore, the relationships between knowledge scores, previous training, professional experience, software access, data availability, and technical support require empirical assessment in this workforce. Understanding perceived barriers is also important for identifying feasible strategies to strengthen quantitative research capacity. Therefore, this study aimed to assess knowledge and application of differential equations among laboratory professionals in Kenema District, Sierra Leone. The specific objectives were to estimate knowledge scores and identify areas of strength and weakness; describe the reported application of differential equations across different domains; examine the association between knowledge and application scores; determine the professional and institutional factors associated with application; and identify perceived barriers to applying differential equations in laboratory research and decision-making.

METHODS

Study Design and Setting: A quantitative analytical cross-sectional study was conducted among laboratory professionals working in Kenema District, Sierra Leone. The study assessed participants' knowledge of differential equations, their reported application in laboratory research and professional decision-making, and the professional and institutional factors associated with application.

Study Population: The study population comprised laboratory professionals employed in government and private healthcare facilities, university and college laboratories, public health and surveillance laboratories, and nongovernmental or research institutions in Kenema District. Eligible participants included medical laboratory scientists, technologists, technicians, laboratory researchers, and laboratory managers aged 18 years or older with at least six months of laboratory work experience. Individuals without an approved laboratory appointment, those temporarily assigned to laboratory duties, and laboratory professionals unavailable throughout the survey period were excluded.

Sample Size Determination: The minimum sample size was estimated using Cochran's formula for a single population proportion: $(n = \frac{Z^2 p(1-p)}{d^2})$, where (n) represents the required sample size, (Z) is the standard normal value corresponding to a 95% confidence level (1.96), (p) is the assumed population proportion (0.50), and (d) is the margin of error (0.05). The estimated minimum sample size was approximately 384 participants. The target was increased to 500 to allow for potential nonresponse and invalid questionnaires.

Sampling Technique: Stratified sampling was used to improve representation across institution types and professional cadres. Participants were grouped according to these characteristics, and simple random sampling was conducted within the defined strata. A prespecified reserve list of randomly selected eligible participants was used for replacement when necessary. Two reminders were sent to encourage participation and completion of the questionnaire.

Data Collection Instrument: Data were collected using a structured questionnaire covering sociodemographic and professional characteristics, knowledge of differential equations, reported application, enabling factors, and perceived barriers. Professional variables included cadre, years of experience, and prior modelling or statistics training. Institutional variables included access to relevant software, availability of suitable data, and technical support. Knowledge was assessed using objective questions and converted to a score ranging from 0 to 100. Participants were classified as having low knowledge (score below 50), moderate knowledge (50–69), or high knowledge (70 or above).

Application was assessed using a score ranging from 0 to 4, with higher scores indicating greater reported application of differential equations. Application domains included disease modelling, diagnostic research, treatment-response analysis, quality control or improvement, and healthcare decision support. Participants could also identify multiple barriers to application. Questionnaire development and evaluation were guided by established recommendations for scale development and validation. Internal consistency and construct performance were intended to be assessed using appropriate procedures, including Cronbach's alpha where applicable. The actual reliability coefficients and validation results should be reported if these analyses were performed.

Study Variables

The primary outcome variable was the reported application score for differential equations. The principal explanatory variable was the knowledge score. Additional explanatory variables included prior modelling or statistics training, access to relevant software, adequate data access, technical support, years of professional experience, and research or management role. Perceived barriers to application were summarised descriptively.

Statistical Analysis

Data were analysed using descriptive and inferential statistical methods. Frequencies and percentages were used to summarise categorical variables, including sex, professional category, institution type, training status, software access, knowledge categories, application domains, and perceived barriers. Pearson's correlation coefficient was used to assess the relationship between knowledge and application scores, while Spearman's rank correlation coefficient was used to examine the relationship between years of experience and application. Independent-samples t-tests were used to compare mean application scores between participants with and without prior training, software access, and technical support.

Multivariable linear regression was performed to examine factors independently associated with the application score. The model included knowledge score, prior training, software access, adequate data access, technical support, years of experience, and research or management role. Knowledge was expressed per 10-point increase to facilitate interpretation of the regression coefficient. Regression coefficients, standard errors, 95% confidence intervals, standardised beta coefficients, and p-values were reported. Standard errors were clustered by institution to account for potential within-institution correlation. The number of institutions and the suitability of cluster-robust inference should be reported. Statistical significance was set at p less than 0.05.

Ethical Considerations: Ethical approval was obtained from the relevant ethics committee before data collection. Participation was voluntary, and written informed consent was obtained from all participants. Data were analysed without personal identifiers, and confidentiality was maintained throughout the study.

RESULTS

The analysis included 500 laboratory professionals from the participating institutions in Kenema District. The results are presented in Tables 1–10, beginning with demographic and professional characteristics and followed by knowledge, application, associated factors and reported barriers.

Sex	Frequency	Percent
Male	300	60.0
Female	200	40.0
Total	500	100.0

Table 1. Distribution of participants by sex

Table 1 shows that 300 participants (60.0%) were male, whereas 200 (40.0%) were female. Male participants therefore outnumbered female participants by 100, a difference of 20.0 percentage points. Overall, men constituted the majority of the 500 laboratory professionals.

Professional category	Frequency	Percent
Medical laboratory scientist	150	30.0
Technologist	125	25.0
Technician	150	30.0
Laboratory researcher	40	8.0
Laboratory manager	35	7.0
Total	500	100.0

Table 2. Distribution of participants by professional category

Table 2 indicates that medical laboratory scientists and technicians were the largest professional groups, with 150 participants (30.0%) in each category. Technologists accounted for 125 participants (25.0%), while laboratory researchers and laboratory managers accounted for 40 (8.0%) and 35 (7.0%), respectively. Together, medical laboratory scientists and technicians represented 300 participants (60.0%) of the sample.

Table 3 shows that 260 participants (52.0%) worked in government facilities and 110 (22.0%) worked in private facilities. University or college laboratories accounted for 50 participants (10.0%), while public health or surveillance laboratories and nongovernmental or research institutions accounted for 45 (9.0%) and 35 (7.0%), respectively. Government facilities therefore contributed the largest share of the 500 participants.

Institution type	Frequency	Percent
Government facility	260	52.0
Private facility	110	22.0
University or college laboratory	50	10.0
Public health or surveillance laboratory	45	9.0
Nongovernmental or research institution	35	7.0
Total	500	100.0

Table 3. Distribution of participants by institution type

Prior modelling	Frequency	Percentage
Yes	210	42.0
No	290	58.0
Total	500	100.0

Table 4. Distribution of participants by prior modelling or statistics training

Table 4 shows that 290 participants (58.0%) had not received prior modelling or statistics training, whereas 210 (42.0%) had received such training. The group without prior training exceeded the trained group by 80 participants, a difference of 16.0 percentage points. Prior modelling or statistics training was therefore less common among the 500 laboratory professionals. Table 5 shows that 260 participants (52.0%) lacked access to relevant software, while 240 (48.0%) had access. The two groups differed by 20 participants, equivalent to 4.0 percentage points. Access was nearly balanced, although slightly more than half of the 500 participants did not have relevant software.

Access to relevant software	Frequency	Percentage
Yes	240	48.0
No	260	52.0
Total	500	100.0

Table 5. Distribution of participants by access to relevant software

Knowledge category	Score range	Frequency	Percentage
Low	Below 50	145	29.0
Moderate	50 to 69	240	48.0
High	70 or above	115	23.0

Table 6. Distribution of differential equation knowledge scores

Table 6 shows that 240 participants (48.0%) had moderate knowledge of differential equations. Low knowledge was recorded for 145 participants (29.0%), while 115 (23.0%) had high knowledge. Thus, 355 participants (71.0%) had at least moderate knowledge, although fewer than one-quarter reached the high-knowledge category. Table 7 shows that quality control or improvement was the most frequently reported application domain, cited by 226 participants (45.2%), followed by diagnostic research with 204 (40.8%). Disease modelling was reported by 178 participants (35.6%) and healthcare decision support by 155 (31.0%). Treatment response analysis was the least frequently reported domain, with 142 participants (28.4%). Table 8 shows a positive moderate correlation between knowledge and application scores ($r = 0.58$, $p < 0.001$), while years of experience had a weaker positive correlation ($\rho = 0.19$, $p < 0.001$). Mean application scores were higher among participants with prior training than among those without it (2.62 versus 2.03; $t = 9.15$, $p < 0.001$) and among those with software access than among those without access (2.55 versus 2.03; $t = 8.05$, $p < 0.001$).

Participants with technical support also had a higher mean application score than those without support (2.58 versus 2.11; $t = 6.83$, $p < 0.001$). Table 9 shows that each 10-point increase in knowledge score was associated with a 0.21-point increase in application score after adjustment (95% CI: 0.17 to 0.25; $p < 0.001$). Prior training ($B = 0.29$), software access ($B = 0.24$), adequate data access ($B = 0.18$) and technical support ($B = 0.15$) were also significant positive predictors, with p values ranging from < 0.001 to 0.015. Years of experience ($B = 0.01$, $p = 0.080$) and a research or management role ($B = 0.11$, $p = 0.126$) were not statistically significant at the 5% level.

Category or domain	Frequency	Percentage
Disease modelling	178	35.6
Diagnostic research	204	40.8
Treatment response analysis	142	28.4
Quality control or improvement	226	45.2
Healthcare decision support	155	31.0

Table 7. Level and domains of differential equation application

Explanatory variable	Statistic	Application result	Test statistic	p value
Knowledge score	Pearson correlation	$r = 0.58$	-	<0.001
Years of experience	Spearman correlation	$\rho = 0.19$	-	<0.001
Prior training	Yes vs no	2.62 vs 2.03	$t = 9.15$	<0.001
Software access	Yes vs no	2.55 vs 2.03	$t = 8.05$	<0.001
Technical support	Yes vs no	2.58 vs 2.11	$t = 6.83$	<0.001

Table 8. Bivariate associations with application score

Table 10 shows that limited mathematical or modelling training was the most frequently reported barrier, cited by 365 participants (73.0%), followed by inadequate software access with 310 (62.0%) and insufficient protected research time with 295 (59.0%). Limited modelling expertise, insufficient funding, limited data and weak institutional support were reported by 285 (57.0%), 270 (54.0%), 235 (47.0%) and 225 (45.0%) participants, respectively.

Because participants could report more than one barrier, the percentages were not expected to sum to 100%.

Predictor	B	Standard error	95% confidence interval	Standardised beta	p value
Knowledge score per 10 points	0.21	0.02	0.17 to 0.25	0.38	<0.001
Prior training yes	0.29	0.06	0.17 to 0.41	0.18	<0.001
Software access yes	0.24	0.06	0.12 to 0.36	0.16	<0.001
Adequate data access yes	0.18	0.06	0.06 to 0.30	0.12	0.003
Technical support yes	0.15	0.06	0.03 to 0.27	0.1	0.015
Years of experience	0.01	0.01	0.00 to 0.02	0.07	0.08
Research or management role	0.11	0.07	-0.03 to 0.25	0.05	0.126

Table 9. Multiple linear regression predicting application score

Barrier reported	Frequency	Percent	Rank
Limited mathematical or modelling training	365	73.0	1
Inadequate access to relevant software	310	62.0	2
Insufficient protected research time	295	59.0	3
Limited access to modelling expertise	285	57.0	4
Insufficient research funding	270	54.0	5
Limited availability or quality of data	235	47.0	6
Weak institutional support	225	45.0	7

Table 10. Barriers to applying differential equations

DISCUSSION

This analytical cross-sectional study assessed knowledge and reported application of differential equations among 500 laboratory professionals in Kenema District, Sierra Leone. The findings demonstrated a positive association between knowledge and application, with additional associations observed for prior modelling or statistics training, software access, data availability, and technical support. Limited mathematical or modelling training was the most frequently reported barrier.

Collectively, these findings suggest that both individual knowledge and workplace resources are relevant to the application of mathematical methods in laboratory research and decision-making. Most participants were classified as having moderate knowledge (48.0%), while 29.0% had low knowledge and 23.0% had high knowledge. Although 71.0% of participants had moderate or high knowledge, fewer than one-quarter achieved the high-knowledge category. This distribution suggests that familiarity with differential equations may exist among laboratory professionals, but advanced understanding may be less common.

Such a distinction is important because recognising mathematical concepts is not equivalent to being able to develop, evaluate, or interpret a mathematical model independently. The positive correlation between knowledge and application scores ($r = 0.58$, $p < 0.001$) further indicates that higher knowledge scores were associated with greater reported application. In the adjusted regression model, every 10-point increase in knowledge was associated with a 0.21-point increase in application score (95% CI: 0.17–0.25; $p < 0.001$). This association remained significant after adjustment for the other variables included in the model. The result is consistent with the broader role of differential equations in infectious disease modelling, pharmacokinetics, and systems biology, where an understanding of dynamic processes can support the interpretation of biomedical data [1,2,5,9,10]. However, the cross-sectional design does not establish whether greater knowledge leads to increased application or whether practical experience contributes to improved knowledge. The findings therefore support an association rather than a causal relationship.

Quality control or improvement was the most frequently reported application domain (45.2%), followed by diagnostic research (40.8%) and disease modelling (35.6%). Treatment response analysis was reported by 28.4% of participants. These findings indicate that reported application extended across several professional activities rather than being restricted to infectious disease modelling. Mathematical models can describe changes in biological variables over time and represent relationships between different components of biological systems. Differential equations have established applications in infectious disease epidemiology and pharmacokinetic–pharmacodynamic modelling [1,5,9].

They may also contribute to investigating dynamic biological processes and interpreting longitudinal research data [2,10]. Laboratory professionals can contribute to these activities through their knowledge of biological mechanisms, diagnostic measurements, data quality, and relevant clinical or laboratory endpoints. Nevertheless, the reported application domains require careful interpretation. Quality assurance and improvement activities do not necessarily involve differential equations directly; they may instead rely on routine statistical methods or other analytical approaches. Therefore, the questionnaire should clearly distinguish direct use of differential equations from general use of quantitative methods. This distinction is essential for interpreting the reported application rate accurately.

Participants with prior modelling or statistics training had a higher mean application score than those without such training (2.62 versus 2.03; $p < 0.001$). Prior training remained positively associated with application in the adjusted model ($B = 0.29$, 95% CI: 0.17–0.41; $p < 0.001$). These findings highlight the potential importance of educational opportunities in developing quantitative research capacity among laboratory professionals. Previous capacity-building initiatives in Africa have emphasised structured training, mentorship, and collaborative learning as approaches to strengthening mathematical modelling skills [11–23]. Such programmes provide useful examples for developing professional training that responds to local research and public health needs. In laboratory settings, training could introduce the principles of differential equations through practical examples involving infectious disease surveillance, longitudinal laboratory measurements, and treatment-response data. Training should be tailored to participants' existing mathematical backgrounds and professional responsibilities. The aim should not necessarily be to prepare every laboratory professional to construct complex models independently, but to improve their ability to recognise appropriate applications, interpret model outputs, understand limitations, and collaborate with mathematical and statistical specialists. More than half of the participants reported lacking access to relevant software (52.0%). In the adjusted regression analysis, software access was positively associated with application score ($B = 0.24$, 95% CI: 0.12–0.36; $p < 0.001$). Adequate data access ($B = 0.18$, 95% CI: 0.06–0.30; $p = 0.003$) and technical support ($B = 0.15$, 95% CI: 0.03–0.27; $p = 0.015$) were also significant predictors.

These findings suggest that individual knowledge may not be sufficient when professionals lack the resources needed to apply mathematical methods. Differential equation modelling requires appropriate data, suitable computational tools, and the ability to evaluate assumptions and interpret results. Best-practice guidance for quantitative and systems pharmacology modelling also emphasises transparency, reproducibility, and the appropriate use and reuse of models [20]. Institutions could therefore consider improving access to suitable computing resources, software, well-managed datasets, and technical guidance. Where specialist expertise is limited, partnerships with universities and departments of mathematics, statistics, epidemiology, or data science may provide opportunities for collaborative research. Such initiatives should complement rather than replace training in the underlying mathematical concepts.

Limited mathematical or modelling training was the most frequently reported barrier, identified by 73.0% of participants. Inadequate software access was reported by 62.0%, while 59.0% identified insufficient protected research time. Other reported barriers included limited access to modelling expertise (57.0%), insufficient research funding (54.0%), limited availability or quality of data (47.0%), and weak institutional support (45.0%). The pattern of responses indicates that barriers occur at both individual and organisational levels. Training addresses knowledge and skills, whereas software access, protected research time, funding, data availability, and technical support require institutional planning. Previous modelling capacity-building initiatives in Africa have highlighted the relevance of training, mentorship, and research networks in strengthening local capacity [11–13].

The present findings extend the practical relevance of these approaches to the laboratory workforce studied in Kenema District. A coordinated approach may therefore be more appropriate than relying on isolated training activities. Potential measures include short courses, mentorship arrangements, protected time for research, access to appropriate analytical tools, and collaborative projects involving laboratory professionals and quantitative researchers. The priority given to each intervention should reflect local needs and available resources. The findings have potential implications for laboratory research capacity and public health preparedness.

Laboratory professionals contribute to diagnostic services, surveillance, outbreak investigation, and biomedical research. WHO laboratory and public health competency frameworks emphasise research, surveillance, and outbreak investigation as important areas of professional and institutional capacity development [3,4,22]. Improved quantitative literacy may help laboratory professionals identify research questions that involve dynamic processes and participate more effectively in multidisciplinary research. However, differential equations are not required for every laboratory activity, and their use should be determined by the research question and suitability of the available data. Collaboration with mathematical modellers may be particularly valuable when a research problem requires expertise beyond the scope of routine laboratory practice. Because this study was conducted in Kenema District, its findings may inform local training and resource-planning discussions. Further research involving additional districts and laboratory systems would be needed before extending the findings to the entire laboratory workforce of Sierra Leone.

Strengths and Limitations: A strength of this study is the inclusion of 500 laboratory professionals from different professional categories and institution types. The study assessed knowledge alongside reported application, training, resource availability, and perceived barriers, providing a broader view of the factors associated with mathematical modelling practice. Stratification by institution type and professional cadre, followed by simple random sampling within strata, was intended to support representation across the defined sampling groups. Several limitations should be acknowledged.

First, the cross-sectional design prevents conclusions about temporal relationships or causality. Second, self-reported application may be affected by recall and social desirability bias. Third, the findings may not be generalisable beyond the participating institutions and Kenema District. Fourth, the validity and reliability of the questionnaire, including the thresholds used to categorise knowledge and the construction of the application score, should be fully documented. Finally, the use of cluster-robust standard errors depends on the number and structure of participating institutions; this information should be reported to allow readers to assess the precision of the regression estimates.

Recommendations for Future Research

Future studies should evaluate whether structured training improves knowledge and practical application of differential equations among laboratory professionals. Pretest–post-test studies with follow-up assessments could determine whether training is associated with sustained improvements in quantitative skills. Practical exercises using laboratory or surveillance datasets could complement questionnaire-based assessments and help distinguish conceptual knowledge from applied competence. Multicentre research across additional districts could assess the consistency of these findings in different laboratory settings. Further studies could also investigate how institutional resources, mentorship, protected research time, and collaboration with quantitative specialists influence the use of mathematical modelling in laboratory research.

CONCLUSION

This study found that knowledge of differential equations was positively associated with their reported application among laboratory professionals in Kenema District, Sierra Leone. Most participants demonstrated moderate knowledge, while fewer than one-quarter achieved a high knowledge level. Knowledge scores remained significantly associated with application scores after adjustment for other factors. Previous modelling or statistics training, access to relevant software, adequate data availability, and technical support were also positively associated with application. Limited mathematical or modelling training was the most frequently reported barrier, followed by inadequate software access and insufficient protected research time. These findings highlight the importance of addressing both individual training needs and institutional resource constraints. Integrating mathematical modelling into pre-service and in-service professional development, improving access to appropriate software and reliable data, providing mentorship, and promoting collaboration between laboratory professionals and quantitative researchers may strengthen research capacity. As the study was cross-sectional, the observed associations should not be interpreted as causal relationships. Further studies across multiple districts are needed to validate these findings and evaluate the effectiveness of targeted capacity-building interventions.

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