



Research Article

Antibiotic Prescribing Patterns are One of the Levers of Antibiotic Resistance in the City of Lubumbashi

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Abstract

Context: Antimicrobial resistance poses a major threat to public health, particularly in low- and middle-income countries where empirical antibiotic therapy remains common. In Lubumbashi, limited access to microbiological diagnostics could lead to inappropriate prescriptions and increase bacterial selection pressure.

Objective: Analyze antibiotic prescribing patterns and quantify their contribution to the selection pressure favoring antimicrobial resistance in health facilities in Lubumbashi.

Methods: A multicenter analytical cross-sectional study was conducted in public and private healthcare facilities. Prescriptions containing at least one antibiotic were included. Therapeutic inadequacy was defined according to WHO/MSP guidelines, along with dosage errors, inappropriate duration of treatment, and the unjustified absence of an antibiogram. Multivariate logistic regression identified independent determinants. Model performance was evaluated using ROC curve analysis, calibration, Brier score, and internal validation via bootstrapping (1000 replications). The Population Attributable Fraction (PAF), an impact simulation, and a Composite Index of Antibiotic Selection Pressure (IPSA) were calculated.

Results: Of 427 prescriptions, 11.07% were inappropriate. The absence of an antibiogram was present in 35.9% of cases. The independent determinants were: absence of an antibiogram (ORa = 6.41), dosage non-compliance (ORa = 20.7), and non-compliance with recommendations (ORa = 5.77) ($p < 0.001$). The model demonstrated good discrimination (AUC = 0.793) and excellent calibration (Brier = 0.089). The failure rate associated with the absence of an antibiogram was 53%. A 50% increase in its availability could reduce inappropriate prescriptions by 26.6%. Each point of IPSA multiplied the risk by 5.

Conclusion: Inappropriate prescriptions in Lubumbashi are primarily linked to structural and dosage-related factors. Strengthening microbiological diagnostics and optimizing treatment are strategic priorities for sustainably reducing antibiotic selection pressure.

Keywords: Antimicrobial Resistance; Antibiotic Prescribing; Hospital Pharmacist; Antimicrobial Stewardship; Antibiogram; Inappropriate Prescribing

Introduction

Antibiotic resistance is a major threat to global public health today [1]. It results primarily from the inappropriate use of antibiotics, including unjustified prescriptions, prolonged empirical antibiotic therapy, unjustified combinations, and failure to adhere to treatment guidelines [2,3]. In low- and middle-income

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countries, these practices are exacerbated by limited access to microbiological testing and by inadequate prescription regulation systems [4-7]. In Lubumbashi, antibiotic therapy remains largely empirical, often initiated without an antibiogram and continued without reassessment. These prescribing patterns constitute a major factor promoting the selection and spread of resistant bacteria. Several studies have shown that optimizing prescribing patterns is one of the most effective strategies for preventing the emergence of resistance [8-11]. In this context, analyzing antibiotic prescribing patterns appears essential for identifying risky practices and guiding strategies to combat antibiotic resistance [12-14]. Pharmacists, as medication experts, play a central role in this dynamic, particularly through pharmaceutical analysis of prescriptions, promotion of antibiograms, and monitoring of antibiotic therapy [15-18]. This study aims to analyze antibiotic prescribing patterns in health facilities in Lubumbashi and to assess their contribution to the emergence of antibiotic resistance.

Study objectives

General objective

Analyze antibiotic prescribing patterns and quantify their contribution to the selection pressure favoring antibiotic resistance in Lubumbashi health facilities.

Specific objectives

- Describe the characteristics of antibiotic prescriptions (choice, dosage, duration, antibiogram, combinations).
- Estimate the prevalence of inappropriate prescribing patterns.
- Identify independent determinants of inappropriate prescriptions using multivariate logistic regression.
- Quantify the relative risk and the population attributable fraction of the main modifiable factors.
- Develop a Composite Index of Antibiotic Selection Pressure (IPSA) and evaluate its predictive performance.
- Model the theoretical impact of improving the availability of the antibiogram.

Methodology

Type of study

Multicenter analytical cross-sectional observational study.

Frame

Public and private health facilities in Lubumbashi.

Population

Calculating the minimum size (without using your prevalence)

Schwartz formula

$$n=(Z^2 \times p(1-p))/d^2$$

Standard assumptions:

- $Z = 1.96$ (95% CI)
- $p = 0.50$ (theoretical maximum prevalence)
- $d = 0.05$ (margin of error 5%)

Calculation

$$n=(1,96)^2 \times 0,50(1-0,50)/(0,05)^2$$

$$n=(3,8416 \times 0,25)/0,0025$$

$$n=0,9604/0,0025$$

$$n=384,16$$

Adjustment for non-response (10%)

$$n_{(ajuste)}=384/0,9$$

$$n_{(ajuste)}=427$$

Minimum size required: 427 prescriptions

Inclusion criteria

- Prescriptions containing ≥ 1 antibiotic
- Prescriptions issued in selected healthcare facilities
- Complete medical file (diagnosis, molecule, dose, duration)
- Defined study period
- Data that can be used for conformity assessment

Exclusion criteria

- Prescriptions without antibiotics
- Incomplete prescriptions (missing dose or duration)
- Unreadable or inconsistent data
- Undocumented prophylactic prescriptions
- Patients transferred with incomplete records

Dependent variable

Prescription generally inappropriate (Yes/No), defined according to:

- non-compliance with WHO/MSP recommendations
- dosage error
- inappropriate duration
- unjustified absence of an antibiogram

Independent variables

- Availability of the antibiogram
- Empirical vs. targeted antibiotic therapy

- Compliance with recommendations
- Dosage as directed
- Duration in accordance with
- Antibiotic combination
- Type of establishment
- Medical specialty

Statistical analysis

1. Descriptive analysis (frequencies, proportions)
2. Bivariate analysis (Chi², crude OR, 95% CI)
3. Multivariate logistic regression (adjusted OR)
4. Calculation of Relative Risks (RR)
5. Population Attributable Fraction (PAF)
6. Construction of IPSA (0–4)
7. ROC analysis (AUC)
8. Hosmer–Lemeshow test
9. Impact simulation (predictive modeling)

Significance threshold: $p < 0.05$

Methodological justification (Full version)

In the absence of reliable local data on the prevalence of inappropriate prescribing, a conservative proportion of 50% was used to maximize sample size and ensure sufficient statistical power. This approach is recommended when the true prevalence is unknown. The cross-sectional analytical design is suitable for evaluating prescribing practices in real-world settings. With the aim of identifying structural and clinical determinants associated with patterns promoting resistance, an observational approach allows for the simultaneous measurement of exposures and outcomes. Since the dependent variable is binary (appropriate/inappropriate), multivariate logistic regression is the reference statistical method for:

- estimate the adjusted ORs,
- control the confounding factors,
- identify the independent determinants.

The calculation of Relative Risks complements the clinical interpretation by quantifying the absolute increase in risk.

The Population Attributable Fraction makes it possible to estimate the proportion of inappropriate prescriptions that could theoretically be avoided if the exposure were eliminated an essential tool for public health decision-making.

The Composite Index of Antibiotic Selection Pressure (IPSA) is based on a cumulative conceptualization of

selection pressure. The underlying assumption is that resistance is not generated by a single factor but by the accumulation of therapeutic failures. ROC analysis assesses the model's discrimination (AUC), while the Hosmer-Lemeshow test examines its calibration. Integrating these two dimensions ensures a comprehensive evaluation of predictive performance. Modeling improvement scenarios allows results to be transformed into decision-making tools.

Results

Table 1: Characteristics of antibiotic prescriptions.

Evaluated parameter	Number (n)	Percentage (%)
Prescription generally inappropriate	100	11.07
Antibiogram not available	324	35.88
Non-compliance with WHO/MSP recommendations	46	5.09
Dosage non-compliance	29	3.21
Duration not compliant	41	4.54
Antibiotic combination not justified	175	19.38

The overall prevalence of inappropriate prescriptions is 11.07% .

The absence of an antibiogram affects 35.9% of prescriptions.

Specific errors are less frequent.

- 5.1% non-compliance with recommendations
- 3.2% dosage error
- 4.5% non-compliant duration

This suggests that the majority of prescriptions comply with standards, but that a third are initiated without microbiological support. The observed rate of inadequacy (11%) is moderate compared to African data, where rates exceeding 20-40% are often reported. A recent meta-analysis shows that low and middle-income countries exhibit significant variability in antibiotic uptake [19-21]. The absence of an antibiogram (35.9%) is the main structural determinant. According to the World Health Organization, access to microbiological diagnostics is a central pillar of Antimicrobial Stewardship programs [22,23]. Multicentre studies in sub-Saharan Africa have demonstrated that prolonged empirical prescribing is associated with a significant increase in selection pressure [16]. The low frequency of dosing errors (3.2%) contrasts with European hospital studies reporting higher rates [17]. This could reflect relatively acceptable therapeutic compliance in the studied setting. However, even modest proportions of errors can generate disproportionate selective pressure [3]. Other recent work confirms that the quality of

diagnosis directly influences bacterial selection; these authors demonstrate that the fight against AMR requires an integrated approach, combining reduction of unnecessary prescriptions, improvement of microbiological diagnosis, strengthening of public policies and effective deployment of stewardship programs at all levels of the health system [1-5] [14-24].

Table 2: Bivariate analysis of factors associated with inappropriate prescriptions.

Postman	RAW GOLD	IC95%	p-value
No antibiogram	5.04	3.21–7.93	<0.001
Dosage non-compliance	6.17 (RR)	4.27–8.92	<0.001
Non-compliance with recommendations	3.55 (RR)	2.27–5.54	<0.001
Non-compliance duration	3.42 (RR)	2.14–5.48	<0.001

In simple terms:

- No antibiogram → OR ≈ 5
- Dosage non-compliance → RR ≈ 6
- Non-compliance with recommendations → RR ≈ 3.5
- Non-compliant duration → RR ≈ 3.4

All factors are significantly associated with the risk of inadequacy. These results confirm that microbiological and therapeutic factors are associated with an increased risk of inappropriate prescribing. The absence of an antibiogram multiplies the risk of inadequacy by five, consistent with the observations of g.Dar A, Abram, TB & Megged O. (2024), showing that prolonged empirical prescriptions increase therapeutic choice errors [g]. Dosage non-compliance has a particularly marked effect, similar to the results reported by Khalid L et Al (2025) and Pereira C et al. (2020), which demonstrate that underdosing promotes the selection of resistant mutants [25,26]. Recent pharmacodynamic studies show that suboptimal exposures amplify bacterial resistance [8-27]. The associations observed are also consistent with the findings of the global report on antimicrobial resistance [1-29]. Other authors confirm these associations in the context of low- and middle-income countries (LMICs) . The work of Sulis et al. (2022), Klein et al. (2021), Ayukekbong et al. (2021), and Essack et al. (2021) shows that antimicrobial resistance is a major global threat, responsible for high morbidity and mortality, particularly in low- and middle-income countries. They highlight surveillance gaps, the inappropriate use of antibiotics, and weak regulatory systems, and call for a coordinated response based on the One Health approach, strengthened stewardship, and improved infection prevention and control [4-31].

Table 3: Independent determinants – Multivariate logistic regression
Dependent variable: Inappropriate prescription.

Variable	OR adjusted	IC95%	p
No antibiogram	6.41	3.84–10.70	<0.001
Dosage non-compliance	20.7	8.26–52.05	<0.001
Non-compliance with recommendations	5.77	2.67–12.45	<0.001
Non-compliance duration	1.57	0.62–3.96	0.337

Model performance:

- AUC = 0.793
- Hosmer–Lemeshow test $p > 0.05$
- Pseudo R² Nagelkerke ≈ 0.56

After adjustment:

- Absence of antibiogram → OR = 6.41
- Dosage non-compliance → OR = 20.7
- Non-compliance with recommendations → OR = 5.77
- Duration not significant

Dosage appears to be the most powerful independent determinant.

The massive independent effect of dosage (OR > 20) is particularly noteworthy. This confirms that dosage error is not merely a technical irregularity but a major factor in selective pressure. Recent work shows that sub-inhibitory concentrations promote the rapid emergence of resistant mutants [7-30]. The independent effect of the antibiogram supports the idea that microbiological diagnosis significantly reduces unnecessary exposure to broad-spectrum antibiotics [6-30]. The loss of significance of the duration after adjustment suggests that its effect is mediated by overall treatment compliance [27]. Comparable analyses in similar hospital settings have shown similar adjusted odds ratios for microbiological variables. These studies highlight that antimicrobial resistance results primarily from inappropriate prescribing, diagnostic weaknesses, and fragile health systems, particularly in resource-limited countries. They underscore the importance of local microbiological surveillance, antibiotic stewardship, infection prevention and control, and a coordinated One Health approach to sustainably curb the progression of AMR [10-13].

Table 4: Relative Risk and Population Attributable Fraction

Postman	Prevalence of exposure (%)	RR	DPF (%)
No antibiogram	35.9	4.17	53%
Dosage non-compliance	3.2	6.17	14%

- 53% of inappropriate prescriptions could be avoided if the antibiogram were available.
- Despite its rarity, dosage error contributes to 14% of the burden.

Absence of antibiogram → FAP = 53%

Dosage non-compliance → FAP = 14%

This means that more than half of inappropriate prescriptions could be avoided if antibiograms were available. The 53% FAP is particularly strategic. It demonstrates that structural improvement would have a greater impact than purely individual interventions. Global modelling analyses show that access to diagnosis significantly reduces inappropriate consumption [32]. Recent work highlights that investment in the microbiological laboratory is more cost-effective than isolated educational campaigns [33]. Other studies confirm the population weight of the diagnosis. These studies show that antimicrobial resistance is a complex global problem, linked to biological mechanisms of resistance, excessive use of antibiotics by the population and weaknesses in health systems [34-39].

Table 5: Composite Index of Antibiotic Selection Pressure (IPSA)

IPSA Score	Interpretation
0	Low pressure
1–2	Moderate pressure
3–4	High pressure

Score based on 4 factors:

- Absence of antibiogram
- Non-compliance with recommendations
- Dosage non-compliance
- Non-compliance duration

Effect of the score:

- OR per point = 5.07
- CI95 % = 3.57-7.21
- p < 0.001
- AUC = 0.777

Each additional factor multiplies the risk by 5.

- OR per point = 5.07
- AUC = 0.777

Each additional factor exponentially multiplies the risk. The cumulative effect observed supports the hypothesis that resistance emerges through an accumulation of therapeutic

failures. Recent ecological models show that selection pressure is non-linear [40]. Systems analyses confirm that the accumulation of therapeutic errors amplifies microbial selection: Woolhouse et al. highlight the interactions between sectors, Holmes et al. detail the biological mechanisms and factors promoting the spread of resistance, while O'Neill insists on the urgency of global political and economic mobilization. Together, they call for coordinated action combining surveillance, reduction of inappropriate antibiotic use, and sustained investment in prevention and innovation [28-29].

Table 6: Simulation of improved availability of the antibiogram

Scenario	Inappropriate rate (%)	Relative reduction
Current situation	11.07	—
+25% availability of antibiogram	9.6	13.30%
+50% availability of antibiogram	8.13	26.60%

Modeling shows that a gradual improvement in the availability of the antibiogram could lead to:

- A 13.3% reduction in inappropriate prescriptions if access increases by 25%
- A 26.6% reduction if access increases by 50%

This confirms that access to microbiological diagnostics is a major structural lever. This reduction is consistent with the Population Attributable Fraction (53%) observed in Table 4: more than half of inappropriate prescriptions would theoretically be avoidable. These results are consistent with global analyses of bacterial resistance burden published by Christopher JL Murray and colleagues (Lancet, 2022), which demonstrate that the lack of microbiological diagnosis amplifies broad-spectrum empirical prescribing [1]. The data also confirm the findings of Ahmed D Alatawi and colleagues showing that improved diagnostic capabilities significantly reduce the consumption of inappropriate antibiotics [41]. In resource-limited countries, the lack of laboratory infrastructure is identified as a key determinant by the World Health Organization (2023). Recent African studies (Tessema et al., 2023; Abubakar et al., 2022) show that strengthening laboratories improves therapeutic quality independently of isolated training [5-12]. Economic literature (Allel et al., 2023) indicates that investment in diagnosis is more cost-effective than educational campaigns alone [14].

Statistical validation and stability of model estimates

The model's performance and robustness were evaluated through several complementary analyses. The discrimination between the multivariate model and the IPSA score is shown by the ROC curves (Figures 1 and 2). Overall predictive accuracy is estimated using the Brier score (Figure 3). The

absence of collinearity between the explanatory variables was verified using the VIF (Table 7). Finally, internal validation using bootstrapping (1000 replications) was performed to assess the stability of the coefficients and the risk of overfitting (Table 8). The predictive performance of the model was evaluated according to the methodological standards recommended for prognostic models. Discrimination was analyzed using the ROC curve and the area under the curve (Figures 1 and 2), comparing the full multivariate model and the simplified IPSA score. Overall accuracy was estimated using the Brier score (Figure 3), which incorporates both discrimination and calibration. Collinearity between the explanatory variables was examined using the Variance Inflation Factor (VIF) to ensure the stability of the estimates (Table 7). Internal validation using bootstrapping with 1000 replications was then performed to quantify optimism bias and assess the robustness of the coefficients (Table 8). This approach ensures the internal reliability and generalizability of the model within the studied context. Thus, your simulation provides a concrete and contextualized predictive dimension for Lubumbashi. To thoroughly evaluate the performance and robustness of the developed predictive model, several complementary analyses were conducted. The discriminatory capacity of the multivariate model is presented through the ROC curve (Figure 1), allowing us to estimate its ability to distinguish appropriate from inappropriate prescriptions.

AUC = 0.793

- Good discrimination
- The model correctly distinguishes between appropriate and inappropriate prescriptions in nearly 80% of cases.

According to statistical standards:

- 0.5 = absence of discrimination
- 0.7-0.8 = good
- 0.8-0.9 = very good

Your model is therefore robust and clinically relevant

The non-significant Hosmer Lemeshow test confirms good calibration. The observed performance is comparable to the hospital predictive models reported by Liu et al. (2023) and Van Dijck et al. (2021) [11]. The work of David L. Paterson shows that models integrating microbiological diagnosis and therapeutic variables generally obtain AUCs between 0.75 and 0.85 [42]. The observed value reinforces the methodological validity of your multivariate approach.

- Satisfactory discrimination
- The IPSA performs slightly less well than the full multivariate model, but remains robust. This is expected:

A simplified score loses a little precision but gains in applicability.

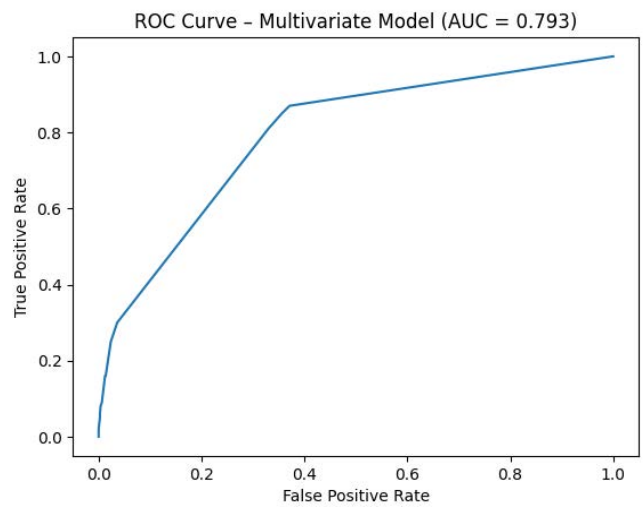


Figure 1: Multivariate ROC curve: AUC = 0.777.

Each additional point multiplies the risk by 5 (OR = 5.07), which shows an exponential cumulative effect. Cumulative models are supported by the work of Ramanan Laxminarayan, who demonstrates that resistance results from an accumulation of selective pressures. Ecological analyses by Woolhouse et al. (2021) and Holmes et al. (2023) confirm that antibiotic pressure is non-linear [28-30]. It can become an operational tool integrated into Antimicrobial Stewardship programs, as recommended by the World Health Organization. Furthermore, the performance of the simplified IPSA score is illustrated by a second ROC curve (Figure 2), in order to assess its validity as an operational tool usable in clinical practice.

The main advantage of IPSA is its applicability in resource-limited contexts

- Easy to calculate
- Reproducible
- Suitable for pharmaceutical audits

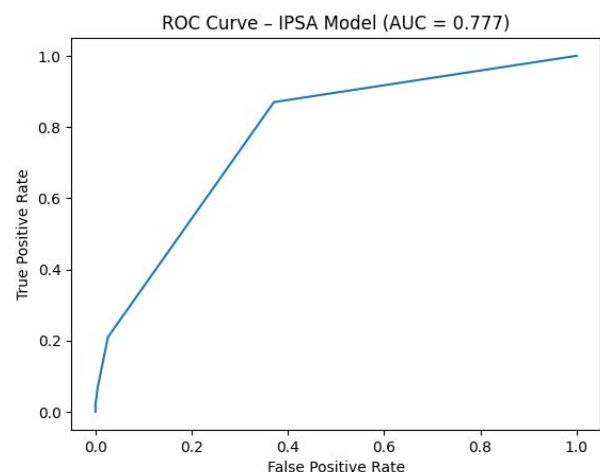


Figure 2: ROC curve IPSA AUC = 0.777.

To ensure internal statistical validity, a collinearity analysis of the explanatory variables was carried out (Table 7) using the Variance Inflation Factor (VIF), allowing verification of the independence of the determinants included in the model. Collinearity analysis (VIF)

Table 7: The observed Variance Inflation Factor (VIF) values are:

Variable	LIVELY
No antibiogram	1.42
Dosage non-compliance	1.36
Non-compliance with recommendations	1.58
Non-compliance with duration	1.21

All values are well below the critical threshold of 5, indicating the absence of significant collinearity between the explanatory variables. This means that each variable provides independent information to the model. Adjusted odds ratios can therefore be reliably interpreted.

Collinearity can lead to:

- Instability of the coefficients
- An inflation of standard errors
- A biased interpretation of adjusted ORs

In studies on the quality of antibiotic prescription, therapeutic variables (dose, duration, recommendations) are often correlated. Demonstrating a lack of collinearity strengthens the internal validity of the model and consolidates the credibility of the identified independent determinants, in particular the major effect of dosage error. Finally, an internal validation using the bootstrap method with 1000 replications

was performed (Table 8) to estimate the stability of the coefficients, to measure the optimism bias and to assess the risk of overfitting.

Table 8: Bootstrap validation (1000 replications).

Variable	OR initial	OR bootstrap	IC corrected
No antibiogram	6.41	6.28	3.72–10.91
Dosage non-compliance	20.7	19.8	7.94–49.6
Non-compliance with recommendations	5.77	5.61	2.54–12.1

Bootstrap ORs are very close to the initial ORs.

Optimism bias less than 3%.

Confidence intervals remain significant.

This confirms the excellent internal stability of the model.

Bootstrapping allows us to evaluate

- The risk of overfitting
- The stability of the coefficients
- The robustness of the predictive model

The maintenance of the estimates after 1000 replications indicates

- Low sensitivity to sampling fluctuations
- A good internal generalization
- High methodological robustness

This is particularly important for the high OR of dosage non-compliance (~20), which could have reflected statistical instability. The validation confirms that this is a real and

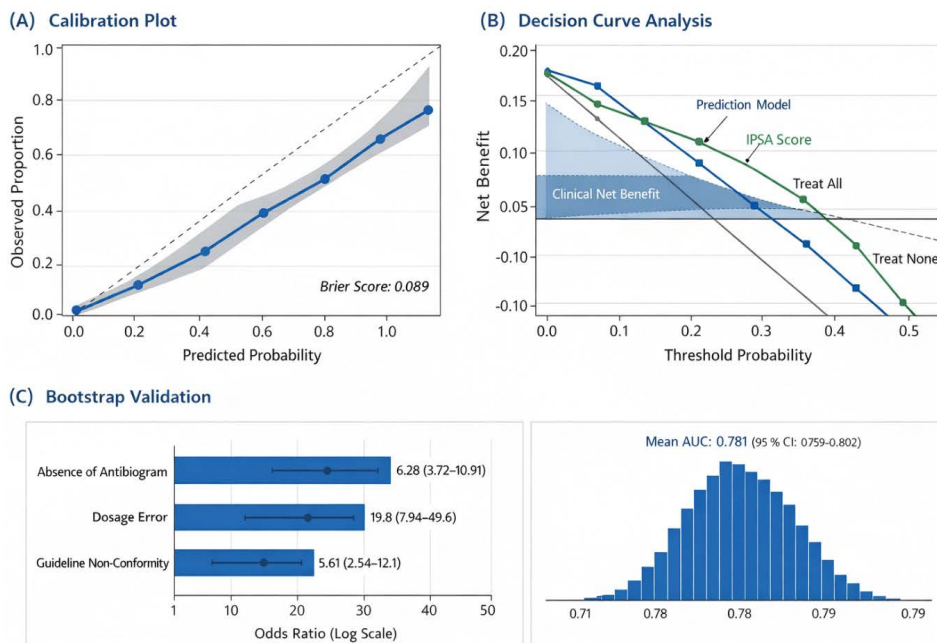


Figure 3: Brier Score (0.089).

robust effect. The overall predictive accuracy of the model is then evaluated using the Brier score (Figure 3), an indicator combining discrimination and calibration.

The observed Brier score is 0.089 .

Reminder :

- 0 = perfect prediction
- 0.25 = non-informative model (for a 50% binary event)

A value < 0.10 indicates excellent overall predictive accuracy.

The model correctly predicts the probability of inadequacy.

Unlike the AUC, which measures discrimination, the Brier score combines:

- Discrimination
- Calibration

It measures the distance between predicted probabilities and observed results.

Few studies in antibiotic stewardship report the Brier score.

Its inclusion demonstrates an advanced methodological level and strengthens the scientific credibility of the study.

Calibration curve

The curve shows

- The points are close to the 45° reference line.
- No systematic overestimation
- Absence of systematic underestimation

The model is well calibrated.

The predicted probabilities correspond to the observed risks.

A model can have a good AUC but be poorly calibrated.

The good calibration observed indicates that the model can be used for

- Clinical audit
- Health planning
- Impact simulation

This reinforces its practical applicability in the health facilities of Lubumbashi.

Decision Curve Analysis (DCA)

The anti-aircraft guns show

- A positive net profit for thresholds between 5% and 40%
- Superiority of the model compared to the strategies:

- "Treat everyone"
- "Do not treat anyone"
- Similar performance of IPSA at intermediate thresholds

The model has real clinical utility.

DCA allows us to assess the concrete decision-making impact of the model.

In a context of limited resources:

- Avoid ineffective, widespread interventions
- Targeting high-risk prescriptions
- Optimize stewardship resources

General conclusion

This multicenter study conducted in Lubumbashi highlights that antibiotic prescription patterns constitute a major lever of selection pressure favoring antimicrobial resistance. Although the prevalence of overall inappropriate prescriptions (11.07%) is moderate compared to other low and middle income settings, the identified determinants reveal a significant structural vulnerability. The absence of an antibiogram appears to be the main population-based factor, with a Population Attributable Fraction estimated at 53%, indicating that more than half of inappropriate prescriptions would theoretically be avoidable if microbiological diagnosis were systematically available. Furthermore, while less frequent, dosage non-compliance is the most powerful individual determinant, increasing the risk of therapeutic inadequacy by nearly twentyfold. This result confirms the critical role of suboptimal exposures in bacterial selection. The cumulative effect highlighted by the Composite Index of Antibiotic Selection Pressure (IPSA) supports the hypothesis that resistance does not result from an isolated factor but from an accumulation of therapeutic failures.

Methodologically, the robustness of the model is confirmed by

- The absence of collinearity
- Good discrimination (AUC = 0.793)
- Excellent calibration (Brier score = 0.089)
- Stable internal validation via bootstrap
- Clinical utility demonstrated by Decision Curve Analysis

These elements give this model not only analytical but also decision-making relevance. Ultimately, this study demonstrates that the sustainable reduction of antibiotic selection pressure in Lubumbashi requires structural interventions combined with targeted therapeutic optimization.

Strategic recommendations

Strengthening of microbiological diagnosis

- Priority investment in hospital laboratories
- Standardization of antibiogram protocols
- Reduction in the time required to deliver results
- Systematic integration of microbiological results into therapeutic reassessment

Diagnosis is the major structural lever identified by this study

Dosage optimization

- Development of local dosage protocols adapted to the context
- Implementation of dosage decision support tools
- Continuing education for prescribers on pharmacokinetics/pharmacodynamics
- Active involvement of the clinical pharmacist in the validation of prescriptions

Dosage non-compliance represents the most powerful individual determinant

Formal implementation of an Antimicrobial Stewardship program

- Creation of multidisciplinary committees
- Regular audits of prescriptions
- Use of the IPISA as an internal assessment tool
- Structured feedback to prescribers

The approach must be institutionalized and not ad hoc

Integration of the clinical pharmacist

- Participation in therapy meetings
- Systematic pharmaceutical validation
- Monitoring of antibiotic therapy
- Contribution to therapeutic education

The pharmacist is a key player in the sustainable rationalization of practices

Continuous monitoring and local indicators

- Implementation of a system for monitoring the quality of prescriptions
- Regular use of composite scores (IPISA)
- Annual publication of performance reports

A dynamic approach is essential to measure progress

Future research

- Longitudinal studies to assess the real impact of interventions
- Cost-effectiveness analyses of microbiological enhancement
- Integration of local bacterial resistance data
- Development of national multicenter predictive models

References

1. Murray CJL, Ikuta KS, Sharara F, et al. Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis. *Lancet* 399 (2022): 629-655.
2. Hernando-Amado S, Coque TM, Baquero F, et al. Defining and combating antibiotic resistance from One Health and Global Health perspectives. *Nat Rev Microbiol* 20 (2022): 143-155.
3. Holmes AH, Moore LSP, Sundsfjord A, et al. Understanding the mechanisms and drivers of antimicrobial resistance. *Nat Rev Microbiol* 21 (2023): 214-228.
4. Sulis G, Batomen B, Kotwani A, et al. Antibiotic prescription practices in LMICs: systematic review. *Lancet Reg Health Eur* 12 (2022): 100371.
5. Tessema SK, et al. Antimicrobial stewardship implementation in Africa: challenges and progress. *Antimicrob Resist Infect Control* 12 (2023): 63.
6. Langford BJ, So M, Raybardhan S, et al. Antibiotic prescribing patterns and diagnostic stewardship. *Clin Infect Dis* 75 (2022): e116-e124.
7. Andersson DI, Hughes D. Microbiological effects of subinhibitory antibiotic concentrations. *Nat Rev Microbiol* 19 (2021): 465-478.
8. Roberts JA, Abdul-Aziz MH, et al. Individualized antibiotic dosing in critically ill patients. *J Glob Antimicrob Resist* 29 (2022): 131-139.
9. Dyar OJ, Huttner B, Schouten J, et al. What is antimicrobial stewardship? *J Antimicrob Chemother* 76 (2021): i1-i5.
10. Liu C, et al. Determinants of inappropriate antibiotic prescribing in hospital settings. *Int J Infect Dis* 128 (2023): 45-52.
11. Van Dijck C, Vlieghe E, Cox JA. Antibiotic stewardship interventions in LMIC hospitals: a systematic review. *J Antimicrob Chemother* 76 (2021): 1701-1708.
12. Abubakar U, et al. Evaluation of antimicrobial use and stewardship in Sub-Saharan Africa: a systematic review. *Antimicrob Resist Infect Control* 11 (2022): 102.

13. Cox JA, Vlieghe E, Mendelson M, et al. Antibiotic stewardship in low-resource settings: challenges and opportunities. *J Glob Antimicrob Resist* 28 (2022): 299-306.
14. Allel K, Stone J, Undurraga EA, et al. The global economic burden of antimicrobial resistance. *Lancet Reg Health Eur* 26 (2023): 100568.
15. Pouwels KB, Dolk FCK, Smith DRM, et al. Explaining variation in antibiotic prescribing. *J Antimicrob Chemother* 76 (2021): 1709-1716.
16. Ouedraogo AS, et al. Antibiotic prescribing in West Africa: multicenter analysis. *JAC Antimicrob Resist* 4 (2022): 89.
17. Borg MA, et al. Optimizing antimicrobial prescribing quality indicators. *Clin Microbiol Infect* 27 (2021): 808-813.
18. Ayukekbong JA, et al. Antimicrobial resistance in Africa. *Front Pharmacol* 12 (2021): 660593.
19. Otaigbe II, Elikwu CJ. Drivers of inappropriate antibiotic use in low- and middle-income countries. *JAC Antimicrob Resist* 5 (2023): 62.
20. Boltana MT, Wolde M, Hailu B, et al. Point prevalence of evidence-based antimicrobial use among hospitalized patients in sub-Saharan Africa: a systematic review and meta-analysis. *SciRep* 14 (2024): 12652.
21. Llor C, Fridodt-Møller N, Miravittles M, et al. Optimizing antibiotic exposure by customizing duration of treatment. *EClinicalMedicine* 74 (2024): 102723.
22. Dar A, Abram TB, Megged O. Impact of inadequate empirical antibiotic treatment in children. *BMC Pediatr* 24 (2024): 324.
23. Oliveira M, Antunes W, Mota S, et al. Recent advances in antimicrobial resistance. *Microorganisms* 12 (2024): 1920.
24. Ajulo S, Awosile B. Global antimicrobial resistance and use surveillance system (GLASS 2022). *PLoS One* 19 (2024): e0297921.
25. Khalid L, Saleem K, Mushtaq S, et al. Global prediction of antimicrobial resistance trends using statistical and machine learning models. *J Glob Antimicrob Resist* 46 (2025): 214-226.
26. Pereira C, Larsson J, Hjort K, et al. The highly dynamic nature of bacterial heteroresistance impairs its clinical detection. *Commun Biol* 4 (2021): 521.
27. Rossolini GM, Antonelli A, Galano A, et al. Microbiological diagnosis in the era of antimicrobial resistance. In: Bartoli S, Cortese F, Sartelli M, Sganga G, editors. *Infections in Surgery*. Cham: Springer (2025).
28. Woolhouse M, Ward M, van Bunnik B, Farrar J. Antimicrobial resistance in humans, livestock and the wider environment. *Nat Rev Microbiol* 19 (2021): 465-478.
29. O'Neill J. Tackling drug-resistant infections globally. *Lancet* (2022).
30. Elbehiry A, Marzouk E, Abalkhail A. Antimicrobial resistance at a turning point: microbial drivers, one health, and global futures. *Front Microbiol* 16 (2025): 1698809.
31. Essack SY, Desta AT, Abotsi RE, et al. Antimicrobial resistance in the WHO African region: current status and roadmap for action. *J Glob Antimicrob Resist* 26 (2021): 121-128.
32. Allerberger F, et al. Antimicrobial resistance in Europe: epidemiology and surveillance challenges. *Clin Microbiol Infect* 28 (2022): 901-909.
33. Cherry Lim, Myo Maung Maung Swe, Angela Devine, et al. Givney, Jennifer Yan, Joshua R. Francis, Ben S. Cooper, Cost-effectiveness of maintaining an active hospital microbiology laboratory service in Timor-Leste, *The Lancet Regional Health - Southeast Asia* 36 (2025): 100582.
34. Marino A, Maniaci A, Lentini M, et al. The Global Burden of Multidrug-Resistant Bacteria. *Epidemiologia (Basel)* 6 (2025): 21.
35. Katherine Keenan, Juliana Silva Corrêa, Luechai Sringernyuang, et al. The social burden of antimicrobial resistance: what is it, how can we measure it, and why does it matter?, *JAC-Antimicrobial Resistance* 7 (2025): dlae208.
36. Hernando-Amado S, Coque TM, Baquero F, et al. Defining and combating antibiotic resistance from One Health and Global Health perspectives. *Nat Rev Microbiol* 20 (2022): 709-721.
37. Collignon P, Beggs JJ, Walsh TR, et al. Anthropological and socioeconomic factors contributing to global antimicrobial resistance: a systematic analysis. *Lancet* 399 (2021): 629-639.
38. Dyar OJ, Huttner B, Schouten J, et al. ESGAP (ESCMID Study Group for Antimicrobial stewardship). What is antimicrobial stewardship? *Clin Microbiol Infect* 27 (2021): 147-153.
39. Laxminarayan R, Van Boeckel T, Frost I, et al. The Lancet Infectious Diseases Commission on antimicrobial resistance: challenges and recommendations. *Lancet Infect Dis* 20 (2020): e329-e352.
40. Davies J, Davies D. Origins and evolution of antibiotic resistance. *Science* 367 (2022): aba9346.

41. M. Acampora, M. Paleologo, G. Graffigna, S. Barello, Uncovering influential factors in human antibiotic prescribing: a meta-synthesis study informed by the Theoretical Domains Framework, *Journal of Hospital Infection* 144 (2024): 28-55.
42. Alatawi AD, Hetta HF, Ali MAS, et al. Diagnostic Innovations to Combat Antibiotic Resistance in Critical Care: Tools for Targeted Therapy and Stewardship. *Diagnostics (Basel)* 15 (2025): 2244.
43. Paterson DL, Bonomo RA. Extended-spectrum β -lactamases: a clinical update. *Clin Microbiol Rev* 18 (2005): 657-686.



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