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Reanalyzing the Economic Burden of Antimicrobial Resistance: Socioeconomic Inequality and Local Policy Recommendations in U.S. Low-and Middle-Income Regions

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Abstract

Antimicrobial resistance (AMR) is one of the greatest global and public health crises of the modern age. AMR has contributed to increased healthcare costs, prolonged hospitalization, reduced productivity, and rising mortality rates worldwide. While AMR is commonly viewed as a global threat, existing studies fail to account for socioeconomic disparities present in low- and middle-income countries (LMICs) and low- and middle-income regions (LMIRs) within high-income countries such as the United States. This study investigates how socioeconomic vulnerabilities in LMIRs in the United States affect contributors to AMR's economic burden and identifies policy interventions that could improve domestic AMR containment strategies. Because direct healthcare expenditures were not measured, this study utilized surveillance capacity, AMR-related outbreak rates, antibiotic prescription patterns, diagnostic capacity, and supply shortages as established proxies for factors that influence the economic burden of AMR. This study utilized a mixed-methods research design combining targeted survey data from physicians, health economists, and healthcare administrations with secondary data analysis from public health databases. The results show that higher socioeconomic vulnerability was associated with lower diagnostic and infrastructural capacity and increased supply shortages. These disparities support the implementation of local policy changes, including expanded rapid diagnostic technologies, improved antimicrobial stewardship programs, standardized surveillance systems, increased healthcare funding, and broader educational initiatives.

Keywords

Antimicrobial Resistance (AMR), Low- and Middle-Income Regions

(LMIRs), Socioeconomic Vulnerability, Economic Burden, Diagnostic Capacity

1. Introduction

Antimicrobial resistance (AMR) has become one of the most pressing global health threats of the 21st century (Ahmed et al., 2024; Oliveira et al., 2024). Antimicrobials treat bacterial infections and have been widely used since the 1940s (Dadgostar, 2019). AMR is the ability of microbes to survive in the presence of antimicrobials through physiological mechanisms, including changes in the structure and composition of the bacterial envelope or the production of degradative enzymes (Founou et al., 2017; OECD, 2018). Because many antibiotics belong to the same class of medicines, resistance to one specific antibiotic agent can lead to resistance to a whole related class through the exchange of genetic material (WHO, 2015).

While AMR is driven by many complex biological mechanisms, it is heavily impacted by the overuse of less-effective and broad-spectrum antibiotics. Global antibiotic consumption increased by 40% between 2000 and 2010 (Thorpe et al., 2018; World Bank Group, 2017). AMR is a drain on the global economy, with economic losses due to reduced productivity caused by illness and higher costs of treatment (WHO, 2015). Current models estimate that by 2050, AMR will cause 10 million deaths, 100 trillion USD in losses, and push 28 million people into severe poverty globally (Oliveira et al., 2024; Gandra et al., 2020).

Socioeconomic disparities are strongly associated with the increased prevalence of AMR in low- and middle-income countries (LMICs) and in socioeconomically disadvantaged regions in high-income countries. In this study, these areas are referred to as low- and middle-income regions (LMIRs). Unlike the World Bank (2017)'s classifications for LMICs, countries that are characterized by higher social deprivation and are more susceptible due to inadequate infrastructure, quality-control systems, and a lack of government regulation (Tesema & Birhanu, 2024), no universally accepted definition exists for LMIRs within the United States. Therefore, this study operationalizes LMIRs as U.S. counties or states exhibiting higher levels of socioeconomic disadvantage according to deprivation indices that incorporate income, education, employment, housing quality, and related social determinants of health. These multidimensional measures have been widely used in health disparities research and are more comprehensive than income alone (Kind & Buckingham, 2018; Butler et al., 2013; ATSDR, 2024).

In fact, antibiotic use increased by 114% in LMICs in the same period compared to 40% (McGowan, 2001). These disparities have led many economists and public health experts to argue that addressing the local needs of countries in medical, societal, and political contexts could be more effective in combating AMR than a centralized global response (Poudel et al., 2023; Shrestha et al., 2018).

Thus, there is a growing debate about whether AMR should be approached globally or domestically. This study synthesizes the existing literature on AMR and the economic and public health implications across different geographical scales, and it is organized into key perspectives: 1) the global approach emphasizing international coordination, 2) evidence that complicates the global approach by highlighting the disproportionate burden of AMR in LMICs, and 3) the local approach that addresses these disparities by prioritizing country- and region-specific interventions. By comparing these perspectives, this review identifies a key debate between global interventions and local needs, ultimately revealing how this conversation can be applied to fill United States-based gaps. This study is guided by a conceptual framework in which socioeconomic vulnerability is associated with variations in healthcare system capacity, diagnostic access, infrastructure, and prescribing behavior. This conceptual framework is based on variables that have been consistently identified in previous health economics literature as contributors to increased healthcare costs, treatment delays, and prolonged hospitalization. This makes them justified proxies for contributors to AMR's economic burden rather than direct measures of cost (Gandra et al., 2014; Shrestha et al., 2018; Poudel et al., 2023). Thus, this paper aims to answer the question: How do socioeconomic vulnerabilities in LMIRs in the United States influence contributors to the economic burden of AMR, and what policy changes are needed to better inform domestic AMR containment?

2. Literature Review

2.1. The Global Approach

The World Economic Forum and scholars contend that AMR constitutes a global health crisis that no single country or organization can address independently. Because resistant pathogens do not respect borders, international cooperation is necessary to tackle the problem (World Bank Group, 2017; OECD, 2018). Some experts argue that fragmented national policies are insufficient, and instead, a collective global response is required to curb antimicrobial misuse (World Bank Group, 2017; WHO, 2014). AMR containment will benefit all countries and the global economy as a whole, providing incentives for sustained cooperation. International bodies, including the WHO and World Bank, are well-positioned to lead this coordinated response (World Bank Group, 2017; OECD, 2018).

A focal point of this global strategy is the Global Action Plan on AMR, created and endorsed by the WHO (2015). The plan outlines key strategic objectives, including improving awareness of AMR through education, strengthening surveillance and research, and reducing the incidence of infection by optimizing the use of antimicrobial agents (CDC, 2019). A central pillar of the global approach is surveillance, particularly laboratory-based surveillance systems that collect and analyze data on antimicrobial susceptibility. The WHO's Global Antimicrobial Surveillance System (GLASS) is essential in promoting standardized methodologies, data comparability, and international data sharing, enabling countries to strengthen domestic laboratory capacity (WHO, 2014; CDC, 2019). In summary, there is an argument for an improved and coordinated global effort (WHO, 2014).

2.2. Disparities in AMR Burden

This global approach, however, overlooks the individual disparities between countries and regions within countries. Many experts have argued that AMR's impact is magnified in LMIRs as a result of limited surveillance, weak public health systems, and inadequate infection control. From a health economics perspective, evidence shows that LMICs are still far behind high-income countries (HICs) in terms of having the financial resilience and health systems to absorb the rising costs of AMR, contributing to long-term economic risks and inequality (Sosa et al., 2010; Dadgostar, 2019). For instance, 4.3 million of the 5 million AMR-related annual deaths occur in LMICs in Africa and Asia (Masoambeta et al., 2025). LMIC surveillance systems are hindered by weak infrastructure and staffing shortages (World Bank Group, 2017). For instance, findings from the WHO African region, South Asia, and Southeast Asia reveal that inadequate laboratory capacity and inconsistent surveillance systems are linked to higher reported levels of resistant pathogens (Mestrovic et al., 2022; Gandra et al., 2020). AMR is predicted to cause significant health and economic impacts, particularly in LMICs due to weak public health systems and very low government expenditure on health services. Of the additional 24 million people who would be forced into extreme poverty by 2030 due to AMR, most would reside in LMICs (World Bank Group, 2017). As a result of these discrepancies, consideration of a local approach is warranted.

2.3. The Local Approach

Recent studies highlight the methodological consensus that measuring the local economic burden of AMR could be more effective and efficient than a global framework (Poudel et al., 2023; Shrestha et al., 2018). The World Bank (2017) acknowledges that country strategies and AMR implementation plans may need to differ across countries, and LMICs may require assistance (World Bank Group, 2017). While international coordination and economic incentives have their merits, acknowledging the alternative local perspective is critical in addressing AMR. This domestic approach will require a multi-faceted, mixed-method approach incorporating macroeconomic and micro-level patient data from local hospitals (Gandra et al., 2014; Masoambeta et al., 2025). Furthermore, both direct (hospitalization and medical expenses) and indirect costs (output loss due to premature deaths) need to be considered (Shrestha et al., 2018; OECD, 2018). Thus, estimating the economic burden of AMR warrants the use of new local economic and epidemiological models. In fact, national surveillance programs, such as the United States Centers for Disease Control and Prevention (CDC) and the National Healthcare

Safety Network (NHSN), already collect data from healthcare facilities across their regions to monitor resistance trends, identify emerging threats, and provide benchmarks to compare resistance rates between different locations (Oliveira et al., 2024). These existing organizations and surveillance systems can overcome the limitations of the global approach, which would require significant investment and time. That being said, there is an urgent need for more localized economic burden models (Gandra et al., 2014).

2.4. Research Gaps

The current literature reveals several significant gaps from the global, disparity-focused, and local perspectives. In the global approach, policy recommendations are based too heavily on data from HICs, underrepresenting LMICs. This creates a significant gap in global surveillance systems and action plans where both LMICs and LMI subregions in HICs are underrepresented. Moreover, many studies overlook infrastructural and institutional causes of AMR acceleration, including diagnostic capacity disparities (World Bank Group, 2017; CDC, 2019). The absence of accurate surveillance and the presence of diagnostic capacity limitations skew global estimations (WHO, 2014). Additionally, while prior research identifies overuse of antimicrobials as a key driver of AMR, there is a lack of consistent, localized data on antibiotic prescription practices and rates, particularly in LMIRs.

Although the local approach attempts to address these disparities, there is a lack of integration between healthcare system factors that contribute to the economic burden of AMR, including diagnostic access, supply shortages, surveillance capacity, and prescription behavior (WHO, 2014). Specifically, there is a major lack of U.S.-based AMR economic research, particularly regarding disparities between LMIRs in the United States. Existing U.S.-based surveillance systems (e.g., NHSN, CDC databases) collect large amounts of data, yet they remain fragmented and are rarely analyzed in conjunction with socioeconomic indicators, particularly at the state and county levels. Furthermore, many datasets across all geographic scopes are outdated, inconsistently reported, or lack coordination across institutions (WHO, 2014). Together, these gaps necessitate a study that links socioeconomic vulnerability to significant drivers of AMR's economic burden, including diagnostic capacity, surveillance systems, and prescription rates.

In response, this study aims to address multiple gaps, including a lack of data on LMIRs in the United States and a lack of standard policy recommendations. While AMR is widely recognized as a global health crisis, this study prioritizes an underexamined, localized, domestic scale to better capture how state- and county-level inequalities can mirror vulnerabilities observed in LMICs globally. Thus, this study aims to 1) identify key factors that affect AMR's economic burden in LMIRs in the United States through surveys and secondary analysis, and 2) produce AMR policy recommendations, informed by survey data, that are domestically actionable while also adaptable to broader global AMR containment efforts.

3. Methods & Findings

The objective of this study is to assess how socioeconomic vulnerability and infrastructural limitations in LMIRs in the United States are associated with several healthcare system factors that contribute to the economic burden of AMR. LMIR designation was determined using socioeconomic deprivation indices as described in Section 3.0, allowing for regions to be classified using reproducible criteria. Because direct healthcare expenditures and patient-level treatment costs were not available for this study, outcomes including diagnostic capacity, surveillance performance, AMR-related outbreak rates, antibiotic prescribing patterns, and supply shortages were analyzed as proxy indicators of contributors to AMR's economic burden. This mixed-method research design (targeted surveys and secondary data analysis) was selected to address the main gaps of existing AMR literature, including 1) the underrepresentation of LMIRs in the United States, 2) unclear key factors that affect AMR's economic burden in LMIRs in the United States, 3) a lack of direct policy recommendations, and is informed by the existing AMR literature, which emphasizes the need for more localized economic burden models (Gandra et al., 2014; Masoambeta et al., 2025; Shrestha et al., 2018) (**Figure 1**).

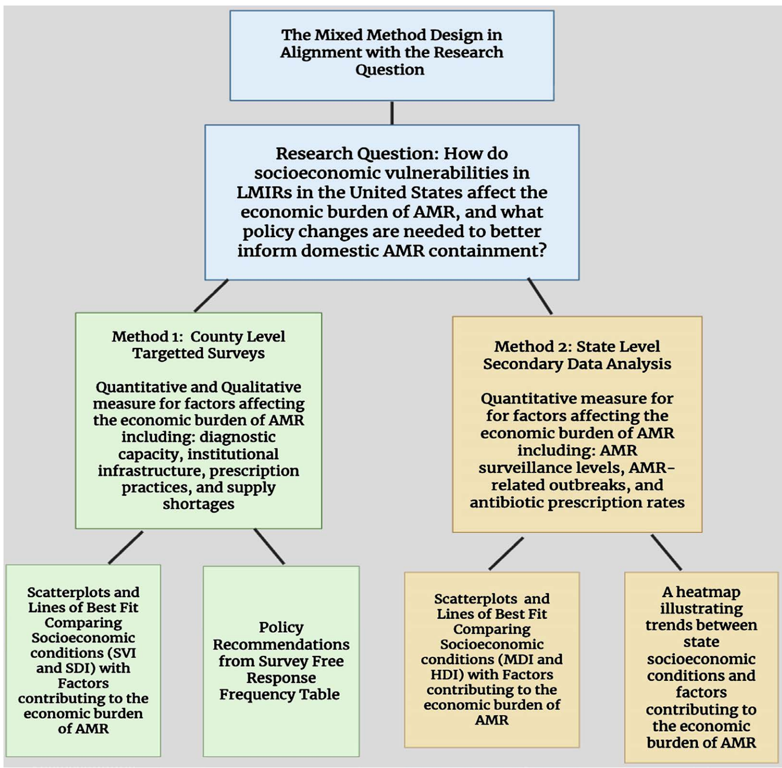


Figure 1. A flowchart breaking down the research design and alignment with the research question.

4. Operational Definition of Low-and Middle-Income Regions (LMIRs)

Because no standard definition is available for low-and middle-income regions

(LMIRs) within the United States, this study establishes a reproducible operational classification informed by existing socioeconomic deprivation measures. U.S. counties that were included in the survey analysis were classified using the 2022 CDC Social Vulnerability Index (SVI) and the 2019 Social Deprivation Index (SDI). The SVI measures disparities in the fields of economics, education, housing, and environment, currently used by the CDC and the Agency for Toxic Substances and Disease Registry to help public health officials prepare and respond to crises to mitigate economic and health inequalities. Meanwhile, the SDI measures economic, educational, environmental, and transportation disparities at the county level, developed by the Robert Graham Center to quantify levels of disadvantage across small areas, evaluate their associations with health outcomes, and address health inequities (ATSDR, 2022; ATSDR, 2024; Robert Graham Center, 2019). For each county, SVI values (0 - 1), where 0 represents low vulnerability, were multiplied by 100 and averaged with SDI scores (0 - 100), where 0 is low vulnerability, to generate a composite socioeconomic vulnerability score ranging from 0 to 100.

Drawing from approaches commonly used in population health research, counties with composite scores greater than or equal to the national median were operationally classified as LMIRs, whereas counties below the national median were classified as relatively higher-income regions. This method was selected to provide a transparent and reproducible method (Kind & Buckingham, 2018; Butler et al., 2013).

For secondary data analysis, socioeconomic vulnerability was measured independently using the 2023 Multidimensional Deprivation Index (MDI) and the 2022 Human Development Index (HDI). State socioeconomic indexes were chosen rather than the same county-level indexes used in survey analysis, due to the infeasibility of recording each U.S. County. Furthermore, state-level data would result in more generalizable findings and trends that could be applied to more socially and economically deprived regions in the United States. The MDI measures standard of living, health, education, economic security, housing quality, and neighborhood quality, while the HDI measures education, income, and life expectancy (United States Census Bureau, 2019; Global Data Lab, 2023). These indices were analyzed continuously to minimize information loss and improve statistical power (Altman & Royston, 2006). The MDI measures social vulnerability from 0 to 100, with 100 being the most vulnerable. Meanwhile, the HDI measures development from 0 to 1, with 1 being the most developed. Because the MDI and HDI operate in opposite directions, this study measured the correlation between each individual index and each dependent variable separately.

Consequently, the term LMIRs throughout this manuscript refers operationally to counties or states demonstrating relatively higher socioeconomic deprivation according to these composite indices.

4.1. Targeted Survey

A structured, anonymous survey was developed to collect self-reported expert perspectives on infrastructural limitations, diagnostic delays, antibiotic access, and the perceived economic burden of AMR in localized settings. This survey incorporates Likert scales (ranging from 1: strongly disagree to 5: strongly agree) and multiple-choice questions to ensure standardized results. Key topics included were repeatedly referenced in public health reports and the current literature (WHO, 2014; CDC, 2019).

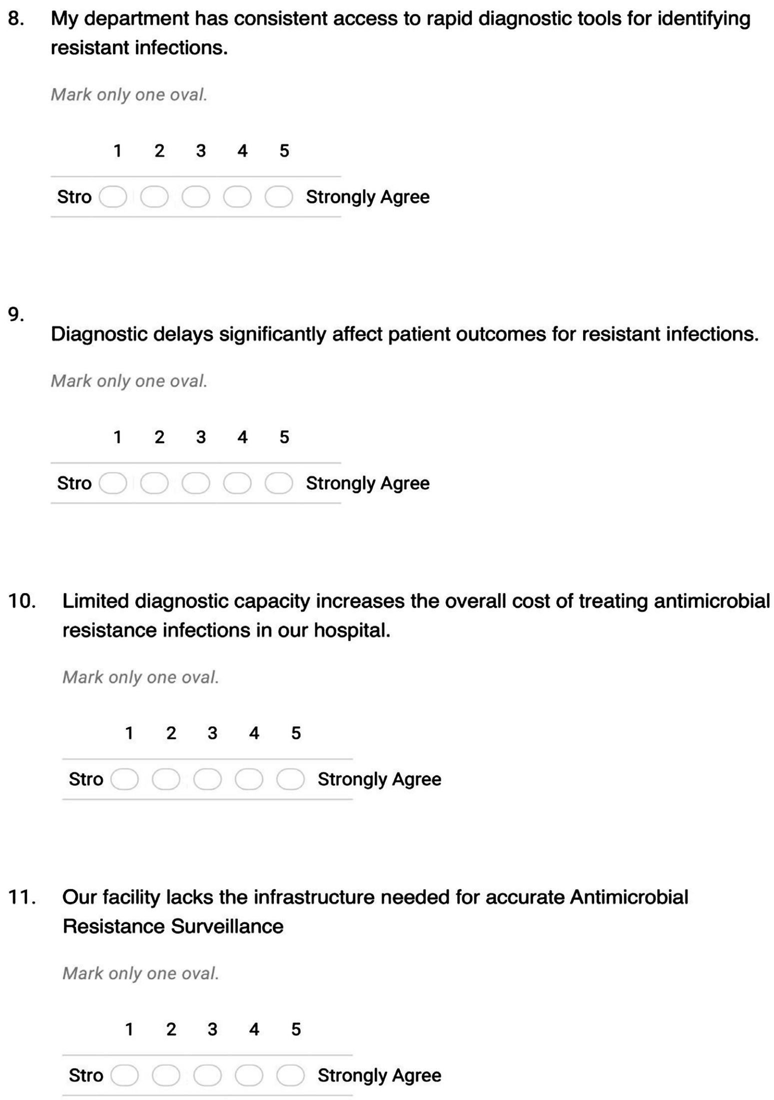
Participants were recruited over a five-month period through professional cold-contact and personal contacts. Potential participants were identified through publicly available faculty, hospital, and institutional directors. Potential participants included physicians, hospital epidemiologists, health researchers, healthcare administrators, economists, and lab technicians. This sampling strategy ensured that respondents had direct experience with AMR management and provided insights from an expert sample. Recruitment emails describing the purpose of the study and containing a secure Google Forms survey link (with an optional downloadable PDF version) were distributed to eligible professionals affiliated with universities, hospitals, research institutes, and healthcare systems throughout the United States. Respondents were presented with an informed consent statement outlining the study's purpose, voluntary participation, anonymity, and data storage procedures. In order to preserve respondent confidentiality, individual institutions and participants are not identified in this manuscript.

A total of 731 experts were contacted during recruitment. Eligibility criteria required participants to 1) be at least 18 years old, 2) be professionally affiliated with a healthcare, public health, research, health economics, or related institution within the United States, 3) provide a U.S. county-level practice location, and 4) complete all required survey questions.

After data screening, 62 submitted surveys were excluded because they did not satisfy the inclusion criteria. The most common reasons for exclusion were incomplete surveys, partially completed surveys, missing geographic identification, duplicate responses, and responses indicating primary practice outside the United States. After exclusions, 325 completed surveys were retained for analysis, resulting in a response rate of 52.6% and a completion rate of 84%.

Demographic information, including the respondent's location (county level), occupation, and institution classification, was collected at the start of the survey (**Figure 2**).

The first set of questions was centered around diagnostic capacity (*e.g.*, *my department has consistent access to rapid diagnostic tools for identifying resistant infections*). The next section was focused on institutional infrastructure (*e.g.*, *our facility lacks the infrastructure needed for accurate antimicrobial resistance surveillance*). The last set of questions included prescription practices (*e.g.*, *targeted antibiotics are often used over broad-spectrum antibiotics*) and supply shortages (*e.g.*, *local supply shortages impact antibiotic selection in clinical practice*). Each of these categories covers areas that contribute to the economic cost of AMR but have been under researched in the current literature.



8. My department has consistent access to rapid diagnostic tools for identifying resistant infections.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

9. Diagnostic delays significantly affect patient outcomes for resistant infections.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

10. Limited diagnostic capacity increases the overall cost of treating antimicrobial resistance infections in our hospital.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

11. Our facility lacks the infrastructure needed for accurate Antimicrobial Resistance Surveillance

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Figure 2. Four sample questions from administered targeted surveys, utilizing Likert Scales.

To reduce subjectivity, established county-level socioeconomic indices were used as the independent variable rather than self-reported perceptions. Specifically, this method incorporated the average value of the 2022 Social Vulnerability Index (SVI) and the 2019 Social Deprivation Index (SDI). Specifically, counties were assigned composite socioeconomic vulnerability scores by averaging the adjusted SVI and SDI scores.

Rather than analyzing individual respondents, the county level served as the unit for analysis. For counties with multiple respondents, Likert-scale responses were first averaged to calculate a single county-level mean score. These county means were then paired with the corresponding composite socioeconomic vulnerability score and used in scatterplot analyses. Aggregating responses at the county level reduced the influence of unequal respondent representation across counties and was more practical as a majority of respondents were based in the same counties, including Kings County, New York County, Los Angeles County, and Allegheny County (Table 1).

Table 1. A sample of the table used to calculate the mean of socioeconomic vulnerability. For example, New York County's SVI (0.7283) was multiplied by 100 (72.83) and averaged with New York County's SDI (82), resulting in New York County's mean value that will be used as its x/independent variable (77.42).

Location	Social Vulnerability Index 2022 (County Level Data)	Adjusted SVI (Multiplied by 100)	Social Deprivation Index (County Level Data) (2019)	Average Value
Brooklyn, NY	High (0.8874)	88.74	High (98)	93.37
Brooklyn, NY	High (0.8874)	88.74	High (98)	93.37
NY	Medium-High (0.7283)	72.83	High (82)	77.42

The survey responses using Likert scales were separated into the aforementioned designated question categories and averaged together with the Likert values of questions in the same category (Table 2).

Table 2. Illustrating how dependent values were calculated (diagnostic category in this case). For instance, for a respondent from New York County, the values for the three questions categorized in the diagnostic question group were 5, 1, and 2. Thus, the mean value from New York County for the diagnostic question group was 2.667. This value will serve as the y/dependent value for the association between socioeconomic vulnerabilities and the diagnostic capacity graph.

County(s)	Diagnostic Questions (Average)	My department has consistent access to rapid diagnostic tools for identifying resistant infections.	Limited diagnostic capacity increases the overall cost of treating antimicrobial resistance infections in our hospital.	Diagnostic delays significantly affect patient outcomes for resistant infections.
Kings County	**5**	5	5	5
New York County	**2.667**	5	1	2
Allegheny County	**5**	5	5	5

This process would be repeated for the remaining question categories (infrastructure, prescriptions, and supply shortages).

4.2. Survey Results & Statistical Analysis

Figures 3-6 are scatterplots showing relationships between county-level socioeconomic vulnerability and survey-based AMR factors. The lines of best fit were included to quantify trends across multiple under researched factors contributing to the economic burden of AMR. Because county-level averages served as the unit of analysis, each point in Figures 3-6 represents counties rather than individual respondents. Due to the limited number of locations surveyed and the limited number of answer choices, the graphed points appear highly concentrated. For counties with multiple respondents, responses within each question category were averaged prior to regression analysis, resulting in only one mean outcome value for each county.

County-level survey data and state-level secondary datasets were analyzed using basic linear regression to evaluate associations between socioeconomic vulnerability and AMR-related dependent variables. For the survey analyses (Figures 3-6), the unit of analysis was county level (n = 10 for Figures 3-5) and (n = 9 for Figure 6 due to missing prescription data). For secondary data analysis (Figures 7-12), all 50 states and the District of Columbia were included (n = 51).

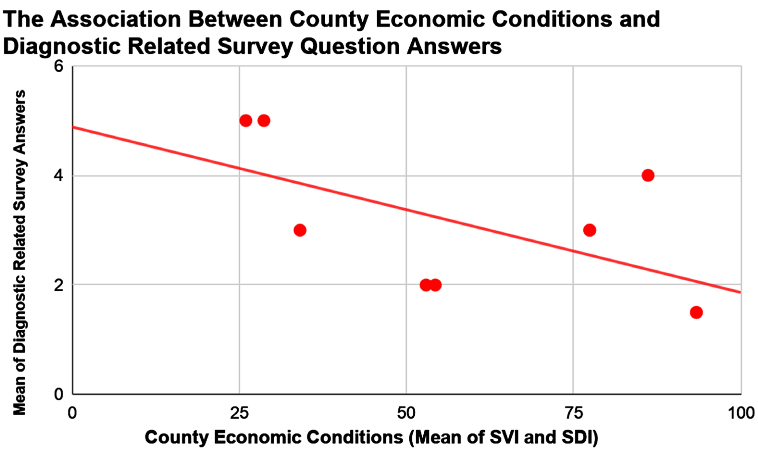


Figure 3. Demonstrating a moderate negative association between socioeconomic vulnerability and infrastructure-related survey responses (n = 10, r = −.612, β = −0.0302, $p = 0.060$). This indicates that counties with greater socioeconomic vulnerability tend to report lower infrastructure-related scores. Since this relationship did not reach statistical significance, the result should be interpreted cautiously.

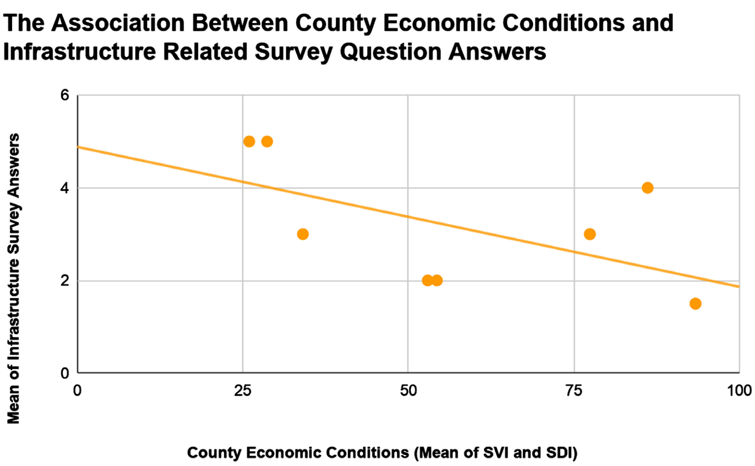


Figure 4. Summarizing responses related to infrastructural capacity and AMR surveillance.

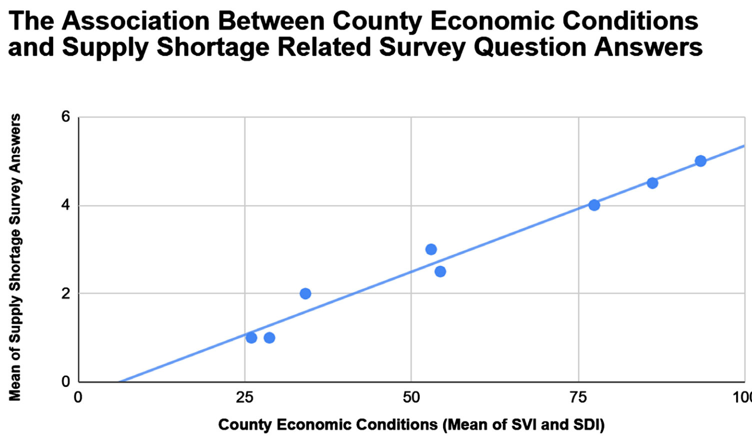


Figure 5. Displaying a very strong positive association between socioeconomic vulnerability and reported supply shortages (n = 10, r = 0.989, β = 0.0570, $p < 0.001$), indicating socioeconomic vulnerabilities are associated with increased cases of shortages of targeted antibiotics and microbial infection treatments.

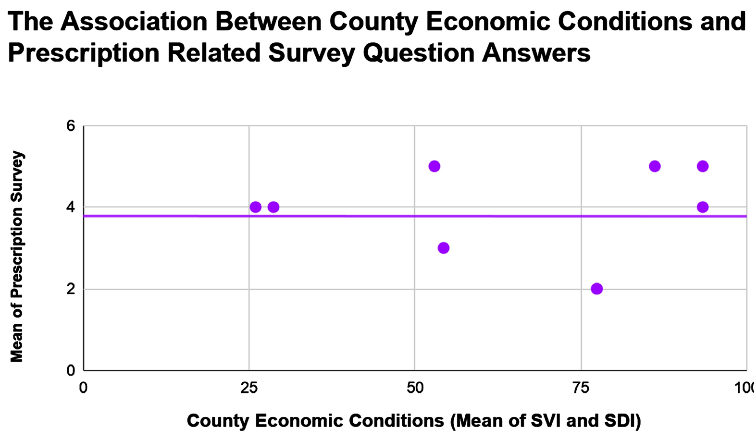


Figure 6. Showing a nearly zero relationship between socioeconomic vulnerability and prescription practices (n = 9, r = −0.002, β = −0.00009, $p = 0.996$). As socioeconomic vulnerability increased, the rate of targeted prescriptions decreased slightly. This suggests that prescribing practices may be more influenced by clinical protocols than by socioeconomic conditions alone.

For all figures, scatterplots were paired with regression lines. For each association, the Pearson correlation coefficient (r), slope of the line of best fit (β), and corresponding p-values were calculated. Statistical significance was evaluated using α = 0.05. Finally, because this study was observational, regression analyses were interpreted as measures of association rather than evidence of causation.

Specifically, Figure 4 illustrates the response to the survey item "Our facility lacks the infrastructure needed for accurate antimicrobial resistance surveillance". Lower scores indicated less agreement that infrastructure was lacking, not lower infrastructure capacity itself. The negative trend should not be interpreted as evidence that infrastructure capacity decreases as socioeconomic vulnerability increases. In fact, this line of best fit could suggest that as socioeconomic conditions improve, infrastructural capacity declines. More significantly, however, the relationship illustrates the differences in respondents' agreement with the statement involving infrastructural capacity. This finding suggests that expert perceptions of infrastructure vary across counties, and does not demonstrate lower infrastructure capacity in more socioeconomically vulnerable regions. Figure 4 demonstrated a weak negative association ($n = 10$, $r = -0.166$, $\beta = -0.00626$, $p = 0.646$). This relationship was not statistically significant.

In summary, the surveys identify mechanisms that explain the broader trends observed in secondary data. To address the study's identified research gaps in diagnostic capacity, surveillance, and prescription practices, select policy-focused questions included both predefined response options and an "other" free-response field to capture perspectives not represented by the set categories (Figure 13), These questions, including "*What are the major reasons for diagnostic delays*?" were intended to capture physician and expert insights and were not reflected in existing databases. For questions involving diagnostic delays, prescribing barriers, and infrastructure gaps, respondents could provide additional explanations through open-ended responses.

To increase simplicity and data interpretation, survey instruments only included up to four predefined responses in addition to an "Other" option. The responses under the "Other" section were thoroughly reviewed and grouped into recurring themes in Table 3.

After data collection, the responses were grouped into repeating categories to reduce redundancy. For instance, responses such as "waiting for culture growth" and "waiting for organism growth" were consolidated into the category "waiting for pathogen growth on media". Likewise, responses related to staffing or prescription practices were grouped into the larger categories "Clinician Preferences" or "Limited antibiotic stewardship staffing". These categories supplemented the predefined survey options and were included in the frequency analysis.

The most frequently reported cause of diagnostic delays was slow turnaround times ($n = 80$), followed by equipment limitations ($n = 68$), staffing shortages ($n = 59$), and financial barriers ($n = 48$). These findings reinforce the negative relationship observed between socioeconomic vulnerability and diagnostic capacity, suggesting that delays are driven by resource constraints. Similarly, infrastructural gaps were most commonly identified as a lack of hospital-level surveillance systems ($n = 87$), in addition to limited patient follow-up resources ($n = 64$), limited infection control staffing ($n = 57$), and outdated/insufficient lab equipment ($n = 52$). These responses support the previous literature suggesting that fragmented surveillance systems and inadequate infrastructure contribute to mechanisms that increase the economic burden of AMR. Contrastingly, barriers to prescribing targeted antibiotics were more heterogeneous, with insurance restrictions ($n = 52$) and clinician preferences ($n = 48$) appearing the most often. This variability aligns with the relatively weak correlation observed between prescription practices, suggesting that prescription behavior is largely driven by clinical judgment and institutional policy rather than socioeconomic vulnerability alone. These open-ended responses play a critical role in explaining gaps in correlational relationships and provide actionable policy recommendations informed by real-world clinical experience.

Table 3. A frequency table summarizing physician-reported causes of diagnostic delays, prescription barriers, and infrastructural gaps based on survey responses. Survey answers were organized in a frequency table, and the most frequent responses will be synthesized to offer potential solutions to mitigate the economic burden of AMR. Responses included both predefined answer choices and additional themes that were derived from "Other" free responses through survey coding. These additional categories, derived through the recording process, are also included in the table to provide a more complete representation of participant responses.

Question	Answer Frequency
How often do you encounter diagnostic delays for suspected resistant infections?	**-Sometimes (175)** **-Rarely (90)** -Often (30) -Never (28)
What are the major reasons for diagnostic delays	**-Slow turnaround times (80)** **-Equipment limitations (68)** **-Lab staffing shortages (59)** **-Insurance/Financial Barriers (48)** -Waiting for pathogen growth on media (19) -High Cost (15) -Inability to Access Drugs (10) -Healthcare policy restrictions (7)
What is the most common barrier to prescribing targeted antibiotics?	**-Insurance Restrictions (52)** **-Clinician Preference (48)** -Healthcare Policy (45) -Diagnostic Uncertainty (43) -Pharmacy supply issues (40) -Waiting for the sensitivity patterns (28) -Knowledge Gaps (27) -Lack of information (20) -Severity of patient illness (16)
Which infrastructure gaps most affect antimicrobial resistance management?	**-Lack of a hospital-level surveillance system (87)** **-Limited patient follow-up resources (64)** **-Limited infection control staffing (57)** **-Outdated or insufficient lab equipment (52)** -Long turnaround time (20) -Difficulty staffing micro lab (19) -Difficulty reporting updates (14) -Limited antibiotic stewardship staffing (10)

4.3. Secondary Data Analysis

While targeted surveys served as this study's primary method, the relatively small sample pool could limit generalizability. Thus, to address this limitation, the research design will include secondary data analysis at the state level to supplement gaps in physician data.

Rather than relying on arbitrary thresholds, MDI and HDI values were analyzed as continuous socioeconomic indicators. States that had relatively higher socioeconomic deprivation according to these indices and represent the operational equivalent of LMIRs for state-level analysis (**Table 4**).

Table 4. A sample of recorded MDI and HDI across the U.S. states.

Location	Multidimensional Deprivation Index (MDI) (2023)	HDI (Education, Income, Life Expectancy)
Alabama	17.32	0.887
Alaska	13.9	0.94
Arizona	14.55	0.917
Arkansas	18.79	0.89
California	16.17	0.94

This method aimed to measure three key dependent variables: AMR surveillance levels, AMR-related outbreaks, and antibiotic prescription rates. Each of these categories represents under researched areas that contribute to the economic burden of AMR. Although these variables do not directly quantify healthcare expenditures, they represent mechanisms that are consistently linked to increased economic burden in prior AMR literature. Lower surveillance capacity can delay outbreak detection and, in turn, increase health costs. Likewise, higher antibiotic prescribing rates increase resistance rates. Finally, a greater outbreak incidence increases healthcare utilization. Consequently, these variables were interpreted as proxy measures of contributors to AMR's economic burden rather than direct economic outcomes.

The first category, AMR surveillance, measures the percentage of a state's facilities that report AMR cases in addition to implementing long-term antibiotic care stewardship. These data points were extracted from the CDC AMR & Patient Safety Portal (AR & PSP) (CDC, 2026; CDC, 2024a; CDC, 2024b; CDC, 2024c). Each individual data point measuring AMR surveillance was averaged to create a mean surveillance percentage that would be used as the dependent variable to compare with the independent variable (**Table 5** & **Table 6**).

The next major under researched contributor to the economic burden of AMR is AMR-related outbreak disparities. Specifically, this study extracted data from the NHSN's Antimicrobial Use Option Report, the National Antimicrobial Resistance Monitoring System (NARMS), and the Bacteria, Enterics, Ameba and Myotics (BEAM) Dashboard (CDC, 2024d; BEAM, 2026). Specific common resistant infections measured include the 2024 acute central line-associated bloodstream infections and 2024 acute ventilator-associated infections (CDC, 2024d). The study also measured common resistant microbe cases, including the number of 2024 acute hospital Staphylococcus aureus resistant infections, Clostridioides difficile resistant infections, and 2024 emerging Zoonotic resistant infections (NCEZID) (CDC, 2024d; BEAM, 2026). Because the outbreak data were recorded as raw counts, they were standardized by each state's population (count/population) to produce a population-standardized outbreak rate, which would allow for comparisons across states with vastly different populations (United States Census Bureau, 2026). This standardization generated a rate (outbreaks per resident) rather than a percentage and would reduce bias present through comparing raw data across states. The standardized outbreak rates were then averaged across the selected outbreak indicators and were compared with socioeconomic indices using the same process as AMR surveillance, to be compared with the independent variable. The final contributor to the AMR economic burden that was measured was antibiotic prescription rates. Outpatient antibiotic prescriptions (antibiotic prescriptions per 1,000 persons by state in 2024) were extracted from the CDC's Antibiotic Use and Stewardship in the United States (CDC, 2024e).

Table 5. A table showing Alabama's percentage of reporting across data points (54, 25.6, 98 and 76), and Alabama's average value of 63.4.

Location	Percentage of hospitals ever reporting to the Antimicrobial Use Option among National Healthcare Safety Network acute care hospitals (Jan. 1 2025) (In Percent)	Inpatient Antibiotic Prescription (2021-2023) (Percentage of Eligible Facilities reporting SAAR Data by State)	Hospital Antibiotic Stewardship by State (Hospitals Implementing All 7 Core Elements in 2024)	Long-Term Care Antibiotic Stewardship by State (Percentage Reporting)	Average Surveillance Value
Alabama	54	25.6	98	76	**63.4**
Alaska	54	36.8	95	83	**67.2**
Arizona	44	25.9	93	76	**59.725**
Arkansas	54	50.7	99	85	**72.125**
California	57	51	99	85	**73**

Table 6. Providing a visual for how the independent variable and dependent variables are compared, in this case, MDI and the average of AMR surveillance in Alabama.

State	MDI (X Axis)	Average of Reporting Systems (Y Axis)
Alabama	17.32	63.4
Alaska	13.9	67.2
Arizona	14.55	59.725
Arkansas	18.79	72.125

Figures 7-12 show scatterplots and lines of best fit comparing state-level socioeconomic indices (MDI and HDI) with AMR surveillance rates, outbreak rates, and antibiotic prescription rates.

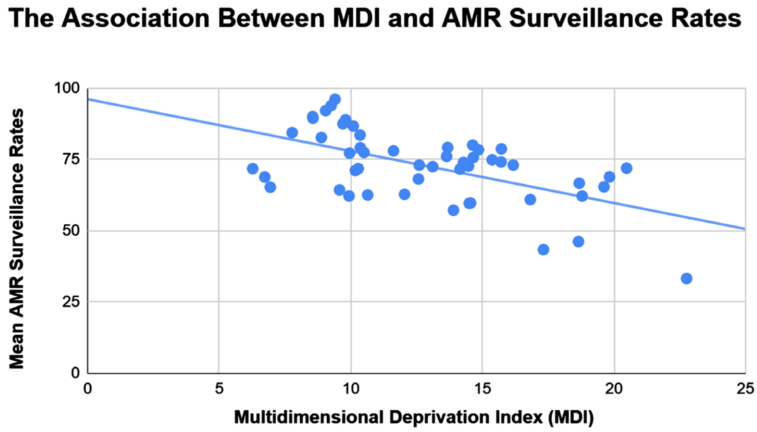


Figure 7. The relationship between MDI and AMR surveillance demonstrated a moderate negative association (n = 51, r = −0.573, β = −1.819, $p < 0.001$), indicating that states with higher socioeconomic deprivation generally exhibited lower surveillance capacity.

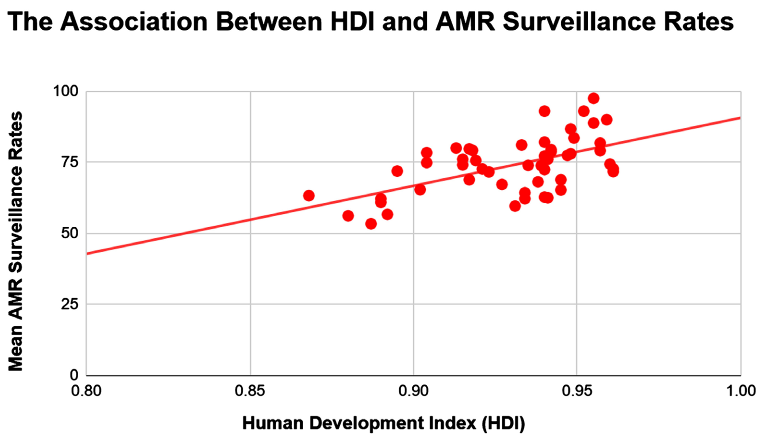


Figure 8. Demonstrating a moderate positive association between HDI and AMR surveillance (n = 51, r = 0.568, β = 239.23, $p < 0.001$), reinforcing the conclusion that higher development levels are associated with better AMR monitoring systems.

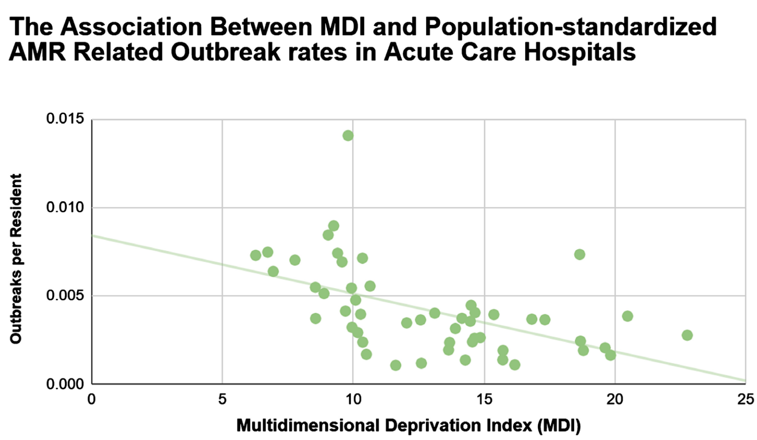


Figure 9. A moderate negative association between MDI and standardized outbreak rates (n = 51, r = −0.514, β = -3.28×10^{-4}, $p < 0.001$). Although the association was statistically significant, additional factors beyond socioeconomic deprivation contribute to differences across states.

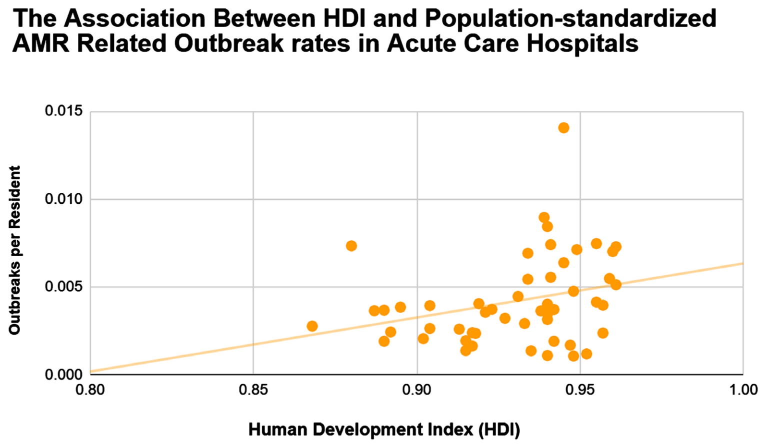


Figure 10. HDI vs standardized outbreak rates demonstrated a weak positive association (n = 51, r = 0.287, β = 0.0308, $p = 0.041$). Although statistically significant, the small correlation coefficient suggests these findings should be interpreted cautiously and indicates that outbreak rates may be influenced by additional confounding variables, including reporting differences and sanitation standards.

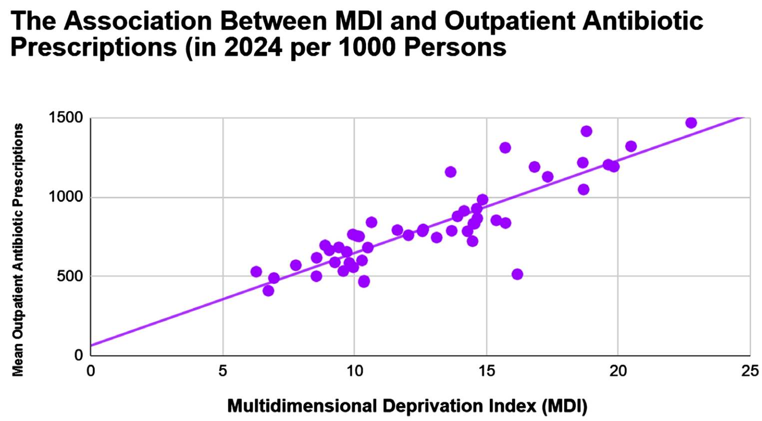


Figure 11. Illustrating a very strong positive association between MDI and antibiotic prescription rates (n = 51, r = 0.866, β = 58.33, $p < 0.001$). This aligns with this study's hypothesis and the current AMR literature, which argues that overprescription is an important contributor to downstream healthcare costs and AMR, especially in U.S. LMIRs.

Compared to survey results, the secondary data results provide stronger and more generalizable evidence due to larger sample sizes, the use of objective state-level measures, and stronger statistical relationships. This distinction is important because it supports the study's argument that socioeconomic vulnerability is significantly connected to the economic burden of AMR, beyond individual perceptions captured in survey responses, underscoring the urgency for statewide and national policy reforms, particularly in LMIRs. While survey data provides insights into the mechanisms driving disparities (e.g., diagnostic delays, infrastructure gaps, and supply shortages), the secondary data confirms that these mechanisms can be translated to larger scales. These findings suggest that interventions should not only target individual clinical practices but also systemic inequities in healthcare infrastructure and resource allocation.

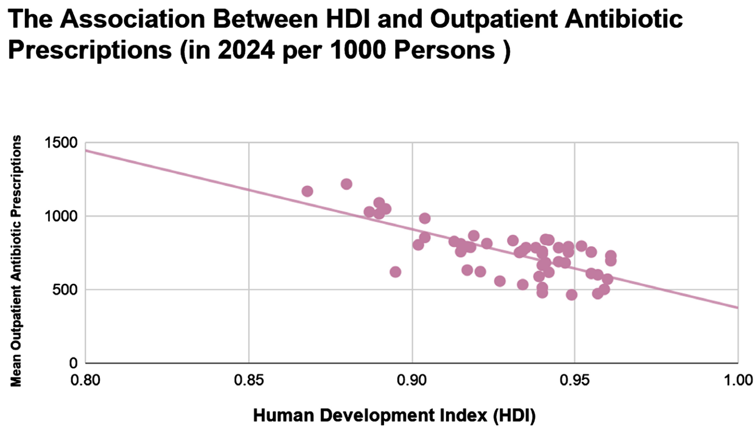


Figure 12. Demonstrating a strong negative association between HDI and antibiotic prescription rates (n = 51, r = −0.725, β = −5340.11, $p < 0.001$), indicating that more highly developed states generally reported lower outpatient antibiotic prescribing rates.

19. How often do you encounter diagnostic delays for suspected resistant infections?

Mark only one oval.

- Never
- Rarely
- Sometimes
- Often
- Always

20. (If applicable) What are the major reasons for diagnostic delays (select all that apply

Check all that apply.

- Lab staffing shortages
- Slow turnaround times
- Equipment limitations
- Insurance/financial barriers
- Other: ______

21. What is the most common barrier to prescribing targeted antibiotics?

Mark only one oval.

- Pharmacy supply issues
- Insurance restrictions
- Time pressure
- Other:

Figure 13. How these free policy-targeted questions were presented to survey respondents?

As mentioned previously, the MDI and HDI (independent variables) were compared with each of the three dependent variables (AMR surveillance, AMR-related outbreaks, and antimicrobial prescriptions). In addition to creating six scatterplots, this study also created a heatmap to visually represent trends. The aforementioned independent variables (MDI and HDI) were recorded for each state in addition to other economic markers, including health insurance data (percent on Medicaid and percent uninsured) extracted from the KFF database (KFF, 2024). For each measurement, the mean and standard deviation were calculated (**Table 7**). Below-average states were characterized as states below 1 standard deviation from the mean, states within 1 standard deviation were classified as average, and states greater than 1 standard deviation from the mean were classified as above average (**Table 8**). Next, the modes were taken to classify a state as above, below, or average. For example, if Colorado were categorized as below average 0 times, average 3 times, and above average 4 times, Colorado would be categorized as an above-average state (**Table 9**). This same process would be conducted for the AMR surveillance and AMR outbreak dependent variables.

Table 7. Illistrating this ecoconomic catergrorization process for Colorado (Bolded).

	Multidimensional Deprivation Index (MDI) (2023)	Average Personal Income (2024)	Poverty (Percent below Poverty)
Average Value (U.S. Mean)	12.9	71459	12.24%
Standard Deviation from the Mean (Population Setting) (Rounded to the nearest whole number)	3.899	11076	2.594

Table 8. The process for Colorado's economic categorizatio (bolded), specifically how Colorado's values more commonly above the 1 standard deviation from the mean threshold.

Average States (Within +/− 1 Standard Deviation from the Mean)	9.001 - 16.799	60,383 - 82,535	9.646 - 14.834
	MT	AK	NE
	NE	AZ	NV
	NV	DE	NJ
	NJ	FLA	NY
	NY	GA	NC
	NC	OH	TN
	OH	TN	TX
	OR	TX	VT
	VA	UT	VA
	WA	VT	WA
	WI	VA	WI
	WY	WI	WY

Continued

	Less than 9.001	More than 82,535	Less than 9.646
Above Average States (More than 1 Standard Deviation from the Mean)	**CO**	CA	**CO**
	MA	**CO**	MD
	MN	CT	MN
	NH	NY	NH
	UT	WA	OK
	VT	WY	UT

Table 9. . Illustrating that Colorado (CO) is categorized as a high-income state.

States Categorized as Low Income (Mode)	AL (4:3:0) AR (5:2:0) KY (6:1:0) LA (4:3:0)	***KEY:*** ***Ratio*** ***Number of times in Below Average: Number of times in Average: Number of times in Above Average***
States Categorized as Mid-Income (Mode)	AK (1:6:0) AZ (1:6:0) DC (1:4:2) FLA (1:5:1) GA (1:6:0)	
States Categorized as High Income (Mode)	**CO (0:3:4)** CT (0:5:2)	

There was not enough information for prescription rates. Lastly, each state's economic categorizations were compared to its AMR surveillance and AMR-related outbreak categorization. For example, if Alabama is classified as a below-average state economically, it's predicted to have an above-average AMR-related outbreak and below-average AMR surveillance (**Table 10**).

The heatmap synthesizes multiple relevant variables and reveals clear national patterns. States classified as economically low or below average (e.g., Alabama, Louisiana, Oklahoma, and West Virginia) are more frequently associated with higher AMR outbreaks and low surveillance capacity. This aligns with trends observed in the MDI and HDI scatterplots, reinforcing that socioeconomic vulnerability is associated with the healthcare system characteristics that have been linked to increased AMR burden and higher economic costs in previous research. These results support the current AMR literature promoting a domestic approach and the vulnerability of LMIRs. On the other hand, states classified as high or above average (e.g., Colorado, Maryland, and Utah) tend to show higher AMR surveillance capacity and lower outbreak levels. However, several states fall into "average" categories across all variables, suggesting that the burden of AMR isn't only determined by economic status. This nuance suggests that while socioeconomic vulnerability is a major factor, the economic burden of AMR is also dependent on other variables, such as policy implementation and healthcare systems. The heatmap is useful as it integrates multiple economic and AMR burden indicators, making it a strong visual tool for identifying systemic disparities and reinforcing patterns illustrated in scatterplots.

Table 10. A heatmap categorizing states by economic status (below the mean, at the mean, or above the mean) and comparing these categorizations to AMR outbreaks and surveillance levels. Categories are defined using the standard deviation from the mean. The boxes are color-coded (see key) in order to improve the visualization of the trends.

State	Economic categorization	AMR Outbreak Categorization	AMR Surveillance Categorization
Key	Low	Low	Low
	Average	Average	Average
	High	High	High
Alabama	Low	High	Low
Alaska	Average	Average	Average
Arizona	Average	Average	Low
Arkansas	Low	Average	Average
California	Average	Average	Average
Colorado	High	Low	High
Connecticut	High	Average	Average
Delaware	High	Low	High
District of Columbia	Average	Average	Average
Florida	Average	Average	Average
Georgia	Average	Average	Average
Hawaii	Average	Average	Average
Idaho	Average	Average	Average
Illinois	Average	Average	Average
Indiana	Average	Average	Average
Iowa	Average	Average	Low
Kansas	Low	High	Low
Kentucky	Low	Average	High
Louisiana	Low	High	Low
Maine	Average	Average	High
Maryland	High	Low	High
Massachusetts	High	Average	Average
Michigan	Average	Average	Average
Minnesota	Average	Average	Average
Mississippi	Low	Average	Average
Missouri	Average	Average	Average
Montana	Average	Average	Low
Nebraska	Average	Average	Low
Nevada	Average	Average	Average

Continued

New Hampshire	High	Average	Average
New Jersey	Average	Average	High
New Mexico	Low	Average	Average
New York	Average	Average	Average
North Carolina	Average	Average	High
North Dakota	Average	Average	Low
Ohio	Average	Average	Average
Oklahoma	Low	High	Low
Oregon	Average	Average	Average
Pennsylvania	Average	Average	Average
Rhode Island	Average	Average	Average
South Carolina	Average	Average	Average
South Dakota	Low	High	Low
Tennessee	Average	Average	Average
Texas	Average	Average	Average
Utah	High	Low	High
Vermont	Average	Average	Average
Virginia	Average	Average	High
Washington	Average	Low	Average
West Virginia	Low	High	Low
Wisconsin	Average	Average	Average
Wyoming	Low	High	Low

5. Discussion & Conclusion

5.1. Discussion

The existing literature presented two competing perspectives: a global approach and a local context-specific approach. While global frameworks emphasize international collaboration, they fail to consider local disparities in infrastructure and healthcare access. As a result, this study predominantly drew inspiration from the localized framework, while incorporating a global interconnected context. This project narrowed the scope to the United States to address a key gap in U.S.-focused studies, incorporating global and local frameworks into an under researched geographic region. To operationalize this approach, this study utilized a mixed-methods design incorporating targeted survey data, providing clinical and institutional insights, with secondary data analysis, offering broader trends across states.

The findings of this study contribute a new understanding to the field by arguing that higher socioeconomic vulnerability is associated with lower diagnostic and surveillance capacity, which is correlated with higher AMR economic burden at the state and county levels. Importantly, this study did not directly estimate the healthcare expenditures or societal costs attributable to AMR. Rather, it examined several proxies that previous economic studies have identified as major determinants of AMR-related costs. Hence, conclusions regarding economic burden should be interpreted as relationships between socioeconomic vulnerability and contributors to economic burden rather than direct cost estimates. This study introduces a reproducible operational definition of LMIRs that is applicable to the United States. While previous AMR studies described disadvantaged communities, they did not specify objective criteria for identifying them. As a result, this study's framework improves methodological transparency and creates room for future replication in domestic AMR research.

The strongest association was observed between socioeconomic vulnerability and reported supply shortages (**Figure 5**), suggesting that healthcare systems serving more socioeconomically vulnerable populations are substantially more likely to experience shortages of antibiotics, diagnostic supplies, or related resources. Conversely, the relationships between socioeconomic vulnerability and both infrastructure capacity (**Figure 4**) and diagnostic capacity (**Figure 3**) were weaker and did not reach statistical significance. Similarly, prescription practices (**Figure 6**) demonstrated virtually no measurable relationship with socioeconomic vulnerability, suggesting that prescribing behavior may be influenced more by institutional policies and clinician decisions. Although infrastructure survey items also demonstrated negative associations with socioeconomic vulnerability, the items measured respondents' agreement with statements describing infrastructural deficiencies rather than quantitative measures. Thus, this result cannot be interpreted as direct evidence of a relationship and should instead be viewed as a reflection of differences in perceived infrastructural limitations.

Secondary data analysis strengthened these trends, suggesting that more LMI states tended to display lower AMR surveillance capacity and higher antibiotic prescription rates, reinforcing that socioeconomic vulnerability is associated with systemic constraints influencing AMR outcomes. Higher MDI scores were associated with lower AMR surveillance capacity (**Figure 7**), lower standardized outbreak rates (**Figure 9**), and substantially higher outpatient antibiotic prescription rates (**Figure 11**). Similarly, higher HDI values were associated with improved surveillance capacity (**Figure 8**) and lower antibiotic prescribing rates (**Figure 12**). Although HDI also demonstrated a statistically significant positive association with standardized outbreak rates (**Figure 10**), the relationship was relatively weak, indicating that socioeconomic development alone explains only a small proportion of the variation in outbreak frequency.

Despite these associations, this study does not establish causal relationships. Rather, findings indicate correlations between socioeconomic conditions and contributors to the economic burden of AMR. As such, differences in state and county policy, reporting standards, and clinical protocol can influence correlations. For example, inconsistencies in population-standardized outbreak rates suggest that AMR outcomes may be influenced by local reporting practices, healthcare infrastructure, and policy implementation rather than socioeconomic conditions alone.

5.2. Stakeholder Implications and Expanded Policy Recommendations

The findings of this study highlight key stakes and significance for healthcare administrators, physicians, healthcare providers, epidemiologists, policymakers, public health institutions, and researchers in both local and national contexts. Firstly, this study argues for the investment in rapid diagnostic technologies. The most commonly cited cause of diagnostic delays was slow turnaround times and lab staffing shortages, in addition to the overreliance on slow pathogen growth methods and outdated equipment. Thus, policies should prioritize funding rapid diagnostic tools (e.g., PCR-based testing), which could help decrease the unnecessary use of broad-spectrum antibiotics and shorten hospital stays, decreasing overall treatment costs. As a result, policymakers and healthcare administrators should allocate greater funding to the hiring and training of microbiology lab staff, modernized lab equipment, and automation systems, improving diagnostic accuracy and efficiency, which would decrease costs associated with prolonged treatments. In addition, policymakers, healthcare administrators, and public health institutions should advocate for structural changes to insurance policies, including coverage for rapid diagnostic tests and reducing authorization barriers for targeted antibiotics. Addressing these barriers would improve timely access to appropriate therapies and reduce costs associated with treatment complications and overprescription.

Additionally, findings frequently cited poor education and knowledge gaps as a major cause of AMR. Consequently, physicians, epidemiologists, and public health institutions should enact public health initiatives to expand education and awareness. Both Economist Jim O'Neill in his 2014 UK-sponsored report and the WHO (2015) emphasize the importance of education in reducing the impacts of AMR (O'Neill, 2016). The inclusion of AMR protocol in school curricula will promote better understanding and awareness from an early age (WHO, 2015).

Finally, survey responses frequently recommended strengthening antimicrobial stewardship programs and standardizing hospital-level surveillance systems, findings that align with earlier literature emphasizing optimized antimicrobial use as a core strategy for AMR containment (World Bank Group, 2017; CDC, 2019). Thus, new policies should mandate AMR stewardship programs in hospitals and increase funding for stewardship personnel. This improvement in stewardship may slow AMR and lower long-term healthcare costs. Furthermore, survey responses suggested that a major infrastructure gap was the lack of hospital surveillance systems. As a result, state- and county-level policymakers in all regions, especially LMIRs, should require mandatory, standardized AMR surveillance reporting across existing platforms such as the CDC's NHSN. Specifically, policies should connect federal and state funding (i.e., Medicaid reimbursements or public hospital grants) to ensure consistency. Additionally, policymakers should fund the development of real-time data-sharing platforms between local hospitals and public health agencies, reducing the reporting delays and fragmentation identified in survey responses. While this study primarily focuses on AMR from a local scope, local institutions should take inspiration from the global approach's GLASS systems that promote data sharing and standardized methodologies, allowing for more efficient allocation of healthcare resources and a reduction in the economic burden of AMR.

5.3. Limitations & Future Directions

Despite this study's contributions to the field of AMR and healthcare policy, several limitations must be acknowledged. Firstly, the survey captured a relatively small, semi-random sample (n = 325) recruited through professional networks and cold contacts. While this approach ensures participants have relevant expertise, it introduces sampling bias, as individuals within similar professional networks may share comparable experiences, limiting the generalizability of the findings. Secondly, the survey responses were self-reported and, thus, subject to recall bias, response bias, and subjective interpretation. While the surveys utilized Likert scales to standardize responses, the constructs measured (e.g., perceived diagnostic capacity) are inherently subjective. Additionally, although aggregating responses to the county level increased efficiency, this approach also may have masked potential variation between individuals within the same county.

Thirdly, the socioeconomic vulnerability index may oversimplify the complex socioeconomic conditions. Differences in scale and directionality (e.g., MDI vs. HDI) may result in inconsistencies when comparing results. Fourthly, secondary data analysis may be constrained by variations in reporting standards and data quality across states. For example, a higher reported outbreak rate may be a result of stronger surveillance systems rather than a result of increased incidence. Moreover, the use of state-level data, while improving overall sample size and trend detection, may obscure important variations at the county or institutional level. An additional limitation is that this study did not directly measure healthcare expenditures, hospitalization costs, productivity losses, or other economic outcomes. Instead, this study analyzed several health system proxies informed by the current AMR literature. Although these indicators are widely recognized contributors to AMR-related costs, they should not be viewed as direct estimates of economic burden. Lastly, this study cannot establish causal relationships between socioeconomic vulnerability and AMR-related outcomes. While correlations and trends were identified, these relationships may be influenced by confounding variables (i.e., institutional policies).

Future research should build on the methodological limitations identified in this study to strengthen both the validity and applicability of findings related to socioeconomic vulnerability and AMR. Future studies should incorporate larger, more representative samples across diverse healthcare settings, especially LMIRs. To reduce the overreliance on subjective, self-reported data, future research should integrate institutional-level observations in diagnostic turnaround times, antibiotic utilization records, and staffing capacity. Future studies should also integrate patient-level cost data, hospital financial records, or cost-effectiveness analyses to quantify the economic consequences of the relationships in this study more directly. To address the limitations associated with county-level aggregates, future studies should incorporate larger samples from more counties and apply statistical models to account for respondent and county-level variation.

Additionally, to overcome inconsistencies in reporting standards, future studies should collaborate directly with public health agencies and healthcare systems, incorporating multi-level modeling that integrates state, county, and institutional data, which would allow researchers to examine how broader socioeconomic trends affect local healthcare outcomes. Moreover, to expand beyond correlational findings, studies should utilize longitudinal and quasi-experimental designs to better assess causality and evaluate the effectiveness of recommended policy interventions. For example, evaluating changes in AMR outcomes following the implementation of specific policy interventions (e.g., expanded diagnostic funding or stewardship programs).

Finally, future investigations on localized strategies should be integrated with global frameworks to mitigate the contributors to the economic burden of AMR on a larger scale, ensuring the needs of all regions, especially the LMIRs, are met while promoting collaborative and efficient action plans.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix A: Survey Questions and Answer Format

Question	Answer Format
By clicking "Agree", you indicate that you have read the information above and consent to participate in this study. Press "Disagree" if you do not agree with the terms and would not like to continue.	• Yes • No
What is your profession?	• Physician • Nurse • Administrator • Medical Resident • Lab Technician • Researcher • Scientist • Economist • Professor • Other
Where are you based? (City/County, State, Country)	• Free Response
How would you describe the geographic setting of your practice or institution? (if applicable)	• Urban • Suburban • Rural • Remote • Other
Which population does your institution primarily serve? (select all that apply) (if applicable)	• Medically underserved populations • Predominantly low-income patients • Mixed-income populations • Privately insured patients • Other
How would you classify your institution? (select all that apply) (if applicable)	• General Hospital • Specialty Hospital • Community Hospital • Teaching Hospital • Academic Medical Center • Trauma Center • Acute Hospital • Clinic • Research Institution • Other
My department has consistent access to rapid diagnostic tools for identifying resistant infections.	1 (Strongly Disagree) to 5 (Strongly Agree)
Diagnostic delays significantly affect patient outcomes for resistant infections.	1 (Strongly Disagree) to 5 (Strongly Agree)
Limited diagnostic capacity increases the overall cost of treating antimicrobial resistance infections in our hospital.	1 (Strongly Disagree) to 5 (Strongly Agree)
Our facility lacks the infrastructure needed for accurate antimicrobial resistance surveillance.	1 (Strongly Disagree) to 5 (Strongly Agree)
Targeted antibiotics are often used over broad-spectrum antibiotics.	1 (Strongly Disagree) to 5 (Strongly Agree)
Local supply shortages impact antibiotic selection in clinical practice.	1 (Strongly Disagree) to 5 (Strongly Agree)
Financial constraints affect patients' access to appropriate antibiotics.	1 (Strongly Disagree) to 5 (Strongly Agree)

Continued

Resource limitations (staffing, lab capacity, isolation rooms) increase the cost of treating antimicrobial resistance.	1 (Strongly Disagree) to 5 (Strongly Agree)
Antimicrobial resistance-related costs are underestimated in our region.	1 (Strongly Disagree) to 5 (Strongly Agree)
Antimicrobial resistance is a growing economic burden in my hospital and local community.	1 (Strongly Disagree) to 5 (Strongly Agree)
Socioeconomic vulnerabilities in local neighborhoods contribute to higher antimicrobial resistance incidence.	1 (Strongly Disagree) to 5 (Strongly Agree)
How often do you encounter diagnostic delays for suspected resistant infections?	● Never ● Rarely ● Sometimes ● Often ● Always
(If applicable) What are the major reasons for diagnostic delays (select all that apply)	● Lab staffing shortages ● Slow turnaround times ● Equipment limitations ● Insurance/financial barriers ● Other (free-text response field; responses were grouped into thematic categories during the recording analysis)
What is the most common barrier to prescribing targeted antibiotics?	● Pharmacy supply issues ● Insurance restrictions ● Time pressure ● Other (free-text response field; responses were grouped into thematic categories during the recording analysis)
Which infrastructure gaps most affect antimicrobial resistance management? (select all that apply)	● Limited infection control staffing ● Outdated or insufficient lab equipment ● Lack of a hospital-level surveillance system ● Limited patient follow-up resources ● Other (free-text response field; responses were grouped into thematic categories during the recording analysis)