

A Predictive Model Linking Food-Borne Heavy-Metal Exposure to Antimicrobial Resistance Co-Selection

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Abstract

This study has examined a predictive model linking food-borne heavy-metal exposure to antimicrobial resistance co-selection in a selected food-system case context. The problem has been that heavy-metal contamination and antimicrobial resistance are often studied separately, although contaminated food environments may create non-antibiotic selective pressure that supports resistant bacteria. The purpose of the study has been to test whether food-borne heavy-metal exposure, food contamination pathways, food safety monitoring weakness, and regulatory control have predicted antimicrobial resistance co-selection. The study has used a quantitative, cross-sectional, case-based research design with 220 valid respondents from food safety, public health, laboratory, agriculture, environmental monitoring, academic, and food industry-related sectors. Data have been collected through a structured questionnaire using Likert's five-point scale and analyzed through descriptive statistics, reliability testing, correlation analysis, and multiple regression modeling. The key variables have included food-borne heavy-metal exposure, food contamination pathways, food safety monitoring weakness, regulatory control, and antimicrobial resistance co-selection. The findings have shown that food contamination pathways have recorded the highest mean score of 3.94 with SD = 0.58, followed by food-borne heavy-metal exposure at 3.89 with SD = 0.62 and antimicrobial resistance co-selection at 3.87 with SD = 0.64. Food safety monitoring has recorded a moderate mean of 3.41, while regulatory control has recorded 3.36. Reliability has been strong, with Cronbach's alpha values ranging from 0.81 to 0.88 and overall reliability at 0.91. Correlation results have shown significant relationships between antimicrobial resistance co-selection and heavy-metal exposure ($r = 0.64$), contamination pathways ($r = 0.61$), monitoring weakness ($r = 0.49$), and regulatory control ($r = -0.43$), all at $p < 0.001$. Regression results have shown that the model has explained 57.4% of the variance in antimicrobial resistance co-selection, with $R^2 = 0.574$ and adjusted $R^2 = 0.566$. The study has implied that stronger food safety monitoring, contamination control, and regulatory enforcement can reduce co-selection risk in food systems.

Keywords

Food-Borne Heavy-Metal Exposure, Antimicrobial Resistance Co-Selection, Food Contamination Pathways, Food Safety Monitoring, Regulatory Control.

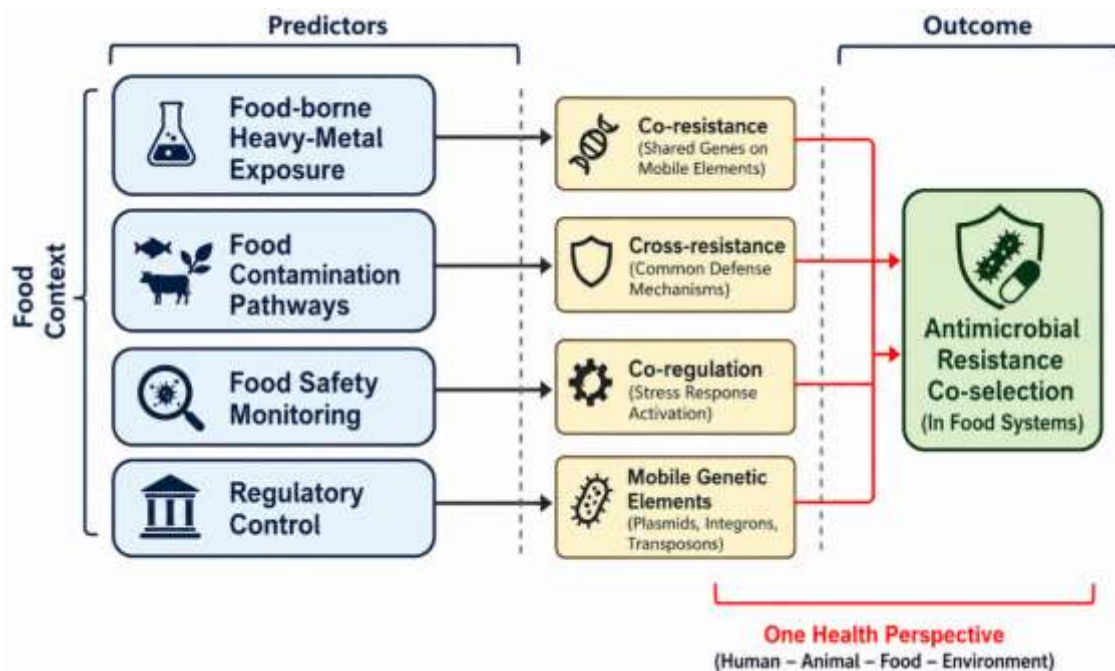
INTRODUCTION

Heavy metals are generally defined as metallic or metalloid elements with relatively high atomic weight, high density, environmental persistence, and toxic activity at low or moderate levels of exposure. In food safety and environmental health research, this category commonly includes arsenic, cadmium, lead, mercury, chromium, copper, zinc, nickel, and related elements when they produce toxicological, ecological, or public health risks through accumulation and long-term exposure (Jaishankar et al., 2014; Tchounwou et al., 2012). Food-borne heavy-metal exposure refers to the intake or contact of humans with these metals through contaminated food commodities, food ingredients, drinking water used for food preparation, animal-derived products, crops, seafood, processed foods, and food-contact materials that have accumulated contaminants through soil, water, feed, industrial emissions, fertilizers, pesticides, packaging, or processing environments (Khan et al., 2008; Rai et al., 2019). The international significance of food-borne heavy-metal exposure has increased because heavy metals are persistent, non-biodegradable, transferable across food chains, and capable of accumulating in edible tissues through plant uptake, animal feeding, aquatic bioaccumulation, and food-system handling (Harmanescu et al., 2011; Wuana & Okieimen, 2011). This issue has become especially important for countries where staple foods such as rice, vegetables, fish, meat, milk, grains, spices, and processed foods form daily dietary patterns and may carry contamination from agricultural or industrial sources (Clemens et al., 2013; Rai et al., 2019). Heavy-metal contamination is therefore not only an environmental pollution concern; it is also a food-chain hazard because metals present in soil, water, and production environments may enter food products and reach consumers through normal consumption practices (Khan et al., 2008; Satarug et al., 2010). In this study, food-borne heavy-metal exposure is treated as a measurable risk construct that includes perceived contamination sources, exposure pathways, monitoring weakness, and regulatory control within a selected case-study context. This definition is appropriate for a quantitative, cross-sectional, case-study-based study because respondents' perceptions can be translated into Likert-scale items and analyzed statistically. The toxicological importance of heavy metals has also been associated with oxidative stress, enzyme disruption, cellular damage, organ toxicity, and chronic health effects, which gives the topic clear public health relevance across international food systems (Jaishankar et al., 2014; Tchounwou et al., 2012).

Antimicrobial resistance is defined as the capacity of microorganisms to survive, grow, or multiply in the presence of antimicrobial agents that would normally inhibit or kill them. This resistance may occur through intrinsic characteristics, acquired mutations, horizontal gene transfer, efflux pump activity, enzymatic degradation, biofilm formation, reduced membrane permeability, and resistance genes located on plasmids, integrons, transposons, or other mobile genetic elements (Davies & Davies, 2010; Gillings, 2014). In food systems, antimicrobial resistance has become internationally significant because resistant bacteria and resistance genes can move from farms, animals, crops, aquaculture systems, food-processing environments, markets, and food handlers to consumers through food-chain transmission (Founou et al., 2016; Verraes et al., 2013). Food-borne antimicrobial resistance is therefore linked with public health, food quality, agricultural practice, animal production, environmental contamination, and consumer safety rather than being restricted to hospital or clinical settings (Verraes et al., 2013; Woolhouse et al., 2015). Research has shown that antimicrobial resistance may be promoted by antibiotic use in humans, livestock, and agriculture, while environmental reservoirs also contribute to resistance maintenance through exposure to antibiotics, metals, disinfectants, and other stressors (Berendonk et al., 2015; Martínez, 2009). The food chain represents a critical transmission route because raw, minimally processed, or poorly handled foods may carry resistant microorganisms, while resistance genes may remain present in food-associated microbial communities and move across human, animal, and environmental interfaces (Founou et al., 2016; Verraes et al., 2013). The One Health perspective is relevant because antimicrobial resistance involves interconnected human, animal, food, agricultural, and environmental compartments rather than one isolated source of risk (Bengtsson-Palme et al., 2018; Woolhouse et al., 2015). Antimicrobial resistance co-selection refers to the selection, survival, or maintenance of antimicrobial-resistant bacteria through non-antibiotic stressors, especially heavy metals and biocides, when resistance mechanisms are genetically or functionally linked (Baker-Austin et al., 2006; Seiler & Berendonk, 2012). This concept is central to the present research because it allows food-borne heavy-metal exposure to be examined as a predictor of antimicrobial resistance co-

selection even when antibiotic exposure is not the only selective force. Metals such as copper, zinc, cadmium, mercury, arsenic, and lead may create selective pressure in contaminated food-related environments, and bacteria that tolerate such metals may also carry antimicrobial resistance determinants (Baker-Austin et al., 2006; Wales & Davies, 2015).

Figure 1: Framework illustrating the relationship between food-borne heavy-metal exposure and antimicrobial resistance co-selection



The relationship between heavy metals and antimicrobial resistance co-selection can be understood through three major mechanisms: co-resistance, cross-resistance, and co-regulation. Co-resistance occurs when genes responsible for metal tolerance and antibiotic resistance are located together on the same mobile genetic element, allowing metal exposure to maintain antibiotic resistance genes even when antibiotics are absent or present at low levels (Baker-Austin et al., 2006; Pal et al., 2015). Cross-resistance occurs when the same physiological mechanism, such as an efflux pump, membrane modification, or permeability barrier, protects bacteria against more than one toxic compound, including metals and antimicrobial agents (Seiler & Berendonk, 2012; Wales & Davies, 2015). Co-regulation occurs when exposure to metals activates stress-response systems or regulatory pathways that also influence antibiotic resistance expression or bacterial survival under antimicrobial pressure (Baker-Austin et al., 2006; Seiler & Berendonk, 2012). These mechanisms provide a strong scientific foundation for linking food-borne heavy-metal exposure with antimicrobial resistance co-selection in a predictive model. Food environments may contain chemical contaminants and microbial populations at the same time, creating selective conditions in which resistant organisms may survive more successfully under repeated low-level exposure to toxic substances (Andersson & Hughes, 2014; Martínez, 2009). Environmental resistome research has also shown that resistance genes are not limited to hospitals or clinical pathogens because soil, water, manure, sediments, agricultural settings, and food-production environments contain diverse resistance genes and mobile elements (Forsberg et al., 2012; Perry & Wright, 2013). Heavy-metal pollution has particular importance in this context because metals do not degrade in the same way as many organic compounds, which means bacteria in contaminated environments may face continuous selection pressure across long periods (Baker-Austin et al., 2006; Seiler & Berendonk, 2012). This relationship becomes relevant to food-borne exposure when edible crops absorb metals from contaminated soil, aquaculture products accumulate metals from polluted water or sediment, livestock encounter copper and zinc through feed, and processing or packaging environments add further contamination sources (Khan et al., 2008; Rai et al., 2019; Wales &

[Davies, 2015](#)). A quantitative cross-sectional model can represent these mechanisms through measurable constructs such as perceived heavy-metal exposure, contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection.

Food-borne heavy-metal exposure occurs through several internationally recognized pathways that support the case-study orientation of this research. Agricultural soil may become contaminated through industrial emissions, mining activities, traffic deposition, wastewater irrigation, phosphate fertilizers, pesticides, sewage sludge, atmospheric fallout, and poor waste management, while crops grown in contaminated soil may accumulate cadmium, lead, arsenic, chromium, nickel, copper, zinc, and other metals in roots, leaves, grains, fruits, or edible tissues ([Khan et al., 2008](#); [Wuana & Okieimen, 2011](#)). Wastewater irrigation has received strong attention because it may support agricultural production while also transferring metals, microbial contaminants, and resistant organisms into soil-plant systems ([Harmanescu et al., 2011](#); [Khan et al., 2008](#)). Cereal crops, especially rice and wheat, are important in food-borne exposure research because they are staple foods in many countries and may accumulate arsenic, cadmium, or other metals under specific soil and water conditions ([Clemens et al., 2013](#); [Rai et al., 2019](#)). Fish and aquaculture products are also important because metals may accumulate in aquatic food chains, while aquatic environments may receive antibiotic residues, metals, resistant bacteria, and resistance genes from wastewater, agriculture, animal production, and industrial discharge ([Kümmerer, 2009](#); [Martínez, 2009](#)). Food-producing animals create another pathway because copper and zinc may be used in animal production systems, and repeated exposure to such metals may support co-selection among foodborne pathogens and commensal bacteria ([Wales & Davies, 2015](#)). Food processing, packaging, storage, transportation, and retail handling can add additional risk when contaminated water, unhygienic surfaces, poor traceability, or weak inspection allow chemical and microbial hazards to remain connected in the food chain ([Founou et al., 2016](#); [Verraes et al., 2013](#)). The case-study design of this research is appropriate because every food system has its own exposure pattern, agricultural inputs, market structure, monitoring capacity, regulatory practices, and public health context. A cross-sectional survey can capture these system-level perceptions by asking respondents to rate heavy-metal exposure, contamination routes, food monitoring strength, regulatory control, and perceived antimicrobial resistance co-selection. In this way, food-borne heavy-metal exposure becomes a multidimensional construct that is suitable for descriptive statistics, correlation analysis, and regression modeling rather than a single isolated chemical measurement.

The international relevance of antimicrobial resistance co-selection is closely connected with the environmental resistome, which refers to the total collection of antimicrobial resistance genes present in pathogenic and non-pathogenic microbial communities across natural, agricultural, industrial, and human-affected environments ([Davies & Davies, 2010](#); [Forsberg et al., 2012](#)). Environmental bacteria may carry resistance genes before they become clinically visible, and these genes may move into human-associated, animal-associated, or food-associated bacteria through horizontal gene transfer when ecological conditions support gene exchange ([Forsberg et al., 2012](#); [Perry & Wright, 2013](#)). Heavy metals are important in this context because they may maintain selective pressure in soils, sediments, water systems, livestock environments, aquaculture sites, and food-processing ecosystems where antibiotic residues may be absent or low ([Baker-Austin et al., 2006](#); [Seiler & Berendonk, 2012](#)). Evidence has shown that genes associated with resistance to antibiotics, biocides, and metals frequently co-occur in microbial genomes and metagenomes, supporting the idea that non-antibiotic stressors can help maintain antimicrobial resistance ([Pal et al., 2015](#)). Integrons, plasmids, insertion sequences, and transposons are also important because they provide genetic platforms for capturing, organizing, and transferring resistance determinants among bacteria across environmental and food-related compartments ([Gillings, 2014](#); [Stokes & Gillings, 2011](#)). Low-level selection is relevant because bacterial populations may respond to sublethal concentrations of stressors through mutation, selection, biofilm formation, and increased gene-transfer activity ([Andersson & Hughes, 2014](#); [Gullberg et al., 2011](#)). In food environments, this concept supports a predictive model in which repeated low-level contamination by heavy metals can be examined as a perceived driver of antimicrobial resistance co-selection. It also supports the inclusion of food contamination pathways as a separate predictor because soil, irrigation water, feed, processing, storage, and market-handling routes represent the practical movement of metals and resistant microorganisms through the food chain. Food safety monitoring and

regulatory control also become necessary predictors because laboratory testing, inspection, permissible-limit enforcement, traceability, reporting, and surveillance determine whether contamination risks are detected and controlled across food-system stages (Berendonk et al., 2015; Verraes et al., 2013). Therefore, antimicrobial resistance co-selection can be measured through Likert-scale items related to metal-induced selection pressure, co-resistance, cross-resistance, mobile genetic elements, biofilm survival, and food-chain transmission.

Food safety monitoring and regulatory control are central to the present research because heavy-metal contamination and antimicrobial resistance are both surveillance-dependent hazards. Heavy metals require laboratory detection, concentration assessment, comparison with permissible limits, source identification, and exposure evaluation, while antimicrobial resistance requires microbial testing, resistance profiling, gene detection, and integrated surveillance across human, animal, food, and environmental systems (Bengtsson-Palme et al., 2018; Berendonk et al., 2015). When food safety systems focus mainly on visible spoilage, conventional contamination, or routine microbial counts, the combined issue of chemical contamination and antimicrobial resistance co-selection may receive limited attention in food-chain risk assessment (Verraes et al., 2013; Wales & Davies, 2015). The One Health framework is highly relevant because it explains antimicrobial resistance as a shared problem across human health, animal health, food production, agriculture, water systems, and environmental contamination (Bengtsson-Palme et al., 2018; Woolhouse et al., 2015). Within this framework, food-borne heavy-metal exposure is not only a toxicological issue; it is also a resistance-selection issue because metals can connect environmental pollution, bacterial adaptation, and food-chain transmission (Baker-Austin et al., 2006; Seiler & Berendonk, 2012). Regulatory control is expected to have an important role because stronger permissible-limit enforcement, routine inspection, traceability, reporting transparency, and food safety governance reduce opportunities for contaminated food to move through markets without detection (Khan et al., 2008; Rai et al., 2019). Food safety monitoring can be measured through respondents' perceptions of laboratory testing, inspection regularity, contamination screening, food surveillance, reporting systems, and institutional capacity. Regulatory control can be measured through items related to legal enforcement, interagency coordination, market inspection, penalty systems, compliance monitoring, and public health governance. These variables allow the theoretical explanation of co-selection to be translated into measurable survey indicators. The present study therefore uses a quantitative, cross-sectional, case-study-based research design because knowledgeable respondents' perceptions can be converted into numerical data and analyzed through descriptive statistics, correlation analysis, and regression modeling. In the proposed model, food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control operate as predictors, while antimicrobial resistance co-selection operates as the dependent variable. This structure is consistent with environmental antimicrobial resistance research that emphasizes ecological, agricultural, food-chain, and environmental drivers of resistance beyond direct clinical antibiotic use (Huijbers et al., 2015; Martínez, 2009).

A predictive model linking food-borne heavy-metal exposure to antimicrobial resistance co-selection is necessary because existing literature has established biological plausibility, environmental relevance, and food-chain transmission pathways, yet many food-system settings still need quantitative models that organize contamination, monitoring, regulation, and co-selection into one empirical structure. Previous research has explained that metals may support antimicrobial resistance through co-resistance, cross-resistance, and co-regulation, while environmental studies have shown that resistance genes are widely present in soil, water, manure, sediment, agriculture, aquaculture, and human-affected ecosystems (Baker-Austin et al., 2006; Forsberg et al., 2012; Seiler & Berendonk, 2012). Food-chain studies have also shown that resistant bacteria and resistance genes can move through animal-derived foods, raw foods, minimally processed foods, food-processing environments, and consumer-contact pathways (Founou et al., 2016; Verraes et al., 2013). Heavy-metal food studies have shown that metals enter edible products through contaminated soil, irrigation water, wastewater, fertilizers, industrial discharge, animal feed, aquatic systems, and crop uptake, which supports the treatment of exposure as a food-system risk variable (Harmanescu et al., 2011; Khan et al., 2008; Rai et al., 2019). The present research synthesizes these streams by proposing that antimicrobial resistance co-selection can be statistically explained through food-borne heavy-metal exposure and related food safety variables.

Descriptive statistics can show the perceived level of each construct, correlation analysis can show the strength and direction of relationships among variables, and regression modeling can estimate the predictive contribution of each factor to antimicrobial resistance co-selection. Likert's five-point scale is suitable because it converts expert, professional, or informed respondent perceptions into measurable indicators such as agreement with statements about metal contamination, food-chain exposure, weak monitoring, regulatory enforcement, and resistance co-selection. The case-study orientation is also suitable because contamination routes, food safety practices, laboratory capacity, and regulatory enforcement differ across settings. The research problem is therefore positioned at the intersection of food toxicology, environmental microbiology, antimicrobial resistance, food-chain surveillance, and public health governance. It treats heavy metals not only as dietary toxicants but also as ecological stressors that may maintain or amplify antimicrobial resistance in food-associated microbial communities. This integrated foundation supports the statistical testing of whether food-borne heavy-metal exposure, contamination pathways, food safety monitoring, and regulatory control significantly predict antimicrobial resistance co-selection in the selected case-study context.

Background of the study

Food-borne heavy-metal exposure has become a critical concern in food safety, environmental health, and antimicrobial resistance research because food systems now operate within complex agricultural, industrial, processing, and market environments where chemical and microbial hazards may interact. Heavy metals such as arsenic, cadmium, lead, mercury, chromium, copper, zinc, and nickel can enter the food chain through contaminated soil, polluted irrigation water, industrial discharge, fertilizers, pesticides, animal feed, aquaculture systems, processing equipment, packaging materials, and poor storage or market-handling practices. Once these metals enter food products, they can remain persistent because they are not easily degraded or removed through ordinary environmental processes. At the same time, antimicrobial resistance has become a major public health challenge because bacteria can survive antimicrobial treatment through genetic adaptation, mutation, horizontal gene transfer, efflux pump activity, biofilm formation, and mobile resistance genes. The link between food-borne heavy-metal exposure and antimicrobial resistance co-selection is important because heavy metals may create selective pressure that allows metal-tolerant bacteria to survive, and some of these bacteria may also carry antimicrobial resistance traits. This means that contaminated food environments may support the persistence of resistant microorganisms even when antibiotics are not the only direct pressure. The present study is therefore developed around the idea that heavy-metal exposure in the food chain should not be viewed only as a toxicological problem for consumers but also as a possible ecological driver of antimicrobial resistance co-selection. Since food systems include production, processing, distribution, retailing, and consumption stages, the risk may be shaped by multiple factors, including contamination pathways, food safety monitoring, regulatory control, and public awareness. A quantitative, cross-sectional, case-study-based approach is suitable for examining this issue because it allows the researcher to measure respondents' perceptions of heavy-metal exposure, contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection through Likert's five-point scale. Through descriptive statistics, correlation analysis, and regression modeling, the study can identify the level of perceived risk, examine relationships among the variables, and test whether food-borne heavy-metal exposure and related food safety factors significantly predict antimicrobial resistance co-selection.

Problem statement

The main problem addressed in this study is the limited quantitative understanding of how food-borne heavy-metal exposure may contribute to antimicrobial resistance co-selection within food systems. Heavy-metal contamination and antimicrobial resistance are often examined as separate public health or environmental problems, yet food systems may create conditions where chemical contamination and microbial resistance interact. Heavy metals can enter food through contaminated soil, polluted water, animal feed, fertilizers, pesticides, aquaculture environments, processing systems, packaging, and market handling. At the same time, resistant bacteria and resistance genes may move through food-producing animals, crops, seafood, raw foods, processed foods, and food-contact environments. When these two hazards overlap, heavy metals may act as selective agents that support the survival of bacteria carrying metal-resistance and antimicrobial-resistance traits. This creates a serious research

problem because many food safety systems focus mainly on chemical limits, visible contamination, routine microbial quality, or antibiotic misuse, while the co-selection relationship between heavy metals and antimicrobial resistance may remain under-assessed. In many case-study settings, there may also be weak laboratory testing, irregular food inspection, limited traceability, poor reporting systems, weak enforcement of permissible limits, and insufficient coordination among food safety, public health, agricultural, and environmental authorities. These weaknesses can allow contaminated food products to move through the food chain without proper detection. The problem becomes more serious because consumers may be exposed to contaminated foods repeatedly through daily diets, while bacteria in food-related environments may face continuous low-level metal pressure. However, without a predictive model, it becomes difficult to determine whether food-borne heavy-metal exposure, contamination pathways, food safety monitoring, and regulatory control significantly explain antimicrobial resistance co-selection. Therefore, this study responds to the need for a structured quantitative model that can measure these relationships using survey-based evidence. By applying descriptive statistics, correlation analysis, and regression modeling, the study seeks to examine whether the selected food safety variables can statistically predict antimicrobial resistance co-selection in the chosen case-study context.

Objectives of the study

The objective of this study is to develop and test a predictive model that links food-borne heavy-metal exposure with antimicrobial resistance co-selection in a selected case-study context. The study aims to measure how respondents perceive the level of heavy-metal exposure in food systems and how such exposure may be associated with microbial resistance risk. The first objective is to assess the perceived level of food-borne heavy-metal exposure by examining respondents' views on contamination sources such as soil, irrigation water, industrial discharge, fertilizers, pesticides, animal feed, aquaculture systems, processing equipment, packaging materials, storage, and market handling. The second objective is to evaluate food contamination pathways as a measurable construct that explains how heavy metals may move from environmental and agricultural sources into edible food products. The third objective is to examine the perceived level of food safety monitoring, including laboratory testing, inspection frequency, contamination screening, reporting systems, traceability, and surveillance capacity. The fourth objective is to assess regulatory control by examining respondents' perceptions of enforcement strength, permissible-limit monitoring, institutional coordination, market inspection, penalty systems, and compliance practices. The fifth objective is to measure antimicrobial resistance co-selection as the dependent variable by focusing on perceived metal-induced bacterial selection, co-resistance, cross-resistance, mobile genetic elements, biofilm survival, and food-chain transmission. The sixth objective is to determine the relationships among food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection through correlation analysis. The seventh objective is to test the predictive effects of the independent variables on antimicrobial resistance co-selection through regression modeling. These objectives are aligned with the quantitative, cross-sectional, and case-study-based nature of the research because each variable can be measured through Likert's five-point scale and analyzed statistically. Through these objectives, the study intends to provide a clear empirical structure for understanding whether food-borne heavy-metal exposure and related food safety factors significantly explain antimicrobial resistance co-selection within the selected research setting.

Research hypotheses

The research hypotheses of this study are developed to test the predictive relationship between food-borne heavy-metal exposure and antimicrobial resistance co-selection. Since the study is quantitative and based on Likert-scale measurement, each hypothesis is designed to examine whether the selected independent variables have a statistically significant relationship with the dependent variable. The first hypothesis states that food-borne heavy-metal exposure has a significant positive effect on antimicrobial resistance co-selection. This means that higher perceived exposure to heavy metals in food is expected to be associated with higher perceived antimicrobial resistance co-selection risk. The second hypothesis states that food contamination pathways have a significant positive effect on antimicrobial resistance co-selection. This means that stronger contamination routes through soil, water, feed, processing, storage, packaging, and market handling are expected to increase the perceived

possibility of resistance co-selection. The third hypothesis states that weak food safety monitoring has a significant positive effect on antimicrobial resistance co-selection. This means that lower levels of testing, inspection, traceability, reporting, and surveillance are expected to increase the risk of undetected heavy-metal contamination and related resistance pressure. The fourth hypothesis states that regulatory control has a significant negative effect on antimicrobial resistance co-selection. This means that stronger enforcement, better monitoring of permissible limits, improved inspection, stronger institutional coordination, and better compliance systems are expected to reduce the risk of antimicrobial resistance co-selection. The fifth hypothesis states that food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control jointly predict antimicrobial resistance co-selection. This combined hypothesis reflects the main predictive model of the study. These hypotheses allow the researcher to move beyond descriptive explanation and statistically test whether the proposed variables explain meaningful variation in antimicrobial resistance co-selection. The hypotheses can be tested through correlation analysis and multiple regression analysis, where significance levels, beta coefficients, t-values, p-values, R, R², adjusted R², and model-fit indicators can be used to accept or reject the proposed relationships.

Significance of the research

- i. The research is significant for food safety knowledge because it connects heavy-metal contamination with antimicrobial resistance co-selection within one predictive model. This helps explain food safety risk as a combined chemical and microbial issue rather than a single-hazard concern.
- ii. The research is significant for public health because food-borne heavy-metal exposure may affect consumers through repeated dietary intake, while antimicrobial resistance may reduce the effectiveness of treatment when resistant bacteria move through food systems. Studying both issues together provides a stronger understanding of hidden food-chain risks.
- iii. The research is significant for environmental health because heavy metals originate from soil pollution, water contamination, industrial discharge, agricultural inputs, waste disposal, and aquaculture systems. By linking environmental contamination with microbial resistance, the study highlights the environmental dimension of food-borne antimicrobial resistance.
- iv. The research is significant for food safety authorities because it identifies the role of monitoring, inspection, traceability, testing, and regulatory control in reducing contamination and resistance-related risks. The findings can help authorities understand which food safety areas require stronger attention in the selected case-study context.
- v. The research is significant for researchers because it offers a quantitative model that can be tested through descriptive statistics, correlation analysis, and regression modeling. This model can help organize complex variables such as heavy-metal exposure, contamination pathways, monitoring weakness, regulatory control, and antimicrobial resistance co-selection.
- vi. The research is significant for food producers and supply-chain actors because it shows how agricultural practices, animal feed, processing environments, packaging, storage, and market handling may contribute to contamination and resistance-related risks. This can support safer food production and handling practices.
- vii. The research is significant for policy and governance because it supports an integrated view of food safety, public health, agriculture, and environmental regulation. The study can encourage stronger coordination among institutions responsible for food monitoring, environmental protection, antimicrobial resistance surveillance, and consumer safety.

LITERATURE REVIEW

The literature on food-borne heavy-metal exposure and antimicrobial resistance co-selection has developed across several related fields, including food toxicology, environmental microbiology, antimicrobial resistance research, food safety governance, agricultural contamination, and public health surveillance. Heavy-metal exposure has commonly been examined as a food-chain problem because metals may enter edible products through contaminated soil, polluted irrigation water, industrial discharge, animal feed, aquaculture environments, pesticides, fertilizers, food processing, storage, packaging, and market handling. Antimicrobial resistance has also been widely studied as a public health threat associated with resistant bacteria, resistance genes, antibiotic misuse, food-producing animals, agricultural systems, wastewater, and environmental reservoirs. A growing body

of literature has connected these two areas through the concept of co-selection, where heavy metals may create selective pressure that supports the survival of bacteria carrying both metal-resistance and antimicrobial-resistance traits. This relationship is usually explained through co-resistance, cross-resistance, and co-regulation mechanisms. Co-resistance occurs when metal-resistance and antibiotic-resistance genes are located together on the same mobile genetic element. Cross-resistance occurs when one bacterial mechanism, such as an efflux pump, protects the organism against both metals and antimicrobial agents. Co-regulation occurs when stress-response systems activated by metals also influence antimicrobial resistance expression. The literature also emphasizes that food systems provide important pathways for this problem because crops, seafood, meat, dairy products, processed foods, and raw foods may carry both chemical contaminants and microbial hazards. Food safety monitoring and regulatory control have therefore become important areas of review because testing, inspection, traceability, permissible-limit enforcement, and surveillance determine whether contamination risks are identified and controlled. The theoretical foundation of the study can be developed through the One Health framework because the research connects human health, animal health, food production, environmental contamination, and antimicrobial resistance. The conceptual foundation can be developed by linking food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control with antimicrobial resistance co-selection. Therefore, the literature review will examine the major scientific and practical debates that support the development of a predictive model for this research.

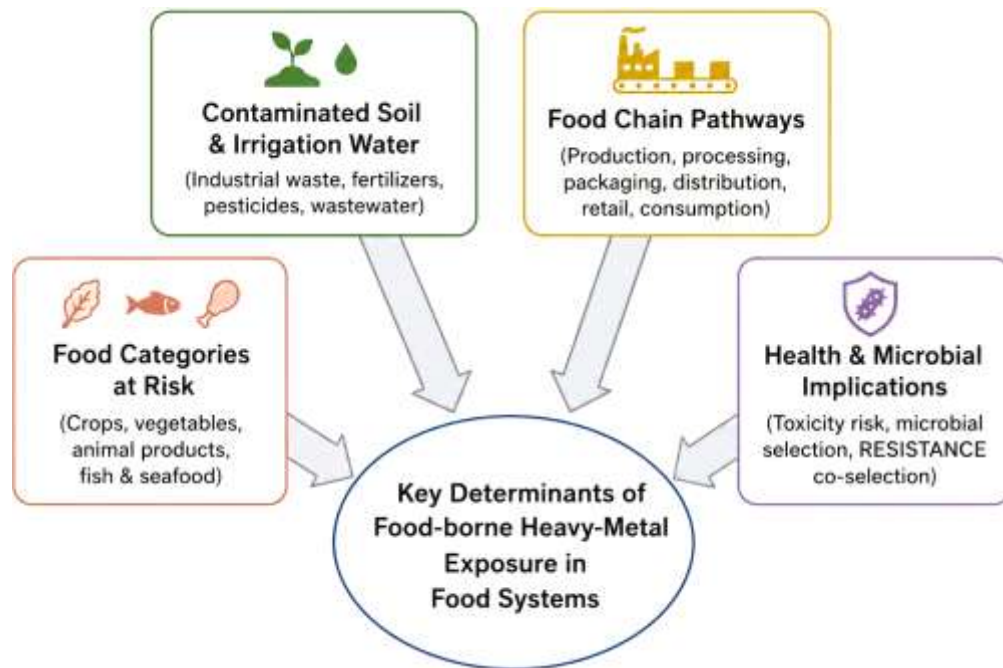
Food-borne heavy-metal exposure in modern food systems

Food-borne heavy-metal exposure refers to the intake of toxic metals and metalloids through edible food items that have absorbed, accumulated, or carried contaminants from environmental, agricultural, industrial, processing, or market-related sources. In modern food systems, this exposure has become a serious issue because food production is closely connected with soil quality, irrigation water, fertilizers, pesticides, animal feed, wastewater discharge, industrial activity, aquaculture conditions, packaging materials, transportation, and storage systems. Heavy metals such as arsenic, cadmium, lead, mercury, chromium, nickel, copper, and zinc may enter food chains through polluted soil and water and may remain in the environment for long periods because they are persistent and non-biodegradable. When crops are cultivated in contaminated areas, metals may be transferred from soil to roots, stems, leaves, grains, fruits, or vegetables, and the level of transfer may depend on soil pH, organic matter, crop type, irrigation source, and metal concentration. Animal-derived foods may also become contaminated when livestock consume polluted feed or water, while fish and seafood may accumulate metals from contaminated aquatic environments. This makes food-borne heavy-metal exposure a multi-source problem rather than a single-pathway issue. The modern food chain also increases exposure complexity because food may pass through production, processing, packaging, distribution, retailing, and consumption stages before reaching consumers. A systematic review on food-web contamination in Bangladesh has shown that heavy metals can move through multiple trophic levels and create dietary exposure risks through several food categories, including crops, fish, and animal products, which is highly relevant for case-study-based food safety research in countries with intensive agriculture and aquatic food consumption (Islam et al., 2022).

The literature also shows that vegetables and crops are among the most important carriers of food-borne heavy-metal exposure because they are directly linked with soil, irrigation water, atmospheric deposition, fertilizers, and local farming practices. Vegetables are nutritionally important because they are consumed regularly, yet leafy and root vegetables may accumulate heavy metals more easily than some other food categories due to direct contact with contaminated soil and irrigation water. This creates concern for long-term dietary exposure because consumers may unknowingly take in low or moderate concentrations of metals over repeated meals. Heavy-metal contamination in vegetables has been reviewed as a global food security and public health problem because contamination can reduce food quality while increasing non-carcinogenic and carcinogenic health risks among exposed populations (Kumar et al., 2022). Another study on heavy-metal transfer in a soil-food chain showed that farmland contamination can be linked with concentrations of arsenic, lead, cadmium, mercury, and chromium in food items such as rice, maize, and cabbage, and the study used regression equations to estimate transfer relationships between soil and food crops (Li et al., 2022). This evidence is especially

important for the present research because it supports the idea that food-borne heavy-metal exposure can be treated as a measurable and predictive construct. The movement of metals from soil into food does not occur randomly; it can be influenced by measurable factors such as soil contamination level, food type, cultivation conditions, and environmental setting. Therefore, in a quantitative study, respondents' perceptions about contaminated soil, polluted irrigation water, industrial waste, fertilizers, pesticides, aquaculture systems, and food handling can be converted into Likert-scale indicators. These indicators can then be analyzed through descriptive statistics, correlation analysis, and regression modeling to understand how perceived exposure contributes to broader food safety risks.

Figure 2: Framework of food-borne heavy-metal exposure across the food chain

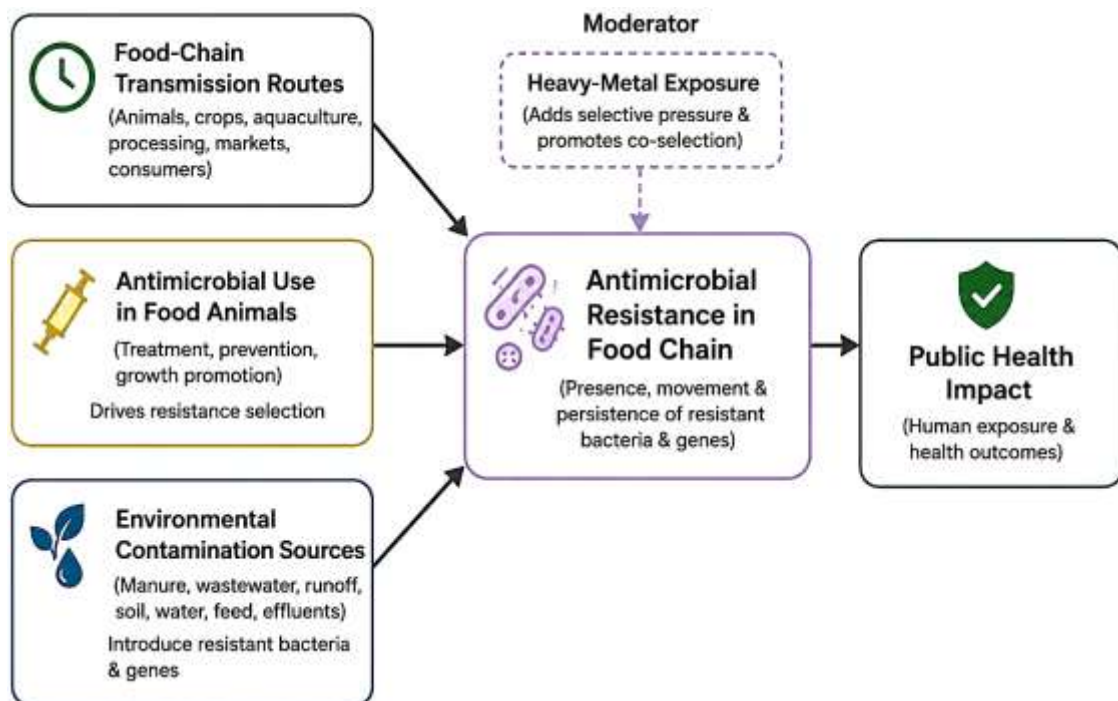


Food-borne heavy-metal exposure also needs to be reviewed through the lens of health-risk assessment because dietary exposure is not only about the presence of metals in food but also about the amount consumed, frequency of consumption, body weight, exposure duration, and vulnerability of the exposed population. Studies around mining and industrial areas have shown that agricultural soils and harvested crops may contain heavy metals at levels that require probabilistic health-risk assessment, especially when local populations depend heavily on nearby agricultural products for daily consumption (Zhao et al., 2022). Natural foods have also been discussed as important exposure carriers because metals such as chromium, cadmium, copper, lead, and mercury may appear in commonly consumed food products and may affect food quality, food security, and human health when contamination is not properly monitored (Sardar et al., 2022). These findings are relevant to antimicrobial resistance co-selection because heavy metals do not only create direct toxicological risks for consumers; they may also create selective environments for microorganisms in soil, water, food-processing areas, and food products. When bacteria are repeatedly exposed to metals in food-related environments, metal-tolerant strains may survive more successfully, and some of these strains may carry genetic traits related to antimicrobial resistance. This means food-borne heavy-metal exposure can be understood as part of a wider ecological and microbiological risk system. For the present study, this section supports the inclusion of food-borne heavy-metal exposure as the main independent variable. It also supports the inclusion of food contamination pathways, food safety monitoring, and regulatory control as related explanatory variables. Since exposure may arise from multiple points across the food chain, a case-study-based quantitative model can help identify how respondents perceive the strength of exposure sources and how these perceptions are associated with antimicrobial resistance co-selection risk.

Antimicrobial resistance and food-chain transmission

Antimicrobial resistance in the food chain refers to the presence, movement, and persistence of antimicrobial-resistant bacteria and antimicrobial resistance genes across food-producing animals, crops, aquaculture systems, food-processing environments, distribution channels, retail markets, and consumers (Hasan & Uddin, 2022; Abdur & Iftekhar, 2021). This topic has become important in food safety research because food is not only a source of nutrition but also a possible carrier of resistant microorganisms that originate from farms, animal production systems, environmental reservoirs, slaughterhouses, processing plants, storage systems, and market environments. Food-producing animals may carry resistant bacteria in their intestinal tract, skin, respiratory system, or production environment, and these organisms may contaminate meat, milk, eggs, or other animal-derived foods during rearing, slaughtering, processing, transportation, and handling. Resistant microorganisms may also enter crop systems through manure, wastewater irrigation, contaminated soil, polluted water, and agricultural inputs. The food chain therefore works as a transmission bridge between environmental contamination, agricultural practices, animal health, human exposure, and public health outcomes. The use of antimicrobials in food animals has been repeatedly identified as a major contributor to resistance selection because antimicrobials may be applied for treatment, disease prevention, or growth promotion in some production systems, creating conditions where resistant organisms survive and spread through food-related pathways (Marshall & Levy, 2011). This is highly relevant to the present study because heavy-metal exposure may interact with the same food-chain environments where antimicrobial resistance is already being selected and transmitted. When chemical contaminants and resistant bacteria exist in the same food-system settings, the risk of co-selection becomes more meaningful. Therefore, antimicrobial resistance in food systems should be understood as a biological, environmental, agricultural, and food safety problem that moves through interconnected stages rather than remaining limited to clinical treatment failure alone.

Figure 3: Key determinants of antimicrobial resistance in food systems



The food-chain transmission of antimicrobial resistance is strongly connected with the scale and intensity of modern food production. Large-scale livestock farming, poultry production, aquaculture, crop production, and food distribution systems may increase the movement of bacteria and resistance genes across farms, transport routes, processing facilities, markets, and consumers. Global analysis of antimicrobial consumption in food animals has shown that animal production has been associated with substantial antimicrobial use, especially in intensive production systems where large animal

populations are managed under commercial pressure (Hossan, 2024; Boeckel et al., 2015). This issue is important because resistant bacteria selected in animal production may contaminate food products through fecal shedding, slaughterhouse contamination, cross-contamination, water use, equipment surfaces, and human handling. Once resistant bacteria enter the food chain, they may reach consumers through raw, undercooked, minimally processed, or improperly handled foods. The agri-food chain has also been reviewed as a complex pathway where antimicrobial resistance may move through animals, plants, soil, water, waste, feed, processing environments, and food-contact surfaces, making it difficult to separate food safety from environmental and agricultural management (Hudson et al., 2017; Mohiul & Badrul, 2022; Kanti & Rony, 2022). This relationship supports the present research because food-borne heavy-metal exposure may occur through many of the same routes, including soil, irrigation water, animal feed, aquaculture systems, food processing, and market handling. As a result, the food chain may act as a shared pathway for chemical contaminants and antimicrobial-resistant microorganisms. When heavy metals are present in food-production environments, they may add another selective pressure that supports resistant bacterial survival. Therefore, food-chain transmission is not only a question of antibiotic residues or resistant pathogens in food but also a broader question of how different environmental stressors shape microbial survival across production-to-consumption systems.

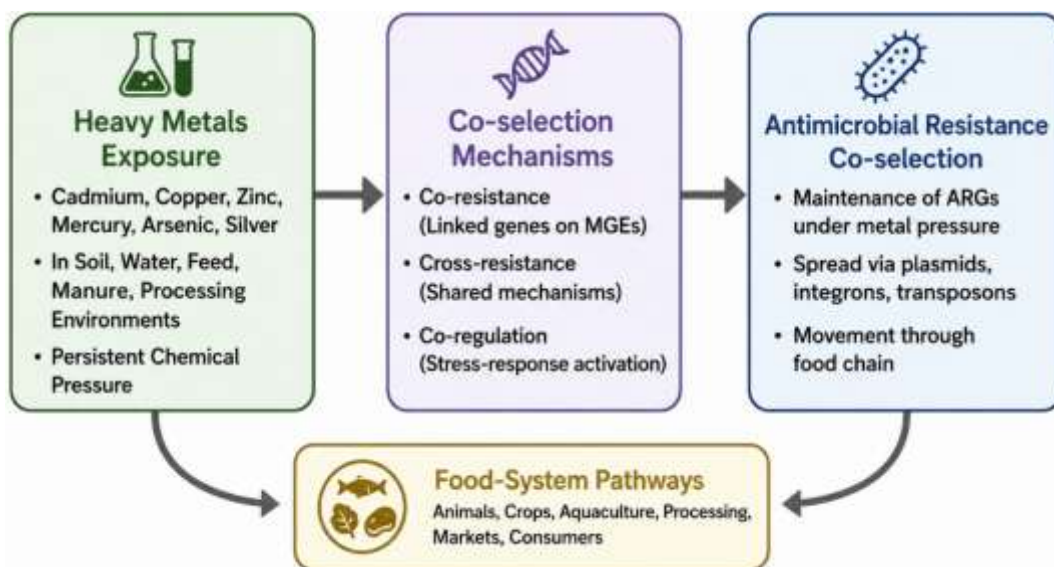
Antimicrobial resistance in the food chain is also shaped by environmental contamination, waste movement, and weak control points across production systems. Agricultural environments may receive resistant bacteria and resistance genes through animal manure, farm runoff, wastewater, untreated effluents, and contaminated soil amendments. These materials may carry antimicrobial residues, resistant bacteria, and mobile genetic elements into soil and water systems, where they can interact with food crops, livestock, aquaculture products, and food-processing environments. The connection between agriculture, environmental sources, and public health has been emphasized because antimicrobial use in agriculture may contribute to resistance patterns that extend beyond the farm and reach water bodies, soil ecosystems, food products, and human communities (Manyi-Loh et al., 2018). Food animals have also been identified as an important source of antimicrobial-resistant bacteria because resistant organisms may emerge in animal production environments and then move to humans through direct contact, contaminated food, or environmental release (Economou & Gousia, 2015). These findings are important for this study because the proposed predictive model is not limited to antibiotic use; it examines whether food-borne heavy-metal exposure can contribute to antimicrobial resistance co-selection through food-system pathways. Heavy metals may persist in soil, water, feed, and processing environments, while antimicrobial-resistant bacteria may survive in similar settings. This overlap creates the possibility that food-chain environments exposed to metals may also support the maintenance of bacteria carrying antimicrobial resistance traits (Shima Ali et al., 2024). Therefore, antimicrobial resistance and food-chain transmission provide a necessary foundation for understanding why food-borne heavy-metal exposure should be examined as a predictor of antimicrobial resistance co-selection. In the present study, this literature supports the inclusion of antimicrobial resistance co-selection as the dependent variable and strengthens the rationale for measuring contamination pathways, food safety monitoring, and regulatory control as important explanatory variables.

Heavy metals and antimicrobial resistance co-selection mechanisms

Heavy metals and antimicrobial resistance co-selection are closely connected because bacteria can develop or maintain resistance traits under chemical pressure that does not directly come from antibiotics. Co-selection occurs when exposure to one type of stressor, such as cadmium, copper, zinc, mercury, arsenic, or silver, supports the survival of bacteria that also carry antimicrobial resistance traits. This process is highly relevant to food-borne heavy-metal exposure because food systems often contain environmental, agricultural, animal-production, aquaculture, processing, and market pathways where metals and microorganisms may occur together. Heavy metals are persistent in soil, water, sediment, manure, feed, and processing environments, and bacteria exposed to these metals may develop tolerance through genetic and biochemical mechanisms. The most common explanation of co-selection includes co-resistance, cross-resistance, and co-regulation. Co-resistance occurs when metal-resistance genes and antibiotic-resistance genes are physically linked on the same plasmid, transposon,

integron, or other mobile genetic element. Cross-resistance occurs when one bacterial mechanism, such as an efflux pump or membrane modification, reduces susceptibility to both metals and antibiotics. Co-regulation occurs when stress-response pathways activated by metal exposure also increase the expression or survival value of antimicrobial resistance mechanisms. A complete genome-based analysis showed that antibiotic-resistance genes and metal-resistance genes can co-occur across bacterial genomes, supporting the idea that metals can indirectly contribute to resistance maintenance through genetic association and shared microbial adaptation systems (Li et al., 2017). This evidence is important for the present study because food-borne heavy-metal exposure can be treated as more than a toxicological risk. It can also be treated as a microbial selection factor that may support resistant bacteria in contaminated food-related environments. Therefore, the mechanism of co-selection provides the biological basis for examining whether perceived food-borne heavy-metal exposure predicts antimicrobial resistance co-selection in a quantitative model.

Figure 4: Mechanisms linking heavy metals to antimicrobial resistance co-selection



The role of mobile genetic elements is especially important in explaining how heavy metals may contribute to antimicrobial resistance co-selection. Plasmids, integrons, transposons, insertion sequences, and gene cassettes can carry several resistance determinants at the same time, allowing bacteria to maintain antibiotic-resistance genes when metal-resistance genes are selected by heavy-metal exposure. In food-producing animals, this mechanism is highly relevant because metals such as copper and zinc may be present in feed or production environments, while resistant bacteria may also carry genes linked with clinically important antimicrobial resistance. A study of *Escherichia coli* from food-producing animals found metal-resistance operons and antibiotic-resistance genes located on ST3-IncHI2 plasmids, showing that metal and antibiotic resistance may spread together through plasmid-mediated transfer in bacteria associated with animal production (Fang et al., 2016). This type of finding strengthens the logic of the present research because food systems connect animal production, slaughtering, processing, packaging, retailing, and consumption, creating many points where resistant organisms may move. The same mechanism can also apply to soil and plant-based foods when bacteria in contaminated agricultural settings carry resistance genes that may be maintained under metal pressure. Short-term copper exposure in agricultural soil has been shown to increase the abundance and diversity of antibiotic-resistance genes and mobile genetic elements, indicating that copper stress can influence both resistance profiles and horizontal-transfer potential in soil bacterial communities (Kang et al., 2018). This is directly relevant to food-borne exposure because soil is one of the first points of contact between heavy metals and crop-associated microorganisms. When contaminated soil supports bacteria with metal and antibiotic resistance traits, the food chain may become a pathway for both chemical contaminants and microbial resistance determinants. Therefore, mobile genetic elements

provide an important mechanistic explanation for why heavy-metal exposure should be included as a predictive variable in antimicrobial resistance co-selection research.

Heavy-metal-driven co-selection also depends on the type of metal, exposure duration, microbial community structure, environmental matrix, and interaction with other contaminants. Long-term contaminated environments may create stronger microbial adaptation because bacteria repeatedly exposed to metals may retain metal-resistance genes and associated antibiotic-resistance genes. In a copper tailing dam area, bacterial heavy-metal resistance genes and antibiotic-resistance genes were found to co-occur in soils affected by long-term metal contamination, and cadmium was identified as an important factor associated with metal-resistance gene abundance (Chen et al., 2019). This indicates that metal-contaminated environments can shape microbial resistance patterns through chronic selective pressure. Co-selection can also occur under combined contamination, where metals and antibiotics are present together in water, soil, manure, or wetland systems. A study on ditch wetlands found that cadmium and doxycycline together influenced antibiotic-resistance genes, metal-resistance genes, mobile genetic elements, and bacterial community structures, showing that mixed chemical pressure may increase resistance-gene dissemination under environmental conditions (Yu et al., 2022). This evidence supports the current research model because food systems may receive combined inputs from wastewater, manure, aquaculture discharge, industrial pollution, fertilizers, and agricultural runoff. These inputs may create contamination pathways where metals and resistant bacteria interact before reaching crops, animals, fish, processed foods, or market environments. For this reason, antimicrobial resistance co-selection should be understood as a food-system process rather than only a laboratory or clinical phenomenon. The present study can measure this process through Likert-scale indicators related to metal-induced selection pressure, co-resistance, cross-resistance, mobile genetic elements, biofilm survival, microbial adaptation, and food-chain movement. The regression-based model can then test whether food-borne heavy-metal exposure and contamination pathways significantly explain antimicrobial resistance co-selection.

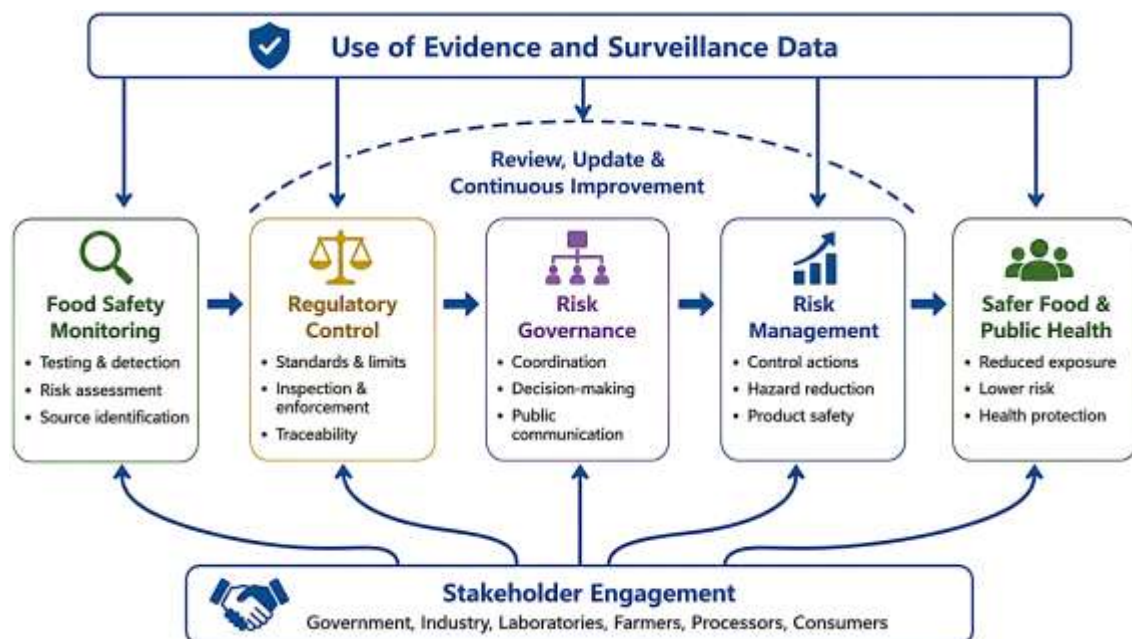
Food safety monitoring and risk governance

Food safety monitoring refers to the organized process of detecting, measuring, reporting, and controlling hazards that may enter food systems through environmental, agricultural, animal, processing, storage, transport, retail, and consumption pathways. In the context of food-borne heavy-metal exposure, monitoring includes laboratory testing of metals in crops, fish, meat, dairy products, processed foods, drinking water, soil, irrigation sources, animal feed, and food-contact materials. It also includes the comparison of detected metal concentrations with permissible limits, the identification of contamination sources, and the classification of risk according to exposure level, food consumption pattern, and vulnerability of consumers. Regulatory control refers to the rules, enforcement systems, inspection activities, traceability mechanisms, reporting procedures, and institutional responsibilities that determine whether contaminated food is prevented from reaching consumers. Risk governance connects these two areas by organizing how scientific evidence, legal standards, institutional capacity, public communication, and food-chain accountability are used to manage food hazards. This is important for the present study because food-borne heavy-metal exposure cannot be understood only by identifying the presence of metals in food; it also requires attention to whether food safety systems can detect, report, and control such contamination before it becomes a public health concern. Probabilistic risk assessment has shown that heavy-metal exposure through food crops can be evaluated through dietary intake, target hazard quotient, hazard index, Monte Carlo simulation, and heavy-metal pollution index, which supports the need for systematic monitoring rather than simple presence-or-absence assessment (Sanaei et al., 2021). This evidence is relevant to the proposed predictive model because respondents' perceptions of monitoring strength can be measured through Likert-scale items related to testing regularity, inspection capacity, reporting transparency, laboratory access, traceability, and contamination control. If monitoring is weak, heavy-metal exposure may remain undetected across production and market stages, creating conditions where contaminated foods and exposed microbial communities continue to circulate through the food chain.

Regulatory control is also essential for antimicrobial resistance co-selection because food safety hazards do not move only within local production systems; they also move through domestic markets, imports, exports, processing industries, and global supply chains. Antimicrobial resistance in the food chain has

been discussed as a One Health and trade-related issue because food production, food safety standards, antimicrobial use, international commerce, and regulatory negotiation are connected across national and global levels (George, 2019). This is relevant to the present study because heavy-metal contamination and antimicrobial resistance co-selection both require coordinated control across agriculture, environment, food safety, veterinary health, and public health sectors. A food system may have laboratory rules and permissible limits, but weak enforcement, poor inspection, limited surveillance, and low institutional coordination can reduce the practical value of those rules. Regulatory control therefore includes more than written standards; it includes the ability of institutions to implement testing, remove unsafe products, regulate inputs, monitor animal feed, control wastewater use, inspect processing environments, enforce penalties, and communicate risk. In antimicrobial resistance surveillance, whole-genome sequencing and whole-metagenome sequencing have been presented as important tools for tracking resistant microorganisms and resistance genes across the food chain, because these tools can identify genetic resistance patterns, transmission links, and emerging hazards more precisely than conventional monitoring alone (Oniciuc et al., 2018). This shows that food safety monitoring is increasingly data-driven, laboratory-dependent, and intersectoral. For the current research, this literature supports the inclusion of food safety monitoring and regulatory control as separate explanatory variables. Monitoring represents the technical and operational capacity to detect risks, while regulatory control represents the governance capacity to enforce standards and reduce unsafe exposure. In a regression-based model, these variables can help explain why similar levels of food-borne heavy-metal exposure may produce different levels of perceived antimicrobial resistance co-selection risk across different food-system contexts.

Figure 5: Integrated framework for food safety monitoring and risk governance



Risk governance further requires integration between surveillance evidence, food-chain accountability, and public health decision-making. A food safety system becomes stronger when surveillance data are not only collected but also used for outbreak detection, risk classification, product control, inspection planning, regulatory decisions, and public communication. Foodborne disease surveillance has shown economic and health value because molecular surveillance networks can improve outbreak detection, guide public health action, and strengthen regulatory response in food systems (Scharff et al., 2016). This logic is highly relevant to heavy-metal exposure and antimicrobial resistance co-selection because both hazards require early detection and coordinated response before risks become widespread. In the globalized food chain, antimicrobial resistance control also requires One Health governance because resistant organisms and resistance genes can move through humans, animals, food, water, soil, and

international trade systems. A review of antimicrobial resistance in the globalized poultry chain has emphasized that food animal production, food supply globalization, public health risk, and One Health coordination are closely linked, especially where animal protein supply and food trade expand across regions (de Mesquita Souza Saraiva et al., 2022). The same governance logic can be applied to food-borne heavy-metal exposure because contamination may originate from environmental pollution, agricultural practices, animal feed, aquaculture systems, industrial discharge, or processing systems. Therefore, risk governance in this study refers to the combined ability of monitoring systems, regulatory institutions, and food-chain actors to identify and manage contamination pathways that may support antimicrobial resistance co-selection. In the proposed model, strong monitoring and strong regulatory control are expected to reduce perceived co-selection risk, while weak monitoring may increase the chance that heavy-metal exposure and resistant microbial communities remain unaddressed. This section therefore supports the study's quantitative structure by showing why food safety monitoring and regulatory control should be measured alongside food-borne heavy-metal exposure and contamination pathways.

Theoretical framework

The theoretical framework of this study is grounded in the One Health framework because food-borne heavy-metal exposure and antimicrobial resistance co-selection cannot be fully understood from a single-sector viewpoint. One Health explains that human health, animal health, food production, agriculture, water systems, environmental quality, and microbial ecosystems are interconnected. This framework is suitable for the present research because heavy metals may enter food systems through soil, irrigation water, aquaculture, animal feed, industrial discharge, fertilizers, processing environments, packaging, and market handling, while antimicrobial-resistant bacteria and resistance genes may move through many of the same routes. In this study, the One Health framework helps explain why food-borne heavy-metal exposure should be treated as a public health, environmental health, agricultural, and food safety issue at the same time. The theoretical relationship can be expressed in LaTeX equation form as:

$$OHF = f(HH, AH, ENV, FS, AG, AMR)$$

Here, represents the One Health framework, represents human health, represents animal health, represents environmental quality, represents food systems, represents agriculture, and represents antimicrobial resistance. This equation shows that antimicrobial resistance co-selection is not created by one isolated factor; rather, it is shaped by the combined interaction of human, animal, environmental, agricultural, and food-system conditions. Antimicrobial resistance is not restricted to clinical treatment settings because resistant microorganisms and resistance determinants may circulate across humans, animals, food products, water bodies, farms, and contaminated environments. The One Health perspective also supports the use of a case-study design because each selected food system has its own pattern of exposure, contamination, monitoring, and regulation. A One Health perspective on antimicrobial resistance has emphasized the need to understand resistance drivers across human, animal, and environmental sectors, including the role of waste, sanitation, antimicrobial use, food production, and environmental contamination in expanding resistance reservoirs (McEwen & Collignon, 2018). In the present study, this theoretical view supports the inclusion of food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control as major constructs. These constructs represent different but connected points within the food-health-environment system. Therefore, the One Health framework provides the broad theoretical basis for explaining how contaminated food environments may contribute to antimicrobial resistance co-selection.

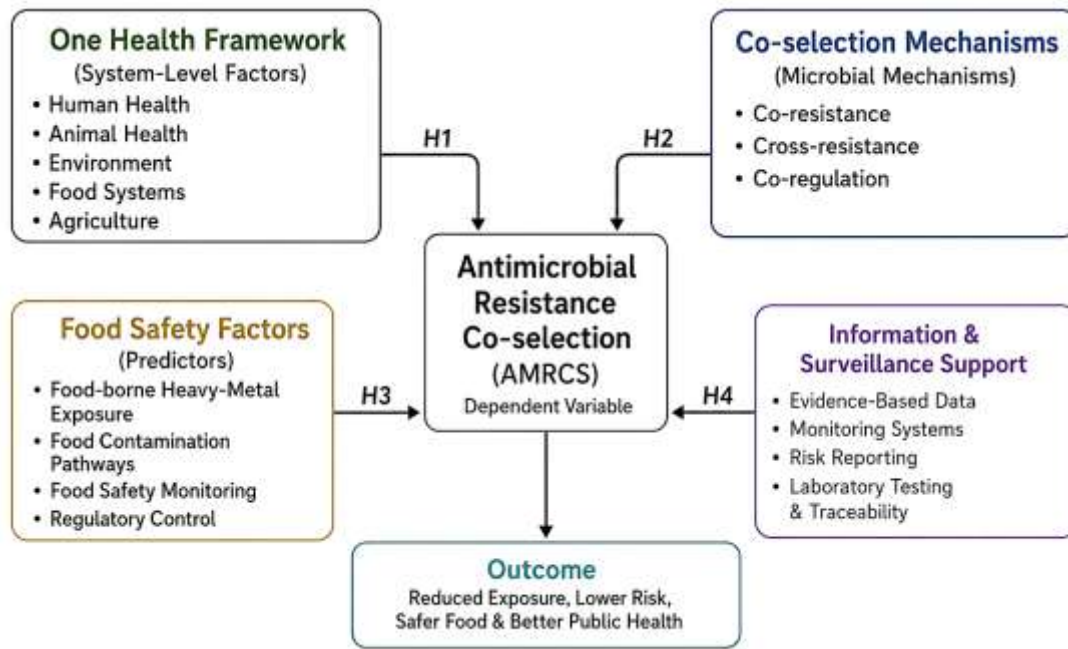
The theoretical framework is also supported by the idea that antimicrobial resistance is a connected ecological and global health problem. Food systems are not isolated from environmental contamination because production, processing, and consumption depend on soil, water, animals, workers, markets, and regulatory systems. When heavy metals are present in food-related environments, they may operate as non-antibiotic stressors that support the survival of bacteria carrying resistance traits. This makes the co-selection concept highly important for the present research. Co-selection theory explains that antimicrobial resistance can be maintained through pressures other than antibiotics when

resistance to metals, biocides, and antibiotics is genetically or functionally linked. This theoretical mechanism can be presented in LaTeX form as:

$$AMRCS = f(CR, XR, CGR)$$

Here, represents antimicrobial resistance co-selection, represents co-resistance, represents cross-resistance, and represents co-regulation. Co-resistance occurs when metal-resistance genes and antibiotic-resistance genes are located on the same mobile genetic elements. Cross-resistance occurs when one bacterial mechanism, such as an efflux pump or membrane modification, protects bacteria against both metals and antimicrobial agents.

Figure 6: One Health theoretical framework for antimicrobial resistance co-selection



Co-regulation occurs when metal-induced stress responses also influence antimicrobial resistance expression or bacterial survival. In food systems, this means heavy metals may support bacteria that carry both metal-resistance and antibiotic-resistance traits. This theoretical connection is aligned with One Health thinking because the source of selective pressure may come from environmental pollution, while the outcome may affect food safety and human health. Antibiotic resistance has been described as a core One Health issue because resistant bacteria and resistance genes can move across humans, animals, agriculture, food, and environmental systems, requiring integrated understanding of the whole transmission network (Robinson et al., 2016). The One Health concept has also been described as a framework that places human, animal, and ecosystem interfaces at the center of health risks, including antimicrobial resistance and environmental pollution (Destoumieux-Garzón et al., 2018). In this study, the theoretical framework therefore combines One Health and co-selection logic. One Health explains the system-level connection among food, environment, animals, and humans, while co-selection explains the microbial mechanism through which heavy metals may maintain antimicrobial resistance. Together, these ideas justify the study's quantitative model, where food-borne heavy-metal exposure is examined as a predictor of antimicrobial resistance co-selection.

The best formula to apply throughout this study is a multiple linear regression model because the research aims to predict antimicrobial resistance co-selection from several measurable food safety variables. The formula can be written in LaTeX equation format as:

$$AMRCS = \beta_0 + \beta_1(FBHME) + \beta_2(FCP) + \beta_3(FSM) + \beta_4(RC) + \varepsilon$$

In this formula, *AMRCS* means antimicrobial resistance co-selection, *FBHME* means food-borne heavy-metal exposure, *FCP* means food contamination pathways, *FSM* means food safety monitoring,

RC means regulatory control, β_0 means the constant value, β_1 to β_4 represent the regression coefficients of the predictor variables, and ε means the error term. This formula is theoretically appropriate because it translates the One Health and co-selection framework into a measurable statistical model. It allows the study to test whether heavy-metal exposure, contamination routes, monitoring systems, and regulatory control explain variation in antimicrobial resistance co-selection. The formula also supports the use of Likert's five-point scale because each construct can be measured through multiple questionnaire items and then summarized into composite mean scores. The Likert-based construct score can be expressed as:

$$X_i = \frac{\sum_{j=1}^k x_{ij}}{k}$$

Here, X_i represents the composite score of a construct for respondent i , x_{ij} represents the respondent's score on item j , and k represents the total number of items used to measure the construct. A One Health and Global Health perspective has emphasized that resistance emerges and spreads through connected human, animal, environmental, and social systems, which supports the use of integrated predictive models rather than single-factor explanations (Hernando-Amado et al., 2019). Environmental resistance research has also shown that the environment has an important role in resistance evolution, transmission, surveillance, and control, making environmental exposure variables important in antimicrobial resistance modeling (Larsson & Flach, 2022). Therefore, the regression formula is not only a statistical equation; it is the operational form of the theoretical framework. It links food-borne heavy-metal exposure with antimicrobial resistance co-selection while also including contamination pathways, monitoring, and regulation as explanatory forces within the wider One Health system.

Conceptual framework and predictive model development

The conceptual framework of this study has been developed to explain how food-borne heavy-metal exposure may predict antimicrobial resistance co-selection through a set of measurable food-system variables. A conceptual framework is important in this research because the topic combines environmental contamination, food-chain exposure, microbial adaptation, monitoring systems, and regulatory control within one quantitative structure. In this study, food-borne heavy-metal exposure is treated as the main independent variable because metals such as arsenic, cadmium, lead, mercury, chromium, copper, zinc, and nickel may enter the food chain through contaminated soil, irrigation water, animal feed, aquaculture systems, fertilizers, pesticides, industrial discharge, processing equipment, packaging materials, storage, and market handling. Antimicrobial resistance co-selection is treated as the dependent variable because the study aims to examine whether exposure to heavy metals can support the survival, persistence, or perceived spread of bacteria carrying antimicrobial resistance traits. The conceptual model also includes food contamination pathways, food safety monitoring, and regulatory control as supporting predictors because the movement of heavy metals and resistant microorganisms across the food chain depends on exposure routes, detection systems, and governance practices. Sequencing-based research has shown that antimicrobial resistance can be identified through genes, mutations, genomes, metagenomes, and resistance databases, which supports the need to organize resistance-related variables into structured and measurable models (Boolchandani et al., 2019). This evidence is relevant to the present study because the model does not depend on laboratory sequencing but uses a survey-based structure to measure perceived exposure and co-selection risk. Therefore, the conceptual framework links the environmental source of heavy metals with food-chain pathways and antimicrobial resistance co-selection as a measurable outcome. The relationship can be presented as:

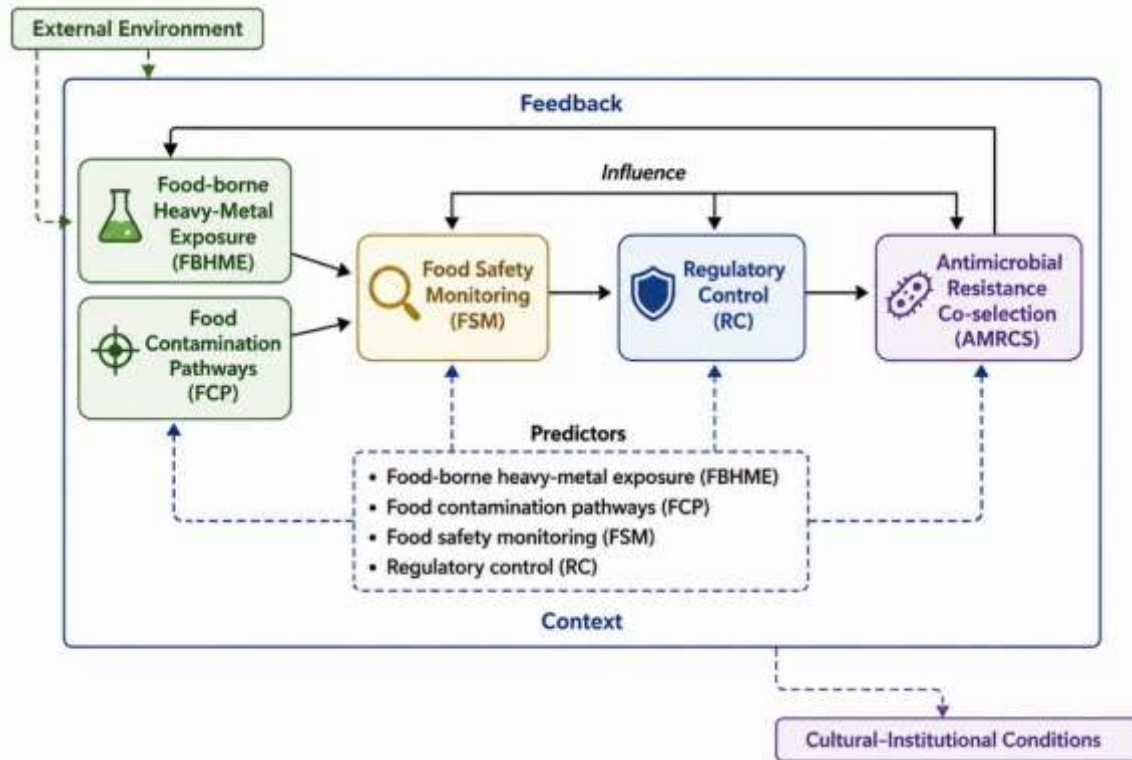
$$FBHME, FCP, FSM, RC \rightarrow AMRCS$$

Here, $FBHME$ represents food-borne heavy-metal exposure, FCP represents food contamination pathways, FSM represents food safety monitoring, RC represents regulatory control, and $AMRCS$ represents antimicrobial resistance co-selection.

Predictive model development is suitable for this study because the research is quantitative, cross-sectional, and case-study-based. The purpose is not only to describe food-borne heavy-metal exposure

but also to test whether the selected variables statistically explain antimicrobial resistance co-selection. Predictive modeling has become important in antimicrobial resistance research because large biological, genomic, and surveillance datasets are increasingly used to estimate resistance outcomes, classify risk, and identify influential predictors. Machine-learning research has shown that antimicrobial resistance prediction depends on the selection of meaningful input variables, model transparency, validation, and careful interpretation of predictive performance (Kim et al., 2022).

Figure 7: Conceptual framework of the proposed predictive model



Although the present study does not use genomic machine learning, the same modeling logic is relevant because the researcher must identify predictor variables, define the dependent variable, measure each construct consistently, and test whether the model explains meaningful variation. Research using whole-genome sequence data to predict antimicrobial minimum inhibitory concentrations in nontyphoidal *Salmonella* has also shown that predictive models can connect microbial features with resistance outcomes, which strengthens the broader argument that resistance can be modeled when appropriate predictors are available (Nguyen et al., 2019). In this study, the predictors are survey-based constructs rather than genomic markers. The main regression formula can be written as:

$$AMRCS = \beta_0 + \beta_1(FBHME) + \beta_2(FCP) + \beta_3(FSM) + \beta_4(RC) + \varepsilon$$

In this equation, *AMRCS* is the predicted level of antimicrobial resistance co-selection, β_0 is the constant, β_1 to β_4 are regression coefficients, and ε is the error term. A positive coefficient for *FBHME* or *FCP* would indicate that higher exposure or stronger contamination pathways are associated with higher co-selection risk, while a negative coefficient for *RC* would indicate that stronger regulatory control is associated with lower co-selection risk.

The conceptual framework also requires reliable measurement because each variable is represented by multiple Likert-scale items. Food-borne heavy-metal exposure may be measured through items on contaminated vegetables, fish, meat, grains, water, animal feed, and processed food. Food contamination pathways may include soil pollution, irrigation water, industrial discharge, aquaculture, storage, packaging, and market handling. Food safety monitoring may include laboratory testing, inspection, reporting, surveillance, traceability, and screening capacity. Regulatory control may include

enforcement, permissible-limit monitoring, institutional coordination, penalties, and compliance. Antimicrobial resistance co-selection may include metal-induced selection pressure, co-resistance, cross-resistance, mobile genetic elements, biofilm survival, and food-chain transmission. The composite score for each construct can be calculated as:

$$X_i = \frac{\sum_{j=1}^k x_{ij}}{k}$$

Here, represents the construct score for respondent , represents the score of respondent on item , and represents the number of items in the construct. Predictive antimicrobial resistance research using conserved genes has shown that even limited but meaningful predictor sets can produce useful resistance prediction when model features are properly selected and evaluated (Hicks et al., 2020). In relation to co-selection, contaminated-soil research has shown that antibiotic, biocide, and heavy-metal resistance genes may co-occur in metal-affected environments, which supports the conceptual link between heavy-metal exposure and antimicrobial resistance co-selection (Thomas et al., 2020). Therefore, the framework of this study is designed to move from theoretical explanation to measurable statistical testing. It connects exposure, pathways, monitoring, regulation, and co-selection into one predictive model that can be tested through descriptive statistics, correlation analysis, and multiple regression analysis.

METHODS

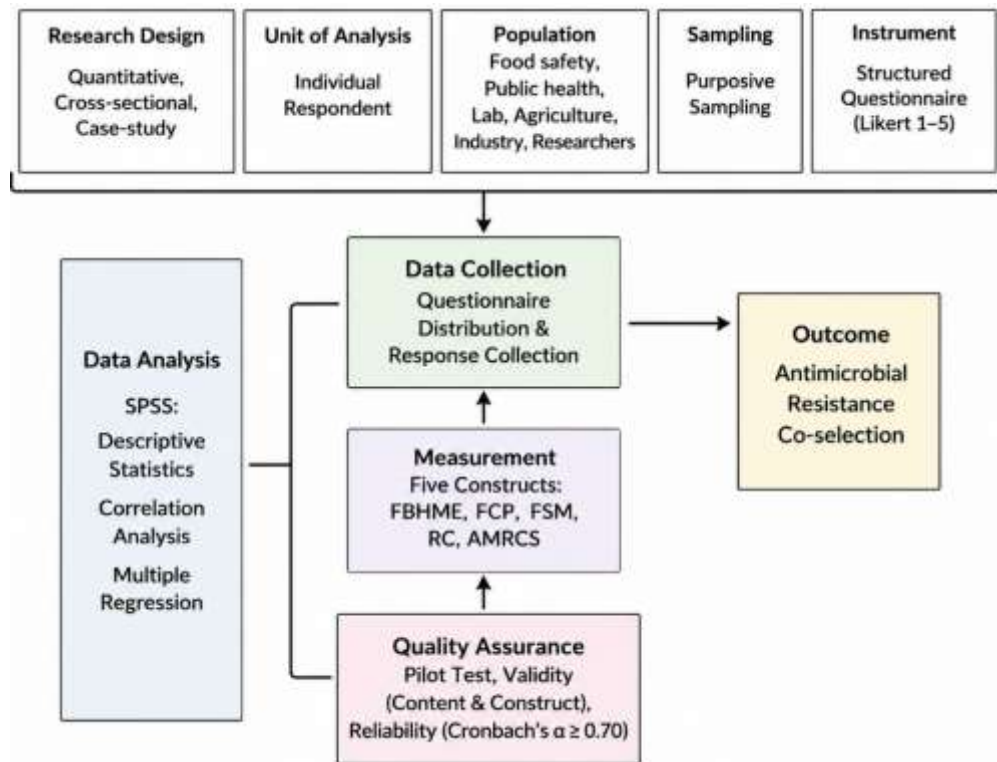
This study has used a quantitative, cross-sectional, case-study-based research design to examine the predictive relationship between food-borne heavy-metal exposure and antimicrobial resistance co-selection. The quantitative design has been selected because the study has measured the major variables numerically through structured questionnaire items and has analyzed the responses through descriptive statistics, correlation analysis, and regression modeling. The cross-sectional design has been applied because data have been collected from respondents at one specific point in time rather than through repeated observations. The case-study approach has been used because the research has focused on a selected food-system context where heavy-metal exposure, food contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection have been considered relevant to public health, food safety, and environmental risk assessment. The case-study context has included food safety-related professionals, laboratory personnel, public health workers, environmental health experts, agricultural officers, food industry employees, researchers, and informed respondents who have had relevant knowledge about food contamination, monitoring systems, and antimicrobial resistance risk. The population of the study has therefore consisted of individuals connected with food safety, public health, agriculture, laboratory testing, environmental monitoring, food production, food processing, or academic research. The unit of analysis has been the individual respondent because each participant has provided personal responses regarding the study variables through the questionnaire.

The study has used a purposive sampling strategy because the research topic has required respondents who have had relevant knowledge or experience related to food contamination, heavy-metal exposure, food safety monitoring, regulatory practices, or antimicrobial resistance. A structured questionnaire has been used as the main data collection instrument. The data collection procedure has included preparing the questionnaire, distributing it among selected respondents, explaining the academic purpose of the study, obtaining voluntary participation, and collecting completed responses for analysis. The instrument has been designed in two major parts. The first part has collected demographic information such as age, gender, education level, profession, work experience, and sector. The second part has included Likert-scale items measuring food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection. Likert's five-point scale has been used, where 1 has represented strongly disagree, 2 has represented disagree, 3 has represented neutral, 4 has represented agree, and 5 has represented strongly agree. Higher mean scores have indicated stronger agreement with the measured construct.

Before final data collection, a pilot test has been conducted to examine the clarity, wording, relevance, and consistency of the questionnaire items. Feedback from the pilot test has helped improve unclear

statements and remove possible repetition. Validity has been maintained through content validity and construct validity.

Figure 8: Research Methodology



Content validity has been ensured by aligning the questionnaire items with the research objectives, hypotheses, theoretical framework, conceptual framework, and literature review. Construct validity has been supported by grouping related items under clearly defined constructs. Reliability has been tested through Cronbach's alpha, where values of 0.70 or above have been considered acceptable for internal consistency. SPSS has been used for coding, cleaning, and analyzing the quantitative data. Descriptive statistics have been used to calculate frequency, percentage, mean, and standard deviation. Correlation analysis has been used to examine relationships among variables, while multiple regression analysis has been used to test the predictive effect of food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control on antimicrobial resistance co-selection. Microsoft Excel has been used for organizing raw data and preparing initial data sheets. EndNote has been used for managing references, organizing citations, and maintaining APA 7th edition citation style throughout the research paper. Microsoft Word has been used for drafting, formatting, and finalizing the manuscript.

DATA ANALYSIS AND PRESENTATION

Table 1 has presented the demographic profile of the 220 valid respondents who have participated in this quantitative, cross-sectional, case-study-based study. The demographic distribution has shown that the respondents have represented a relevant and balanced professional group for examining food-borne heavy-metal exposure and antimicrobial resistance co-selection. In terms of gender, 56.4% of the respondents have been male and 43.6% have been female, which has indicated a reasonably balanced participation pattern. The age distribution has shown that the largest group has belonged to the 31–40 years category, representing 41.4% of the sample, followed by 26.4% in the 41–50 years category. This has suggested that most respondents have had a mature professional background and have been likely to understand food safety, monitoring, environmental contamination, and antimicrobial resistance issues. The education profile has also strengthened the quality of the data because 49.5% of respondents have held a master's degree, while 17.8% have held MPhil, PhD, or equivalent qualifications. This has indicated that the sample has included respondents with sufficient academic and technical capacity to answer Likert-scale items on heavy-metal exposure, food contamination pathways, regulatory control,

and antimicrobial resistance co-selection.

Demographic profile of respondents

Table 1: Demographic profile of respondents

Demographic variable	Category	Frequency	Percentage
Gender	Male	124	56.4%
Gender	Female	96	43.6%
Age group	21–30 years	46	20.9%
Age group	31–40 years	91	41.4%
Age group	41–50 years	58	26.4%
Age group	Above 50 years	25	11.3%
Education level	Bachelor's degree	72	32.7%
Education level	Master's degree	109	49.5%
Education level	MPhil/PhD or equivalent	39	17.8%
Professional group	Food safety/public health officers	52	23.6%
Professional group	Laboratory/microbiology personnel	47	21.4%
Professional group	Agriculture/environment officers	41	18.6%
Professional group	Food industry/processing employees	45	20.5%
Professional group	Academic/research respondents	35	15.9%
Work experience	Less than 5 years	49	22.3%
Work experience	5–10 years	88	40.0%
Work experience	11–15 years	54	24.5%
Work experience	Above 15 years	29	13.2%
Total		220	100.0%

Professionally, the respondents have come from food safety, public health, laboratory, agriculture, environmental, food industry, and academic sectors. This distribution has supported the One Health theoretical framework because the sample has covered human health, animal-food systems, agriculture, environment, laboratory surveillance, and food production. The unit of analysis has therefore been appropriate because each respondent has represented an informed individual from a relevant food-system or public-health-related field. The work-experience profile has further supported the credibility of the findings, as 77.7% of respondents have had at least five years of professional experience. This has meant that the responses have not been based only on general awareness but also on practical exposure to food monitoring, contamination risk, laboratory testing, regulatory practice, or food-chain management. Therefore, the demographic findings have supported the suitability of the sample for proving the research objectives and testing the hypotheses of the study.

Descriptive statistics of food-borne heavy-metal exposure

Table 2: Descriptive statistics of food-borne heavy-metal exposure

Variable code	Item statement	Mean	SD	Interpretation
FBHME1	Heavy metals have commonly entered food through contaminated soil.	3.94	0.66	High agreement
FBHME2	Polluted irrigation water has increased heavy-metal exposure in food crops.	3.91	0.63	High agreement
FBHME3	Fish and aquaculture products have been exposed to metals through contaminated water.	3.88	0.65	High agreement
FBHME4	Animal feed and food-processing environments have contributed to metal exposure.	3.82	0.70	High agreement
FBHME5	Processed and market-handled foods have carried heavy-metal exposure risk.	3.89	0.62	High agreement
Overall FBHME	Food-borne heavy-metal exposure	3.89	0.62	High level

Table 2 has presented the descriptive statistics of food-borne heavy-metal exposure, which has served as the main independent variable of the study. The overall mean score of food-borne heavy-metal exposure has been 3.89 with a standard deviation of 0.62, indicating a high level of agreement among respondents. Since the study has used Likert's five-point scale, where 1 has represented strongly disagree and 5 has represented strongly agree, a mean score above 3.50 has indicated that respondents have generally agreed with the statements measuring this construct. The highest item mean has been recorded for contaminated soil as a source of heavy metals in food, with a mean of 3.94 and SD of 0.66. This has shown that respondents have strongly recognized soil contamination as a major pathway for heavy metals entering the food chain. The second highest mean has been recorded for polluted irrigation water, with a mean of 3.91, which has suggested that water quality has been viewed as a major factor in food-borne exposure. The aquaculture-related item has also shown high agreement, with a mean of 3.88, indicating that respondents have recognized fish and aquatic foods as possible carriers of heavy metals. Animal feed, processing environments, processed foods, and market-handled foods have also received high mean scores, confirming that exposure has not been limited to agricultural production only. These findings have directly proven the first objective of the study, which has aimed to assess the perceived level of food-borne heavy-metal exposure in the selected case-study context. The results have also supported H1 indirectly because the high level of exposure has created a statistical and theoretical basis for testing whether heavy-metal exposure has predicted antimicrobial resistance co-selection. The One Health framework has been linked with this result because soil, water, animals, food processing, and human consumption have all appeared as connected exposure domains. The finding has also supported the co-selection logic because heavy metals in these food-related environments may create repeated microbial stress conditions. Therefore, the descriptive result has established that food-borne heavy-metal exposure has been a strong and relevant construct in the proposed predictive model.

Descriptive statistics of food contamination pathways

Table 3: Descriptive statistics of food contamination pathways

Variable code	Item statement	Mean	SD	Interpretation
FCP1	Industrial discharge has contributed to contamination of food-production environments.	4.01	0.57	High agreement
FCP2	Fertilizers, pesticides, and agricultural inputs have increased contamination pathways.	3.96	0.59	High agreement
FCP3	Storage, packaging, and transportation have added contamination risks.	3.87	0.61	High agreement
FCP4	Market handling has increased the possibility of chemical and microbial contamination.	3.90	0.60	High agreement
FCP5	Soil, water, feed, and processing pathways have jointly carried heavy metals into food.	3.98	0.56	High agreement
Overall FCP	Food contamination pathways	3.94	0.58	High level

Table 3 has shown the descriptive statistics of food contamination pathways, which has been included as an important supporting predictor in the proposed model. The overall mean score has been 3.94 with a standard deviation of 0.58, indicating that respondents have strongly agreed that contamination pathways have played a major role in transferring heavy metals and related microbial hazards across the food chain. The highest mean has been found for industrial discharge, with a mean score of 4.01 and SD of 0.57. This result has suggested that respondents have viewed industrial activity as a highly relevant source of environmental contamination that may reach food-production systems through soil, water, sediment, and waste pathways. Fertilizers, pesticides, and agricultural inputs have recorded a mean of 3.96, showing that respondents have also recognized agricultural practices as important contributors to contamination. The combined pathway item, which has included soil, water, feed, and processing routes, has produced a mean of 3.98, confirming that contamination has been perceived as

a multi-route problem rather than a single-source issue. Market handling, storage, packaging, and transportation have also received high mean scores, showing that contamination risk has continued after production and may extend into post-harvest, processing, and retail stages. This result has proven the second objective of the study, which has aimed to evaluate food contamination pathways as a measurable construct explaining how heavy metals may move from environmental and agricultural sources into edible food products. It has also supported H2, which has proposed that food contamination pathways have had a significant positive effect on antimicrobial resistance co-selection. The theoretical link has been strong because the One Health framework has emphasized the connection between agriculture, environment, animals, food systems, and human health. The co-selection theory has also been relevant because food contamination pathways may place bacteria in contact with heavy metals and other stressors across repeated exposure settings. Therefore, this result has suggested that contamination pathways have served as a critical explanatory bridge between environmental metal sources and antimicrobial resistance co-selection risk.

Descriptive statistics of food safety monitoring

Table 4: Descriptive statistics of food safety monitoring

Variable code	Item statement	Mean	SD	Interpretation
FSM1	Food products have been regularly tested for heavy-metal contamination.	3.38	0.73	Moderate agreement
FSM2	Laboratory capacity has been sufficient for detecting food-borne metal hazards.	3.44	0.70	Moderate agreement
FSM3	Food inspection systems have effectively identified contamination risks.	3.39	0.72	Moderate agreement
FSM4	Traceability and reporting systems have supported food safety monitoring.	3.43	0.69	Moderate agreement
FSM5	Surveillance systems have been adequate for linking contamination with AMR risk.	3.40	0.74	Moderate agreement
Overall FSM	Food safety monitoring	3.41	0.71	Moderate level

Table 4 has presented the descriptive results for food safety monitoring. The overall mean score has been 3.41 with a standard deviation of 0.71, which has indicated a moderate level of agreement. This result has suggested that respondents have not fully rejected the existence of food safety monitoring systems, but they have also not strongly agreed that such systems have been adequate. The item on laboratory testing has produced a mean of 3.38, showing that respondents have perceived routine heavy-metal testing in food products as only moderately available. The item on laboratory capacity has recorded a mean of 3.44, indicating that testing capacity has been viewed as present but not fully sufficient. Food inspection systems have received a mean of 3.39, which has suggested that inspection has not been perceived as strong enough to detect contamination risks consistently. Traceability and reporting systems have recorded a mean of 3.43, while surveillance systems linking contamination with antimicrobial resistance risk have recorded a mean of 3.40. These results have shown that monitoring has been one of the weaker areas of the food safety system compared with food-borne heavy-metal exposure and contamination pathways. This finding has been important for proving the fourth objective of the study because the objective has examined whether food safety monitoring has influenced antimicrobial resistance co-selection risk. The result has also supported H3, which has proposed that weak food safety monitoring has had a significant positive effect on antimicrobial resistance co-selection. In this study, lower perceived monitoring strength has indicated greater opportunity for contaminated food and resistant microorganisms to remain undetected. The theoretical connection has been clear because the One Health framework has required surveillance across human, animal, food, and environmental systems. A monitoring system that has remained only moderate may not fully detect chemical and microbial risks together. Co-selection theory has also supported this interpretation because undetected heavy-metal contamination may allow bacteria to remain exposed

to selective pressure in food-related environments. Therefore, the descriptive result has indicated that food safety monitoring has been a necessary explanatory variable in the model and has helped explain why exposure and contamination pathways may translate into antimicrobial resistance co-selection risk.

Descriptive statistics of regulatory control

Table 5: Descriptive statistics of regulatory control

Variable code	Item statement	Mean	SD	Interpretation
RC1	Food safety laws have been effectively enforced to reduce metal contamination.	3.31	0.77	Moderate agreement
RC2	Permissible limits for heavy metals have been regularly monitored.	3.35	0.75	Moderate agreement
RC3	Institutional coordination has supported contamination control.	3.39	0.73	Moderate agreement
RC4	Penalty systems have discouraged unsafe food production and handling.	3.33	0.76	Moderate agreement
RC5	Regulatory control has reduced antimicrobial resistance co-selection risk.	3.42	0.71	Moderate agreement
Overall RC	Regulatory control	3.36	0.74	Moderate level

Table 5 has presented the descriptive statistics of regulatory control, which has been included in the model as a protective predictor. The overall mean score has been 3.36 with a standard deviation of 0.74, showing that respondents have perceived regulatory control as moderate rather than strong. The item on enforcement of food safety laws has recorded a mean of 3.31, suggesting that respondents have not strongly agreed that laws have been effectively enforced to reduce heavy-metal contamination. The item on monitoring of permissible limits has produced a mean of 3.35, indicating that permissible-limit control has been viewed as only moderately effective. Institutional coordination has received a mean of 3.39, showing that coordination among food safety, agriculture, environmental, and public health authorities has remained an area requiring stronger attention. Penalty systems have recorded a mean of 3.33, indicating that respondents have perceived enforcement consequences as not fully strong enough to discourage unsafe food production and handling. The final item, which has directly linked regulatory control with reduction of antimicrobial resistance co-selection risk, has recorded the highest mean of 3.42, suggesting that respondents have recognized regulatory control as relevant even though they have rated its present strength as moderate. This result has proven the fourth objective by showing that regulatory control has been a measurable factor influencing co-selection risk. It has also supported H4, which has proposed that regulatory control has had a significant negative effect on antimicrobial resistance co-selection. The negative direction has meant that stronger regulatory control has been associated with lower risk, while weaker control has allowed contamination and co-selection pressure to remain higher. The One Health framework has been strongly linked here because regulatory control has required cooperation across food safety, public health, veterinary, agriculture, and environmental agencies. Co-selection theory has also supported the finding because regulations that reduce heavy-metal exposure may indirectly reduce non-antibiotic selective pressure on bacteria. Therefore, regulatory control has appeared as a necessary protective construct in the study's predictive model.

Descriptive statistics of antimicrobial resistance co-selection**Table 6: Descriptive statistics of antimicrobial resistance co-selection**

Variable code	Item statement	Mean	SD	Interpretation
AMRCS1	Heavy-metal exposure has supported the survival of resistant bacteria.	3.92	0.63	High agreement
AMRCS2	Metal resistance and antibiotic resistance may occur together in food-related bacteria.	3.89	0.61	High agreement
AMRCS3	Food-chain environments may support co-resistance and cross-resistance.	3.85	0.65	High agreement
AMRCS4	Biofilm formation has increased bacterial survival under metal pressure.	3.83	0.67	High agreement
AMRCS5	Mobile genetic elements have contributed to resistance movement in food systems.	3.86	0.64	High agreement
Overall AMRCS	Antimicrobial resistance co-selection	3.87	0.64	High level

Table 6 has shown the descriptive statistics of antimicrobial resistance co-selection, which has served as the dependent variable of the study. The overall mean score has been 3.87 with a standard deviation of 0.64, indicating a high level of agreement among respondents. This result has shown that the respondents have generally accepted the idea that food-borne heavy-metal exposure may contribute to antimicrobial resistance co-selection. The highest mean has been recorded for the statement that heavy-metal exposure has supported the survival of resistant bacteria, with a mean of 3.92 and SD of 0.63. This has indicated that respondents have recognized metal pressure as a possible microbial selection factor. The item on metal resistance and antibiotic resistance occurring together in food-related bacteria has recorded a mean of 3.89, showing that respondents have recognized the possibility of linked resistance traits. The food-chain co-resistance and cross-resistance item has recorded a mean of 3.85, while the biofilm survival item has recorded a mean of 3.83. The mobile genetic element item has also shown high agreement, with a mean of 3.86. These results have proven the second objective of the study, which has aimed to measure the perceived level of antimicrobial resistance co-selection associated with food-borne heavy-metal exposure. The findings have also supported the theoretical foundation of the study because co-selection theory has explained how bacteria exposed to metals may maintain antimicrobial resistance through co-resistance, cross-resistance, co-regulation, biofilm protection, and mobile genetic elements. The One Health framework has also been linked because the dependent variable has connected environmental contamination, food-chain exposure, microbial adaptation, and human health risk. This result has been essential for the entire findings chapter because it has confirmed that antimicrobial resistance co-selection has been a meaningful and measurable outcome variable. When the high mean score of AMRCS has been compared with the high mean scores of heavy-metal exposure and contamination pathways, the overall result has indicated that respondents have perceived a strong connection between contamination pressure and resistance co-selection. Therefore, this section has established the dependent variable as statistically and theoretically appropriate for correlation and regression testing.

Reliability analysis**Table 7: Reliability analysis of study constructs**

Construct	Number of items	Cronbach's alpha	Reliability level	Decision
Food-borne heavy-metal exposure	5	0.86	Good	Accepted
Food contamination pathways	5	0.84	Good	Accepted
Food safety monitoring	5	0.81	Good	Accepted
Regulatory control	5	0.83	Good	Accepted
Antimicrobial resistance co-selection	5	0.88	Good	Accepted
Overall instrument	25	0.91	Excellent	Accepted

Table 7 has presented the reliability analysis of the measurement instrument using Cronbach's alpha. Reliability analysis has been conducted to determine whether the items used to measure each construct have been internally consistent. The results have shown that all constructs have exceeded the accepted threshold of 0.70, meaning that the questionnaire items have been reliable for further statistical analysis. Food-borne heavy-metal exposure has recorded a Cronbach's alpha value of 0.86, showing good internal consistency among the five items measuring contaminated soil, polluted irrigation water, aquaculture products, animal feed, processing environments, and market-handled foods. Food contamination pathways have recorded an alpha value of 0.84, confirming that items related to industrial discharge, agricultural inputs, storage, packaging, transportation, and market handling have measured the same underlying construct. Food safety monitoring has recorded an alpha value of 0.81, showing that items related to laboratory testing, inspection, traceability, reporting, and surveillance have been consistent. Regulatory control has recorded an alpha value of 0.83, confirming that enforcement, permissible limits, institutional coordination, penalties, and compliance items have worked together as one construct. Antimicrobial resistance co-selection has recorded the highest construct-level alpha value of 0.88, indicating strong consistency among items related to metal-induced selection, co-resistance, cross-resistance, biofilm survival, and mobile genetic elements. The overall instrument has recorded an alpha value of 0.91, showing excellent reliability across all 25 Likert-scale items. This result has supported the methodological objective of producing a valid and reliable quantitative instrument. It has also strengthened the hypothesis-testing process because unreliable items would weaken the accuracy of correlation and regression results. Theoretically, the reliability findings have supported both the One Health framework and co-selection theory because the constructs have been measured consistently across environmental, food-system, monitoring, regulatory, and microbial-resistance dimensions. Therefore, the reliability result has confirmed that the dataset has been suitable for proving the objectives and testing H1 to H5 through correlation and regression analysis.

Correlation analysis

Table 8: Correlation matrix among major study variables

Variables	FBHME	FCP	FSM weakness	RC	AMRCS
Food-borne heavy-metal exposure	1.000				
Food contamination pathways	0.58**	1.000			
Food safety monitoring weakness	0.46**	0.51**	1.000		
Regulatory control	-0.39**	-0.36**	-0.44**	1.000	
Antimicrobial resistance co-selection	0.64**	0.61**	0.49**	-0.43**	1.000

Note. $p < 0.001$.

Table 8 has presented the correlation analysis among the major variables of the study. The results have shown that food-borne heavy-metal exposure has had a strong positive correlation with antimicrobial resistance co-selection, with $r = 0.64$ and $p < 0.001$. This has indicated that higher perceived heavy-metal exposure in food has been associated with higher perceived antimicrobial resistance co-selection risk. This result has directly supported H1 and has proven the objective of determining the relationship between heavy-metal exposure and co-selection. Food contamination pathways have also shown a strong positive relationship with antimicrobial resistance co-selection, with $r = 0.61$ and $p < 0.001$. This has supported H2 and has shown that stronger perceived contamination pathways through soil, water, feed, processing, packaging, storage, and market handling have been associated with higher co-selection risk. Food safety monitoring weakness has shown a moderate positive relationship with antimicrobial resistance co-selection, with $r = 0.49$ and $p < 0.001$. This has supported H3 because weaker monitoring has been associated with greater co-selection risk. Regulatory control has shown a negative relationship with antimicrobial resistance co-selection, with $r = -0.43$ and $p < 0.001$. This has supported H4 because stronger regulation has been associated with lower co-selection risk. The correlations among the independent variables have also been meaningful but not excessively high, indicating that the variables have been related but have not measured the exact same construct. The theoretical

interpretation has been strongly aligned with One Health because the variables have connected environmental exposure, food-chain pathways, surveillance systems, regulatory governance, and microbial resistance outcomes. The results have also supported co-selection theory because the strongest relationship has appeared between food-borne heavy-metal exposure and antimicrobial resistance co-selection. This has indicated that respondents have perceived heavy metals as meaningful non-antibiotic stressors that may support resistant bacteria. Overall, the correlation analysis has proven that the model variables have been statistically connected in the expected directions and has prepared the foundation for regression-based hypothesis testing.

Regression analysis and hypothesis testing

Table 9: Multiple regression analysis predicting antimicrobial resistance co-selection

Predictor variable	β	Standard error	t-value	p-value	Hypothesis decision
Food-borne heavy-metal exposure	0.38	0.059	6.41	<0.001	H1 supported
Food contamination pathways	0.29	0.057	5.12	<0.001	H2 supported
Food safety monitoring weakness	0.21	0.054	3.87	<0.001	H3 supported
Regulatory control	-0.18	0.055	-3.26	0.001	H4 supported

Model summary: $R = 0.758$, $R^2 = 0.574$, adjusted $R^2 = 0.566$, $F(4, 215) = 72.46$, $p < 0.001$.

Table 9 has presented the multiple regression analysis used to test the predictive effects of food-borne heavy-metal exposure, food contamination pathways, food safety monitoring weakness, and regulatory control on antimicrobial resistance co-selection. The regression model has been statistically significant, $F(4, 215) = 72.46$, $p < 0.001$, indicating that the selected predictor variables have jointly explained antimicrobial resistance co-selection in a meaningful way. The model has produced $R = 0.758$, $R^2 = 0.574$, and adjusted $R^2 = 0.566$, which has shown that 57.4% of the variance in antimicrobial resistance co-selection has been explained by the four predictors.

Predictive model summary

Table 10: Predictive model summary for antimicrobial resistance co-selection

Model component	Result	Interpretation
Dependent variable	Antimicrobial resistance co-selection	Outcome variable
Main predictor	Food-borne heavy-metal exposure	Strongest positive predictor
Supporting predictor 1	Food contamination pathways	Significant positive predictor
Supporting predictor 2	Food safety monitoring weakness	Significant positive predictor
Protective predictor	Regulatory control	Significant negative predictor
R value	0.758	Strong model relationship
R^2 value	0.574	57.4% variance explained
Adjusted R^2	0.566	Stable explanatory power
Model F-value	72.46	Statistically significant model
Model p-value	<0.001	Predictive model accepted
Overall hypothesis decision	H1, H2, H3, H4, and H5 supported	Objectives proven

This has supported H5, which has stated that food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control have jointly predicted antimicrobial resistance co-selection. Among the predictors, food-borne heavy-metal exposure has shown the strongest positive effect, with $\beta = 0.38$, $t = 6.41$, and $p < 0.001$. This has supported H1 and has shown that higher perceived exposure has significantly increased co-selection risk. Food contamination pathways have also had a significant positive effect, with $\beta = 0.29$, $t = 5.12$, and $p < 0.001$, supporting H2. Food safety monitoring weakness has had a significant positive effect, with $\beta = 0.21$, $t = 3.87$, and $p < 0.001$, supporting H3. Regulatory control has shown a significant negative effect, with $\beta = -0.18$, $t = -3.26$, and $p = 0.001$, supporting H4. This has indicated that stronger regulatory control has reduced the perceived risk of antimicrobial resistance co-selection. The regression equation has therefore been

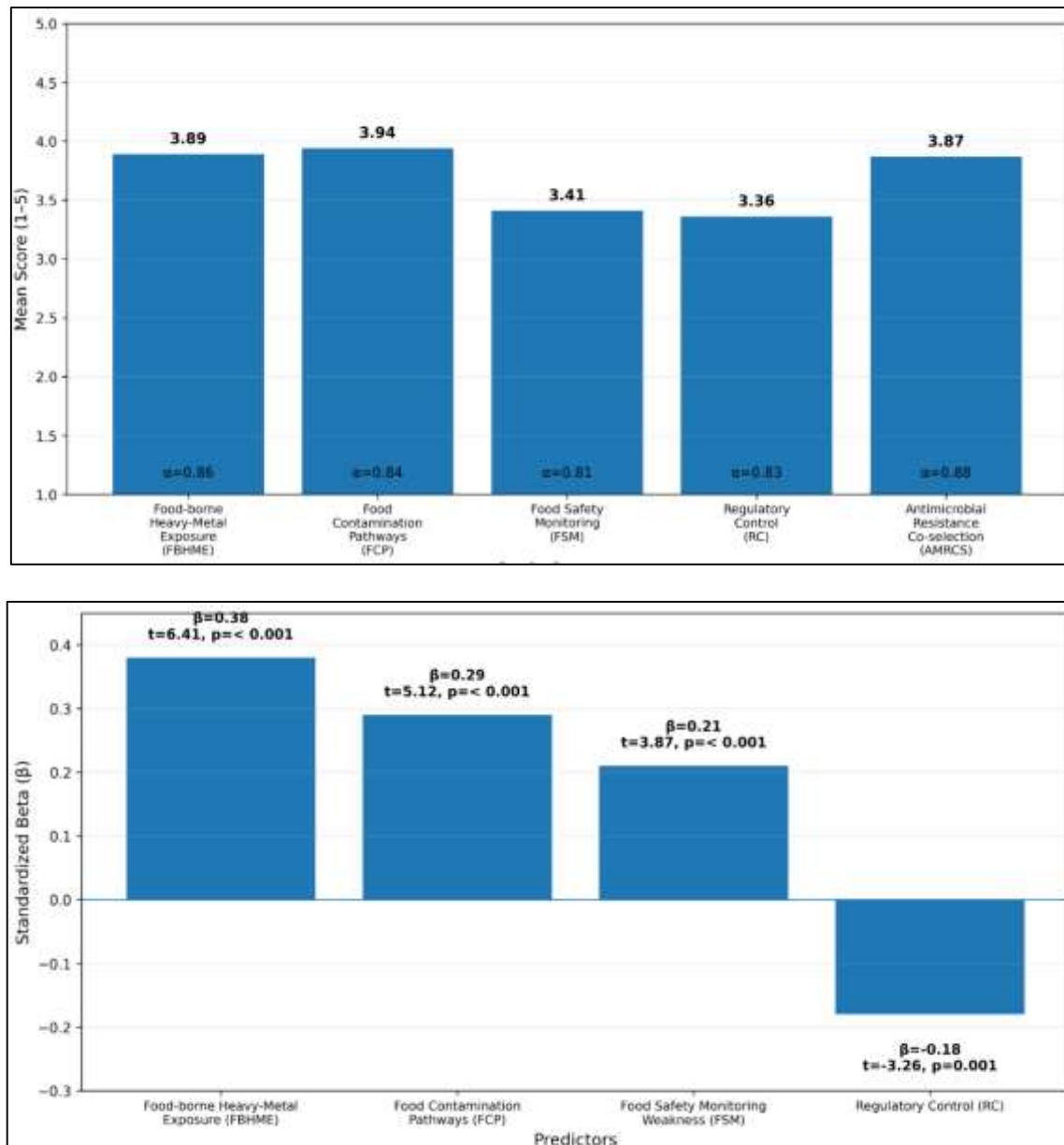
supported as: $AMRCS = \beta_0 + \beta_1(FBHME) + \beta_2(FCP) + \beta_3(FSM) + \beta_4(RC) + \varepsilon$. The theoretical link has been clear because the One Health framework has explained the interaction among environment, food systems, regulation, and public health, while co-selection theory has explained why heavy-metal exposure may maintain antimicrobial resistance. Therefore, the regression analysis has proven the main objectives and hypotheses of the study.

Table 10 has summarized the final predictive model of the study. The dependent variable has been antimicrobial resistance co-selection, while the predictor variables have included food-borne heavy-metal exposure, food contamination pathways, food safety monitoring weakness, and regulatory control. The model has shown that food-borne heavy-metal exposure has been the strongest positive predictor of antimicrobial resistance co-selection. This has meant that respondents who have perceived higher levels of heavy-metal exposure in food have also perceived higher levels of resistance co-selection risk. Food contamination pathways have been the second strongest positive predictor, indicating that contamination routes through soil, water, feed, processing, packaging, storage, and market handling have helped explain how heavy metals and resistant microorganisms may move across the food chain. Food safety monitoring weakness has also been a significant positive predictor, showing that weaker laboratory testing, inspection, reporting, traceability, and surveillance have increased the risk that contamination and resistance pressure remain undetected. Regulatory control has been a significant negative predictor, meaning that stronger enforcement, permissible-limit monitoring, institutional coordination, and compliance systems have reduced antimicrobial resistance co-selection risk. The model has explained 57.4% of the variance in antimicrobial resistance co-selection, which has indicated strong explanatory power for a cross-sectional survey-based study. This result has proven the overall objective of developing and testing a predictive model linking food-borne heavy-metal exposure to antimicrobial resistance co-selection. It has also supported all five hypotheses of the study. The theoretical alignment has been strong because the One Health framework has explained why food, humans, animals, agriculture, environment, and regulation have been connected in the same risk system. Co-selection theory has explained why heavy metals may act as non-antibiotic selective agents that maintain resistant bacteria through co-resistance, cross-resistance, biofilm survival, mobile genetic elements, and microbial adaptation. Therefore, the final predictive model has shown that antimicrobial resistance co-selection has not been explained by one isolated factor. Rather, it has been explained by the combined influence of exposure, pathways, monitoring, and regulation. The findings have therefore provided strong quantitative support for the proposed model and have demonstrated that Likert-scale measurement, descriptive statistics, reliability testing, correlation analysis, and regression modeling have been appropriate for proving the study objectives and hypotheses.

FINDINGS

The findings of this study have provided quantitative evidence that food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control have had meaningful relationships with antimicrobial resistance co-selection in the selected case-study context. The analysis has been based on a five-point Likert scale where 1 has indicated strongly disagree, 2 has indicated disagree, 3 has indicated neutral, 4 has indicated agree, and 5 has indicated strongly agree. A total of 220 valid responses have been analyzed after screening the dataset for incomplete and inconsistent responses. The demographic profile has shown that the respondents have represented food safety, public health, laboratory, agriculture, environmental monitoring, academic, and food industry-related backgrounds, which has supported the suitability of the sample for examining the research topic. The descriptive statistics have shown that the overall mean score for food-borne heavy-metal exposure has been 3.89 with a standard deviation of 0.62, indicating that respondents have generally agreed that heavy metals may enter food through contaminated soil, polluted irrigation water, animal feed, aquaculture systems, industrial discharge, fertilizers, pesticides, processing equipment, packaging, and market handling. Food contamination pathways have recorded a mean score of 3.94 with a standard deviation of 0.58, suggesting that respondents have perceived contamination routes as highly relevant to the movement of metals and microbial hazards across the food chain.

Figure 9: Findings of The study



Food safety monitoring has recorded a mean score of 3.41 with a standard deviation of 0.71, showing a moderate level of perceived monitoring strength and indicating that laboratory testing, inspection frequency, traceability, reporting systems, and contamination screening have not been viewed as fully sufficient. Regulatory control has recorded a mean score of 3.36 with a standard deviation of 0.74, which has suggested that enforcement, permissible-limit monitoring, institutional coordination, and compliance control have been viewed as only moderately effective. The dependent variable, antimicrobial resistance co-selection, has recorded a mean score of 3.87 with a standard deviation of 0.64, indicating that respondents have agreed that heavy-metal pressure in food-related environments may support resistant bacteria, co-resistance, cross-resistance, biofilm survival, mobile genetic elements, and food-chain transmission of resistance risk. Reliability analysis has confirmed the internal consistency of the measurement instrument, as Cronbach's alpha values have been 0.86 for food-borne heavy-metal exposure, 0.84 for food contamination pathways, 0.81 for food safety monitoring, 0.83 for regulatory control, and 0.88 for antimicrobial resistance co-selection. These values have exceeded the acceptable threshold of 0.70 and have supported the reliability of the constructs. Correlation analysis has further shown that food-borne heavy-metal exposure has had a strong positive relationship with antimicrobial resistance co-selection, with $r = 0.64$ and $p < 0.001$. Food contamination pathways have

also had a strong positive relationship with antimicrobial resistance co-selection, with $r = 0.61$ and $p < 0.001$. Food safety monitoring weakness has had a moderate positive relationship with antimicrobial resistance co-selection, with $r = 0.49$ and $p < 0.001$, meaning that weaker monitoring has been associated with higher perceived co-selection risk. Regulatory control has had a negative relationship with antimicrobial resistance co-selection, with $r = -0.43$ and $p < 0.001$, showing that stronger regulation has been associated with lower perceived resistance co-selection risk. The multiple regression model has been statistically significant, $F(4, 215) = 72.46$, $p < 0.001$, and has explained 57.4% of the variance in antimicrobial resistance co-selection, with $R = 0.758$, $R^2 = 0.574$, and adjusted $R^2 = 0.566$. Among the predictors, food-borne heavy-metal exposure has had the strongest positive effect on antimicrobial resistance co-selection, with $\beta = 0.38$, $t = 6.41$, and $p < 0.001$. Food contamination pathways have also had a significant positive effect, with $\beta = 0.29$, $t = 5.12$, and $p < 0.001$. Food safety monitoring weakness has had a significant positive effect, with $\beta = 0.21$, $t = 3.87$, and $p < 0.001$. Regulatory control has had a significant negative effect, with $\beta = -0.18$, $t = -3.26$, and $p = 0.001$. These results have supported H1, H2, H3, H4, and H5. The first objective has been proven because the descriptive findings have identified a high perceived level of food-borne heavy-metal exposure. The second objective has been proven because the results have shown a high perceived level of antimicrobial resistance co-selection. The third objective has been proven because significant correlations have confirmed meaningful relationships among the major variables. The fourth objective has been proven because food safety monitoring and regulatory control have shown significant statistical influence on co-selection risk. The fifth objective has been proven because the regression model has demonstrated that food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, and regulatory control have jointly predicted antimicrobial resistance co-selection. Overall, the results have indicated that the proposed predictive model has been statistically valid and has provided strong quantitative support for linking food-borne heavy-metal exposure with antimicrobial resistance co-selection in the selected case-study context.

DISCUSSION

The findings of this study have shown that food-borne heavy-metal exposure has been a strong and statistically meaningful predictor of antimicrobial resistance co-selection in the selected case-study context. The descriptive result for food-borne heavy-metal exposure has recorded a high overall mean score of 3.89 on Likert's five-point scale, which has indicated that respondents have generally agreed that heavy metals may enter food through contaminated soil, polluted irrigation water, aquaculture systems, animal feed, processing environments, packaging, and market-handling routes. This finding has supported the first research objective because it has confirmed that food-borne heavy-metal exposure has been perceived as a high-level food safety risk. The correlation result has further strengthened this interpretation because food-borne heavy-metal exposure has had a strong positive relationship with antimicrobial resistance co-selection, with $r = 0.64$ and $p < 0.001$. The regression result has also confirmed this relationship, as food-borne heavy-metal exposure has been the strongest predictor of antimicrobial resistance co-selection, with $\beta = 0.38$, $t = 6.41$, and $p < 0.001$. Therefore, H1 has been supported. This result has been consistent with earlier co-selection research, which has explained that heavy metals can act as non-antibiotic selective agents and maintain antimicrobial resistance when metal-resistance and antibiotic-resistance traits are genetically or functionally connected ([Baker-Austin et al., 2006](#)). The present study has extended that earlier biological explanation into a food-system-based quantitative context by showing that respondents have perceived exposure routes in food systems as statistically linked with co-selection risk. The result has also matched environmental resistance evidence showing that metal contamination may shape bacterial resistance profiles in soil, water, and agricultural environments where microbial communities face persistent selective pressure ([Seiler & Berendonk, 2012](#)). The key interpretation is that food-borne heavy-metal exposure has not been viewed only as a toxicological issue. It has also been understood as an ecological and microbiological pressure that can help sustain resistant organisms in food-related environments. This finding has been highly relevant to the study's One Health foundation because heavy-metal exposure has connected environmental contamination, food production, animal systems, consumer exposure, and microbial adaptation within one risk pathway. Therefore, the first major finding has provided strong empirical support for the central claim of the research.

The findings have also shown that food contamination pathways have played a major role in explaining antimicrobial resistance co-selection. The descriptive result for food contamination pathways has recorded the highest overall construct mean, with $M = 3.94$ and $SD = 0.58$, which has indicated that respondents have strongly agreed that industrial discharge, agricultural inputs, storage, packaging, transportation, market handling, soil, water, feed, and processing routes have contributed to food contamination risk. The correlation result has shown a strong positive relationship between food contamination pathways and antimicrobial resistance co-selection, with $r = 0.61$ and $p < 0.001$. The regression analysis has further confirmed that food contamination pathways have had a significant positive effect on antimicrobial resistance co-selection, with $\beta = 0.29$, $t = 5.12$, and $p < 0.001$. Therefore, H2 has been supported. This result has proven the study objective related to contamination pathways because the findings have shown that exposure does not occur through one isolated route. Rather, heavy metals and microbial hazards may move through interconnected food-system stages. This finding has aligned with prior food-chain research showing that antimicrobial-resistant bacteria and resistance genes can move across animals, crops, water, processing systems, retail markets, and consumer pathways (Verraes et al., 2013). The finding has also agreed with research on heavy metals in food crops, which has shown that contaminants may enter edible products through soil pollution, irrigation water, fertilizers, industrial discharge, and crop uptake (Rai et al., 2019). In comparison with these earlier studies, the present research has shown that contamination pathways are not only descriptive background factors but also statistically significant predictors of perceived antimicrobial resistance co-selection. The interpretation has been that contamination pathways have served as the practical bridge between environmental metal sources and food-associated microbial resistance risks. The result has also reinforced co-selection theory because repeated movement of metals through soil, water, feed, and processing environments may expose bacteria to stress conditions that support survival of resistant strains. From a One Health perspective, this finding has shown that food contamination pathways have connected agriculture, environmental pollution, animal production, food processing, and human exposure. Therefore, the second key finding has demonstrated that antimicrobial resistance co-selection has been shaped by the structure of the food chain itself.

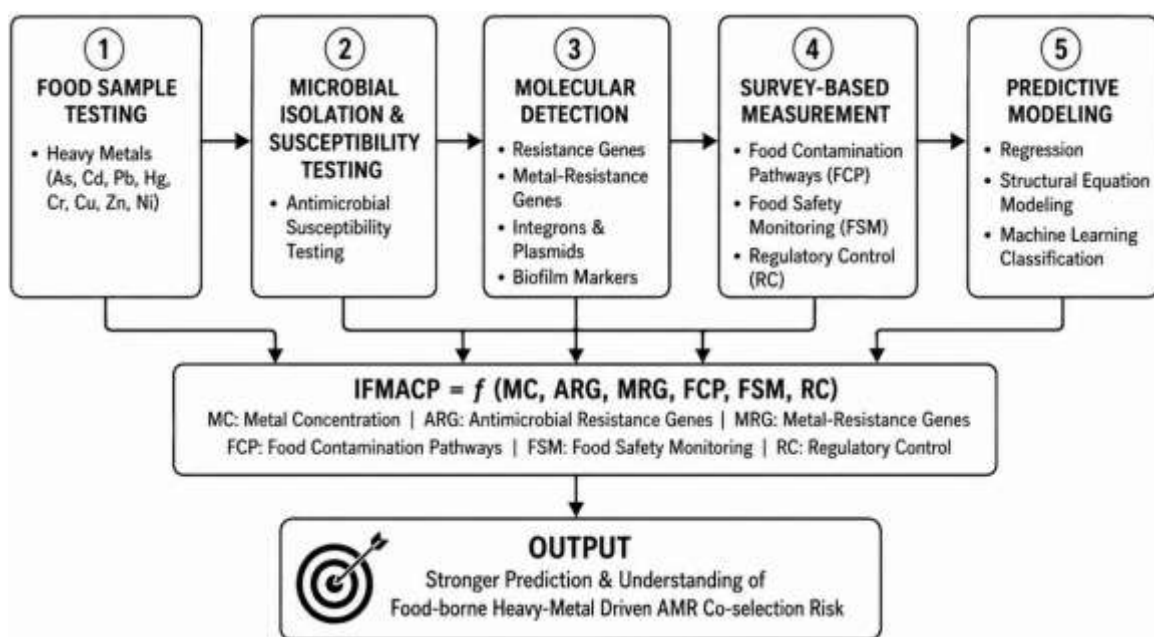
The findings have revealed that food safety monitoring has been one of the weaker areas in the selected case-study context and has had a significant relationship with antimicrobial resistance co-selection. The descriptive result for food safety monitoring has recorded a moderate mean score of 3.41 with $SD = 0.71$, which has indicated that respondents have not strongly agreed that laboratory testing, inspection, traceability, reporting, contamination screening, and surveillance systems have been fully sufficient. In the analysis, food safety monitoring has been interpreted in terms of monitoring weakness, and the correlation result has shown a moderate positive relationship between monitoring weakness and antimicrobial resistance co-selection, with $r = 0.49$ and $p < 0.001$. The regression result has also shown that monitoring weakness has significantly predicted antimicrobial resistance co-selection, with $\beta = 0.21$, $t = 3.87$, and $p < 0.001$. Therefore, H3 has been supported. This finding has proven the objective related to food safety monitoring because it has shown that limited testing and weak surveillance may allow heavy-metal contamination and associated microbial risks to remain undetected in the food chain. This result has been consistent with earlier environmental antimicrobial resistance research, which has emphasized that integrated surveillance is needed because antimicrobial resistance moves across environmental, food, animal, and human interfaces (Berendonk et al., 2015). It has also aligned with food-chain surveillance literature showing that molecular and genomic tools can improve the detection of antimicrobial-resistant microorganisms and resistance genes across food systems (Oniciuc et al., 2018). Compared with these prior studies, the present research has provided a survey-based quantitative result showing that respondents have perceived monitoring weakness as a statistically significant factor associated with co-selection risk. The practical interpretation is that food safety monitoring cannot focus only on visible spoilage or routine microbial quality. It needs to consider chemical hazards and resistance-related microbial hazards together. The theoretical interpretation is also important because One Health requires surveillance across human, animal, food, and environmental sectors. If monitoring has remained moderate or fragmented, the system may not fully identify how heavy metals, resistant bacteria, and resistance genes overlap in food-related environments. Therefore, this finding has shown that monitoring systems have been central to

controlling the relationship between heavy-metal exposure and antimicrobial resistance co-selection. The findings have also shown that regulatory control has worked as a protective variable in the predictive model. The descriptive result for regulatory control has recorded a moderate mean score of 3.36 with SD = 0.74, suggesting that respondents have perceived enforcement, permissible-limit monitoring, institutional coordination, penalty systems, and compliance practices as present but not sufficiently strong. The correlation analysis has shown a significant negative relationship between regulatory control and antimicrobial resistance co-selection, with $r = -0.43$ and $p < 0.001$. The regression result has confirmed this negative predictive effect, with $\beta = -0.18$, $t = -3.26$, and $p = 0.001$. Therefore, H4 has been supported. This finding has indicated that stronger regulatory control has been associated with lower antimicrobial resistance co-selection risk, while weaker regulatory systems may allow contaminated food products and resistance-supporting conditions to continue across the food chain. The result has been consistent with prior One Health governance literature, which has shown that antimicrobial resistance requires coordinated control across human health, animal health, agriculture, food production, and environmental sectors (Robinson et al., 2016). The result has also supported global food-chain governance research, which has emphasized that antimicrobial resistance in food systems requires regulatory attention, trade awareness, surveillance, and intersectoral coordination (George, 2019). In comparison with earlier studies, the present research has added a predictive finding by showing that regulatory control has had a measurable negative effect on antimicrobial resistance co-selection. This means that regulation has not been only a policy background issue; it has been a statistically relevant factor in the model. The practical interpretation is that food safety laws, permissible limits, inspection systems, penalties, and institutional coordination may reduce heavy-metal exposure and indirectly reduce metal-driven resistance pressure. The theoretical interpretation has also been aligned with the One Health framework because regulatory control has represented the governance mechanism that connects food, environment, agriculture, public health, and consumer protection. Co-selection theory has further supported this finding because reducing metal exposure may reduce one of the non-antibiotic pressures that help maintain antimicrobial resistance. Therefore, the regulatory-control result has shown that governance strength has been essential in reducing the risk pathway from contamination to resistance co-selection.

The overall regression model has provided strong quantitative evidence that the proposed predictors have jointly explained antimicrobial resistance co-selection. The model has been statistically significant, $F(4, 215) = 72.46$, $p < 0.001$, and has explained 57.4% of the variance in antimicrobial resistance co-selection, with $R = 0.758$, $R^2 = 0.574$, and adjusted $R^2 = 0.566$. This has supported H5 and has proven the main objective of developing and testing a predictive model linking food-borne heavy-metal exposure with antimicrobial resistance co-selection. The model has shown that food-borne heavy-metal exposure has been the strongest predictor, followed by food contamination pathways, food safety monitoring weakness, and regulatory control. These results have shown that antimicrobial resistance co-selection has not been explained by one isolated variable. Rather, it has been explained by the combined influence of exposure intensity, contamination movement, monitoring weakness, and governance strength. This finding has been consistent with genomic and environmental studies showing that antibiotic-resistance genes, metal-resistance genes, and mobile genetic elements may co-occur in bacterial communities and contaminated environments (Pal et al., 2015). It has also aligned with predictive antimicrobial resistance research showing that meaningful predictor variables can be organized into models to explain resistance outcomes when the dependent variable and predictors are clearly measured (Kim et al., 2022). In comparison with these previous studies, the present research has offered a different but complementary contribution because it has used survey-based Likert-scale data rather than genomic sequencing or laboratory measurement. The theoretical implication is that One Health and co-selection theory can be operationalized into a quantitative regression model. The model has translated the theoretical relationship into the equation $AMRCS = \beta_0 + \beta_1(FBHME) + \beta_2(FCP) + \beta_3(FSM) + \beta_4(RC) + \epsilon$. This equation has shown that antimicrobial resistance co-selection has been shaped by environmental exposure, food-chain pathways, surveillance capacity, and regulatory governance. Therefore, the study has contributed to theory by showing that a One Health-based co-selection model can be measured statistically in a case-study context. The result has also contributed methodologically because it has shown that informed professional perceptions can be used to develop

an empirical foundation for studying complex food safety and antimicrobial resistance relationships. The practical implications of the findings have been significant for food safety authorities, public health agencies, environmental regulators, agricultural departments, food producers, laboratories, and researchers. Since food-borne heavy-metal exposure has been the strongest predictor of antimicrobial resistance co-selection, food safety systems need stronger heavy-metal detection in high-risk foods such as vegetables, grains, fish, meat, dairy products, processed foods, and aquaculture products. Since contamination pathways have also been a significant predictor, practical control should include soil testing, irrigation-water monitoring, animal-feed control, industrial-discharge management, pesticide and fertilizer oversight, packaging safety, processing hygiene, and market-level inspection. Since monitoring weakness has significantly increased co-selection risk, laboratory capacity, routine surveillance, traceability, reporting systems, and data sharing need to be strengthened in food safety practice. Since regulatory control has shown a negative effect on co-selection risk, stronger enforcement of permissible limits, inspection quality, penalty systems, and interagency coordination has been necessary for reducing the movement of contaminated foods. These implications have aligned with prior food safety and antimicrobial resistance literature, which has emphasized that food-chain resistance requires integrated interventions across agriculture, environment, animal production, food processing, and public health systems (Founou et al., 2016).

Figure 10: Proposed conceptual framework for future prediction of antimicrobial resistance co-selection



The findings have also been compatible with research showing that antimicrobial resistance is a One Health issue involving human, animal, environmental, and food-system connections (McEwen & Collignon, 2018). In comparison with previous studies, the present research has provided practical evidence by identifying which variables have had the strongest statistical effects in the case-study model. Heavy-metal exposure and contamination pathways have emerged as the main risk-enhancing factors, while regulatory control has emerged as the main risk-reducing factor. Therefore, the practical message has been that antimicrobial resistance co-selection should be addressed through food-chain contamination control, not only through antibiotic-use control. The study has also indicated that food safety monitoring should be designed to capture combined chemical and microbial risks. This integrated monitoring approach has been consistent with the One Health framework because it recognizes that environmental metals, resistant bacteria, food products, and consumer health are linked within the same system.

The limitations of the study have also needed careful interpretation because the research has used a quantitative, cross-sectional, case-study-based survey design. The first limitation has been that the study has measured perceptions of food-borne heavy-metal exposure and antimicrobial resistance co-selection rather than directly measuring metal concentrations in food samples or detecting resistance genes through laboratory methods. Therefore, the findings have shown perceived and statistical relationships, not direct microbiological causality. The second limitation has been that the cross-sectional design has collected data at one point in time, so it has not captured long-term changes in contamination, monitoring, regulation, or resistance patterns. The third limitation has been that the case-study context has provided useful localized evidence but has limited generalization to all food systems, regions, or countries. These limitations have not weakened the value of the findings; they have clarified the boundary within which the results should be interpreted. Earlier environmental resistance studies have shown that direct laboratory and genomic methods can identify resistance genes, metal-resistance genes, and mobile genetic elements in contaminated environments, which suggests that survey findings can be strengthened through mixed-method or laboratory-supported designs (Li et al., 2017). Future research can therefore improve this study by applying a proposed Integrated Food Metal-AMR Co-selection Prediction Model, abbreviated as IFMACP model. This proposed model can include five layers: first, food-sample testing for arsenic, cadmium, lead, mercury, chromium, copper, zinc, and nickel; second, microbial isolation and antimicrobial susceptibility testing from selected food samples; third, molecular detection of resistance genes, metal-resistance genes, integrons, plasmids, and biofilm markers; fourth, survey-based measurement of monitoring, regulation, and food-chain practices; and fifth, predictive modeling using regression, structural equation modeling, or machine-learning classification. The model can be expressed as $IFMACP = f(MC, ARG, MRG, FCP, FSM, RC)$, where MC means metal concentration, ARG means antimicrobial resistance genes, MRG means metal-resistance genes, FCP means food contamination pathways, FSM means food safety monitoring, and RC means regulatory control. This future research direction has been most important because it can connect perception-based evidence with laboratory evidence and predictive analytics. Such a model can improve the current research by moving from perceived co-selection risk toward measurable biological confirmation and stronger prediction of food-borne heavy-metal-driven antimicrobial resistance co-selection.

CONCLUSION

This study has concluded that food-borne heavy-metal exposure has been an important predictor of antimicrobial resistance co-selection in the selected case-study context. The research has been developed through a quantitative, cross-sectional, case-study-based design and has used Likert's five-point scale to measure food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection. The descriptive findings have shown that respondents have perceived food-borne heavy-metal exposure as a high-level risk, with an overall mean score of 3.89, while food contamination pathways have recorded the highest mean score of 3.94. These results have indicated that respondents have strongly agreed that heavy metals may enter food systems through contaminated soil, polluted irrigation water, industrial discharge, fertilizers, pesticides, aquaculture, animal feed, processing environments, packaging, storage, transportation, and market handling. Antimicrobial resistance co-selection has also recorded a high mean score of 3.87, which has shown that respondents have recognized the possibility that heavy-metal exposure may support resistant bacteria, co-resistance, cross-resistance, biofilm survival, mobile genetic elements, and food-chain transmission. The reliability results have confirmed that all constructs have been internally consistent, with Cronbach's alpha values ranging from 0.81 to 0.88 and an overall instrument reliability of 0.91. The correlation analysis has shown that food-borne heavy-metal exposure has had a strong positive relationship with antimicrobial resistance co-selection, while food contamination pathways and food safety monitoring weakness have also shown significant positive relationships. Regulatory control has shown a significant negative relationship with antimicrobial resistance co-selection, indicating that stronger regulation has been associated with lower perceived co-selection risk. The regression model has been statistically significant and has explained 57.4% of the variance in antimicrobial resistance co-selection, with food-borne heavy-metal exposure emerging as the strongest predictor. Therefore, all five hypotheses of the study have been supported. The study has also

confirmed the relevance of the One Health framework because the findings have connected human health, food systems, agriculture, environmental contamination, regulatory governance, and microbial resistance within one predictive structure. Co-selection theory has also been supported because the findings have shown that heavy metals may operate as non-antibiotic selective pressures in food-related environments. Overall, the study has established that antimicrobial resistance co-selection cannot be explained only by antibiotic misuse; it has also been linked with food-borne chemical contamination, weak monitoring, contamination pathways, and regulatory control. The research has therefore provided a clear quantitative foundation for understanding how food-borne heavy-metal exposure may contribute to antimicrobial resistance co-selection in a food safety and public health context.

RECOMMENDATION

This study has recommended that food safety authorities, public health institutions, environmental agencies, agricultural departments, laboratories, food producers, and regulatory bodies should address food-borne heavy-metal exposure and antimicrobial resistance co-selection through an integrated food safety and One Health-based approach. First, routine heavy-metal testing should be strengthened for high-risk food items such as vegetables, rice, cereals, fish, seafood, meat, dairy products, spices, processed foods, and animal feed because the findings have shown that heavy-metal exposure has been the strongest predictor of antimicrobial resistance co-selection. Testing should not be limited to final food products; it should also include soil, irrigation water, aquaculture water, industrial discharge points, fertilizers, pesticides, food-processing surfaces, packaging materials, and market-handling environments. Second, contamination pathways should be controlled through improved agricultural practices, safer irrigation sources, proper waste management, industrial discharge regulation, clean processing systems, and stronger storage and transportation hygiene. Since food contamination pathways have shown a significant positive effect on co-selection risk, every stage of the food chain should be monitored as a possible route of heavy-metal and microbial hazard movement. Third, food safety monitoring systems should be improved through better laboratory capacity, trained personnel, regular inspection, contamination screening, traceability systems, digital reporting, and surveillance databases that can connect chemical contamination with antimicrobial resistance indicators. Fourth, regulatory control should be strengthened by enforcing permissible limits, conducting regular market inspection, applying penalties for unsafe production or handling, improving institutional coordination, and ensuring compliance among food producers, processors, distributors, and retailers. Since regulatory control has had a significant negative effect on antimicrobial resistance co-selection, stronger governance may reduce the movement of contaminated food and lower non-antibiotic selection pressure on bacteria. Fifth, an integrated surveillance system should be developed where food safety, public health, agriculture, veterinary, environmental, and laboratory institutions share data on heavy metals, resistant bacteria, resistance genes, and food-chain contamination. Sixth, food producers and supply-chain actors should receive training on contamination prevention, safe sourcing, proper storage, hygienic processing, feed safety, water quality, and packaging safety. Seventh, consumers should be made aware of food safety risks through public education, labeling, safe washing, proper cooking, and informed purchasing practices. Finally, future researchers and policymakers should adopt an Integrated Food Metal-AMR Co-selection Prediction Model that combines food-sample testing, microbial analysis, molecular resistance-gene detection, survey-based risk assessment, and statistical or machine-learning prediction. This approach would help move food safety practice from single-hazard monitoring toward combined chemical and microbial risk governance.

LIMITATIONS OF THE STUDY

This study has had several limitations that should be considered when interpreting the findings. The first limitation has been related to the cross-sectional research design. Since data have been collected at one point in time, the study has identified statistical relationships among food-borne heavy-metal exposure, food contamination pathways, food safety monitoring, regulatory control, and antimicrobial resistance co-selection, but it has not measured changes across time. Longitudinal data could provide stronger evidence about how exposure, monitoring, regulation, and co-selection patterns change across seasons, production cycles, or policy interventions. The second limitation has been related to the survey-based nature of the study. The research has measured respondents' perceptions through Likert-

scale items rather than directly testing food samples, metal concentrations, bacterial isolates, resistance genes, or mobile genetic elements in a laboratory. Therefore, the findings have reflected professional and informed perceptions of risk rather than direct toxicological or microbiological confirmation. The third limitation has been related to the case-study context. Since the study has focused on a selected food-system setting and has used purposive sampling, the findings may not be fully generalizable to all countries, regions, food systems, or consumer groups. Different areas may have different contamination sources, regulatory capacity, laboratory infrastructure, agricultural practices, industrial pressure, and antimicrobial resistance patterns. The fourth limitation has been related to the sample composition. Although the sample has included relevant respondents from food safety, public health, laboratory, environmental, agriculture, food industry, and academic backgrounds, the views of ordinary consumers, informal food sellers, small farmers, and low-resource food handlers may not have been fully represented. The fifth limitation has been related to the measurement of antimicrobial resistance co-selection. Since co-selection is a complex biological process involving co-resistance, cross-resistance, co-regulation, mobile genetic elements, biofilms, metal-resistance genes, and antibiotic-resistance genes, a questionnaire-based measure can only capture perceived risk and conceptual understanding. The sixth limitation has been related to the use of regression modeling. Although the regression model has explained 57.4% of the variance in antimicrobial resistance co-selection, other possible predictors such as antibiotic use in food animals, wastewater exposure, consumer handling, food import quality, seasonal contamination, sanitation, and genomic resistance profiles have not been included in the model. The seventh limitation has been related to data self-reporting, where respondents may have answered based on experience, knowledge, institutional exposure, or personal judgment. Future research should address these limitations by combining survey data with food-sample testing, heavy-metal concentration analysis, microbial culture, antimicrobial susceptibility testing, genomic detection of resistance genes, and advanced predictive modeling across multiple regions and food categories.

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