Antibiotic Management Trade-offs When a Veterinary Agent Seeks to Satisfy Multiple Goals

Ruoyu Wang*

Nov 30, 2025

Abstract

Since *Guidance for Industry (GFI) #213* was implemented in the United States, veterinarians have taken overall responsibility for authorizing access to antibiotics in animal health, in turn becoming key actors in antibiotic resistance management. However, prescribing antibiotics is a complex trade-off under uncertainty, involving clinical needs, client expectations, their own interests, and societal risks. To examine how veterinarians weigh these factors, we analyze observed prescription decisions from a discrete choice experiment with U.S. veterinarians using a random-utility framework. We find: first, disease and cure probabilities have independent effects on veterinarians' utility rather than entering only through contingent expected outcomes. Second, veterinarians place much greater weight on increasing cure probability than on reducing the magnitude of potential economic loss, especially in the small-animal sample, where loss avoided is essentially not valued. Third, regarding antibiotic-resistance risk, veterinarians' preferences differ by risk level: low-level risk is almost ignored, whereas high-level risk is strongly rejected. Preference heterogeneity exists, but only along years of experience, with more experienced veterinarians in large- and small-animal practice attaching different weights to welfare and economic outcomes.

JEL Classification: C25, Q18, I18, D81

Keywords: Discrete choice experiment, Veterinary decision-making, Antibiotic resistance, Risk preferences, Antimicrobial stewardship

---

* Working paper, Department of Economics, Iowa State University. Email: rwang549@iastate.edu

. I am grateful to David A. Hennessy for insightful guidance and feedback throughout the development of this research and to Hongli Feng for valuable comments. I also thank Ángel Abuelo and Yanan Jia for leading the data collection. This research was supported by funding from the Elton R. Smith Foundation at Michigan State University. All remaining errors are my own.

1 Introduction

Antibiotics are a cornerstone of modern medicine. However, their widespread use, while lifesaving, has also accelerated antibiotic resistance (AR), which in turn places a heavy burden on public health and the economy. In the United States alone, resistant infections cause more than 2.8 million illnesses and 35,000 deaths annually (CDC, 2019). The situation got worse during the COVID-19 pandemic, when antibiotics were often prescribed for a viral disease, frequently without evidence of bacterial co-infection (Rawson et al., 2020).

One of the most effective ways to slow down the development of antibiotic resistance is to reduce unnecessary antibiotic use, whereas most current efforts in AR management still target human medicine. Yet veterinary use accounts for a large share of total antibiotic consumption and resistance. In 2023, more than 6 million kilograms of antibiotics were used in food animals in the U.S. (CDC, 2024). In addition, companion animals can facilitate the transmission of resistant pathogens through close contact and shared living spaces with humans (Pomba et al., 2017). Therefore, effective management of antibiotic use in veterinary practice is indispensable, and veterinarians, who primarily guide animal owners' medical decisions, play an important role in antibiotic stewardship.

To control antibiotic use in animals, the United States implemented regulatory reforms in 2017 and 2021 that restrict access to medically important antibiotics. These reforms require that such antibiotics be prescribed only by a veterinarian with an established veterinarian–client–patient relationship, with the aim of ensuring that antibiotic-use decisions are made by trained professionals who can weigh therapeutic necessity against the broader societal risks of resistance.

These regulations place veterinarians in a role of controlling access to antibiotics. However, antibiotic stewardship cannot be achieved simply by instructing veterinarians to reduce use. Veterinarians work under a complex and often conflicting set of responsibilities. They must take regulatory expectations about controlling AR risk into account, meet the ethical and clinical standards for animal welfare required by their professional training, and satisfy their clients to maintain business and reputation in a competitive service market. These constraints turn antibiotic prescribing into a multi-objective decision problem that requires difficult trade-offs among competing goals.

The existing literature has widely discussed the multiple goals veterinarians face and their struggle to balance these goals. However, most of this work is qualitative, and there is limited quantitative evidence on how veterinarians actually trade off competing objectives in practice. This paper fills this gap by analyzing U.S. veterinarians' antibiotic prescribing decisions, using data from a discrete choice experiment to quantify the trade-offs they make among cure rate, economic loss avoided, animal welfare improvement, and antibiotic resistance risk.

The remainder of the paper is organized as follows. Section 2 outlines the relevant background and policies. Section 3 reviews the literature. Section 4 introduces the theoretical model. Sections 5 and 6 present the data and econometrics methods. Empirical results are presented in Section 7. Section 8 discusses the main findings and concludes.

2 Background and Policy Context

2.1 Antibiotics and Resistance

Antibiotics are regarded as one form of biological commons: they are non-excludable at the point of use, meaning anyone can access and benefit from treatment, yet their effectiveness is subject to depletion with widespread usage. Unlike natural resources depleted through actual consumption, the effectiveness of antibiotics is eroded through evolutionary selection: each individual use of antibiotics imposes selective pressure on the bacteria, which eliminates the susceptible ones and selects for the resistant strains (Giubilini, 2019). This process cumulatively makes irreversible changes to the effectiveness of antibiotics, which further affects the benefit of antibiotics shared by all users.

Usage control is the most effective method to slow down the development of resistance. However, global antibiotic consumption has been increasing over time. According to pharmaceutical sales data from IQVIA[1], antibiotic consumption in 67 countries increased by 16.3%, from 29.5 billion defined daily doses (DDDs) in 2016 to 34.3 billion in 2023. after extrapolating to non-reporting countries, this corresponds to about a 21% increase in global consumption. By 2030, global antibiotic consumption is expected to reach approximately 75.1 billion DDDs, a 52.3% increase, without intervention (Klein et al., 2024).

In 2014, antimicrobial resistance (AMR) was officially declared by the World Health Organization (WHO) as “a serious threat to global public health”. In 2019 alone, an estimated 4.95 million deaths were associated with bacterial AMR, of which 1.27 million were directly attributed to resistant infections (Murray et al., 2022). Other than these, it also causes high social and economic costs. The global annual direct healthcare costs attributed to antibiotic resistance are estimated at USD 66 billion. Furthermore, antimicrobial resistance could

[1] IQVIA is a multinational company that provides biopharmaceutical development and commercial outsourcing services, including comprehensive pharmaceutical market data and analytics.

reduce global GDP by 1.1% to 3.8% annually by 2050 without effective interventions (World Bank, 2017; World Bank, 2024).

Meanwhile, most of the global antibiotic consumption happens in animals. In 2017, approximately 73%[2] of global antibiotics were used in animals (Mulchandani et al., 2023). The proportion is even higher in the United States, reaching 80%, which is further expected to increase by 29.5% between 2019 and 2040, reaching approximately 143,481 metric tons, if no additional measures are taken (Martin et al., 2015). In addition, much of this livestock antibiotic use, as high as 80% in some countries (WHO, 2017), is for non-therapeutic purposes, such as disease prevention and growth promotion.

Given these facts, controlling the antibiotic use in animals is necessary in AR management.

2.2 Regulation and situation in the United States

The policies for AR management vary across countries. Our paper focuses on the United States because of its large antibiotic consumption, intensive livestock production, and widespread companion-animal practices. In addition, regulatory reforms over the past decade have specifically targeted antibiotic use in animals, and have placed veterinarians in charge of access to medically important antibiotics.

In the United States, unlike the comprehensive stewardship program of human medicines, the regulation of veterinary antibiotic use began later and has developed more slowly. For decades, producers could buy medically important antibiotics over the counter and use them for purposes other than treatment. A turning point came in 2013, when the U.S. Food and Drug Administration (FDA) released *Guidance for Industry (GFI) #213*, asking drug companies to remove growth-promotion claims from antibiotic labels. By 2016, the change was complete: these drugs could now only be used therapeutically, under veterinary supervision.

Following that, in 2017, the *Veterinary Feed Directive (VFD) Final Rule* was issued, which required veterinary oversight for any antibiotics delivered through feed or water. The *GFI #263* in 2021 further tightened the regulation, by moving all remaining over-the-counter antibiotics to prescription-only status. Together, these measures restrict access to antibiotics: now, they can be obtained only by prescription under a valid veterinarian–client–patient

[2] Due to data limitations, antimicrobial use (AMU) is used as a proxy for antibiotic use in this analysis, considering antibiotics comprise the major category of antimicrobials used in livestock and are the primary driver of bacterial resistance.

relationship (VCPR). As a result, veterinarians have become the primary gatekeepers of antibiotic access in animals, determining whether and how these drugs are used in practice.

The impact of these reforms is also discussed in literature. For example, Dillon and Jackson-Smith (2021) examined how the implementation of the Veterinary Feed Directive (VFD) affected cattle operations in Ohio. They found that the use of medicated feed antibiotics decreased, interactions between farmers and veterinarians increased, and there was no significant adverse effect on overall production. This finding is further supported by Abdelfattah et al. (2021), who studied adult cows on California dairies and reported similar conclusions. Additionally, Sarkar and Okafor (2023) observed changes in the prevalence of antibiotic-resistant bacteria in retail meat following the VFD implementation.

3. Literature Review

3.1 Theoretical Foundations

3.1.1 Antibiotic use as a dynamic externality

The effectiveness of antibiotics is a non-renewable common-pool resource, and its use has a strong negative dynamic externality. This problem was first formalized by Laxminarayan and Brown (2001) by combining SIS (Susceptible–Infected–Susceptible) epidemiological model with optimal control theory. They developed a dynamic model to capture the tradeoffs between the effectiveness of antibiotics and the evolution of resistance, and to find a social optimum for this problem.

A key contribution of this study is that it shows when individual decision-makers (such as physicians, patients, or hospitals) focus on immediate private benefits and costs, and do not internalize the long-term social cost for future generations, the private best response would not follow the social optimal path. As a result, policy intervention is necessary to achieve a long-term social optimum.

Laxminarayan and Brown (2001) demonstrated the macro-level market failure. Yet in practice, individual decisions about antibiotic use are mostly made by professional agents (e.g., physicians or institutions), rather than by patients who directly benefit from antibiotic use. This can be interpreted using h the principal–agent framework of regulatory economics (Laffont & Tirole, 1993): a social planner (e.g., regulator or health authority) delegates decision-making to those who hold private information, but the agents' private best responses are not always aligned with the social optimum. In the veterinary context, the agents, veterinarians, actually play two roles in practice: as agents for a social planner, and clinical agents for animal owners. These two roles sometimes have conflicting objectives.

3.1.2 Cure–loss-cost trade-offs in production animals

In the health economics of food-producing animals, the decision of whether to treat often depends on the economic impact of disease, which is typically decomposed into two components: (i) avoided losses in production and animal value and (ii) treatment costs, including veterinary labor, diagnosis, testing, pharmaceuticals (McInerney et al., 1992; Bennett, 2003). To be more specific, let L denote the loss avoided, C the treatment cost, r the probability of the animal being successfully cured. $rL > C$ indicates the treatment is profitable.

This rule has been widely used, especially when evaluating the economic benefit of treating mastitis in dairy cattle. The specific modelling approaches differ, for example, Swinkels, Hogeveen & Zadoks (2005) use a partial budget model, whereas D Nielsen et al. (2010) and Rodriguez et al. (2024) use a dynamic model with stochastic elements, but in all cases, the core idea of evaluating economic benefit is to compare the expected avoided loss rL with the treatment cost C.

Because r and L enter only through their product rL, this framework implicitly assumes r and L is perfect substitutes: for the treatment decision, any proportional change in r or L that leads to the same rL makes no difference. However, treatment decisions, particularly those involving antibiotics, are made by veterinarians, and for them, this implicit assumption may not hold. Survey evidence suggests that veterinarians give more weight to treatment success. In a study of bovine respiratory disease, most respondents reported preferring combinations of therapies primarily because of their perceived efficacy (Mijares et al., 2023). Similarly, Mateus et al. (2014) find that many small-animal veterinarians state they would choose the most efficacious option whenever possible.

Other than that, in practice, veterinarians' risk- and regret-aversion may attach more value to cure success, several studies about the drivers of veterinarians' prescription decisions reported that fear of treatment failure, low tolerance for uncertainty, and the pressure from potential bad outcomes are also regarded as important prescribing decision drivers (Coyne et al. 2014; King et al., 2018; Golding et al., 2019; Servia-Dopazo and Figueiras, 2021). These psychological costs make the treatment failure particularly aversive, and thus lead to a higher weight veterinarian put on the cure success.

In human medicine, similar patterns are documented and widely discussed. For physicians, the outcome of potential treatment failure also includes serious legal, reputational, and relational costs (Boiko et al., 2020; Simeoni et al., 2022; Schuler et al., 2025). Consistent with this, preference-elicitation studies show that physicians place greater weight on avoiding adverse outcomes and are less willing to accept treatment risks than patients (Byun et al., 2016; Zhang et al., 2023).

3.2 Discrete Choice Experiment in Health and Veterinary Contexts

Discrete choice experiment (DCE) is a widely used stated-preference method for analyzing decision problems under uncertainty and for studying how decision makers trade off different attributes (Lancsar & Louviere, 2008; de Bekker-Grob et al., 2012; Wang et al., 2021). In a DCE, respondents are presented with hypothetical choice sets in which each option is described by a vector of attributes, and their choices are analyzed using models such as the multinomial logit, mixed logit, or probit (de Bekker-Grob et al., 2012; Clark et al., 2014).

DCEs have several advantages in healthcare applications. They can be used to value non-market attributes attached to choices, such as process quality, waiting time, or communication style, which are difficult to capture with conventional health-state utility instruments (Ryan et al., 2008; Lancsar & Louviere, 2008). Moreover, flexible model specifications allow researchers to characterize preference heterogeneity across subgroups (de Bekker-Grob et al., 2012; Clark et al., 2014).

In human health economics, DCEs are now widely used to study the preferences of patients, the general public and health professionals. Systematic reviews document a rapid expansion of applications since the 1990s across screening and prevention, chronic disease management, pharmaceuticals and service organization (de Bekker-Grob et al., 2012; Clark et al., 2014; Wang et al., 2021; Kleij et al., 2017; Collacott et al., 2021). A large subset of these studies focuses on how physicians trade off treatment benefits and risks or respond to contextual factors when making prescribing decisions. For example, oncologists' trade-offs between efficacy, toxicity and treatment logistics have been studied in anticancer drug prescribing (Benjamin et al., 2012; Collacott et al., 2021), while Xue et al. (2022) analyze how primary care physicians adjust antibiotic prescribing in response to patient attributes and pressures.

By contrast, applications of DCEs in veterinary medicine remain relatively limited and are mostly framed from the perspective of animal owners or consumers rather than veterinarians themselves (Groves et al., 2024). In livestock systems, most existing studies elicit farmers' or consumers' preferences regarding animal-health services, animal-welfare schemes, and production attributes related to antimicrobial use and welfare label in animal-source foods (Nthambi et al., 2023; Schröter & Mergenthaler, 2021; Paudel et al., 2022; Schwickert, 2023). In companion-animal settings, DCEs are typically used to analyze pet owners' preferences for preventive or therapeutic products and aspects of veterinary care (Bebrysz et al., 2021; Deault et al., 2021; Samper et al., 2023; Groves et al., 2024), while the DCE applications on veterinarians' preferences are still rare, despite their antibiotic prescribing decisions are never a simple problem.

3.3 Veterinarians' Behavioral Drivers and Heterogeneity

3.3.1 Behavioral and Psychological Drivers

When making antibiotic prescription decisions, veterinarians often face trade-offs among multiple objectives including animal welfare, treatment efficacy, client costs, and the long-term risk of antimicrobial resistance (Speksnijder et al., 2014; King et al., 2018; Doidge et al., 2019). These objectives are not always aligned and may even conflict in practice (Golding et al., 2019).

Qualitative and survey evidence documents this dilemma. De Briyne et al. (2013) report that veterinarians generally recognize their responsibility for safeguarding public health, yet their prescribing decisions are also shaped by clients' financial constraints and expectations (Lavigne et al., 2021; Eltholth et al., 2022). In an online survey by Kipperman et al. (2018), more than 50% of respondents indicated that they encounter ethical dilemmas involving conflicts between clients' interests and patients' welfare at least once a week, and other surveys similarly highlight financial limitations and non-clinical factors as common sources of pressure on prescribing decisions (Gibbons et al., 2013; Servia-Dopazo et al., 2021). From the client side, farmers and animal owners often seek rapid recovery at minimal cost and may explicitly request antibiotics, and veterinarians in qualitative interviews report that they sometimes ""*do not like using antibiotics, but [feel] you have to*" in order to retain clients and remain competitive (De Briyne et al., 2013; Golding et al., 2019).

As we discussed in 3.1.2, psychological drivers such as fear and loss aversion also influence antibiotic prescribing decisions (Warreman et al., 2019). A systematic review of non-clinical determinants of antibiotic use identified fear as one of the most frequently cited factors shaping prescribing behavior (Servia-Dopazo et al., 2021). This fear may take various forms: concerns about disease progression (King et al., 2018), potential clinical complications (Servia-Dopazo et al., 2021), or client dissatisfaction with conservative treatment approaches (Tompson et al., 2021). In such cases, veterinarians may prescribe antibiotics "just in case" as a precautionary action. These fears contribute to loss-averse tendencies in clinical practice, which often demonstrate as a strong aversion to treatment failure and a preference on the cure rate.

3.3.2 Heterogeneity across practice types and career stages

Although veterinarians are often treated as a homogeneous group, prescribing behavior varies systematically across practice types. The literature frequently distinguishes between large animal veterinarians (LAVs), who primarily serve food-producing animals, and small animal veterinarians (SAVs), who work with companion animals, given their distinct clinical, economic and institutional contexts.

LAVs typically operate within production systems under long-term client relationships and are guided by technical efficiency, cost-effectiveness and regulatory compliance (Taylor et al., 2020). Consistent with this, McDougall et al. (2016) found in a survey of New Zealand dairy farms that technical factors, such as diagnostic information and responses to prior treatments, were the primary drivers of prescribing decisions. By contrast, SAVs operate in a consumer-oriented market with diverse clientele, and their prescribing decisions are more strongly shaped by client expectations, diagnostic uncertainty, and concerns for animal welfare (Tompson et al., 2021). Empirical evidence suggests that SAVs perceived pressure from the animal owners, which influences their prescription decision significantly, as the clients may turn to another clinic if they fail to get the requested antibiotics or face treatment failure (Hopman et al. 2018).

In addition, interpersonal dynamics further contribute to the heterogeneity. Studies indicate that recent veterinary graduates are generally more cautious with antibiotic use, but tend to adopt more relaxed prescribing patterns as they gain experience, often influenced by colleagues and informal group norms (King et al., 2018; Moya et al., 2022). Meanwhile, junior veterinarians frequently receive feedback or implicit guidance from senior colleagues, and in most cases, align their decisions with established prescribing practices at the clinic or organizational level (Mateus et al., 2014; Moya et al., 2024).

Overall, several gaps remain in the current literature. The role of veterinarians in AR management is widely recognized; however, to our knowledge, no study formalizes their decision-making or quantifies the trade-offs involved. Moreover, existing studies typically compare rL and C to determine whether a treatment should be given, whereas for veterinarians who prescribe antibiotics, this rule may not hold. Veterinarians' preferences over $r$and L have not been fully explored yet.

4 Theoretical Model

Before modeling veterinarians' decision-making, we identify two fundamental features of the problem. First, veterinarians, the decision makers, operate under dual roles in practice: as clinical agents committed to animal welfare and public health, and as economic agents sensitive to client financial concerns.

The first arises from the professional codes of ethics that govern the field: veterinarians are trained to prioritize the animal's well-being when making treatment decisions. At the same time, when treatments involve negative externalities, such as antibiotic use, it is their professional responsibility to ensure the judicious use of antibiotics to mitigate the risks of resistance for the public benefit.

In addition, it must be acknowledged that veterinarians' livelihood is dependent on an intensive service market. The client's satisfaction, as important as the treatment success, directly impacts veterinarians' professional reputation, client retention, and further determines their practice revenue and personal income. Consequently, a veterinarian's economic utility becomes directly or indirectly linked to the client's utility, in which financial outcome plays a significant role.

The second feature is the uncertainty in the decision environment. When a client brings in an animal suspected of being sick for treatment, we need to admit the decision was made under two types of uncertainty: (i) whether the animal is truly diseased, and (ii) whether treatment, if administered, will succeed.

4.1 Decision-making Framework

When facing a treatment decision-making scenario, there are often multiple treatment options that the veterinarians have to weigh against each other. In this section, we mathematically characterized each option by five important attributes widely mentioned in the literature: treatment cost and potential avoided economic losses suffered by the client, cure rate of the treatment, potential animal welfare improvement and the antibiotic resistance risk carried by the treatment.

Let C denote the set of all possible treatment costs, L the set of all potential economic losses, $R \subseteq [0, 1]$ the set of all possible cure rates, AW the set of all animal welfare improvement levels, and AR the set of all antibiotic resistance risk levels[3]. Let X denote the set of all the possible treatment attribute combinations. Then each treatment option can be modeled as a vector of attributes:

$$x_i = (c_i, l_i, r_i, aw_i, ar_i), \qquad x_i \in X$$

[3] These sets have specific values in the data collection process, and the values would be utilized in the following sections.

Where:

- $c_i \in C$ denotes the cost of treatment i, borne by the animal's owner.
- $l_i \in L$, denotes the economic loss avoided if the animal is successfully cured under treatment i, also accruing to the owner.
- $r_i \in R$ denotes the probability of successful treatment i (cure rate).
- $aw_i \in AW$, denotes the level of animal welfare improvement associated with treatment i.
- $ar_i \in AR$, denotes the potential risk of increasing antibiotic resistance from treatment i.

Furthermore, we model the probability of the animal having the disease as $p \in [0,1]$. Given this information, the veterinarian chooses a treatment option to maximize the utility, i.e.:

$$\max_{x_i=(c_i,l_i,r_i,aw_i,ar_i),\ \ x_i \in X} u(x_i, p) \tag{1}$$

4.2 Risk-averse Hypothesis

A key hypothesis we hold and aim to test empirically is that veterinarians are risk-averse in their decision-making; that is, they prefer to avoid uncertain negative outcomes even at the expense of lower expected payoffs. In the veterinary context, this presents as veterinarians potentially placing more weight on reducing disease incidence (preventing uncertain future losses) than on minimizing the immediate magnitude of treatment costs.

To demonstrate the mathematical equivalence between the behavior and risk aversion, consider the following simplified decision-making scenario:

An expected-utility-maximizing agent seeks to respond to client needs when dealing with the cure probability r for the animal and the loss magnitude L, with an initial wealth W and a risk-averse preference, which is characterized by a continuous, differentiable, and concave utility function $U(\cdot)$ over uncertain treatment outcomes. The expected utility of the veterinarian is:

$$(1-r)U(W-L) + rU(W) \tag{2}$$

Holding expected utility fixed, complete differentiation with respect to L and $1-r$ yields the comparative statics:

$$-\frac{[U(W)-U(W-L)]}{L}\frac{d(1-r)}{1-r}=U'(W-L)\frac{dL}{L} \tag{3}$$

This condition describes the marginal rate of substitution between L and r that keeps utility constant.

When L is small, equation (3) simplifies to:

$$\frac{d\ln(1-r)}{d\ln(L)}\approx 1 \tag{4}$$

i.e., the client should be indifferent between a 1% increase in loss avoided and a 1% reduction in the probability of disease continuance.

When L is larger, then risk aversion requires:

$$U'(W-L)>\frac{[U(W)-U(W-L)]}{L} \tag{5}$$

Under equation (3), it further requires:

$$\frac{d\ln(1-r)}{d\ln(L)}<-1 \tag{6}$$

In other words, a 1% increase in loss avoided must be accompanied by a more-than-1% decrease in the probability of disease continuance for client indifference.

4.3 Alternative Utility Specifications

Under uncertainty, decision-makers exhibit preferences toward risk. However, such preferences only reflect the outcome of the decision process. Whether veterinarians place greater weight on reducing uncertainty or not describes the final pattern of choices; it does not reveal how uncertainty is incorporated into their utility function. To explore that, we consider three alternative utility specifications. These specifications differ in how the uncertain components, the probability of the animal having the disease and the cure rate, enter the utility function.

Specification 1 (S1): Expected Outcome

Here each outcome attribute enters utility through its probability-weighted value, thereby implicitly treating cure probability and loss avoided as linearly scaled in their marginal contributions to utility:

$$u_1(x_i, p) = \beta_c c_i + \beta_{ar} ar_i + \gamma_{prl} p \cdot r_i \cdot l_i + \gamma_{praw} p \cdot r_i \cdot aw_i \tag{7}$$

Specification 2 (S2): Additive Attribute

Here each attribute enters utility independently and linearly, thus relaxing the linear-scaling symmetry assumed in the expected-outcome formulation:

$$u_2(x_i, p) = \beta_p p + \beta_c c_i + \beta_r r_i + \beta_l l_i + \beta_{aw} aw_i + \beta_{ar} ar_i \tag{8}$$

Specification 3 (S3): S1+S2

S3 is a hybrid specification that combines these two structures by including probability-outcome interactions while retaining independent attribute effects, providing a more flexible representation of how uncertainty is processed:

$$\begin{aligned} u_3(x_i, p) = {} & \beta_p p + \beta_c c_i + \beta_r r_i + \beta_l l_i + \beta_{aw} aw_i + \beta_{ar} ar_i \\ & + \gamma_{prl} p \cdot r_i \cdot l_i + \gamma_{praw} p \cdot r_i \cdot aw_i \end{aligned} \tag{9}$$

5 Data

Before turning to the empirical results, we next describe the survey instrument and dataset used in the estimation.

Targeted practicing veterinarians across the United States, the data were collected through a web-based survey administered during the winter and early spring of 2020–2021, with assistance from several veterinarian associations and the survey company Dynata (Jia, 2022). A total of 240 valid survey responses were collected, with equal representation from LAVs and SAVs.

Table 5.1 and 5.2 report the main demographic characteristics of the respondents and compare the differences between LAVs and SAVs, respectively.

In our survey, each respondent was required to complete six hypothetical and independent treatment scenarios. In each scenario, given a probability of the animal[4] having the disease, the veterinarian was required to choose from two treatments that differ in treatment cost, AR risk, cure rate, potential loss avoided, and animal welfare improvement. No treatment is also available as an outside option. We constructed the choice sets using a D-orthogonal design, randomizing the levels of the five attributes within context-specific bounds for the LAV and SAV contexts.

Overall, the dataset comprises 240 × 6 = 1,440 choice sets, each containing three alternatives, yielding 4,320 observations in long format. The data have a panel structure, as multiple choices are observed for each respondent, and standard errors in the empirical analysis are clustered at the individual level. The study was conducted with informed consent under approved human-subject protocols.

A sample question:

You believe the cow has mastitis with probability 0%. If the cow has mastitis, treatment options can provide **some benefits**; otherwise, treatment options provide **no benefit**.
Which treatment do you prefer? Please check one.
(T1= Treatment 1, T2= Treatment 2, NT= No treatment)

	T1	T2	NT
Treatment cost	\$20	\$80	\$0
Potential to increase antibiotic resistance	None	Low	None
Cure rate of mastitis *Note: you believe the cow has mastitis with probability 0%*	100%	20%	0
If the cow is cured, animal welfare improvement	Low	High	None
If the cow is cured, loss avoided	\$850	\$250	\$0

- My decision would be to use Treatment 1 (T1)
- My decision would be to use Treatment 2 (T2)
- My decision would be No treatment (NT)

6 Econometric Method

[4] For LAVs, the animal is a cow and the suspect disease is mastitis; for SAVs the animal is a dog and the suspect disease is pyoderma.

6.1 Utility Specification

Based on the theoretical specifications in Section 4.3, we rewrite the three alternative utility functions into a random utility framework. For veterinarian v, treatment alternative i in choice situation t, the random utility is written as

$$U_{vit} = u_k(x_{it}, p_t) + \varepsilon_{vit} \tag{10}$$

where $k \in \{1,2,3\}$ indexes the utility specification, $x_{it} = (c_{it}, l_{it}, r_{it}, aw_{it}, ar_{it})$ represents the attribute vector for the treatment alternative i in situation t, $p_t \in [0, 1]$ represents the probability that the animal has the disease in situation t, ε_{vit} is the error term representing the unobserved utility component, and the vector of error terms across alternatives ε follows a multivariate normal distribution with mean zero and covariance matrix Σ. The deterministic component $u_k(\cdot)$ takes one of the three forms defined in equations (7) – (9).

Under the expected outcome specification S1, the observable utility is:

$$u_1(x_{it}, p_t) = \beta_{ar} ar_{it} + \beta_c c_{it} + \gamma_{praw}\,(p_t r_{it} aw_{it}) + \gamma_{prl}\,(p_t r_{it} l_{it}) \tag{11}$$

which treats potential loss avoided and animal welfare improvement as probability–weighted outcomes.

Under the additive–attribute specification S2, the observable utility is:

$$u_2(x_{it}, p_t) = \beta_p p_t + \beta_c c_{it} + \beta_r r_{it} + \beta_l l_{it} + \beta_{aw} aw_{it} + \beta_{ar} ar_{it} \tag{12}$$

where each attribute enters linearly and independently, allowing the marginal utilities of loss avoided and cure probability to differ from the expected outcome scaling in S1.

The hybrid specification S3 combines these two structures by augmenting S2 with probability–outcome interaction terms:

$$\begin{aligned} u_3(x_{it}, p_t) = {} & \beta_p p_t + \beta_c c_{it} + \beta_r r_{it} + \beta_l l_{it} + \beta_{aw} aw_{it} + \beta_{ar} ar_{it} \\ & + \gamma_{prl}\,(p_t r_{it} l_{it}) + \gamma_{praw}\,(p_t r_{it} aw_{it}) \end{aligned} \tag{13}$$

S3 therefore nests S1 and S2 as special cases, providing a more flexible representation of how veterinarians process uncertainty.

Notably, in all specifications, the no-treatment option serves as the base alternative, and utilities for the two treatment options are interpreted relative to this alternative.

6.2 Estimation

We further estimated the utility specifications using a multinomial probit model. Compared to other discrete choice models, the advantage of the probit model is that it releases the independence of irrelevant alternatives (IIA) assumption, allowing correlation in unobserved utility components (error terms) across treatment alternatives.

Following previous notation and setting, the probability that veterinarian v chooses alternative i in choice situation t can be expressed as:

$$P_{vit} = \Pr\left(U_{vit} > U_{vjt} \ \ for\ all\, j \neq i\right) \tag{14}$$

Given the distribution assumption of the error terms, equation (13) becomes:

$$P_{vit} = \Pr\left[\varepsilon_{vjt} - \varepsilon_{vit} < u_k(x_{it}, p_t) - u_k\left(x_{jt}, p_t\right) \ \ for\ all\, j \neq i\right] \tag{15}$$

Then we can derive the log-likelihood function for the whole sample:

$$l\,n\,L = \sum_{v=1}^{V}\sum_{t=1}^{T}\sum_{i=1}^{I} D_{vit} \ln P_{vit} \tag{16}$$

where D_{vit} is an indicator variable equal to 1 if veterinarian v chooses alternative i in situation t, and 0 otherwise.

The model parameters are estimated using simulated maximum likelihood via Stata's *cmmprobit* command, with clustered standard errors at the veterinarian's level.

6.3 Willingness-to-pay

Having discussed the estimation method, we next describe how marginal trade-offs across attributes are compared using willingness-to-pay (WTP). Specifically, we define veterinarians' WTP for an incremental change in a given attribute j as:

$$\mathrm{WTP}_{\mathrm{j(x,p)}} = -\left(\partial \mathrm{u}/\,\partial \mathrm{x_j}\right) / \left(\partial \mathrm{u}/\,\partial \mathrm{c}\right) \tag{17}$$

For additive attributes specifications, this reduces to the simple ratio of coefficients: $WTP_j = -\beta_j/\beta_c$. For the hybrid specification S3, where attributes enter through interactions (e.g., $p\,\cdot$

$r \cdot aw$), we evaluate the partial derivatives at the sample means of the interacting variables and compute WTP using the delta method.

Although treatment cost is borne by the client rather than the veterinarian, the marginal rate of substitution between an attribute and cost remains an informative measure of trade-offs. Rather than the veterinarian's own monetary payment, WTP in this context should be interpreted as the maximum cost increase the veterinarian is willing to endorse or recommend to the client for an incremental improvement in the attribute j, holding all other attributes constant.

7 Empirical Analysis

Based on the environment we outlined above and the collected decision data, in this section, we aim to quantitatively characterize veterinarians' decision-making to understand the tradeoffs among different factors and the potential heterogeneity behind.

The analysis was organized into three parts. First, we characterize veterinarians' utility under uncertainty to verify whether the risk-averse hypothesis in 4.2 holds. Second, we discuss the weight that the veterinarians put on different factors and compare the differences between LAVs and SAVs. Finally, we explore the heterogeneity among different groups. Considering the large difference of the service markets that LAVs and SAVs are in, all the estimation was conducted separately for LAVs and SAVs.

7.1 How do veterinarians process uncertainty in their utility?

Table 7.1 reports the estimation results, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and pseudo-R^2 among the three specifications.

From the fit statistics at the bottom of Table 1, we can see a clear improvement in fit when moving from S1 to S3. For LAVs (SAVs), pseudo-R^2 increases from 0.35 (0.33) under S1 to 0.37 (0.35) under S2 and to 0.40 (0.36) under S3. AIC also decreases monotonically from S1 to S3 for both groups. For BIC, S3 is preferred for LAVs, while S2 and S3 are very similar and both improve on S1 for SAVs. Overall, these statistics indicate that S3 provides the best, or at least not worse, overall fit among the three specifications.

Besides, we also do the Wald tests on the parameter restrictions. The results show that the pure expected-outcome restriction that disease probability and cure probability affect utility only through the contingent terms prl and $praw$ is strongly rejected (joint Wald tests of H0: $\beta_p = \beta_r = 0$ are rejected at the 1% level for both groups). Also, for animal welfare, both the main effect aw and, in the LAV sample, the interaction term $praw$ are statistically important at the 1% level. In terms of client loss avoided, in LAVs, the joint test : $\gamma_{prl} = \beta_l = 0$ is rejected at 1%, while we cannot distinguish which one contributes the most. In contrast, SAVs' test results on loss-related terms are weak.

Taken together, we conclude three main findings about how uncertainty enters veterinarians' utility. First, a pure expected-outcome representation is rejected: disease probability and cure probability must enter utility directly, in addition to their role in contingent terms. Second, models that allow probability–welfare interactions provide a better description of choices, especially for large-animal veterinarians. Third, the role of client loss avoided is different for the two groups. SAVs, compared to LAVs, are relatively insensitive to loss-related terms.

Based on these results, we take the hybrid specification S3 as our preferred baseline specification in the remainder of the analysis, while results for S1 and S2 are reported in the Appendix.

7.2 How do veterinarians trade off treatment attributes?

Before discussing the tradeoffs, we first summarize some facts found from the estimation results of S3 in Table 7.1.

Overall, the signs line up with our prior expectations. In terms of each attribute, first, treatment cost enters with a negative and statistically significant coefficient in both groups, which confirms that higher client expenses reduce the attractiveness of a treatment option to veterinarians, further supporting our assumption that cost enters veterinarians' utility. Second, veterinarians respond very differently to low and high levels of antibiotic-resistance risk. Low-level AR have coefficients close to zero and are not statistically different from the baseline option no treatment, whereas high-level carries large negative and significant coefficients. For both groups, low-level AR seems tolerable, while they strongly avoid options associated with high resistance risk. The welfare terms are more difficult to interpret directly from the coefficients, as welfare enters utility through two terms in S3.

Considering these coefficients are expressed in different units, we further use WTP derived from S3 to compare the relative importance of attributes on a common scale, and the WTP estimates are reported in Table 7.2.

The WTP results are consistent with our risk-averse hypothesis: veterinarians place more weight on reducing the probability of loss than on reducing the magnitude of loss. To compare these two dimensions on a common scale, we use $WTP_{r=\bar{r}}$ and $WTP_{l=\bar{l}}$, defined as the WTP for increasing the cure rate and the avoided loss by the group-specific sample means which are the WTP of increasing the group average cure rate and group average loss avoided to compare their weight to veterinarians. For both groups, $WTP_{r=\bar{r}}$ is large, around 260-380, whereas $WTP_{l=\bar{l}}$, LAVs is about 141 for LAVs, and almost zero for SAVs.

The WTP results for further support veterinarians have different attitudes towards different level of AR risk. For groups, the WTP for low level is close to zero, showing that low-level risk is largely tolerated. By contrast, the WTP for high resistance is large and negative (about –230 for LAVs and –316 for SAVs), which means they need to be compensated by such an amount to accept the corresponding AR risk.

Welfare-related WTPs are more difficult to interpret. The WTPs for low- and high-level welfare improvement are negative in both samples. For that, we prefer not interpreting it as a dislike toward welfare improvement for animals. because welfare enters the S3 utility function by two terms, and the derivation of the WTP involves several correlated coefficients.

However, the WTPs for the cure rate under different welfare levels offer some clues on how welfare improvement is valued, at least for LAVs: moving from low to high welfare increases the WTP for a unit increase in cure rate by roughly 120 (from about 260 to 380), whereas the results for SAVs offer limit information on this.

7.3 How do preferences vary across veterinarians?

To capture the heterogeneity among different demographic groups, we estimate a series of extensions to the baseline hybrid specification using a set of demographic variables, which includes gender, years of experience, degree type, work setting, and location.

These extensions take two forms:

(i) Attribute–demographic interactions
For this extension, we first interact each demographic variable with all treatment attributes to generate a set of attribute-demographic interaction terms. We then add only one set of interaction terms at a time to the baseline specification to assess how marginal utilities differ across subgroups. In total, this procedure yields five extended specifications.

(ii) Additive demographic shift
In this extension, demographic variables enter the utility as additive shifts simultaneously, capturing level differences in the overall propensity to choose treatment.

We first discuss the results of adding Attribute–demographic interactions for SAVs and LAVs separately.

For LAVs, years of experience are the only demographic characteristic that shows robust preference heterogeneity. Models based on gender, location, degree type, and work setting yield a few significant interaction coefficients, but the joint tests for all interactions and for each attribute family fail to reject the null of homogeneous preferences. By contrast, when we interact attributes with mid- and senior-career indicators, the joint tests for the welfare-related interactions are significant, and the coefficients show that more experienced veterinarians place less weight on welfare improvements. Relative to early-career veterinarians, mid- and senior-career large-animal veterinarians exhibit lower marginal utility for both welfare levels and expected welfare gains, while their sensitivities to cost, cure probability, client loss, and resistance risk remain similar.

For SAVs, the conclusion remains the same, while the direction of the effects differs. For the interaction extensions based on gender, location, and degree type, the joint tests for all interactions and for each attribute family do not reject the null. Meanwhile, the experience-interaction extension generates highly significant joint tests. However, different from LAVs, the coefficients reveal that more experienced SAVs attach higher marginal utility to expected welfare gains and display stronger aversion to losses. Interactions between experience and the expected-welfare terms are positive and significant, whereas interactions with loss and expected loss are negative, indicating that, in small-animal practice, more experienced veterinarians put more weight on improvements in animal welfare and on avoiding economic losses.

In terms of adding demographic shifts, we did not find any evidence of systematic heterogeneity, regardless practice type.

8 Conclusion and Discussion

This paper discusses how veterinarians, when making antibiotic treatment decisions under inherent uncertainty, trade off cure rate, animal welfare, client economic outcomes, and potential antibiotic resistance risk. We use data from a discrete choice experiment targeting both large- and small-animal practitioners in the United States, to estimate a series of utility specifications using a multinomial probit model. We further examine how uncertainty in the decision environment is incorporated into veterinarians' utility and use WTP measures to compare the weight they place on each attribute. The preference heterogeneity across demographic groups is also considered.

Empirically, we reject the pure expected-outcome specification in which probabilities affect utility only through contingent benefits, and find that the hybrid specification, which allows disease and cure probabilities to have independent effects while also including expected-outcome terms, provides a better fit to the data.

Regarding trade-offs among attributes, we find that veterinarians place much greater weight on cure rate than on loss avoided, especially in the small-animal sample, where loss avoided is essentially not valued. The preference for reducing the probability of loss rather than its magnitude verifies our risk-averse hypothesis, and also parallels two concepts in the insurance market: self-protection and self-insurance. For AR risk, it is an important consideration for both groups: veterinarians strongly reject treatments associated with high resistance risk, while low levels of risk are largely tolerated or ignored. Animal welfare improvements clearly influence choices, although the implied WTP is statistically unstable and sensitive to model specification.

In terms of preference heterogeneity, only one dimension, years of experience, is systematically significant. We find the pattern differs in practice type: more experienced LAVs place less weight on welfare, whereas more experienced SAVs place more weight on expected welfare gains and are more averse to avoided economic losses.

We admit the limitations of our analysis: Our sample is not a random draw from all veterinarians, as our survey is voluntary and distributed through several specific professional networks in the US. Thus, generalizing the results to the broader veterinarian population should be done cautiously. Besides, as the decision scenarios and attributes are hypothetical and simplify the case in practice, there are still some factors that may influence the decision that are not taken into account in our case due to the limitation of the experiment, such as the diagnosis cost for the veterinarians, the bargaining process between the client and veterinarian, and so on.

Finally, our specifications simplify the way disease and cure probabilities affect veterinarians' utility, by assuming that they all enter linearly. However, veterinarians may process probabilities in other ways, such as non-linear, threshold, etc., thus the processing of probability in the decision-making process is also worth further exploration.

Tables

Table 5.1. Summary of Respondent Characteristics

Variable	Category	N	Percentage
Practice Type	Large animal	120	50%
	Small animal	120	50%
Location	Urban	107	45%
	Rural	133	55%
Experience	Early-career	59	25%
	Mid-career	85	35%
	Senior	96	40%
Gender	Male	107	45%
	Female	128	53%
Degree	Other	106	56%
	Animal science	134	44%
Work-setting	Clinic/hospital	164	68%
	Farm/industry	76	32%

Table 5.2. Comparison Between LAV and SAV

Variable	Category	LAV(N=120)	SAV (N=120)	p-value
Location	Urban	43%	46%	0.697
	Rural	57%	54%	
Experience	Early-career (exp<10yrs)	45%	4%	0.000
	Mid-career (10-25yrs)	27%	43%	
	Senior (>25yrs)	28%	53%	
Gender	Male	51%	38%	0.147
	Female	48%	59%	
Bachelor Degree	Other	44%	68%	0.000
	Animal science	56%	32%	
Work-setting	Clinic/hospital	37%	100%	0.000
	Farm/industry	63%	0%	

Table 7.1: Regression Results of the Three Specifications

	Large Animal			Small Animal		
	S1	S2	S3	S1	S2	S3
Treatment Cost	-0.007***	-0.002*	-0.003**	-0.004***	-0.001*	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expected loss Avoided	0.003***	-	-0.000	-0.001	-	-0.000
	(0.001)	-	(0.001)	(0.001)	-	(0.001)
Cure rate	-	0.61**	0.08	-	0.57**	0.33**
	-	(0.24)	(0.18)	-	(0.24)	(0.14)
Loss Avoided	-	0.25**	0.42**	-	-0.01	-0.001
	-	(0.12)	(0.21)	-	(0.02)	(0.06)
Low-level AW	3.01***	-2.51***	-1.92***	5.17***	-1.31***	-1.08***
	(0.53)	(0.52)	(0.40)	(0.58)	(0.37)	(0.35)
High-level AW	4.25***	-2.36***	-2.12***	6.99***	-1.05***	-0.62*
	(0.61)	(0.47)	(0.45)	(0.71)	(0.30)	(0.35)
Expected Low Level AW	-	-	2.24*	-	-	1.71
	-	-	(1.24)	-	-	(1.11)
Expected High Level AW	-	-	3.41**	-	-	1.62
	-	-	(1.53)	-	-	(1.14)
Low-level AR	-0.25**	-0.02	-0.001	0.032	-0.01	-0.007
	(0.11)	(0.05)	(0.08)	(0.12)	(0.04)	(0.07)
High-level AR	-1.26***	-0.42**	-0.67***	-1.44***	-0.45**	-0.74**
	(0.19)	(0.18)	(0.20)	(0.21)	(0.20)	(0.29)
Pseudo-R sqr	0.35	0.37	0.40	0.33	0.35	0.36
AIC	1028.7	1003.5	972.2	1009.5	981.7	972.8
BIC	1065.4	1053.9	1036.3	1046.1	1032.0	1036.9

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

S1 – Expected Outcome, S2 - Additive Attribute, S3 – Hybrid (S1+S2)

Table 7.2: Specification 3 WTP Results

Attribute	Large Animal	Small Animal
Loss Avoided ($1)	0.3***	-0.0
Cure Rate under Low AW ($WTP_{r=100\%}$)	472.4***	628.2***
Cure Rate under High AW ($WTP_{r=100\%}$)	694.2***	605.1***
Loss Avoided ($WTP_{l=\bar{l}}$)	140.8***	-1.8
Cure Rate under Low AW ($WTP_{r=\bar{r}}$)	259.9***	383.7***
Cure Rate under High AW ($WTP_{r=\bar{r}}$)	381.9***	369.6***
Low-level AW	-423.2	-213.0
High-level AW	-367.2	-33.7
Low-level AR	-0.2	-2.8
High-level AR	-230.1***	-315.5***

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Reference

1. Acosta A, Tirkaso W, Nicolli F, van Boeckel TP, Cinardi G, Song J. The future of antibiotic use in livestock. Nature Communications. 2025 Dec 1;16(1).
2. Abdelfattah, Essam M., Pius S. Ekong, Emmanuel Okello, Deniece R. Williams, Betsy M. Karle, Joan D. Rowe, Edith S. Marshall, Terry W. Lehenbauer, and Sharif S. Aly. "2019 survey of antimicrobial drug use and stewardship practices in adult cows on california dairies: Post senate bill 27." *Microorganisms* 9, no. 7 (2021): 1507.
3. Alhassan MY, Kabara MK, Ahmad AA, Abdulsalam J, Habib HI. Revisiting antibiotic stewardship: veterinary contributions to combating antimicrobial resistance globally. Bulletin of the National Research Centre. 2025 Apr 11;49(1).
4. Bebrysz M, Wright A, Greaves M, Rathwell Deault D, Hopkins G, Gildea E, et al. How pet owners choose antiparasitic treatments for their dogs: A discrete choice experiment. Preventive Veterinary Medicine. 2021 Nov 1;196.
5. Benjamin L, Cotté FE, Philippe C, Mercier F, Bachelot T, Vidal-Trécan G. Physicians' preferences for prescribing oral and intravenous anticancer drugs: A Discrete Choice Experiment. European Journal of Cancer. 2012 Apr;48(6):912–20.
6. Bennett R. The "direct costs" of livestock disease: The development of a system of models for the analysis of 30 endemic livestock diseases in Great Britain. Journal of Agricultural Economics. 2003;54(1):55–71.
7. Boiko O, Burgess C, Fox R, Ashworth M, Gulliford MC. Risks of use and non-use of antibiotics in primary care: Qualitative study of prescribers' views. BMJ Open. 2020 Oct 19;10(10).
8. Byun JH, Kwon SH, Lee JE, Cheon JE, Jang EJ, Lee EK. Comparison of Benefit-Risk preferences of patients and physicians regarding cyclooxygenase-2 inhibitors using discrete choice experiments. Patient Preference and Adherence. 2016 Apr 26;10:641–50.
9. Centers for Disease Control and Prevention. (2023). *Core Elements of Hospital Antibiotic Stewardship Programs*. https://www.cdc.gov/antibiotic-use/core-elements/hospital.html
10. Cerreia-Vioglio S, Dillenberger D, Ortoleva P. Cautious Expected Utility and the Certainty Effect. Econometrica. 2015;83(2):693–728.

11. Clark MD, Determann D, Petrou S, Moro D, de Bekker-Grob EW. Discrete choice experiments in health economics: a review of the literature. Pharmacoeconomics. 2014;32(9):883-902.
12. Collacott H, Zhang D, Heidenreich S, Tervonen T. A Systematic and Critical Review of Discrete Choice Experiments in Asthma and Chronic Obstructive Pulmonary Disease. Vol. 15, Patient. Adis; 2022. p. 55–68.
13. Collins C, McDonnell T, Vellinga A, Xue T, Liu C, Li Z, et al. OPEN ACCESS EDITED BY Weighing patient attributes in antibiotic prescribing for upper respiratory tract infections: A discrete choice experiment on primary care physicians in Hubei Province Weighing patient attributes in antibiotic prescribing for upper respiratory tract infections: A discrete choice experiment on primary care physicians in Hubei Province, China.
14. Coyne LA, Pinchbeck GL, Williams NJ, Smith RF, Dawson S, Pearson RB, et al. Understanding antimicrobial use and prescribing behaviours by pig veterinary surgeons and farmers: A qualitative study. Veterinary Record. 2014 Dec 13;175(23):593.
15. de Bekker-Grob EW, Ryan M, Gerard K. Discrete choice experiments in health economics: A review of the literature. Health Economics. 2012 Feb;21(2):145–72.
16. de Briyne N, Atkinson J, Pokludová L, Borriello SP, Price S. Factors influencing antibiotic prescribing habits and use of sensitivity testing amongst veterinarians in Europe. Veterinary Record. 2013 Nov 16;173(19):475.
17. Dillon ME, Jackson-Smith D. Impact of the veterinary feed directive on Ohio cattle operations. PLoS ONE. 2021 Aug 1;16(8 August).
18. Doidge C, Hudson C, Lovatt F, Kaler J. To prescribe or not to prescribe? A factorial survey to explore veterinarians' decision making when prescribing antimicrobials to sheep and beef farmers in the UK. PLoS ONE. 2019 Apr 1;14(4).
19. Dolan, Emily D., and Margaret R. Slater. "Veterinarians' Self-Reported Behaviors and Attitudes toward Spectrum of Care Practices." *Animals* 14, no. 10 (2024): 1416
20. Eltholth M, Govindaraj G, Das B, Shanabhoga MB, Swamy HM, Thomas A, et al. Factors Influencing Antibiotic Prescribing Behavior and Understanding of Antimicrobial Resistance Among Veterinarians in Assam, India. Frontiers in Veterinary Science. 2022 Apr 26;9.

21. Florian M, Skurková L, Mesarčová L, Slivková M, Kottferová J. Decision-Making and Moral Distress in Veterinary Practice: What Can Be Done to Optimize Welfare Within the Veterinary Profession? Journal of Veterinary Medical Education. 2024 Jun 1;51(3):292–301.
22. Gibbons JF, Boland F, Buckley JF, Butler F, Egan J, Fanning S, et al. Influences on antimicrobial prescribing behaviour of veterinary practitioners in cattle practice in Ireland. Veterinary Record. 2013 Jan 5;172(1):14.
23. Giubilini A. Antibiotic resistance as a tragedy of the commons: An ethical argument for a tax on antibiotic use in humans. Bioethics. 2019;33(7):776–84.
24. Golding SE, Ogden J, Higgins HM. Shared goals, different barriers: A qualitative study of UK veterinarians' and farmers' beliefs about antimicrobial resistance and stewardship. Frontiers in Veterinary Science. 2019;6(APR).
25. Groves CNH, Coe JB, Grant LE. What do veterinary professionals and clients want? Using discrete choice methods in veterinary research to determine preferences. American Journal of Veterinary Research. 2024 Apr 1;85(4).
26. Groves CNH, Coe JB, Sutherland KA, Bauman C, Grant LE. Clients prefer collaborative decision-making with veterinarians regardless of appointment type. Journal of the American Veterinary Medical Association. 2025 Jan 1;263(1).
27. Hardin G. The Tragedy of the Commons. Vol. 13, New Series. 1968
28. Hopman, Nonke EM, Marlies EJL Hulscher, Haitske Graveland, David C. Speksnijder, Jaap A. Wagenaar, and Els M. Broens. "Factors influencing antimicrobial prescribing by Dutch companion animal veterinarians: A qualitative study." *Preventive veterinary medicine* 158 (2018): 106-113.
29. Jia, Yanan, David A. Hennessy, and Hongli Feng. "Economics of Informed Antibiotic Management and Judicious Use Policies in Animal Agriculture." *Environmental and Resource Economics* 87, no. 7 (2024): 1673-1709.
30. Jonas,Olga B.; Irwin, Alec; Berthe,Franck Cesar Jean; Le Gall,Francois G.; Marquez,Patricio V.*Drug-resistant infections: a threat to our economic future (Vol. 2 of 2) : final report (English).* HNP/Agriculture Global Antimicrobial Resistance Initiative Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/323311493396993758
31. King C, Smith M, Currie K, Dickson A, Smith F, Davis M, et al. Exploring the behavioural drivers of veterinary surgeon antibiotic prescribing: A qualitative study of

companion animal veterinary surgeons in the UK. BMC Veterinary Research. 2018 Nov 7;14(1).
32. Kipperman BS, Kass PH, Rishniw M. Factors that influence small animal veterinarians' opinions and actions regarding cost of care and effects of economic limitations on patient care and outcome and professional career satisfaction and burnout. Journal of the American Veterinary Medical Association. 2017 Apr 1;250(7):785–94.
33. Kipperman BS, Kass PH, Rishniw M. Factors that influence small animal veterinarians' opinions and actions regarding cost of care and effects of economic limitations on patient care and outcome and professional career satisfaction and burnout. Journal of the American Veterinary Medical Association. 2017 Apr 1;250(7):785–94.
34. Kipperman B, Morris P, Rollin B. Ethical dilemmas encountered by small animal veterinarians: Characterisation, responses, consequences and beliefs regarding euthanasia. Veterinary Record. 2018 May 12;182(19):548.
35. Kleij KS, Tangermann U, Amelung VE, Krauth C. Patients' preferences for primary health care - A systematic literature review of discrete choice experiments. Vol. 17, BMC Health Services Research. BioMed Central Ltd.; 2017.
36. Klein EY, Impalli I, Poleon S, Denoel P, Cipriano M, van Boeckel TP, et al. Global trends in antibiotic consumption during 2016-2023 and future projections through 2030. Proceedings of the National Academy of Sciences of the United States of America. 2024 Dec 3;121(49).
37. Laffont JJ, Tirole J, Reuter E, Rumiantseva I, Große M. Technische Universität Dresden DREWAG-Lehrstuhl für Energiewirtschaft (EE 2) A THEORY OF INCENTIVES IN PROCUREMENT AND REGULATION.
38. Lancsar E, Louviere J. Conducting discrete choice experiments to inform healthcare decision making. Pharmacoeconomics. 2008;26(8):661-677.
39. Lavigne SH, Louis S, Rankin SC, Zaoutis TE, Szymczak JE. How companion animal veterinarians in the United States perceive financial constraints on antibiotic decision-making. Veterinary Record. 2021 Jun 1;188(12):no.
40. Laxminarayan R, Brown GM. Economics of Antibiotic Resistance: A Theory of Optimal Use. 2000.

41. Martin MJ, Thottathil SE, Newman TB. Antibiotics overuse in animal agriculture: A call to action for health care providers. Vol. 105, American Journal of Public Health. American Public Health Association Inc.; 2015. p. 2409–10.
42. Mateus, Ana LP, David C. Brodbelt, Nick Barber, and Katharina DC Stärk. "Qualitative study of factors associated with antimicrobial usage in seven small animal veterinary practices in the UK." *Preventive veterinary medicine* 117, no. 1 (2014): 68-78.
43. McDonnell, A., A. Countryman, T. Laurence, S. Gulliver, T. Drake, S. Edwards, C. Kenny et al. "Forecasting the fallout from amr: economic impacts of antimicrobial resistance in humans." *World Organization for Animal Health and World Bank* (2024).
44. McDougall S, Compton CWR, Botha N. Factors influencing antimicrobial prescribing by veterinarians and usage by dairy farmers in New Zealand. New Zealand Veterinary Journal. 2017 Mar 4;65(2):84–92.
45. Mclnerney JP, Howe KS, Schepers JA. A framework for the economic analysis of disease in farm livestock. Vol. 13, Preventive Veterinary Medicine. 1992.
46. Mijares S, Edwards-Callaway L, Roman-Muniz IN, Coetzee JF, Applegate TJ, Cramer MC. Veterinarians' perspectives of pain, treatment, and diagnostics for bovine respiratory disease in preweaned dairy calves. Frontiers in Pain Research. 2023;4.
47. Moghnieh R, Awad L, Abdallah D, Jadayel M, Sinno L, Tamim H, et al. Effect of a "handshake" stewardship program versus a formulary restriction policy on High-End antibiotic use, expenditure, antibiotic resistance, and patient outcome. Journal of Chemotherapy. 2020 Oct 2;32(7):368–84.
48. Moya S, Coviglio A, Belloc C, Comer C, Eberhart J, Fortané N, et al. A qualitative analysis of the unwritten rules influencing antibiotic prescribing practices among French poultry veterinarians. JAC-Antimicrobial Resistance. 2024 Apr 1;6(2).
49. Mulchandani R, Wang Y, Gilbert M, van Boeckel TP. Global trends in antimicrobial use in food-producing animals: 2020 to 2030. PLOS Global Public Health. 2023 Feb 1;3(2).
50. Murray CJ, Ikuta KS, Sharara F, Swetschinski L, Robles Aguilar G, Gray A, et al. Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis. The Lancet. 2022 Feb 12;399(10325):629–55.

51. Nielsen C, Østergaard S, Emanuelson U, Andersson H, Berglund B, Strandberg E. Economic consequences of mastitis and withdrawal of milk with high somatic cell count in Swedish dairy herds. Animal. 2010 May;4(10):1758–70.
52. Nthambi M, Lembo T, Davis A, Nasuwa F, Mmbaga BT, Matthews L, et al. Quantifying farmers' preferences for antimicrobial use for livestock diseases in northern Tanzania. Q Open. 2023;3(1).
53. Paudel B, Kolady D, Grebitus C, Roy A, Ishaq M. Consumers' willingness to pay for pork produced with different levels of antibiotics. Q Open. 2022;2(1).
54. Pomba C, Rantala M, Greko C, Baptiste KE, Catry B, van Duijkeren E, et al. Public health risk of antimicrobial resistance transfer from companion animals. Journal of Antimicrobial Chemotherapy. 2017;72(4):957–68.
55. Rawson TM, Moore LSP, Castro-Sanchez E, Charani E, Davies F, Satta G, et al. COVID-19 and the potential long-term impact on antimicrobial resistance. Journal of Antimicrobial Chemotherapy. 2020 Jul 1;75(7):1681–4.
56. Ryan, M., Gerard, K. and Amaya-Amaya, M. (eds.) (2008) *Using discrete choice experiments to value health and health care* (The economics of non-market goods and resources, 11), vol. 11, Netherlands Antilles, AN. Springer, 256pp.
57. Robinson PA., McIntyre KM. Society for Veterinary Epidemiology and Preventive Medicine : Proceedings of a meeting held in Belfast, Northern Ireland, 23rd - 25th March 2022. Society for Veterinary Epidemiology and Preventive Medicine; 2022. 251.
58. Rodriguez Z, Cabrera VE, Hogeveen H, Ruegg PL. Economic impact of subclinical mastitis treatment in early lactation using intramammary nisin. Journal of Dairy Science. 2024 Jul 1;107(7):4634–45.
59. Samper BA, Rowe JA, Williams RB. Companion Animal Cadaver Donation for Teaching Purposes at Veterinary Medicine Colleges: A Discrete Choice Experiment. Journal of Veterinary Medical Education. 2024 Oct 1;51(5):560–8.
60. Sarkar S, Okafor C. Effect of veterinary feed directive rule changes on tetracycline-resistant and erythromycin-resistant bacteria (Salmonella, Escherichia, and Campylobacter) in retail meats in the United States. PLoS ONE. 2023 Aug 1;18(8 August).

61. Servia-Dopazo M, Taracido-Trunk M, Figueiras A. Non-clinical factors determining the prescription of antibiotics by veterinarians: A systematic review. Antibiotics. 2021 Feb 1;10(2):1–21.
62. Schröter I, Mergenthaler M. Farmers' preferences regarding the design of animal welfare programs: Insights from a choice-based conjoint study in Germany. Animals. 2021 Mar 1;11(3):1–16.
63. Schuler K, Jung IC, Zerlik M, Hahn W, Sedlmayr M, Sedlmayr B. Context factors in clinical decision-making: a scoping review. BMC Medical Informatics and Decision Making. 2025 Dec 1;25(1).
64. Schwickert H. Paying for animal welfare labelling no matter what? A discrete choice experiment. European Review of Agricultural Economics. 2023 Dec 1;50(5):1754–95.
65. Simeoni M, Saragosa M, Laur C, Desveaux L, Schwartz K, Ivers N. Coping with 'the grey area' of antibiotic prescribing: a theory-informed qualitative study exploring family physician perspectives on antibiotic prescribing. BMC Primary Care. 2022 Dec 1;23(1).
66. Speksnijder DC, Jaarsma ADC, van der Gugten AC, Verheij TJM, Wagenaar JA. Determinants associated with veterinary antimicrobial prescribing in farm animals in the Netherlands: A qualitative study. Zoonoses and Public Health. 2015 Apr 1;62(s1):39–51.
67. Swinkels JM, Hogeveen H, Zadoks RN. A partial budget model to estimate economic benefits of lactational treatment of subclinical Staphylococcus aureus mastitis. Journal of Dairy Science. 2005;88(12):4273–87.
68. Taylor, Daniel D., Jennifer N. Martin, Paul S. Morley, Keith E. Belk, Alice E. White, and Elaine J. Scallan Walter. "Survey of production animal veterinarians' prescription practices, factors influencing antimicrobial drug use, and perceptions of and attitudes toward antimicrobial resistance." *Journal of the American Veterinary Medical Association* 257, no. 1 (2020): 87-96.
69. Tompson AC, Mateus ALP, Brodbelt DC, Chandler CIR. Understanding Antibiotic Use in Companion Animals: A Literature Review Identifying Avenues for Future Efforts. Vol. 8, Frontiers in Veterinary Science. Frontiers Media S.A.; 2021.
70. Tsokana CN, Valiakos G, Mwacalimba K, Riley D, Enstone A, Wyn R, et al. A Discrete Choice Experiment to Assess Cat Owners' Preferences for Topical

Antiparasitics and the Comparative Ease of Use of a Combined Selamectin and Sarolaner Formulation: An International Survey. Animals. 2025 Jul 1;15(13).

71. U.S. Food and Drug Administration. 2024. *Timeline of FDA Action on Antimicrobial Resistance*. U.S. Department of Health and Human Services. https://www.fda.gov/animal-veterinary/antimicrobial-resistance/timeline-fda-action-antimicrobial-resistance. Accessed June 29, 2025.
72. van Katwyk SR, Grimshaw JM, Nkangu M, Nagi R, Mendelson M, Taljaard M, et al. Government policy interventions to reduce human antimicrobial use: A systematic review and evidence map. PLoS Medicine. 2019 Jun 1;16(6).
73. Wang Y, Wang Z, Wang Z, Li X, Pang X, Wang S. Application of Discrete Choice Experiment in Health Care: A Bibliometric Analysis. Frontiers in Public Health. 2021 Jun 4;9.
74. Warreman, E. B., M. M. C. Lambregts, R. H. P. Wouters, L. G. Visser, H. Staats, E. Van Dijk, and M. G. J. De Boer. "Determinants of in-hospital antibiotic prescription behaviour: a systematic review and formation of a comprehensive framework." *Clinical Microbiology and Infection* 25, no. 5 (2019): 538-545.
75. World Health Organization. “Stop Using Antibiotics in Healthy Animals to Prevent the Spread of Antibiotic Resistance.” Last modified November 7, 2017. https://www.who.int/news/item/07-11-2017-stop-using-antibiotics-in-healthy-animals-to-prevent-the-spread-of-antibiotic-resistance.
76. Zhang M, He X, Wu J, Xie F. Differences between physician and patient preferences for cancer treatments: a systematic review. BMC Cancer. 2023 Dec 1;23(1).

Appendix

Table 1: Regression Results under Interactive Attributes Specification

	Large Animal		Small Animal	
	Full Sample	drop p = 100%	Full Sample	drop p = 100%
Expected loss Avoided	0.003***	0.004***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Treatment Cost	-0.007***	-0.007***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Low-level AW	3.01***	2.45***	5.17***	5.11***
	(0.53)	(0.57)	(0.58)	(0.56)
High-level AW	4.25***	3.69***	6.99***	7.12***
	(0.61)	(0.61)	(0.71)	(0.72)
Low-level AR	-0.25**	-0.29**	0.032	0.034
	(0.11)	(0.11)	(0.12)	(0.12)
High-level AR	-1.26***	-1.22***	-1.44***	-1.52***
	(0.19)	(0.18)	(0.21)	(0.21)
Pseudo-R sqr	0.35	0.33	0.33	0.32
AIC	1028.7	946.3	1009.5	947.7
BIC	1065.4	981.9	1046.1	983.6

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Drop p = 100% refers to a subsample excluding scenarios where the probability of the animal having the disease was certain (i.e., 100%).

Table 2: WTP Results under Interactive Attributes Specification

	Large Animal		Small Animal	
	Full Sample	drop p = 100%	Full Sample	drop p = 100%
Expected loss Avoided	0.4***	0.5***	−0.2	−0.2
Low-level AW	433.4***	340.9***	1266.2***	1254.4***
High-level AW	611.2***	513.3***	1712.1***	1746.8***
Low-level AR	−36.1**	−40.4**	7.9	8.5
High-level AR	−181.6***	−169.3***	−352.1***	−373.9***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Drop p = 100% refers to a subsample excluding scenarios where the probability of the animal having the disease was certain (i.e., 100%).

Table 3: WTP Results under Interactive Attributes Specification (in % of the group mean)

	Large Animal		Small Animal	
	Full Sample	drop p = 100%	Full Sample	drop p = 100%
Expected loss Avoided	0.6%***	0.8%***	-0.1%	−0.1%
Low-level AW	582.9%***	480.6%***	913.2%***	917.1%***
High-level AW	822.2%***	723.6%***	1234.8%***	1277.0%***
Low-level AR	−48.6%**	−57.0%**	5.7%	6.2%
High-level AR	−244.2%***	−238.6%***	−254.0%***	−273.3%***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Drop p = 100% refers to a subsample excluding scenarios where the probability of the animal having the disease was certain (i.e., 100%).

Table 4: WTP Results under Additive Attributes Specification

	Large Animal		Small Animal	
	Full Sample	drop p = 100%	Full Sample	drop p = 100%
Loss Avoided	120.4***	117.4***	-3.9	-3.9
Cure Rate	296.4***	296.5***	393.0***	382.7***
Low-level AW	-1228.7**	-1229.2**	-898.4**	-898.4**
High-level AW	-1154.4**	-1154.9**	-721.1*	-721.1*
Low-level AR	-7.4	-7.4	-6.3	-6.3
High-level AR	-204.9***	-204.9***	-310.8***	-310.8***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Drop p = 100% refers to a subsample excluding scenarios where the probability of the animal having the disease was certain (i.e., 100%).

Table 5: WTP Results under Additive Attributes Specification

(in percentage of the group mean)

	Large Animal		Small Animal	
	Full Sample	drop p = 100%	Full Sample	drop p = 100%
10% Loss Avoided	16.2%***	16.5%***	−0.3%	−0.3%
10% Cure Rate	39.6%***	41.8%***	28.3%***	28.0%***
Low-level AW	−1652.9%**	−1732.7%**	−648.3%**	−656.9%**
High-level AW	−1553.0%**	−1628.1%**	−520.1%*	−527.3%*
Low-level AR	−9.9%	−10.4%	−4.5%	−4.6%
High-level AR	−275.7%***	−288.9%***	−224.2%***	−227.3%***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Drop p = 100% refers to a subsample excluding scenarios where the probability of the animal having the disease was certain (i.e., 100%).