Veterinary informatics: forging the future between veterinary medicine, human medicine, and One Health initiatives—a joint paper by the Association for Veterinary Informatics (AVI) and the CTSA One Health Alliance (COHA)

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ABSTRACT

Objectives: This manuscript reviews the current state of veterinary medical electronic health records and the ability to aggregate and analyze large datasets from multiple organizations and clinics. We also review analytical techniques as well as research efforts into veterinary informatics with a focus on applications relevant to human and animal medicine. Our goal is to provide references and context for these resources so that researchers can identify resources of interest and translational opportunities to advance the field.

Methods and Results: This review covers various methods of veterinary informatics including natural language processing and machine learning techniques in brief and various ongoing and future projects. After detailing techniques and sources of data, we describe some of the challenges and opportunities within veterinary informatics as well as providing reviews of common One Health techniques and specific applications that affect both humans and animals.

Discussion: Current limitations in the field of veterinary informatics include limited sources of training data for developing machine learning and artificial intelligence algorithms, siloed data between academic institutions, corporate institutions, and many small private practices, and inconsistent data formats that make many integration problems difficult. Despite those limitations, there have been significant advancements in the field in the last few years and continued development of a few, key, large data resources that are available for interested clinicians and researchers. These real-world use cases and applications show current and significant future potential as veterinary informatics grows in importance. Veterinary informatics can forge new possibilities within veterinary medicine and between veterinary medicine, human medicine, and One Health initiatives.

Key words: informatics, one health, translational science, veterinary medicine, medicine
INTRODUCTION

Biomedical informatics has become well-known within the human medical community for its breadth and depth of integration between medicine, computer science, statistics, and biology. This cross-disciplinary approach has led to discoveries in diseases, trends in success and failures for diagnosis and therapies, and evidence-based decision-making. It is now a regular part of physician’s training. While there has been significant progress integrating informatics with human medicine both in practice and education, veterinary medicine lags in both areas. However, informatics in veterinary medicine offers significant possibilities for translational research.

Use of biomedical informatics in veterinary medicine, what we term veterinary informatics, combines the knowledge and techniques currently utilized within the human medical field of biomedical informatics with veterinary domain knowledge. There has been some examination of veterinary informatics within the veterinary sphere,1–4 and the benefits of this combination are starting to emerge with a recent increase in the number of publications.5–8 Even though advances in veterinary informatics offer significant possibilities for translational research, this space remains far behind many other areas of informatics.9–13

One key factor limiting the advancement and integration of veterinary informatics into everyday clinical practice is a lack of external drivers to enforce structure on veterinary data. Unlike in human medical practice, adoption of insurance coverage for pets is still rare (<1% of pets are covered),14 leading most owners to pay for care out of pocket. This removes one of the primary incentives for coding in the medical profession, insurance companies. As a result, veterinary records have billing codes, but they are not standardized between hospitals unless they are in a shared practice group. Depending on whether you use the total veterinary positions available or those specifically identified as a practicing veterinarian, approximately 65–95% of veterinary data is contained within private organizations based on estimates of veterinarians in private practice,15 which represents a data access challenge for non-affiliated groups.

Additional limitations exist in the lack of formal, organized support for robust informatics training and methods development from national veterinary organizations, which limits the ability to set basic standards for data organization that would allow for its reuse. The concept of FAIR (Findable, Accessible, Interoperable, and Reusable) data16 has not become an integral part of management practice for veterinary data. This will change only when clinicians see the value and benefits of using a standardized terminological and ontological representation that is integrated across the veterinary community.

We divide this review into 3 components: a description of available data sources, their characteristics, and research into their development and expansion; a description of current analytical strategies applied to the veterinary data sources with parallels to human medicine, and finally, some highlights of current applications of veterinary informatics to One Health and translational science.

Scope of veterinary small animal practice

While specific data points are sparse, a recent survey by GfK (the Society for Consumer Research) found that 57% of consumers own pets of which dogs are the most popular followed by cats. Some of the highest ownership rates were in Argentina, Mexico, and Brazil (82%, 81%, and 76%, respectively). The United States ranks fifth in dog ownership and third in cat ownership.17

Specifics by country are difficult to acquire, but as of 2016 in the United States, there were approximately 89.7 million owned dogs and 94.2 million owned cats with an average of 3 veterinary visits for dogs and 2.4 veterinary visits for cats per a year. This is estimated to have generated about 269 million and 226 million visits per year, respectively.18–20 Comparatively, in human medicine, according to CDC statistics, there are approximately 364 million hospital outpatient visits per year in the United States.21 Even though there is approximately 30% fewer visits for veterinary patients, the average human patient visits about 3.4 medical professionals per year, and the estimated number of veterinarians per year is approximately 2.6 for dogs and 1.6 for cats.22,23 This is 25–50% of the number of human physicians interactions per patient per year. This could allow for increased intra- and inter-operator agreement in veterinary medicine for a given patient.24–26

Standardization of veterinary medical records have been isolated to individual private organizations that require specific techniques for extraction, but there have been few attempts to integrate structured terminology in veterinary clinical practice.27 In human medicine, many medical records are encoded either during practice or as a post-processing technique once the record is complete.28–31 This is often due to common drivers such as effective insurance billing and documented medical information retrieval, which veterinary medicine currently lacks. The number of animals covered by pet insurance is increasing, but <1% of animals are currently covered limiting the impact it has on encoding in veterinary practice.14

For those looking to integrate standard veterinary terminologies, one such example is the Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT) Veterinary Extension maintained by the Virginia Tech Veterinary Terminology Services Laboratory (United States). Any company in a country that contributes to SNOMED can utilize it, after registration; however, outside of those countries, it might require a commercial license. There are also proprietary terminologies available, such as VeNOM that is based in the United Kingdom. However, the use of these terminologies is challenging and rarely integrated into a regular workflow. One reason is the need for workflows to be centered on billing as this is a key concern for private practitioners, who represent approximately 91% of the clinically practicing veterinarians in the United States. Even in systems where it is possible to utilize standard terms, it is challenging to have clinicians use them consistently as veterinarians have similar time pressures to their human counterparts.32–34

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DATA TYPES AND SOURCES

Electronic medical records
As previously discussed, there are approximately 495 million clinical records for dogs and cats generated by about 80,000 veterinarians each year in the United States. The number of records for large animals, food animals, exotics, and zoo animals is challenging to quantify. For most dogs and cats, their records, in general, are stored as free text as most systems are mainly designed for efficient charging and processing of transactions throughout a patient visit. These systems, called Practice Information Management Systems (PIMS), can organize lab results as separate retrievable analytes, but there is little standardization in naming. It is important to compare the features of a PIMS to human electronic medical record systems as they have different features (Table 1).

Like human medicine, many medical and operational drives increased PIMS adoption within veterinary medicine. As of 2014, a limited survey reported that 80% of veterinary medicine respondents utilized a PIMS though to a varying degree (63% combined electronic with paper, while 17% used only electronic records). Common uses were billing, estimate generation, legal document retention, lab ordering and receiving (when integrated), and client account operations. Some of these systems have capabilities to add diagnoses to the medical record, but the reported adoption rate is difficult to validate.

Deidentification requirements are also very different. In human medicine, significant data points need to be censored for retrospective studies; however, in veterinary medicine, there is little regulation governing sharing of records for both practice and research, with the exception of a few states. In these states, some hospitals have adopted a release form like those used in human medicine. This introduces additional challenges to acquiring data from clinical practices.

When looking to acquire data, on a pure numerical basis, more pets have records in smaller practices (defined as <10 veterinarians) than in larger practices, even though recent years has seen many small practices consolidated by a few larger veterinary practice groups. While clinical data pertaining to veterinary patients is not covered under current HIPAA regulations, owner data is considered sensitive and can sometimes be included in free text fields within medical documentation, making anonymization of veterinary medical records difficult.

Electronic medical records are currently either being aggregated into accessible databases or through services that allow analytics. Though out of scope for this article, we have provided a list of resources and descriptions within the Supplementary Information to aid in their use for clinical research.

Imaging
Most imaging studies employ the Digital Imaging and Communications in Medicine (DICOM) imaging standard for image requests and communication; however, the way the images are stored can vary from vendor to vendor. Most radiographs generated by the practice of veterinary medicine are stored either on-premise or within a private cloud system. Commercial cloud-based systems are usually more rigorous in the implementation of the DICOM standard and can have similar features and capabilities to the Picture Archiving and Communication System implemented within the human space. The on-premise systems tend to be quite varied in implementation ranging from an index folder structure to more sophisticated storage techniques.

| Activity                                      | EMR (human medicine) | PIMS |
|-----------------------------------------------|-----------------------|------|
| Billing and finance                           | ±                     | X    |
| Reminders                                     | X                     | X    |
| Tracking procedures                           | X                     | ±    |
| Free text medical notes                       | X                     | X    |
| Structured medical notes                      | X                     |      |
| Decision support systems                      | X                     | –    |
| Integration with LIMS                         | X                     | X    |
| Integration with PACS                         | X                     | ±    |
| Integration with RIS                          | X                     | ±    |
| Computer physician order entry                | X                     | –    |
| Adverse event detection                       | X                     | –    |

Note: Human EMR features from following citations: Comparison of PIMS capability is from experience combined with availability of features. –: means no current ability or requires 3rd party tool; ±: partial compatibility or function; EMR: electronic medical record; LIMS: Laboratory Information Management System; PACS: Picture Archiving and Communication System; PIMS: Practice Information Management System; RIS: Radiological Information System; X: native capability.

In veterinary medicine, the use of magnetic resonance imaging, computed tomography, fluoroscopy, and ultrasound is expanding both in available sites and studies performed per year. This type of data represents new challenges and new opportunities for study. The main source of these imaging modalities is within the specialty veterinary medicine arena, which is an increasingly popular source of care. These specialty centers are also where advanced research and training occurs offering tremendous opportunity for future collaboration.

Laboratory
Diagnostic laboratory testing is an increasingly crowded arena within veterinary medicine. The two largest private veterinary diagnostic lab services are Antech Diagnostics and IDEXX Laboratories, but there are other smaller vendors. Diagnostic laboratories have various integration capabilities that change frequently. Until recently, only larger providers were “integrated” into the PIMS, meaning that requests could be submitted, and the results could be received digitally. Many reference laboratories that are integrated transmit their results via either an online portal or an interface that uses a proprietary data structure or digital documents such as a PDF. Neither the reference laboratories nor receiving PIMS utilize a standardized nomenclature for tagging data (SNOMED-CT, LOINC, etc.) during transmission, resulting in challenges during extraction and analysis. Some of them are required to annotate records for disease surveillance (eg, state diagnostic laboratories). This large, rich cohort of information represents a significant resource for future work.

One area of diagnostics, the in-house clinic, is frequently overlooked. The retention rate of patients within a veterinary hospital means that sampling variability should be significantly less. Even within a single hospital, the opportunity to correlate diagnostics with textual notes and bill codes (that can be analogous for both disease state and procedure codes) offers advantages that can be challenging to replicate within human medicine.
Genetics

The National Human Genome Research Institute recognized the value of the canine genome (sequenced in 2004) in the study of inherited disorders in man.59–61 Subsequently, an increasing number of Mendelian traits and traits associated with more complex diseases have been identified.62–66 One source for genetic information in dogs, as well as many other animals, is the Online Mendelian Inheritance in Animals.67 As of this publication, there were over 800 Mendelian traits with likely causal variants listed for many different species including dogs, cattle, cats, sheep, horse, chickens, and pigs.

Private companies have created genetic panels for varying purposes,68–70 and canine cancer genetics have been particularly well-researched in terms of translational potential for humans.71 While these companies could be a potential source of information, to date, there have been few resources developed for public use. Some companies have genotyped more than 800,000 dogs, and tens of thousands of tests have been reported by the newer canine sequencing companies. Most tests are sold directly to consumers and are used primarily for breed identity, although a few companies offer disease testing. The underlying technologies and tested markers vary, but the technology is generally based on Illumina microarrays that are proprietary.

Inherited disease screening tests are also now more freely available to help breeders and owners determine if their animals are carriers for disease(s). The University of Pennsylvania maintains a database of available genetic tests that include commercial as well as academic laboratories.72 However, available phenotypic data to pair with genetic data is sparse and is generally based on customer-provided surveys on specific traits and diseases. This is an area of active interest for some genetics companies as many of the inherited diseases do not show complete dominance even in the presence of homogeneity.

In addition, there are genetics testing companies and academic laboratories offering genetic testing for horses and livestock, reporting on genetic markers for physical traits, desirable genetic characteristics, and potential disease-linked traits. These may consist of simple parentage analysis, single-gene testing, single-nucleotide polymorphism assays, or microarrays. Livestock genetic testing is too extensive to cover here, but there has been a recent review on this topic.73

Animal genetic testing has impacts beyond companion and livestock. The National Institutes of Health recently funded the Arizona Cancer Evolution Center to integrate data, including genomics, from a broad array of species to understand the evolutionarily conserved basis for cancer.74 This group is integrating human clinical data with animal clinical and pathology data from zoological collections to examine a multitude of traits such as treatment protocols, pharmaceutical and procedure side-effects, and patient outcomes that are not captured by pathology reports. They hope to achieve a better understanding of the natural history of shared diseases across species and to allow us to better interpret genomic information being produced from “non-traditional” disease models.

Sensor data

The use of sensors has recently expanded from research applications to track animal migration patterns and behavior and for disease surveillance into the commercial and medical markets. Data collection from wearables is expanding rapidly, and market share for pet wearables is estimated to be greater than $3 billion by 2025.75 Wearable sensors can provide a rich source of potential information including physio markers, such as heart rate, respiratory rate, and temperature, as well as gyrosopic measurements reflecting activity levels, sleep metrics, and estimates of calories burned. In some cases, these wearable devices can sample the animal’s interstitial glucose. The non-invasive and continuous method of data collection is relatively inexpensive, longitudinal, and removes the influence of stress induced during veterinary visits. As more research is done, this information can be utilized for more informed health decisions by the owner and veterinarian.

Sensor data is commonly used for assessment of response to specific therapies,76 and, in conjunction with robust machine learning algorithms, it has the powerful potential to allow early identification of at-risk veterinary and human patients, especially when used in shared naturally occurring diseases. Larger companies are storing pet information for additional behavioral and health studies. Data from wearables, in a manner similar to telematics or driver monitoring devices, may be used by insurance companies as an incentive for rates adjustment with certain known preventative behaviors such as activity levels.77

Databases and other resources

There are generally 3 types of databases and resources available within veterinary medicine: Medical Record Aggregation, Laboratory (including Genomic) Information, and Research or Mission Based data sources. For Medical Record Aggregation, one of the primary examples would be the Veterinary Medical Database (www.vmdb.org). They contain annotated medical records from 26 American university veterinary hospitals amounting to over 7 million patient records. Research and mission-based data sources represent the largest set of possible resources and include resources like ESCRA (www.escra.org), an exotic species tumor database, as well as VetCOT (www.vetcot.org), a trauma data collection initiative by the American College of Veterinary Emergency and Critical Care. They are collecting information about trauma cases and their outcomes from veterinary trauma centers nationwide and compiling it into a single resource with more than 27 000 trauma case records to date. There are many other databases and resources available, and we have expanded upon their details and included other resources within the Supplementary Information.

SOME KEY METHODS FOR VETERINARY INFORMATICS

Expert-based rule text extraction and recording

Initial research used expert-based rules for inclusion and exclusion of veterinary text for biosurveillance.78,79 In addition to rules-based identification, experts built data dictionaries with key terms for diseases of interest.80 This approach was often successful for the disease being studied, but the approach was challenging to scale to thousands of additional disease diagnoses, such as those in the SNOMED-CT veterinary extension. Expert-based rules require a significant number of knowledge bases, which often reflect local biases, similarly seen in rule-based systems used in human medicine.81,82 This also creates challenges for scalability and reliability when extending them into other areas.83–85 There have been rule-based machine learning methods that combine both expert and machine learning-based rules for text extraction, but there has been little application within the veterinary space.86,87

Natural language processing

To gain access to the large amount of clinical data within free text inside medical records (human and veterinary), researchers and
companies have focused on utilizing natural language processing (NLP) to extract the information. NLP techniques have been generally developed in the human medical domain, using various patterns and algorithms like n-grams and long- and short-term memory networks to increase performance.

There are many examples that use NLP tools within the human domain such as improving pneumonia screening in the emergency department, assisting in adenoma detection, and simplifying hospital processes by identifying billing codes from clinical notes. Within veterinary medicine, only a handful of publications and proceedings describe using NLP. Use cases include identifying the reasons race horses were retired, extracting medication information from veterinary message boards, and emerging efforts at biosurveillance across large veterinary clinical repositories. More recent efforts have demonstrated success in leveraging academic, coded clinical datasets to apply diagnosis labels to private practice data.

Machine learning and artificial intelligence

More and more pipelines utilizing machine learning and artificial intelligence are being applied to human clinical records and healthcare data, with a variable use of training data or supervision depending on the datasets used to develop these systems. We have visualized one common workflow in biomedical informatics for using common veterinary clinical data types for a variety of applications in Figure 1. One problem with utilizing these approaches with veterinary healthcare datasets is the lack of labeled, open-source, or shareable training data. Most studies focus on single-system or hospital analysis, establishing a gold-standard within a single institution. Newer, "noisy" labeling techniques may be able to help provide training data for machine learning algorithms for specific clinical tasks, and this is an area of possible significant impact. Examining the extent to which the few labeled data that exist can be used to build algorithms to help with prediction task from other domains (private practice, specialty practice) will be important to help advance the field without the massive number of medical coders who work in human healthcare. Research into optimized feature selection and feature engineering for machine learning techniques is ongoing within human healthcare but lags significantly for veterinary applications.

Use of machine learning in radiology has been ongoing for many years. These applications range from generic clinical decision support to specific mammography-based problems. Recently, there is also an effort to apply image processing and analysis within the veterinary sphere. As we see in Figure 2, you can apply segmentation or edge detection to outline areas of interest in a canine thoracic radiograph, but there is much more work to be done. While nascent, many of the same problems in veterinary medicine represent opportunities for application and development of newer algorithms.

Since there is a substantial body of veterinary literature that is not indexed in PubMed, researchers have challenges finding examples of these types of applications. An application of machine learning and NLP can aid in bringing the breadth of the published veterinary knowledge to the forefront from the large, unstructured corpus of clinical texts.

APPLICATIONS OF VETERINARY INFORMATICS

Biosurveillance

A classic example of informatics application is through a zoonotic disease surveillance and reporting system. Studies have shown the
The spread of antimicrobial resistance presents an emerging crisis in veterinary informatics can provide mechanisms for enhanced clinical disease monitoring. Current mechanisms rely solely on the individual, busy practitioner to recognize disease trends. Using machine learning techniques to allow early and accurate identification of increased incidence of clinical disease can lead to improved outcomes through recognition of spatial relationships and by informing targeted research. As discussed below, inclusion of location data in the monitoring can help identify possible environmental associations to animal disease that may precede similar human outcomes.

Extended outbreak detection
Cross-species diseases are increasing as is the need to both detect them and prevent transmission. These diseases (e.g., Lyme disease, Leptospirosis) are not necessarily transmitted between 2 species but can be indicative of the environment that they share. Work is relatively nascent, but sharing environmental data provides multiple opportunities to inform on animal and human health.

Research into methicillin-resistant Staphylococcus aureus (MRSA) in relation to pet ownership provides an example of this work. Specifically, researchers evaluated pets as possible reservoirs of MRSA within the patient population. Other diseases have also been examined (e.g., Toxoplasmosis, Rocky Mountain Spotted Fever, and Hantavirus), but many require additional research efforts to allow for extended detection and treatment in animals and humans. Recently, there has been an increased focus on carbapenem resistance and its transmission both between humans and animals. There is much more research that needs to be done in this area as this represents a challenge in the practice of both human and veterinary medicine.

Disease outcome prediction
Disease outcome prediction is of increasing interest as reflected by publication volume alone: more than 20,000 publications since 2018. In human medicine, disease outcome prediction research not only has to handle the difficulties of the disease but also the challenge of data access and specificity. Many of the techniques can be utilized within veterinary medicine to train the machine learning algorithms prior to utilization within the human healthcare sphere. As previously established, the accessibility and specificity is less of an issue within veterinary medicine and can lead to, in some cases, transfer learning where veterinary medicine directly informs on the knowledge base and algorithms used in human medicine.

Environmental effects on pets and people
Companion animals share homes and food with humans, which in addition to providing comfort and companionship, makes them excellent sentinels for environmental health hazards and bioterrorism. In addition, data show that greater than 60% of emerging infectious diseases in people start as zoonoses. Pets are exposed to environmental contaminants, infectious agents, and pollutants to which they may be more susceptible than humans. Several studies have shown the efficacy of using animal data as environmental indicators outside of the well-known zoonotic risks. This is particularly true within the aquatic environment where animals can be keys to understanding the current environmental status.

Rare diseases
Rare diseases, defined as affecting 1 in 10 (or fewer) Americans, are being identified at increasing rates and present diagnostic and
treatment challenges. A recent study discusses combining existing rare disease knowledge resources and data within the electronic medical record to assist in identifying rare disease phenotypes. In addition, identification of naturally occurring disease models in companion animals that are representative of rare human diseases can result in translation therapies that improve both animal and human lives. For example, osteosarcoma (OSA) is a type of bone cancer that while the most common bone tumor in humans, is very rare with <1000 new cases diagnosed in the United States each year and half of those diagnosed are under the age of 25. Even with diagnosis, they generally require surgery and chemotherapy for disease control, with the continued risk of metastasis. In dogs, however, OSA is the most common primary bone tumor with an incidence 27 times that of humans. There is ongoing research to bridge the gap between OSA in dogs and humans, and this case provides an example of how veterinary informatics, particularly machine learning and statistical analysis techniques, to identify cases of rare diseases to serve as models of human disease has the potential to greatly improve human and veterinary health.

CONCLUSIONS
There are many possibilities for use of the available veterinary data types through both the creation of new algorithms and application of current algorithms within veterinary informatics; we have only been able to touch on a small fraction of initiatives and possibilities within this space. Expansion of veterinary informatics has significant potential benefits for both human and veterinary medicine, and the potential impact will only increase as more work is done in this arena.

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AUTHOR CONTRIBUTIONS
JLL—initiated the paper and was primary for conceptualization, primarily responsible for writing significant components of the document and editing the text. He was a primary writer for electronic medical records, machine learning, biosurveillance, and contributed to the introduction and the conclusions. He is also responsible for review, primary correspondence, formatting, creating, and organization of the references. AZ—involves in initial paper conceptualization. Contributed to multiple sections of the document: primary writer on natural language processing, figure development, and contributed to the introduction and conclusions. WS—contributed significantly to the database detail discovery, write up of the data types and sources as well as their use in current veterinaryinformatics-based projects. EAG—responsible for text for the zoonotic and infectious diseases as they translate from animals to humans. She wrote and edited much of the applications to human medicine that has been interspersed throughout the document. TLW—involves in initial paper conceptualization; primary writer for the environmental impact, sensor data, rare diseases, clinical health application, and contributed significantly to the zoonotic and biosurveillance sections. All authors contributed to the editing of the manuscript and added pertinent references to the paper.

SUPPLEMENTARY MATERIAL
Supplementary material is available at Journal of the American Medical Informatics Association online.

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