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Using natural language processing and patient journey clustering for temporal phenotyping of antimicrobial therapies for cat bite abscesses

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ABSTRACT

Background: Temporal phenotyping of patient journeys, which capture the common sequence patterns of interventions in the treatment of a specific condition, is useful to support understanding of antimicrobial usage in veterinary patients. Identifying and describing these phenotypes can inform antimicrobial stewardship programs designed to fight antimicrobial resistance, a major health crisis affecting both humans and animals, in which veterinarians have an important role to play.

Objective: This research proposes a framework for extracting temporal phenotypes of patient journeys from clinical practice data through the application of natural language processing (NLP) and unsupervised machine learning (ML) techniques, using cat bite abscesses as a model condition. By constructing temporal phenotypes from key events, the relationship between antimicrobial administration and surgical interventions can be described, and similar treatment patterns can be grouped together to describe outcomes associated with specific antimicrobial selection.

Methods: Cases identified as having a cat bite abscess as a diagnosis were extracted from VetCompass Australia, a database of veterinary clinical records. A classifier was trained and used to label the most clinically relevant event features in each record as chosen by a group of veterinarians. The labeled records were processed into coded character strings, where each letter represents a summary of specific types of treatments performed at a given visit. The sequences of letters representing the cases were clustered based on weighted Levenshtein edit distances with KMeans+ + to identify the main variations of the patient treatment journeys, including the antimicrobials used and their duration of administration.

Results: A total of 13,744 records that met the selection criteria was extracted and grouped into 8436 cases. There were 9 clinically distinct event sequence patterns (temporal phenotypes) of patient journeys identified, representing the main sequences in which surgery and antimicrobial interventions are performed. Patients receiving amoxicillin and surgery had the shortest duration of antimicrobial administration (median of 3.4 days) and patients receiving cefovecin with no surgical intervention had the longest antimicrobial treatment duration (median of 27 days).

Conclusion: Our study demonstrates methods to extract and provide an overview of temporal phenotypes of patient journeys, which can be applied to text-based clinical records for multiple species or clinical conditions. We demonstrate the effectiveness of this approach to derive real-world evidence of treatment impacts using cat bite abscesses as a model condition to describe patterns of antimicrobial therapy prescriptions and their outcomes.

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1. Introduction

Antimicrobials are an essential tool in combatting bacteria, fungi and viruses, and have saved countless lives since their discovery (Demain and Sanchez, 2009). However, antimicrobial resistance (AMR) has also been recognized since the introduction of antimicrobials to clinical practice (Rollo et al., 1952). The occurrence of AMR has risen dramatically in the early 2000 s to become an emergent global phenomenon and major public health challenge (Roca et al., 2015). All applications of antimicrobials - in humans, animals and the environment - can select for AMR in bacteria, and bacteria can exchange AMR genes with each other and move readily between hosts. Companion animals living in close contact with their owners and exposed to antimicrobials may serve a reservoir of AMR pathogens for their owners, and vice versa(Allen et al., 2010; Graveland et al., 2010; Guardabassi et al., 2004; Lloyd, 2007). In addition, AMR is associated with negative animal health and welfare outcomes in veterinary medicine (Duff et al., 2017; Johnston and Lumsden, 2017).

Broadly, antimicrobial stewardship (AMS) is the implementation of programs to promote responsible antimicrobial usage, and has been shown to be an effective means of reducing antimicrobial resistance (Baur et al., 2017; Cisneros et al., 2014; Hardefeldt et al., 2022). A key component of AMS is monitoring how antimicrobials are being administered over a period of time for a given condition. The sequence of key interventions, including antimicrobial administration, in the treatment of a patient for a specific clinical condition is known as a 'patient journey' (Donaldson et al., 2021). Describing patient journeys is therefore critical to understanding antimicrobial usage patterns in clinical practice. Different common patient journey sequences are termed 'temporal phenotypes' (Meng et al., 2019).

In medical research, patient journeys are used to describe variability in, and response to, treatment, assist in the analysis of treatment plans, and understand how real-world treatment differs from standard clinical guidelines (Bobroske et al., 2020; Capurro et al., 2020; Chen et al., 2018; Meng et al., 2019; Trebble et al., 2010; Williams et al., 2019). Temporally phenotyping patient journeys for analysis presents several obstacles: variation occurs in the time gap between appointments, how many times a patient is seen, procedures performed, and medications such as antimicrobials administered. Previous studies have demonstrated the usefulness of clustering approaches in extracting temporal phenotypes (Bobroske et al., 2020; Huang et al., 2015; Meng et al., 2019). However, these studies did not utilize the free text associated within the clinical documents and were limited to attributes of the records such as the appointment type and pre-determined labels. Free text within the clinical document provides higher resolution of clinical visits. On the other hand, access to the text of the medical records can be difficult due to privacy issues relating to health records. Veterinary clinical notes, which are less limited by privacy concerns than medical records, are useful data to develop a suitable approach to extract patient journeys based on free text. Acute events in veterinary medicine, such as a cat bite abscess, share similar attributes with conditions likely to be analyzed in human patient journeys, such as high variability in the patterns of antimicrobial administration and surgical interventions. By developing methods to extract comprehensive summaries of patterns, we can create a framework to help understand patterns of other conditions as well.

This study uses natural language processing (NLP) to automatically label clinical free text data, enabling analysis of the free text records at scale. NLP is a field of study that sits at the intersection of artificial intelligence and linguistics, with a broad goal of automating language analysis (Nadkarni et al., 2011). In our context of veterinary notes, it can be used to overcome the challenges of manual labeling of free text data, enabling large-scale extraction of key antimicrobial usage information in a structured format, to allow subsequent analysis (Tao et al., 2017). We focus on the extraction of actionable information from text, and specifically on the use of NLP for text mining, which is the discovery of non-trivial knowledge from unstructured text (Jurafsky and Martin, 2023; Kao and Poteet, 2007). By combining NLP to extract details from free text clinical notes with patient journey clustering to identify temporal phenotypes, this study aims to demonstrate an approach to: (1) extract attributes about treatment of individual patients recorded at the time of their visit, (2) create temporal phenotypes of patient journeys based on patterns over these attributes, and (3) describe the possible clinical implications of the phenotypes for a clinical outcome of interest. We use cat bite abscess as a model condition, antimicrobials prescribed and surgical intervention as the treatment attributes, and the duration of antimicrobial therapy prescribed for the various temporal phenotypes of the patient journey as the outcome.

2. Materials and methods

An overview of the method is presented in Fig. 1.

2.1. Patient journey extraction

De-identified clinical data from 137 companion animal practices was sourced from VetCompass Australia (Version 0.3) (2013–2017 inclusive) (McGreevy et al., 2017). The indication for antimicrobial administration and antimicrobial agents administered in each consultation were automatically identified from free text notes and collated using pre-existing NLP methods described in previous work and briefly summarized here (Hur et al., 2020a, 2019, 2020b). Antimicrobial ingredient was extracted using rules-based methods, combining exact dictionary matching and inexact matching based on Levenshtein Distance as previously described (Hur et al., 2019, 2020b). Consultation records with cat bite abscesses were extracted using the VetBERT model using the Adam optimizer and a softmax loss (Hur et al., 2020a). Antimicrobial dosage and duration of administration were extracted with rules-based methods which analyze prescription descriptions to extract numerical values (Karystianis et al., 2016). The total estimated duration of administration was calculated using the following formula: (total number of units dispensed) / (total daily units). Where the item was injectable, the duration of administration was adjusted to the labeled duration of effect.

When considering patient journeys, consultations of the same patient were grouped together if they had at least one record labeled as having the model condition within 14 days or less as a single cat bite abscess episode. This was based on the time necessary for the wound healing process for a cat bite abscess as agreed on by 4 veterinarians as the authors could not find this data in the literature. As cat bite abscesses are an acute injury, very few records listed a confirmation of resolution, and so cases were considered resolved if the patient attended a consultation a year or more later subsequent to the final visit associated with the model condition. Cases that did not meet this definition of resolved were excluded.

2.2. Patient event labeling

To identify key events in the clinical management of the model condition, three veterinarians evaluated a subset of records to discuss what was important in the sequences for understanding antimicrobial patterns. Key events determined were: if the patient was hospitalized (hosp), whether surgery was performed (surgery), whether the abscess was draining on exam (draining), or if there was a new antibiotic dispensed during the consult (antibiotic). To generate additional data labels, 1500 clinical records were labeled by the same three veterinarians for two events: whether there was a surgical procedure performed (surgery), or whether the abscess was draining on the exam (draining). A set of 20 records was labeled by all three veterinarians and used to calculate inter-annotator agreement scores over the developed labels using Krippendorf's alpha (Krippendorff, 1970). The labeled data was split into 1200 (80%) of the records for training, 150 (10%) for validation, and 150 (10%) for testing the accuracy of the final model.

Surgery and draining: A contextualized language model pretrained

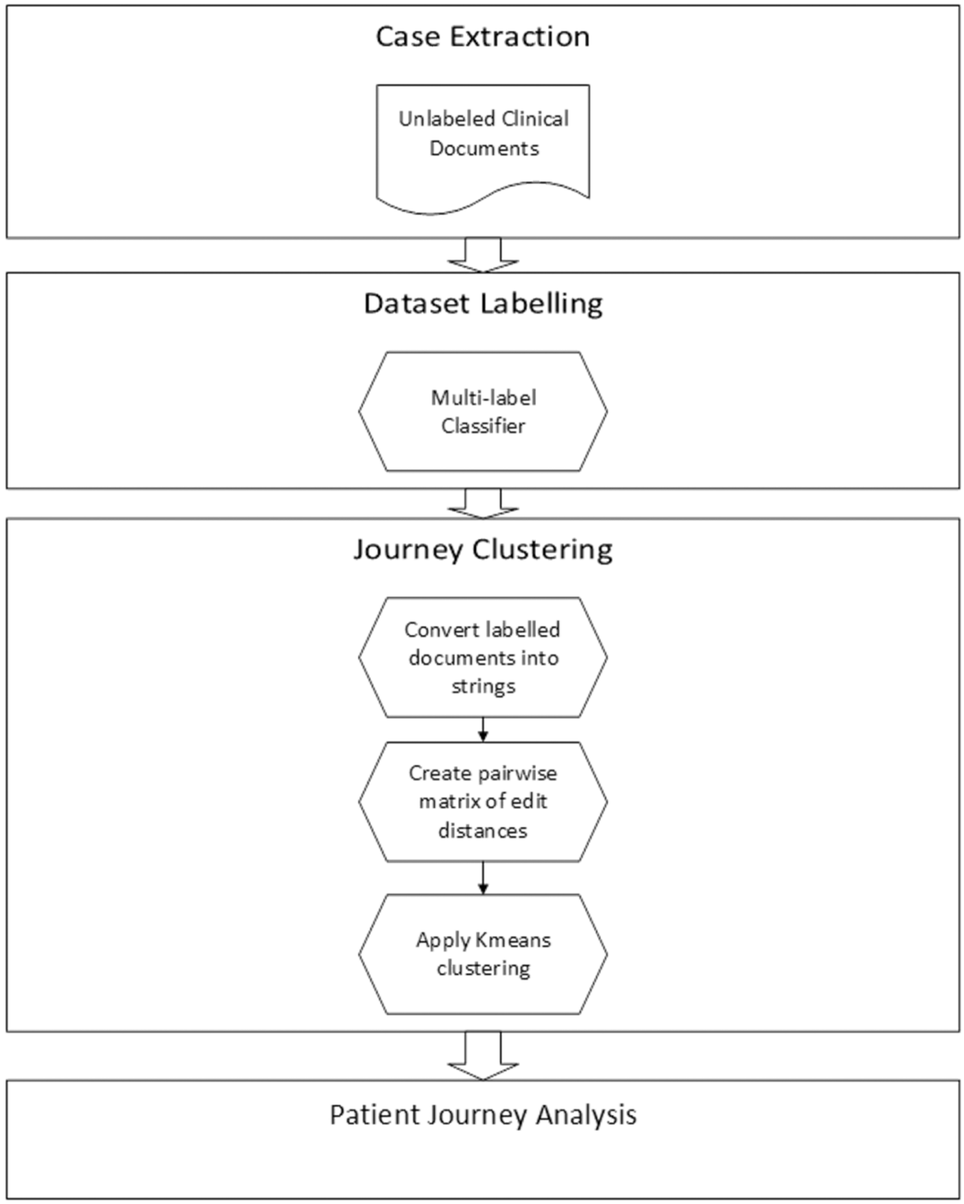

Fig. 1. : Outline of proposed approach.

on VetCompass data, VetBERT (Hur et al., 2020a), was modified to perform multi-label classification of the clinical records by adding a fully connected linear layer with a sigmoid loss. The final model was trained with a 0.3 dropout rate, Adam optimizer, maximum of 512 word pieces, batch size of 32, and Learning Rate of 1e-5.

Hospitalization: The written records often lacked specific reporting of hospitalization, so inventory item names were used to determine whether a patient had been hospitalized. During manual evaluation of the records, the word 'hospitalization' or 'hosp' appeared in the inventory items of relevant cases. Therefore, incidents of hospitalizations within the patient records were identified using a regular expression search for the substring 'hosp'. The precision and recall of this method were evaluated using a random sample of 100 abscess cases.

The remainder of the records were then labeled as 'surgery', 'hosp', or 'draining' when those attributes were present in the clinical record, and 'antibiotic' when a new antibiotic was given to a patient during a cat bite abscess episode which might contain one or many records. The estimated total duration of administration of each medication was determined as the number of days elapsed between (1) the first date of prescription of that antibiotic, and (2) the end date of the labeled duration of administration of the last prescription of that antibiotic recorded. For example, if an antimicrobial was first prescribed on day 1 and last prescribed in the same episode on day 7 as a 7-day course (to be completed on day 13), the estimated total duration of administration would be calculated as 13 days, regardless of whether the prescription was continuous throughout that time period.

2.3. Patient journey clustering

Patient journeys were converted to case sequence patterns based on the chosen attributes for analysis, and cluster analysis used to identify the common temporal phenotypes of the patient journey for our model condition, focusing on antibiotic administration and surgery for cat bite abscess. Short text strings were used to summarize the events of interest (case sequence patterns) in each case series, with a single letter representing each possible combination of attributes for each discrete visit record. Each visit record (appointment) was evaluated on the four attributes labeled (draining, hosp, surgery, and antibiotic) each of which could be either TRUE (attribute occurred during visit) or FALSE (attribute did not occur during visit). The combination of TRUE and FALSE

values for these 4 features allowed for $2^4 = 16$ distinct event types, which were represented using letter codes 'a' through 'p', where 'a' represents all four features being false and 'p' represents all 4 features being true (Table A.1). After coding each visit with a single letter, the time elapsed between appointments was also included as an element of the case sequence pattern describing the patient journey: when the time elapsed was less than 24 h, no letter code was added; between ≥ 1 and ≤ 7 days was coded as 'x'; and > 7 days coded as 'xx'. As an example, a case sequence pattern of 'oxcxx' is a patient journey that can be interpreted as: The first record in the sequence included a draining abscess on examination, surgical intervention was performed and a new antibiotic given (o), followed by a time gap of between 1 and 7 days (x), followed by a second consult where a new antibiotic was given (c), followed by a time gap of more than 7 days (xx) and the end of the sequence. The total length of patient journey sequences were limited to 28 days which was determined to be a reasonable amount of time for the condition to resolve.

A modified version of Levenshtein (edit) distance (Levenshtein, 1966) known as the optimal string alignment distance (Boytsov, 2011) algorithm was used to calculate the differences in the case sequence patterns. This calculation allows for the measurement of the number of character changes required to transform one case sequence pattern into a second case sequence pattern. Patterns that match completely have a value of 0, whereas a one-character difference is 1, a two-character difference is 2, etc. Weight modifiers were applied such that character occurrences within the sequence patterns of antibiotics or surgery were 5x more expensive to delete, insert, or transpose the position within the case sequence. We also made it 1/10 as expensive to perform deletions or insertions of a single time gap. Due to the variable nature of non-emergency procedure scheduling in veterinary practice (surgery is not always scheduled on the most desirable day), there was a decreased penalty for transpositions so that variations in the order of two letters next to each other were not overly penalized. All pairwise weighted edit distances between each of the unique case sequence patterns were summarized in a matrix.

In order to identify common patient journey phenotypes, the clustering algorithm K-means+ + was applied to the set of unique patterns with at least 2 consultations and 10 occurrences (Arthur and Vassilvitskii, 2006). Edit distance was used for the similarity scores in the algorithm, to identify *k* clusters. We tested a range of *k* values ranging from 1 to 40. The elbow (Thorndike, 1953) and Silhouette (Kaufman and Rousseeuw, 2009; Rousseeuw, 1987) methods were used to determine the optimal *k* value. The elbow method did not clearly show an optimum *k* value. The Silhouette scores were visualized, with the lowest Silhouette score peak occurring at nine clusters (Fig. 2a). The Silhouette coefficients for each cluster were also evaluated and were consistently > 0.5 (Fig. 2b). The additional Silhouette score peaks with greater *k* values (Fig. 2a) were also evaluated but had a Silhouette coefficient of < 0.5, indicating those clusters were very similar to each other and that minimal explanatory benefit was obtained by increasing the *k* value. Accordingly, a Kmeans+ + model with a *k* value of 9 was used to predict the appropriate cluster on the remaining sequences.

The nine clustered temporal phenotypes were then evaluated by a group of 3 veterinary clinicians (one original annotator and two who had not previously contributed), who identified two clinically important categorizations within the dataset created based on commonalities between the clusters. The first categories were based on whether patients received (1) antibiotics alone, (2) antibiotics in conjunction with surgery, or (3) no antibiotics. The second categories were phenotypes that represented either (1) simple cases with only a single antibiotic given or (2) complex cases which either had multiple instances of antibiotics and/or surgery.

All code was written in Python, and machine learning models and statistical tests on algorithms performed with scikit-learn and PyTorch libraries. Weighted Levenshtein distance was calculated using the Weighted Levenshtein Python library (weighted-levenshtein, 2021). Code used for developing clusters has been made publicly available at https://github.com/havocy28/patient_journeys/. All descriptive statistics, computations, and visualizations were performed using Tableau 2021 (Wesley et al., 2011).

3. Results

3.1. Case extraction

A total of 15,276 patient journeys consisting of 22,940 records from 13,317 patients with cat bite abscess occurring between 2013–2017 were extracted. The annotations of patient events made on the clinical records had excellent agreement between the clinicians (agreement score of alpha=0.78). Of these records, 8436 patient journeys consisting of 13,744 records from 7053 patients with a resolved abscess treatment series were included in the analysis (Fig. A.1), forming 1355 distinct patterns. Abscess treatment was considered resolved when a patient had a subsequent appointment at least one year after the last cat bite abscess appointment.

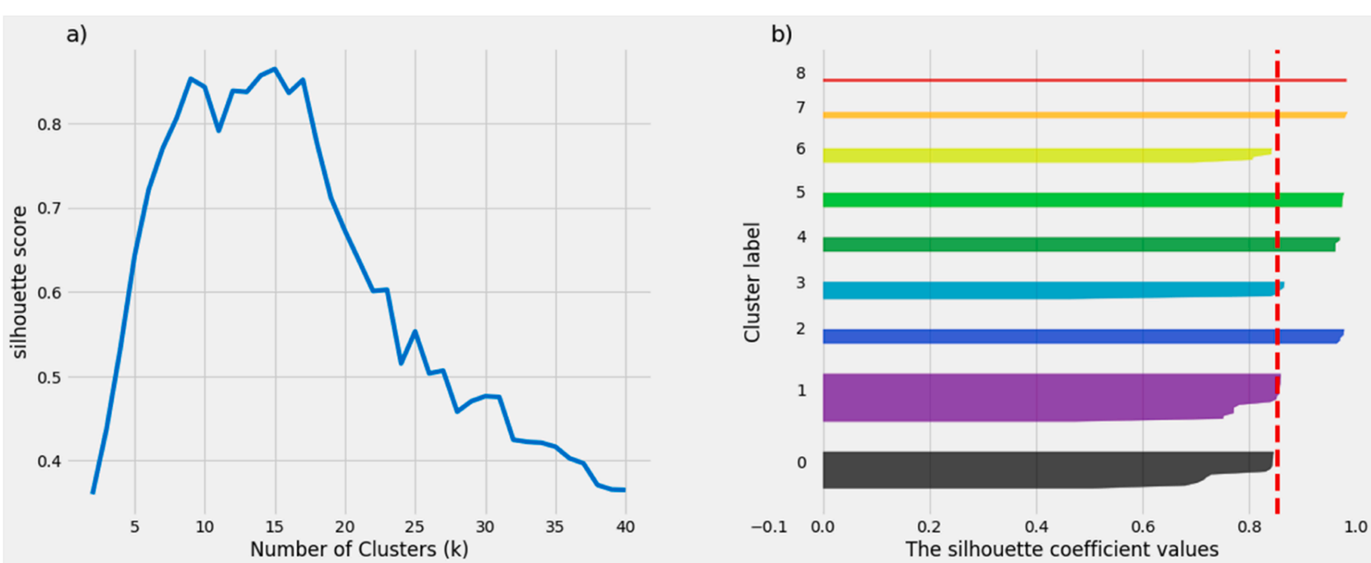

Fig. 2. : KMeans clustering Silhouette analysis of (a) Silhouette score by number of cluster and (b) plot of coefficient values for 9 clusters.

3.2. Automatic patient event labeling

Surgery and draining: The F1 score for correctly labeling surgeries was 0.90 (precision = 0.87 and recall = 0.93), and for detecting whether an antibiotic was draining on exam was 0.74 (precision = 0.66 and recall = 0.83).

Hospitalization: The method for searching for the hospitalized cases were found to be accurate in 100% (N = 100/100) of cases in which the case was properly identified as having been hospitalized when manually evaluated.

3.3. Patient journey clustering

There were 69 distinct patterns with at least 1 consultation and 10 occurrences. Cluster analysis identified 9 clusters to represent the temporal phenotypes of patient journeys for the model condition cat bite abscess, characterized by varied quantities and sequences of antimicrobial administrations and surgical interventions (Fig. A.2).

When evaluating antimicrobial administration between clusters, 5/9 had both antibiotics and surgery performed (49%, 4138 of 8436 patient journeys), 2/9 clusters had only antimicrobials without surgery (38%, 3177 of 8436 patient journeys), and 2/9 clusters had no antimicrobials (13%, 1121 of 8436 patient journeys) (Fig. 3).

Overall, patient journeys involving both surgery and antibiotics were characterized as having shorter duration of antimicrobials given (median of 8.6 days), while patient journeys only receiving antibiotics had longer administration (median of 13 days). When evaluating specific antimicrobials, cases that received antimicrobials, but no surgery most commonly received Cefovecin, as did cases that were treated with both antimicrobials and surgery (4094 of 7315 patient journeys, 56%). Cefovecin administration also had the longest duration of antimicrobial administration (median of 27 days). Amoxicillin prescription had the shortest duration for both patient journeys where antimicrobials were given alone (median of 3.6) and with surgery (median of 3.4) (Fig. 4).

When considering temporal phenotypes grouped as simple or complex cases that received antibiotics, 2/9 phenotypes were considered simple (74%, 6218 of 8436 patient journeys), while 5/9 were considered complex (13%, 1097 of 8436 patient journeys) (Fig. 5).

Overall, simple cases were characterized as having shorter duration of antimicrobial administrations (median of 4.4 days) while complex cases had a longer duration of antimicrobials given (median of 14 days). Cefovecin had the longest duration of administration for complex cases (median of 27 days) and simple cases (median of 14 days), while Procaine penicillin had the shortest duration for simple cases (median of 1.0 days) and amoxicillin had the shortest duration for complex cases (median of 5.5 days) (Fig. 6).

4. Discussion

Effective antimicrobial stewardship programs must be underpinned by detailed understanding of clinicians' treatment choices. These choices can be effectively described by evaluating the duration of antimicrobial therapies across various patient journeys. Traditionally, analyzing this data has been dependent on manual annotation of selected clinical notes. Recent advancements in NLP have enhanced the ability to label free text clinical records, with results comparable to manual annotation by experts (Alsentzer et al., 2019; Devlin et al., 2018). In this study, generated labels together with patient journey extraction methods has enabled the extraction of novel patient journeys with features specified by clinicians and limited only by the data captured within the records. Using temporal phenotyping of patient journeys for our model condition of cat bite abscess, we demonstrate

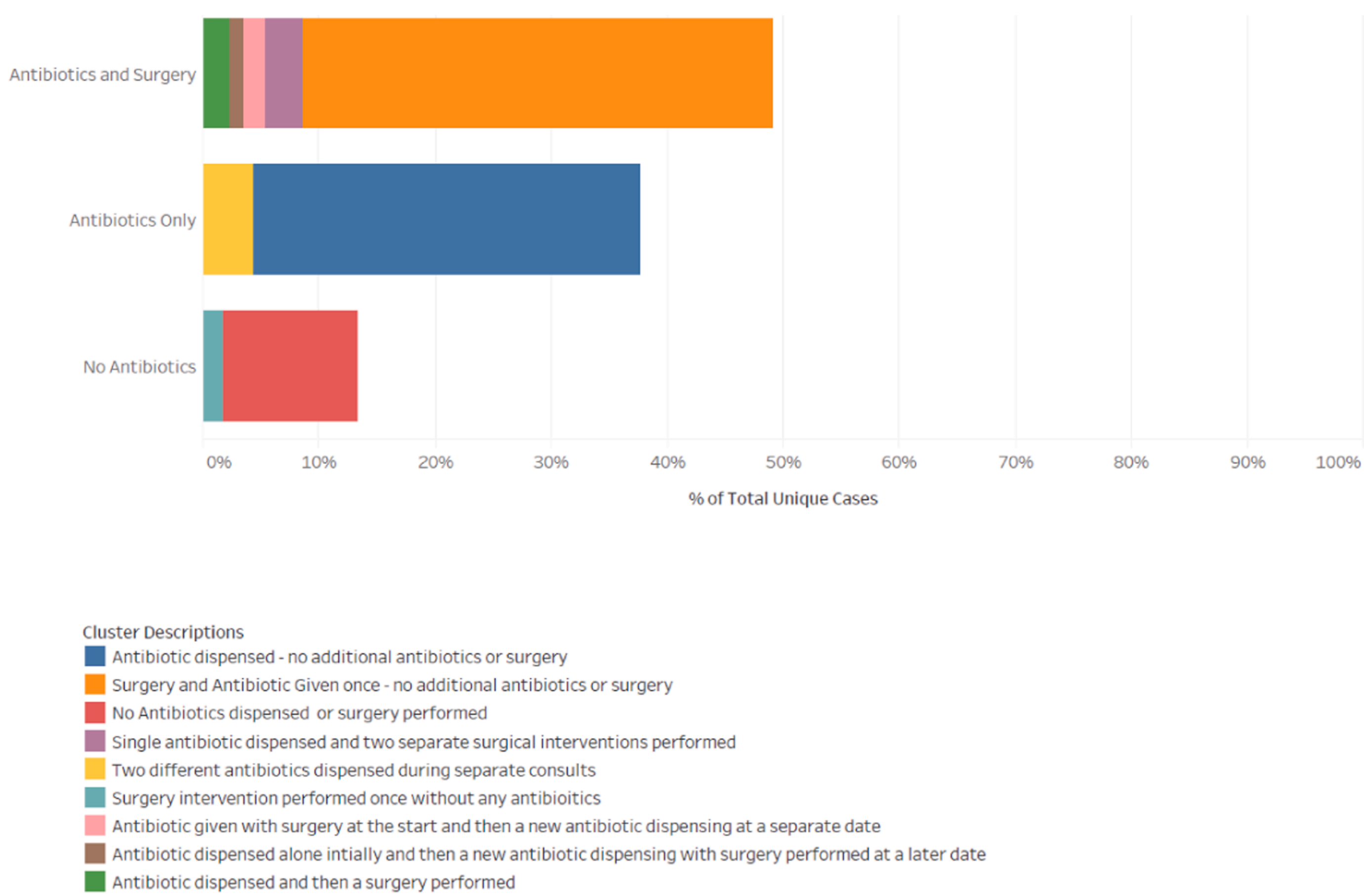

Fig. 3. : Patient journey phenotypes grouped based surgery and antibiotic administration.

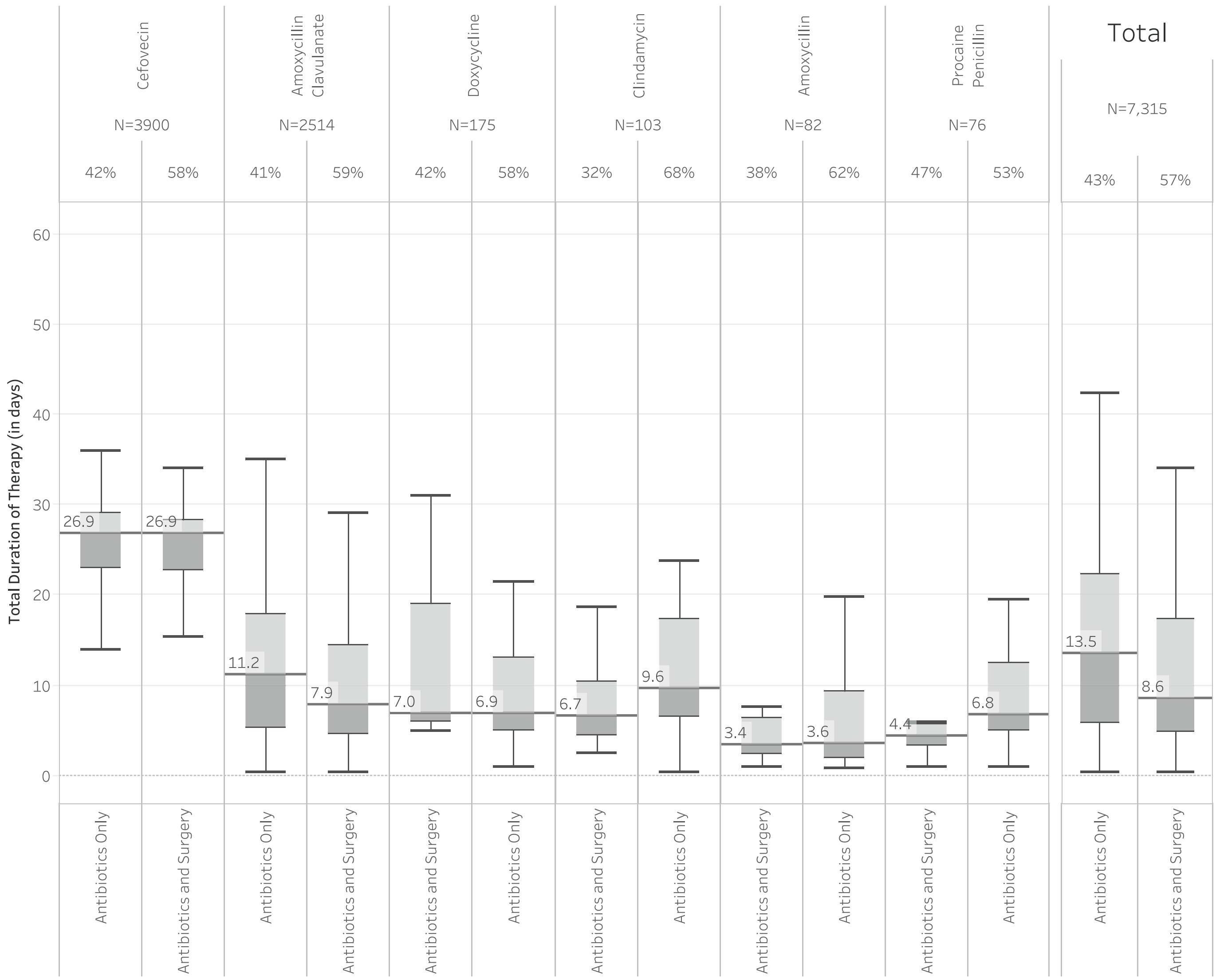

Fig. 4. : Box plots displaying median, interquartile range, upper extreme and lower extreme for the duration of antibiotic administration based on whether cases had antibiotics alone or antibiotics and surgery, the number of cases for each category (N) and percentage (%) of cases in each category. Antibiotics representing fewer than 0.5% of cases omitted.

that it is possible to analyze data that has previously been inaccessible due to it being encoded in unstructured natural language. The understanding of clinical treatments and outcomes that are produced by these analyses can help inform interventions such as antimicrobial stewardship programs. Additionally, understanding patterns better can help inform research that generates guidelines.

This study outlines an approach to extract clinically relevant features out of sequences of clinical texts and use these features to provide an overview of the patient journeys and allow sophisticated analysis of outcomes. This enhances previous studies using insurance claims data that have used KMeans for clustering and Levenshtein (edit) distance to measure the differences in sequences of events that were limited by reliance on manual diagnostic coding (Bobroske et al., 2020; Meng et al., 2019). By leveraging access to clinical notes and applying NLP to create additional features, we have demonstrated how cases can be clustered together and further categorized into compact groups based on clinically relevant patterns that emerge. In this study, we identified clinically important differences in temporal phenotypes between simple and complex cases of the model condition, and between antibiotic use alone or in combination with surgery. While these categorizations such as 'antimicrobials with surgery' compared with 'only antimicrobials' could be formed retrospectively without formal cluster analysis, these groupings could not be clearly identified when evaluating the initial 8436 patterns.

As expected, most patient journeys had only a single instance of an antibiotic, or a single instance of surgery without a change in the antibiotic and were classified as 'simple'. It is possible that many of these cases could in fact have been managed without antimicrobials, as studies of abscesses in humans have shown that when adequate drainage of an uncomplicated subcutaneous abscess is achieved, there was no evidence that adding antimicrobial treatment improved outcomes (Fahimi et al., 2015).

The selection of the four key elements – hospitalization, surgery, draining, and antibiotic – was based on what could be reliably extracted from the clinical text consistently and an understanding of the common clinical workflow of cat fight abscesses in Australia. To understand better which cases might be appropriate for a non-antibiotic patient journey, abscess location and severity of the lesion should be considered. These were not captured in our labels and likely play a significant factor in treatments and outcomes, and would benefit from further evaluation. There was also a lack of laboratory data in the clinical records and microbial culture were infrequently conducted, consistent with previous

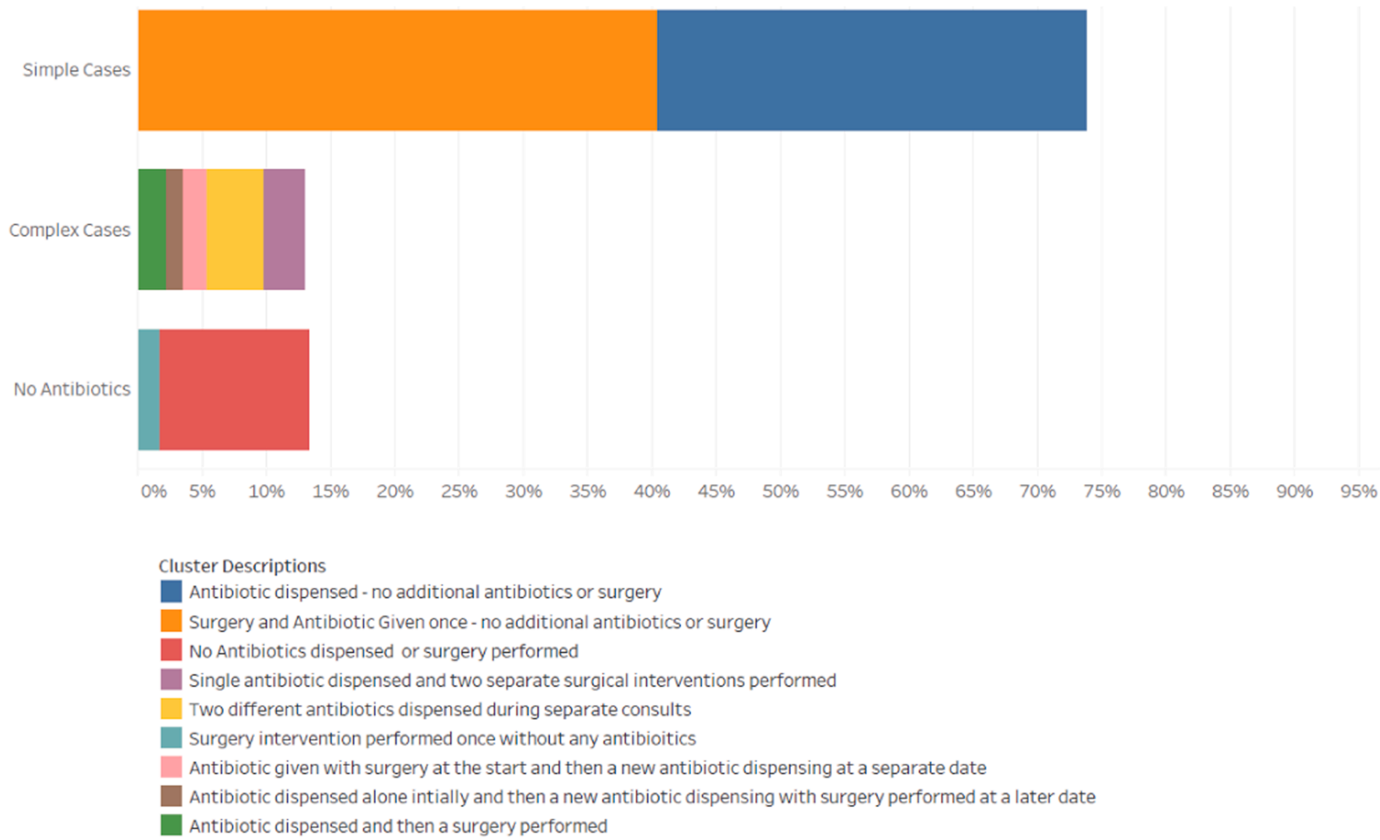

Fig. 5. : Patient journey phenotypes grouped based on case complexity.

research in the study of 5029 cases receiving cefovecin extracted from VetCompass Australia, where only 0.3% had cultures performed (Hardefeldt et al., 2020).

Not all veterinary practices might offer hospitalization services, potentially influencing the patient journey. In cases where hospitalization is necessary but unavailable, patients may be referred to another facility which would not be detected in our research, adding another layer of variability in treatment outcomes. However, we feel this is unlikely to have had a major impact on the outcomes of the research as cats with fight abscesses are generally treated by primary care facilities in Australia and referral is uncommon in our clinical experience. Other elements that could also be evaluated would be the cases which received no antibiotics, the number of revisits, or the length of time between the first and the last consult. Analysis of several of the records that had no antibiotics showed that many were due to them self-healing, and many of the revisits were for unrelated procedures and treatments that were delayed due to the abscess finding. Moreover, there were a large number of cases that had revisits that were not warranted, or revisits recommended that are not followed up on. This could be due to the variation in compliance of the client, or the way revisits are scheduled by the veterinary clinic. Additional methods and analysis are required to better understand these elements.

While the focus of this study was on extracting patient journeys, our approach can also be used to report the duration of antimicrobial administration of various antibiotics prescribed for a specific condition. This represents an advancement over previous studies using VetCompass Australia data that were unable to examine the duration of antimicrobial use because the records were evaluated individually rather than as a case series(Hur et al., 2022). All antimicrobial use can lead to AMR, however long durations have more of an impact (Baur et al., 2017; Chastre et al., 2003; Tam et al., 2007). Guidelines for antimicrobial use in cat bite abscesses are available in Australia, however the evidence base for these guidelines is poor and based on general guidance for skin infections (Greene and Calpin, 2012; AVPG, 2023). Better tools are needed to evaluate the effectiveness for various durations for specific conditions. The case extraction technique developed here has been designed for use in acute conditions, and chronic conditions would require additional methods to account for long-term clinical case management, and the resulting style and structure of clinical records.

The analysis in this study was limited to VetCompass 0.3, and the methods were constrained by the same limitations previously described (Hur et al., 2020b). The cluster number was determined using the silhouette score, which is an objective measure of cluster quality, quantifying how well each data point fits within its assigned cluster compared to other clusters. While the high silhouette score would indicate distinct, well-separated clusters, it's crucial to consider that this might reflect a local rather than a global optimum. Final cluster selection should balance silhouette scores with domain-specific considerations to ensure the most meaningful interpretation of the data. The location of the cat bite abscess was omitted or inconsistently recorded in large numbers of records, limiting opportunities to consider location as a factor in clinical treatment. Similarly, records lacked confirmation that the abscess had resolved, resulting in use of the heuristic of whether the patient was seen again within a year to confirm case resolution. This method might inadvertently include cats that may have succumbed due to abscess-related issues. However, an earlier study of 4009 UK cases found that abscesses were not a primary cause of feline mortality, suggesting such instances are infrequent (O'Neill et al., 2015). Another factor to consider is the potential for clustering at the practice level. Different practices may have varying protocols or resources which can influence outcomes and treatment modalities. If practices consistently manage cases in certain ways, this could introduce variability in the data. Additionally, the duration of antimicrobial administration could not be extracted for many records due to insufficient information to calculate the duration of administration, as discussed in previous studies using this dataset (Hur et al., 2022).

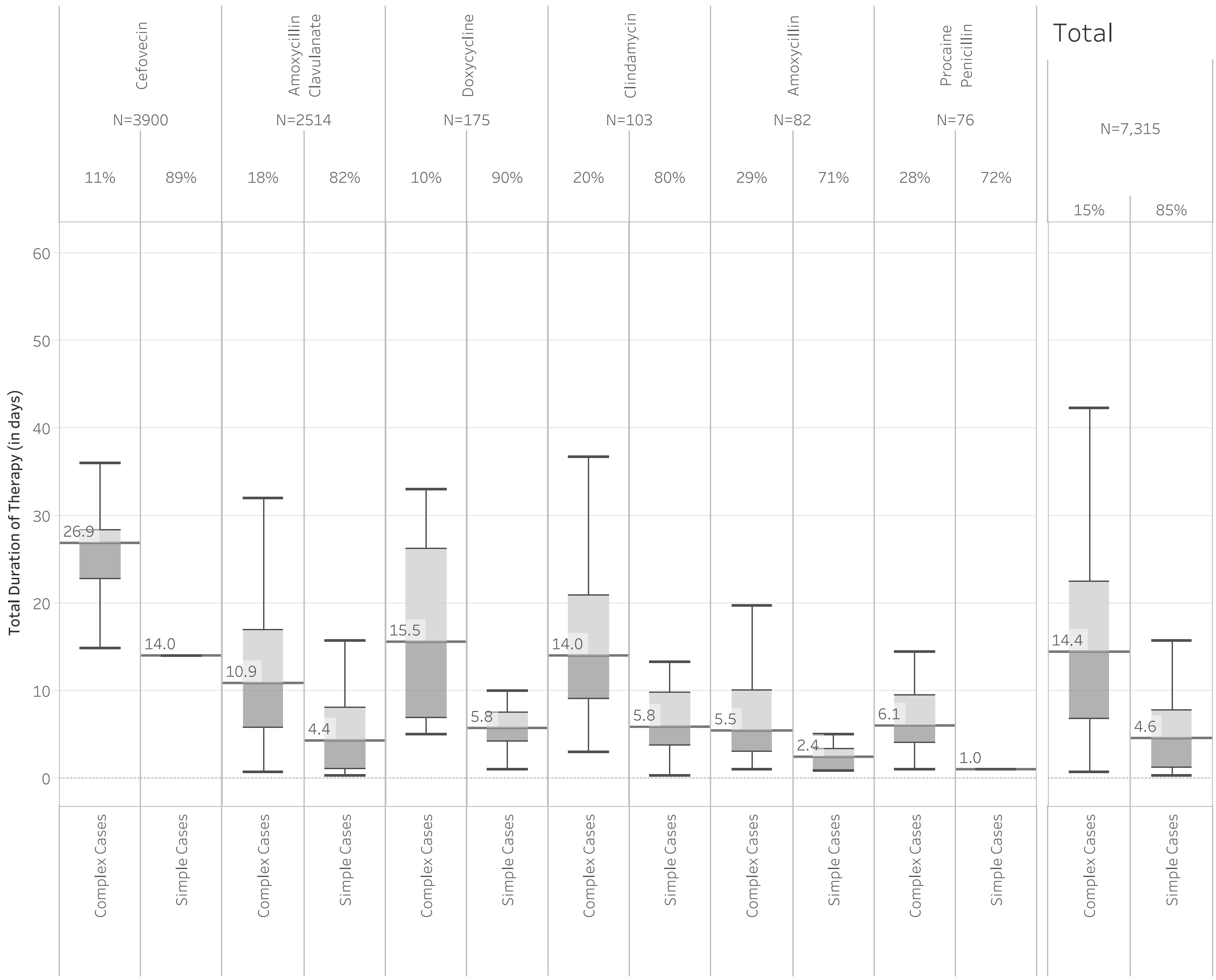

Fig. 6. **:** Box plots displaying median, interquartile range, upper extreme and lower extreme for the duration of antibiotic administration based on complexity, the number of cases for each category (N) and percentage (%) of cases in each category. Antibiotics representing fewer than 0.5% of cases omitted.

5. Conclusions

Using the VetCompass dataset, applying NLP methods and journey clustering techniques, we successfully extracted 9 temporal phenotypes of patient journeys from 8436 cases of a model condition, cat bite abscess. This enabled description of the total duration of antimicrobial administration based on the sequence of events that occurred during clinical case management over one or more consultations. More broadly, our methods demonstrate an approach to extract clinically relevant features out of temporal sequences of clinical texts and use these features to provide an overview of the patient journeys.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.prevetmed.2023.106112.

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