The Success of *Empyrean*: Structural Nostalgia and Emotional Evolution in Contemporary Romantasy

María Yu García Muñoz

4th Year, Business Intelligence and Analytics (BIA)

University of Valencia

This work analyzes why the Empyrean saga (2023–2025) has achieved extraordinary editorial and critical success, with an average rating of 4.50/5 on Goodreads and combined sales exceeding 12 million copies in less than two years. The three volumes, *Fourth Wing*, *Iron Flame*, and *Onyx Storm*, have dominated The New York Times and Amazon bestseller lists, while *Onyx Storm* became the fastest-selling adult novel in 20 years, with 2.7 million copies in its first week. Additionally, *Fourth Wing* received the BookTok Book of the Year Award.

Using a corpus of nine novels, natural language processing (NLP) techniques have been applied to evaluate two hypotheses: (1) that Empyrean presents a more collective and emotional narrative; and (2) that its success combines innovation with narrative structures familiar to readers of young adult sagas. The analysis is organized into four blocks: (1) sentiment analysis with AFINN and NRC lexicons; (2) topic modeling using guided LDA; (3) character co-occurrence networks; and (4) validation with Goodreads ratings.

The results show that Empyrean possesses a denser relational network and a more intense emotional tone, features that do not appear with the same strength in *Shatter Me* and only partially in *The Mortal Instruments*, suggesting that it recovers classic formulas adapted to current sensibilities. This indicates that its success does not depend solely on novelty, but on the combination of established structures with a collective focus, offering solid foundations for narrative recommendation systems beyond genre or popularity.

Introduction

1.1. The emergence of romantasy as a hybrid genre

Young adult literature has been changing according to the social, cultural, and emotional concerns of each generation. Well into the first decade of the 21st century, the publishing market for adolescents focused on two main types of stories, distinct in structure and theme.

On one hand, epic and urban fantasy sagas, such as *Harry Potter* (J. K. Rowling), *A Game of Thrones* (George R. R. Martin), or *The Lord of the Rings* (J.R.R. Tolkien), presented supernatural worlds with their own rules, prophecies, and grand confrontations between good and evil. In these stories, the protagonist's growth depended on their role within the collective conflict, while romance, although present, remained in the background.

On the other hand, young adult romance, represented by sagas such as *Twilight* (Stephenie Meyer), *Hush, Hush* (Becca Fitzpatrick), or *The Selection* (Kiera Cass), focused on emotions, internal conflicts, and romantic relationships. Here, the outside world functioned as the backdrop for the romantic story, often marked by danger, moral ambiguity, and emotional dependence. The action was more individual than collective.

Starting in 2020, with the rise of BookTok, a new type of narrative consolidates that combines both approaches: **romantasy** (romantic fantasy). More than a mixture of genres, it constitutes a narrative model with its own rules and a very active reading community. Works such as *A Court of Thorns and Roses* (Sarah J. Maas) or *The Cruel Prince* (Holly Black) integrate romance and wartime conflict: relationships are strengthened in shared struggle and collective action is supported by emotional bonds. This approach also redefines the heroine, showing a character active in her own destiny and in that of her community.

1.2. Narrative evolution: from the individual to the collective

The evolution of the female archetype in young adult literature reflects not only cultural changes, but also narrative and editorial decisions. Between 2008 and 2015, protagonists were often marked by emotional isolation, trauma, and dependence on male figures who guided or protected them. For example, Juliette Ferrars in *Shatter Me* constructs her identity in relation to others, while Clary Fray in *The Mortal Instruments* gradually gains agency, always tied to key male characters.

In contrast, the heroines of contemporary romantasy, such as Violet Sorrengail in *Empyrean* or Feyre Archeron in *A Court of Thorns and Roses*, are active from the start: they participate in decisions, lead teams, and their emotional development occurs within narrative communities that complement the romantic relationship.

The success of *Empyrean* is not explained solely by this shift: it also recovers classic elements from previous sagas, such as choral structures, balance between romance and action, and clear magical hierarchies. This combination of emotional novelty and familiar structures attracts both new readers and those accustomed to the genre. In a saturated market, being original is not enough: the heroine must actively influence her environment, and *Empyrean* manages to convey this without breaking with the conventions that made its predecessors popular.

1.3. Objectives and hypotheses of the study

The objective of this project is to quantitatively analyze the success of *Empyrean* through natural language processing techniques and unstructured data analysis. To this end, a corpus is constructed from four databases, which allow for comparison of different stages of young adult literature and romantasy.

Three sagas are studied individually: *Empyrean* (2023–2025), representative of contemporary romantasy; *The Mortal Instruments* (2007–2014) and *Shatter Me* (2011–2014), as examples of previous sagas where romance and fantasy coexist but are not fully integrated. Additionally, a comparative dataset is incorporated with popular sagas from the 2010s (*Vampire Academy*, *Divergent*, *Throne of Glass*, *Fallen*, *Hush, Hush*, *Percy Jackson*, and *The Maze Runner*), to situate the results in a broader context of the young adult market.

Four methodological blocks are applied to this corpus:

1. **Sentiment analysis**, with AFINN, NRC, and Bing lexicons and a supervised model, to compare affective profiles across periods.
2. **Topic modeling**, using seeded LDA, to identify the main narrative topics and contrast them with the structure of *Empyrean*.
3. **Character network analysis**, constructing co-occurrence graphs by chapter to measure relational complexity and protagonist centrality.
4. **External reception**, using Goodreads ratings as validation of readers' actual response.

The central hypothesis is twofold: that contemporary romantasy has evolved toward more collective narrative structures compared to the emotional individualism of previous sagas, and that the success of *Empyrean* lies in recombining familiar elements with new emotional demands.

2. Marco teórico y metodológico

This project is based on an interdisciplinary approach that combines computational linguistics techniques, narrative analysis, and data science applied to literary texts. The following sections present the main methodologies employed, along with their theoretical basis and their usefulness for analyzing the evolution of the romantasy genre.

2.1. Sentiment analysis in literary texts

Sentiment analysis allows for the quantification of the emotional valence of a text through the identification of words with affective charge [1]. In this work, three complementary approaches are employed. First, predefined lexicons:

- **AFINN** (Nielsen, 2011), which assigns numerical scores between -5 (very negative) and +5 (very positive) [1];
- **NRC Emotion Lexicon** (Mohammad & Turney, 2013), which categorizes words into eight basic emotions (joy, fear, anger, etc.) according to Plutchik's wheel [2];
- **Bing Liu's lexicon**, which classifies terms as positive or negative in a binary fashion [1].

These methods allow for analysis of the average emotional tone of each saga and how it changes throughout the chapters. Additionally, a supervised logistic regression model with LASSO regularization is trained using the corpus of classic sagas (2008–2015), with TF-IDF as the text representation. Then, this model is applied to *Empyrean* to determine whether its emotional profile follows the patterns of previous sagas or introduces a narrative shift. The combination of lexical analysis and predictive modeling ensures a solid and contextualized interpretation of sentiment in fiction [3].

2.2. Topic modeling with guided LDA

La Topic modeling allows for the discovery of patterns or hidden structures in large volumes of text. Standard LDA [4] functions in an unsupervised manner, that is, it identifies topics on its own, but in literature this can generate unclear results, since the detected topics do not always coincide with important narrative axes. Therefore, in literary contexts, **guided LDA** (seeded LDA) [5] is often more useful, as it allows for the incorporation of prior knowledge through thematic dictionaries.

In this project, a specific dictionary was constructed for *The Mortal Instruments*, with five central topics: romance, identity, supernatural warfare, institutional politics, and underworld. Each topic is defined from coherent words extracted from a previous analysis of the saga, which helps the model identify themes more precisely and in a way that is easier to interpret.

The model is applied only to *The Mortal Instruments*, given that its narrative universe is well-delimited and its thematic conventions are stable. Although it is not directly applied to *Empyrean*, the results serve as a reference for analyzing thematic evolution: while TMI balances romance and institutional politics, *Empyrean* emphasizes collective action and group resilience, even if those themes are not explicitly modeled.

This approach shows that human intervention in topic modeling is fundamental for obtaining interpretable results in literature, allowing for the connection of detected patterns with literary analysis and better understanding of the evolution of narrative genres.

2.3. Character networks and narrative analysis

Character networks represent the narrative as a graph: nodes are the characters and edges show when they appear together in the same context, such as a chapter or scene. Following the proposal of Agarwal et al. (2012), undirected networks are constructed based on the co-occurrence of proper names within each chapter. The main metric is **network density**, which indicates the degree of interaction between characters by comparing existing connections with the maximum possible. The number of nodes (relevant characters) and the degree centrality of the main character, which reflects their importance as the axis of the story, are also analyzed. [6]

This approach allows for differentiation between two types of narrative: **dual**, centered on a binary relationship (protagonist–partner), and **choral**, where multiple characters interact in a balanced way. It is expected that *Shatter Me* and *The Mortal Instruments* will show simpler networks, with lower density and a more centralized protagonist, while *Empyrean* presents a more connected network, where the protagonist acts as a nexus between different subgroups (allies, rivals, mentors).

In this way, this technique not only analyzes the formal structure of the text, but also connects relational architecture with ideological content, showing how relationships between characters reinforce the themes and messages of the narrative.

2.4. Content-based recommendation systems

Content-based recommendation systems suggest similar items by analyzing their own characteristics, without the need for user data [7]. In this project, a vector profile is constructed for each saga that combines four dimensions:

- Average sentiment (AFINN),
- Character network density (as an indicator of collectivism),
- Proportion of key topics (when available),
- Average rating on Goodreads.

2.5. Reception data: Goodreads and BookTok

Finally, external reception data are incorporated to validate the results of the technical analysis. Average ratings on Goodreads, a platform with millions of reviews, offer a quantitative measure of the actual success of each saga. Although individual reviews are not analyzed due to time and scope limitations, the rating of each book in each saga serves as empirical reference: if *Empyrean* shows a balanced narrative structure and emotional tone, and also obtains a high rating, this reinforces the hypothesis that these characteristics coincide with the expectations of the current audience. [9]

Although no quantitative analysis of BookTok is performed, it is mentioned as a cultural phenomenon that has driven modern romantasy. Its logic, centered on emotional identification, the reading community, and the virality of collective plots, coincides with the patterns detected in computational analysis.

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3. Methodology and Data

3.1. Selection and composition of the corpus

The textual corpus analyzed consists of three representative sagas from two distinct historical moments in the evolution of the young adult genre:

- **Classic era (2007–2014)**: *The Mortal Instruments* (Cassandra Clare) and *Shatter Me* (Tahereh Mafi).
- **Contemporary era (2023–2025)**: *Empyrean* (Rebecca Yarros).

This selection responds to criteria of cultural and commercial representativeness. *The Mortal Instruments* is considered one of the foundational sagas of young adult urban fantasy with romantic elements, while *Shatter Me* exemplifies the post-*Twilight* trend toward introspective narratives centered on individual trauma. For its part, *Empyrean* represents the recent rise of romantasy, a hybrid that combines epic fantasy and romance with empowered female protagonists, whose massive success on platforms like BookTok has transformed the young adult publishing market.

Additionally, an expanded corpus of 9 popular sagas published between 2008 and 2015 is included: *Percy Jackson & the Olympians*, *Divergent*, *Vampire Academy*, *A Court of Thorns and Roses*, *Throne of Glass*, *The Maze Runner*, *Fallen*, *Hush, Hush*, and *The Mortal Instruments*. This corpus not only provides the Goodreads ratings used as external reception reference, but also serves as a training set for the supervised emotional classification model. By training on this diverse set of pre-romantasy narratives, the model learns emotional patterns representative of the era prior to the consolidation of modern romantasy. Therefore, this approach allows for contrasting both technical profiles and reader perception in a broader cultural and commercial context.

3.2. Acquisition and structure of the texts

The complete texts of the main sagas (*Shatter Me*, *The Mortal Instruments*, and *Empyrean*) were obtained in .txt format from legal digital editions, respecting copyright and ensuring their exclusive use for academic purposes, without public distribution. Each book was processed individually, preserving essential metadata such as title, author, and saga number [10][11].

The hierarchical structure of the corpus is as follows:

- **Level 1**: Saga (3 categories)
- **Level 2**: Book (9 volumes in total)
- **Level 3**: Chapter (minimum unit of narrative analysis)

This design allows for both global analyses by saga and detailed comparisons by chapter, which is fundamental for studying emotional and thematic evolution throughout the plots.

3.3. Textual preprocessing

Preprocessing was carried out in four phases [10][11]:

- **Phase 1**: Segmentation by chapters
- **Phase 2**: Cleaning and normalization
- **Phase 3**: Tokenization and contextual filtering [12]
- **Phase 4**: Corpus validation

3.4. Sentiment and emotion analysis

Sentiment analysis was approached through a multi-method approach, combining emotional lexicons and supervised models in order to capture both emotional polarity (positive/negative) and the distribution of specific emotions and their evolution throughout the narrative. The analysis was performed at the chapter and saga levels [12].

3.4.1. Emotion analysis with the NRC lexicon

For categorical emotion analysis, the NRC lexicon was used, based on Plutchik's model, which assigns words to eight basic emotions in addition to positive and negative polarity [19].

Proportions of each emotion per chapter were calculated and aggregated by saga and by relative position within the narrative, which allowed for comparison of emotional profiles between sagas and analysis of their evolution throughout narrative progress. Likewise, the most frequent words associated with each emotion were identified to facilitate semantic interpretation of the results.

3.4.2. Emotional valence analysis with AFINN

To measure continuous emotional intensity, the AFINN lexicon was used, which assigns scores between −5 and +5 to words [1].

The average sentiment per chapter was calculated and results were aggregated by saga, allowing for analysis of the overall emotional dynamics and comparisons between narrative universes.

3.4.4. Sentiment analysis with text windows and at sentence level

With the objective of capturing finer emotional variations, two complementary approaches were applied:

- **Bing lexicon** on sliding text windows, calculating net sentiment in consecutive segments, which allowed for detection of abrupt tone changes not necessarily aligned with chapters.
- **sentimentr package** at sentence level, incorporating negation and intensification effects, with subsequent aggregation by chapter to identify relevant emotional peaks.

3.4.5. Comparison between lexical methods

The results obtained with AFINN, NRC (reduced to polarity), and Bing at the chapter level were compared, analyzing the coherence of temporal trends and average values by saga.

This comparison allowed for evaluation of the robustness of detected emotional patterns and justification of the combined use of metrics in later phases of analysis.

3.4.6. Supervised sentiment classification model

Additionally, a supervised sentiment classifier was trained with the objective of evaluating the viability of a model adapted to the narrative domain. Given that manual annotations were not available, weak labeling was used by combining the results of the AFINN and Bing lexicons to generate a binary variable per chapter.

Texts were represented using TF–IDF on document-term matrices and a regularized logistic regression model (LASSO) with cross-validation was trained. Performance was evaluated using the AUC of the ROC curve. The model was subsequently applied to the *Empyrean* saga and its predictions were compared with those obtained by lexical methods, analyzing coincidences and discrepancies, as well as the words with greatest predictive weight.

3.4.7. Comparison between classic and contemporary sagas

Finally, sentiment distributions were compared between classic sagas (2008–2015) and the Empyrean saga (2023–2025), using metrics derived from sentimentr. Differences in emotional variability and polarity bias were analyzed, allowing for exploration of possible changes in narrative tone between editorial periods.

3.5. Topic modeling

To identify the main narrative axes of The Mortal Instruments saga, topic modeling techniques based on Latent Dirichlet Allocation (LDA) were applied, combining a standard unsupervised approach with a guided approach using seeded LDA. The analysis was performed at the aggregated chapter level, with the objective of capturing stable thematic patterns throughout the narrative [13].

3.5.1. Selection of the number of topics in standard LDA

Multiple unsupervised LDA models were trained with different values of K (between 3 and 8 topics), using Gibbs sampling inference. For each model, UMass topic coherence was calculated from the main terms of each topic, and average coherence was analyzed as a function of K. Based on this criterion and on the semantic interpretability of the topics, a model with K=5 was selected as a compromise between simplicity and descriptive capacity (see Figure 9).

3.5.2. Interpretación de tópicos y distribución por libro

From the selected model, the following were analyzed:

- The word–topic distribution (matrix β), to identify the most representative terms of each topic.
- The document–topic distribution (matrix θ), aggregated by book, to estimate the relative weight of each thematic axis in each volume of the saga.

3.5.3. Guided topic modeling using Seeded LDA

In order to evaluate the correspondence between topics automatically discovered and theoretically defined narrative categories, a seeded LDA model was applied using a manually constructed thematic dictionary. Categories included, among others: romantic relationships, supernatural conflict, Clave politics, family identity, and downworld communities.

The model was also trained allowing for the appearance of unguided residual topics, which makes it possible to capture content not covered by the dictionary.

3.6. Character networks

Character network analysis transforms narrative relationships into quantifiable structures. For each saga, co-occurrence networks are constructed by chapter [15]:

- **Character identification**: Controlled lists specific to each saga are used: 16 characters for *Empyrean* (e.g., "violet", "xaden", "tairn") and 22 for *The Mortal Instruments* (e.g., "clary", "jace", "simon"). All names are normalized to lowercase.

- **Network construction**: Undirected pairs of characters that appear together in a chapter are generated and all connections for each saga are aggregated, creating an undirected graph using the igraph library.
- **Calculated metrics**: Number of nodes and edges, network density, and degree centrality of the main character, which allow for evaluation of the distribution of narrative weight and the structure of interaction between characters.

3.7. Reception data and recommendation system

To complement the textual analyses and evaluate the external reception of the sagas, Goodreads ratings were collected. The data were obtained from an Excel file (goodreads_rating.xlsx) that contains the columns Book, Saga, and rating (score per book) [17].

3.7.1. Goodreads rating data

Processing was performed in R through the following workflow:

1. Loading the file using read_excel().
2. Selection of relevant variables, preserving only the saga and the book score.
3. Validation of key sagas, verifying that the sagas of interest (*Empyrean*, *Shadowhunters*, among others) were present in the dataset; otherwise, an alert would be generated.
4. Export of processed data to CSV format for subsequent use in comparative analyses and the recommendation system.

Subsequently, ratings were aggregated by saga calculating the **average rating per saga**, as well as the number of books available for each one, in order to facilitate global reception comparisons between sagas.

3.7.2. Narrative metrics integrated into the profile by saga

In addition to external ratings, the recommendation system incorporates two narrative metrics obtained in previous phases of the analysis:

- **Character network density**, calculated from character co-occurrence graphs by saga using the edge_density() function from the igraph package. This metric approximates the degree of interconnectivity between characters within each narrative universe.
- **Average sentiment per saga**, calculated using the AFINN lexicon.
    - For *Shadowhunters*, the consolidated sentiment file by chapter was used directly.
    - For *Empyrean*, additional processing was performed: aggregation of text by chapter, text cleaning, tokenization and calculation of the average AFINN value per chapter, followed by the global average per saga.

3.7.3. Creation of the comparative technical profile

With the three dimensions—AFINN sentiment, network density, and average Goodreads rating—a technical profile per saga was constructed for the main sagas (*Empyrean* and *Shadowhunters*). Each saga is represented by a feature vector:

- Average sentiment
- Character network density
- Average Goodreads rating

This profile was used both for visual comparative analyses and to contextualize the results of the recommendation system.

3.7.4. Rating similarity-based recommendation system

Given that the set of sagas is small and individual user profiles do not exist, a simple recommendation system based on similarity between sagas was implemented, using average Goodreads rating as the main criterion (see Table 7 and Figure 17).

The procedure was as follows:

1. Calculation of average rating per saga.
2. Generation of all possible combinations of saga pairs.
3. Calculation of the absolute difference in ratings between each pair.
4. Transformation of the difference into a normalized similarity measure, defined as:

$$\text{Similarity} = 1 - \frac{\text{rating}_1 - \text{rating}_2}{\max\left(\text{rating}_1 - \text{rating}_2\right)}$$

5. Ordering of candidate sagas based on the highest similarity with respect to the reference saga.

This approach corresponds to a **content-based recommendation system aggregated by item (saga)**, not at the user level, and is used as interpretive support to identify sagas with similar reception patterns.

4. Results

4.1. Emotional sentiment analysis

Sentiment analysis allows for the quantification of the affective dimensions of literary text, translating subjective emotions into comparable metrics.

4.1.1. Fear as a key narrative emotion (see Tables 1-2)

In *Shatter Me*, fear appears closely linked to the protagonist's identity and her perception of herself as a threat to others. It is, therefore, an internalized fear, experienced as guilt, confusion, and emotional rupture.

In *Empyrean*, although high peaks of fear are also observed, these are concentrated in scenes of combat and collective physical danger. Unlike the previous saga, fear does not lead to paralysis, but rather integrates into action, strategy, and group protection. The result is an intense emotional experience, but oriented toward overcoming the immediate obstacle, not toward psychological self-destruction.

4.1.2. Evolution of emotional tone throughout the saga (see Figures 3-5)

The sentiment analysis with the AFINN lexicon allows for observation of the global evolution of emotional tone chapter by chapter. In *Shatter Me*, the curve shows a pronounced drop from positive values toward clearly negative territories, with a slow and fragile recovery. Positive peaks are brief and are usually quickly negated by new episodes of suffering.

This pattern is consistent with a trauma-centered narrative, where emotional improvement is not cumulative, but constantly interrupted by new crises. The conflict is not resolved, but rather reconfigured again and again, keeping the protagonist in a prolonged state of vulnerability.

In *Empyrean*, in contrast, the evolution is much more stable. Although there are marked descents in moments of battle or loss, the overall tone remains close to positive values, and recovery peaks are more frequent and sustained. This suggests a narrative structure where conflict is progressively overcome, and where each victory contributes to the growth of the group and the protagonist.

4.1.3. Distribution of basic emotions (see Figures 2 and 4)

The comparison of the average proportion of emotions per saga confirms these structural differences. In *Shatter Me*, the dominant emotions are fear and sadness, followed by anger and disgust. Positive emotions, such as joy and trust, appear at significantly lower levels.

In *Empyrean*, the emotional profile is much more balanced. Trust and anticipation occupy a central place, reflecting a narrative based on preparation, alliances, and the expectation of confrontation. Joy and surprise also present high values, associated with collective achievements, discoveries, and evolution of bonds between characters. Negative emotions are present, but do not monopolize the overall tone.

4.1.4. Semantic cores of emotions (see Figures 6-7)

The analysis of the most frequent words associated with each emotion reveals relevant qualitative differences. In *Shatter Me*, fear and sadness are articulated around terms such as *kill*, *pain*, *broken*, or *hurt*, which directly refer to physical and psychological damage. Anger and disgust are expressed through intensely emotional and reactive language, which reinforces the sensation of loss of control and oppression.

In *Empyrean*, positive emotions are linked to words related to the group and shared strength, such as *together*, *squad*, *strong*, or *safe*. Even negative emotions appear contextualized within action and collective sacrifice, rather than in personal isolation.

4.1.5 Comparison of emotional measurement methods (see Figure 8)

The comparison between the results obtained with AFINN and with the binary polarity of NRC shows coherent trajectories between both methods, although with differences in sensitivity to emotional intensity. AFINN better captures emotional extremes, especially in *Shatter Me*, where words with strong negative charge generate more pronounced descents.

In *Empyrean*, the combination of intense negative terms with a high volume of positive vocabulary produces a more stable balance. This reinforces the idea that the saga does not reduce emotional intensity, but rather redistributes it among danger, bonding, and overcoming.

4.1.6. Extreme chapters

The identification of extreme chapters allows for linking quantitative findings with the plot [12].

As observed in Tables 1 and 2, the most negative chapters of both sagas revolve around betrayal or loss, but with a crucial difference in the protagonist's role:

- In *Shatter Me* (Chapter 81 of *Unravel Me*, sentiment = -0.162), it constitutes the end of the book where Juliette is described as a passive victim of betrayal, with language centered on paralysis ("can't", "frozen", "alone").
- In *Empyrean* (Chapter 87 of *Fourth Wing*, sentiment = -0.108), the sentiment is also negative, but the discourse focuses on decision-making under pressure ("command", "choose", "fight"), evidencing an active role even in adversity.

4.1.7. Custom model evaluation

The custom model, trained on chapters from classic sagas, achieved an AUC of 0.668 on the test set, which indicates a moderate ability to discriminate between positive and negative chapters. This result confirms that the model learns contextual emotional patterns specific to the genre, beyond the simple polarity of isolated words.

4.1.8. Comparison of emotional tone with the Bing lexicon (see Table 3)

The average values are similar; however, the standard deviation of classic sagas is much greater, reflecting greater emotional volatility in those texts.

4.1.9. . Evolution of sentiment by method

When comparing the evolution of sentiment chapter by chapter, a distinct pattern is observed between methods (see Figure 11):

- **Bing lexicon**: The red line shows abrupt fluctuations with deep negativity peaks, literally interpreting words like *dragon* or *battle* as negative, although in context they are not.
- **Custom model**: The blue line presents a more stable evolution, with mostly positive values and a slight tendency toward neutrality in the final chapters. This indicates that the model recognizes the contextual charge of words that, although associated with conflict or action, do not imply negativity in the *Empyrean* narrative.

4.1.10. Most predictive words

The model identifies the words with the greatest weight for predicting emotional tone (see Figure 10):

Positive words: *love*, *brilliant*, *romantic*, *beauty*, *polite*, *smiling*, *protective*, *include*, *courage*

- Reflect human connections, personal overcoming, and belonging to groups.

Negative words: *scream*, *hell*

- Indicate physical and emotional conflict, vulnerability or social pressure, rather than failure or general sadness.

4.1.11. Distribution of emotional tone

The density of sentiment values per chapter shows clear differences between sagas (see Figure 12):

- **Classic Sagas**: Curve with a peak centered near 0.0 and long tails toward negative values, indicating predominance of neutral or slightly negative tones and frequent presence of chapters with intensely negative emotions.
- **Empyrean**: Wider curve and slightly shifted toward positive values (0.0–0.1), reflecting greater emotional stability and less focus on individual suffering.

4.2. Topic modeling with guided LDA

Topic modeling allows for the identification of patterns and underlying structures in narrative texts. In this study, guided LDA (seeded LDA) is used, a version of the Latent Dirichlet Allocation model that incorporates prior knowledge through thematic dictionaries, which improves the interpretation of results in literary contexts. [14]

4.2.1. Identified topics

Seeded LDA was applied to the *The Mortal Instruments* corpus, segmented into macro-chapters (groupings of three consecutive chapters) [13]. The results show a clear thematic distribution (see Table 4):

- **Supernatural warfare** is the most frequent topic, with words like "demon", "blade", and "angel".
- **Institutional politics** follows in frequency, highlighting terms like "council" and "inquisitor".
- **Romance** appears with intimate words ("love", "heart", "together"), but with less weight than in purely romantic sagas.
- **Identity** and **Underworld** function as secondary axes that enrich the plot and provide depth.

These results suggest that *The Mortal Instruments* combines collective action and individual introspection, operating with a dual thematic architecture that balances conflict, politics, and personal development.

4.3. Character networks and narrative structure

Character network analysis applied to literary narrative allows for the transformation of relationships between characters into quantifiable structures [16]. In this study, co-occurrence networks are constructed by chapter, where nodes represent relevant characters and edges reflect their joint presence in the same narrative context [15].

Co-occurrence networks show significant differences between sagas (see Table 5):

- ***The Mortal Instruments***: 21 nodes and 438 edges, density 2.09; the maximum centrality (42) indicates that the protagonists (Clary, Jace, Simon, Isabelle, and Alec) are connected with many secondary characters, reflecting a narrative model centered on several main characters (see Figure 13).
- ***Empyrean***: 14 nodes and 194 edges, density 2.13; the maximum centrality (28) reflects that the protagonist (Violet) acts as a link within a more balanced group (Xaden, Tairn, Andarna, Rhiannon, etc.), showing a collective approach to the narrative (see Figure 14).

As we can observe in Figure 15, these results allow for interpretation of how narrative weight is distributed: while *The Mortal Instruments* focuses on a highly connected protagonist, *Empyrean* organizes interaction more equitably among group members, reinforcing the collective dimension of the story.

4.4. Recommendation system based on emotional-structural profile

Finally, this project proposes a content-based recommendation system that combines three quantifiable dimensions: emotional tone, character interaction, and external reception [18].

4.4.1. Profile of each saga

For each saga, a profile is constructed that integrates three main metrics (see Table 6 and Figure 16):

- **Average sentiment (AFINN)**: *Empyrean* shows a value of -0.254, while *Shadowhunters* has a more negative tone, of -0.571.
- **Network density**: *Empyrean* presents a slightly higher density (2.13 versus 2.09), which reflects that its characters are more interconnected.
- **Average Goodreads rating**: *Empyrean* reaches 4.50, compared to 4.18 for *Shadowhunters*.

These three metrics are combined to form a vector that represents each saga, integrating both its internal structure and readers' response.

4.4.2. Comparison between sagas

The proposed recommendation system is not based on individual user preferences, but on similarity between sagas based on their aggregated narrative profiles. Therefore, recommendations should be interpreted as structural and emotional affinities between narrative universes, and not as predictions of reading behavior at the individual level.

The results in Table 8 show that *Throne of Glass* is the saga most similar to *Empyrean*, with a similarity close to 0.95 and a minimal difference in ratings. This closeness can be explained by the combination of epic plots, strong presence of interpersonal bonds, and young protagonists in formation processes, characteristics shared by both sagas.

In intermediate positions appear *Percy Jackson* and *Vampire Academy*, which, although they differ in tone and setting, maintain narrative structures centered on groups of recurring characters and clear emotional progression.

Shadowhunters appears in a lower position, which is consistent with previous analyses that showed differences both in average emotional tone and in thematic distribution, with greater weight of institutional structures and political conflicts.

5. Discussion and Conclusions

5.1. Interpretation of results

The results clearly support the central hypothesis of the study: the success of *Empyrean* is not explained solely by commercial trends, but by a narrative reconFiguretion that combines emotional innovation with known structures. Unlike *Shatter Me*, where fear is experienced as isolation and paralysis, *Empyrean* transforms intense emotions—fear, anticipation, trust—into collective action. This difference is not only thematic: while *Shatter Me* focuses on an isolated protagonist, *Empyrean* constructs a dense relationship network (2.13) in which agency is distributed among several characters, making the story more choral and participatory.

Likewise, the narrative similarity between *Empyrean* and *Shadowhunters* (0.96) indicates that modern romantasy does not break with the past, but rather recycles successful formulas, such as the integration of romance and institutional conflict, adapting them to a more collective and emotionally complex approach. This reinforces the idea that editorial success does not depend only on originality: it is key to offer enough novelty to surprise, but also familiar elements that generate comfort in readers [20].

5.2. Practical implications

These findings have practical applications for both publishers and recommendation platforms:

- **For publishers**: the proposed profile, which combines sentiment, network density, and rating, can serve as a tool for preliminary manuscript evaluation. A text with a solid relational network, vocabulary that fosters collectivity ("squad", "together"), and emotional balance is more likely to connect with the current audience.
- **For platforms like Goodreads or BookTok**: recommendation systems based solely on genre or author are limited. Integrating deeper textual signals, such as relationship structure or emotional profile, allows for generating more precise and relevant suggestions for readers.

5.3. Limitations

The study presents three key limitations:

1. **Corpus scope**: the detailed analysis focuses only on three sagas. This allows for an in-depth study, but does not reflect all the diversity of contemporary romantasy.
2. **Sentiment simplification**: the AFINN and NRC lexicons do not capture irony, context, or emotional ambiguity, which can generate some distortion in the interpretation of some chapters.

3. **Dictionary dependence in specific sagas**: in the case of *Shadowhunters*, it was observed that the performance of sentiment analysis and seeded LDA models depended heavily on the specificity of the lexicon. If the dictionaries were not sufficiently adapted to the narrative universe, the results could be inconsistent or erroneous. This limitation highlights the importance of customizing dictionaries according to the context of each saga.

5.4. Future directions

Future research could:

- **Expand the corpus** to other contemporary sagas (*Powerless* or *Blood and Ash*) to validate the generalization of the collective pattern.
- **Develop a specific thematic dictionary** for *Empyrean* and apply guided LDA comparatively.
- **Integrate BookTok data** (comments, hashtags) to link textual analysis with actual virality.
- **Implement a functional narrative recommendation prototype** on a Shiny-type platform, allowing readers to explore affinities based on emotional architecture, not just on genre.
- **Explore the division of chapters** into smaller segments (micro-documents) to capture emotional or thematic variations within the same chapter. However, this strategy presented difficulties during implementation: it exponentially increased the number of documents and topics, making interpretation more expensive and degrading the overall coherence of the analysis. Although it was not adopted as a definitive approach, this idea could be revisited in future studies to achieve greater granularity without compromising interpretability.

Overall, this work demonstrates that young adult literature not only reflects its cultural context, but encodes it in its narrative structure, and that encoding, today, can be read both with the eyes and with algorithms.

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6. References

1. Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). *Lexicon-based methods for sentiment analysis*. Computational Linguistics, 37, 267–307. https://doi.org/10.1162/coli_a_00049

2. Zad, S., Jimenez, J., & Finlayson, M. (2021). *Hell hath no fury? Correcting bias in the NRC emotion lexicon*. Proceedings of the 5th Workshop on Online Abuse and Harms (WOAH 2021). https://doi.org/10.18653/v1/2021.woah-1.11

3. Chiny, M., Chihab, M., Bencharef, O., & Chihab, Y. (2021). *LSTM, VADER and TF-IDF based hybrid sentiment analysis model*. https://doi.org/10.14569/ijacsa.2021.0120730

4. Jacobs, T., & Tschötschel, R. (2019). *Topic models meet discourse analysis: A quantitative tool for a qualitative approach*. International Journal of Social Research Methodology, 22, 469–485. https://doi.org/10.1080/13645579.2019.1576317

5. Harandizadeh, B., & Morstatter, F. (2021). *Keyword assisted embedded topic model*. Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining. https://doi.org/10.1145/3488560.3498518

6. Min, S., & Park, J. (2016). *Modeling narrative structure and dynamics with networks, sentiment analysis, and topic modeling*. PLoS ONE, 14. https://doi.org/10.1371/journal.pone.0226025

7. Sarma, D., Mittra, T., & Shahadat, M. (2021). *Personalized book recommendation system using machine learning algorithm*. International Journal of Advanced Computer Science and Applications. https://doi.org/10.14569/ijacsa.2021.0120126

8. Watanabe, M., & Fukazawa, Y. (2025). *Quantitative analysis of emotional changes in narrative progression of popular web novels*. Transactions of the Japanese Society for Artificial Intelligence. https://doi.org/10.1527/tjsai.40-5_mo25-c

9. Rani, N. (2025). *The rise of BookTok: How TikTok is transforming literary trends and reader communities*. International Journal of Scientific Research in Engineering and Management. https://doi.org/10.55041/ijsrem49758

10. García, M. (2026). *01a_preprocesado_corpuses_focales.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/01a_preprocesado_corpuses_focales.R

11. García, M. (2026). *01b_preprocesado_shadowhunters.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/01b_preprocesado_shadowhunters.R

12. García, M. (2026). *02_analisis_sentimiento.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/02_analisis_sentimiento.R

13. García, M. (2026). *03_topic_modeling.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/03_topic_modeling.R

14. Joyeux-Prunel, B. (2024). *Digital humanities in the era of digital reproducibility: Towards a fairest and post-computational framework*. International Journal of Digital Humanities, 6, 23–43. https://doi.org/10.1007/s42803-023-00079-6

15. García, M. (2026). *04_redes_personajes.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/04_redes_personajes.R

16. Rodda, I., & Bhavani, D. (2023). *Visualization of the dynamics in character networks using social network analysis*. Proceedings of the 6th Joint International Conference on Data Science & Management of Data (10th ACM IKDD CODS and 28th COMAD). https://doi.org/10.1145/3570991.3571019

17. García, M. (2026). *05_datos_recepcion.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/05_datos_recepcion.R

18. García, M. (2026). *06_sistema_recomendacion.R*. GitHub repository. https://github.com/mariayugarcia/proyecto_romantasy_final/blob/main/scripts/06_sistema_recomendacion.R

19. Semeraro, A., Vilella, S., & Ruffo, G. (2021). *PyPlutchik: Visualising and comparing emotion-annotated corpora*. PLoS ONE, 16. https://doi.org/10.1371/journal.pone.0256503

20. Form, S. (2019). *Reaching Wuthering Heights with Brave New Words: The influence of originality of words on the success of outstanding best-sellers*. Journal of Creative Behavior, 53, 508–518. https://doi.org/10.1002/jocb.230

21. García, M. (2026). *proyecto_romantasy_final* [Repositorio de GitHub]. https://github.com/mariayugarcia/proyecto_romantasy_final/tree/main

22. Montalva Candel, I. (s. f.). *Tema 5*. En **moncanig.quarto.pub/dne2526**. Recuperado 23 de enero de 2026, de https://moncanig.quarto.pub/dne2526/Tema5.html

23. Montalva Candel, I. (s. f.). *Tema 6*. En **moncanig.quarto.pub/dne2526**. Recuperado 23 de enero de 2026, de https://moncanig.quarto.pub/dne2526/Tema6.html

24. Montalva Candel, I. (s. f.). *Tema 7*. En **moncanig.quarto.pub/dne2526**. Recuperado 23 de enero de 2026, de https://moncanig.quarto.pub/dne2526/Tema7.html

25. Montalva Candel, I. (s. f.). *Tema 8*. En **moncanig.quarto.pub/dne2526**. Recuperado 23 de enero de 2026, de https://moncanig.quarto.pub/dne2526/Tema8.html

7. Appendices

7.1. Tables

Book	Chapter	Sentiment	Frequency	Total words	Saga	Percentage
Shatter Me	14	fear	96	332	Shatter Me	0.289
Unravel Me	8	fear	7	41	Shatter Me	0.171
Iron Flame	120	fear	91	552	Empyrean	0.165
Fourth Wing	85	fear	345	2119	Empyrean	0.163
Fourth Wing	87	fear	61	382	Empyrean	0.160

Table A1. Distribution of "fear" sentiment by chapter and saga

Saga	Type	Book	Chapter	Average sentiment	Sentences
Empyrean	MÁS POSITIVO	Onyx Storm (The Empyrean Book 3)	104	0.047	308
Empyrean	MÁS NEGATIVO	Fourth Wing	87	-0.108	126
Shatter Me	MÁS POSITIVO	Shatter Me	14	0.216	126
Shatter Me	MÁS NEGATIVO	Unravel Me	81	-0.162	12

Table A2. Chapters with highest and lowest average sentiment by saga

Saga	Chapters	Average_tone	Standard deviation
Empyrean (2023–2025)	108	-0.370	0.130
Sagas Clásicas (2008–2015)	1058	-0.361	0.265

Table A3. Chapters with highest and lowest average sentiment by saga

Rank	Romance	Identity /Parents	Shadowhunting /War	Clave Politics	Downworlders	Others
1	love	mother	demon	clave	vampire	portal
2	heart	father	blade	inquisitor	pack	magic
3	bed	past	angel	council	warlock	mundane
4	together	family	rune	power	water	lilith
5	touch	mom	mark	gard	faerie	spell
6	brother	cup	stele	city	werewolf	new
7	closer	morgenstern	circle	accords	praetor	dress
8	remembered	truth	fire	law	metal	parabatai

Table A4. Most frequent words by thematic category

Saga	Characters	Connections	Maximum centrality
Empyrean	14	194	28
Shadowhunters	21	438	42

Table A5. Character network by saga

Saga	Positive Sentiment	Network Density	Goodreads Rating
Empyrean	-0.254	2.13	4.50
Shadowhunters	-0.571	2.09	4.18

Table A6. Average sentiment, network density, and Goodreads rating

Saga	Nº of books	Average rating
Throne of Glass	2	4.540
Empyrean	3	4.503
Percy Jackson & the Olympians	5	4.378
Vampire Academy	6	4.277
Shadowhunters	6	4.183
Shatter Me	3	4.130
Divergent	2	4.045
Fallen	3	3.847
The Maze Runner	3	3.840

Table A7. Number of books and average rating by saga

Current saga	Candidate saga	Similarity	Rating difference
Empyrean	Throne of Glass	0.948	0.037
Empyrean	Percy Jackson & the Olympians	0.821	0.125
Empyrean	Vampire Academy	0.676	0.227
Empyrean	Shadowhunters	0.543	0.320
Empyrean	Shatter Me	0.467	0.373

Table A8. Similarity between candidate sagas and Empyrean

7.2. Figures

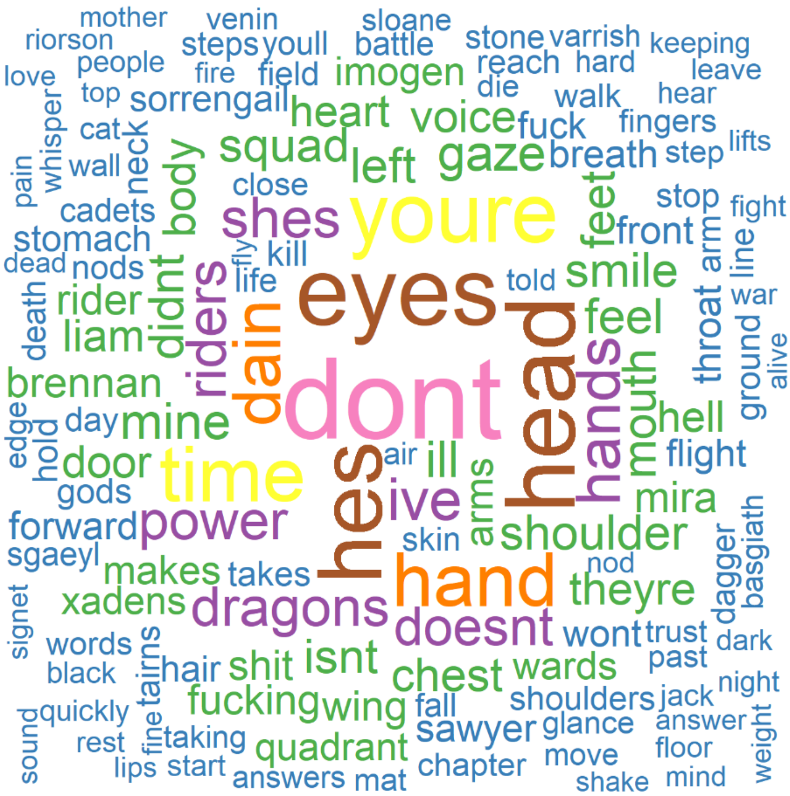


Figure A1. Empyrean word cloud

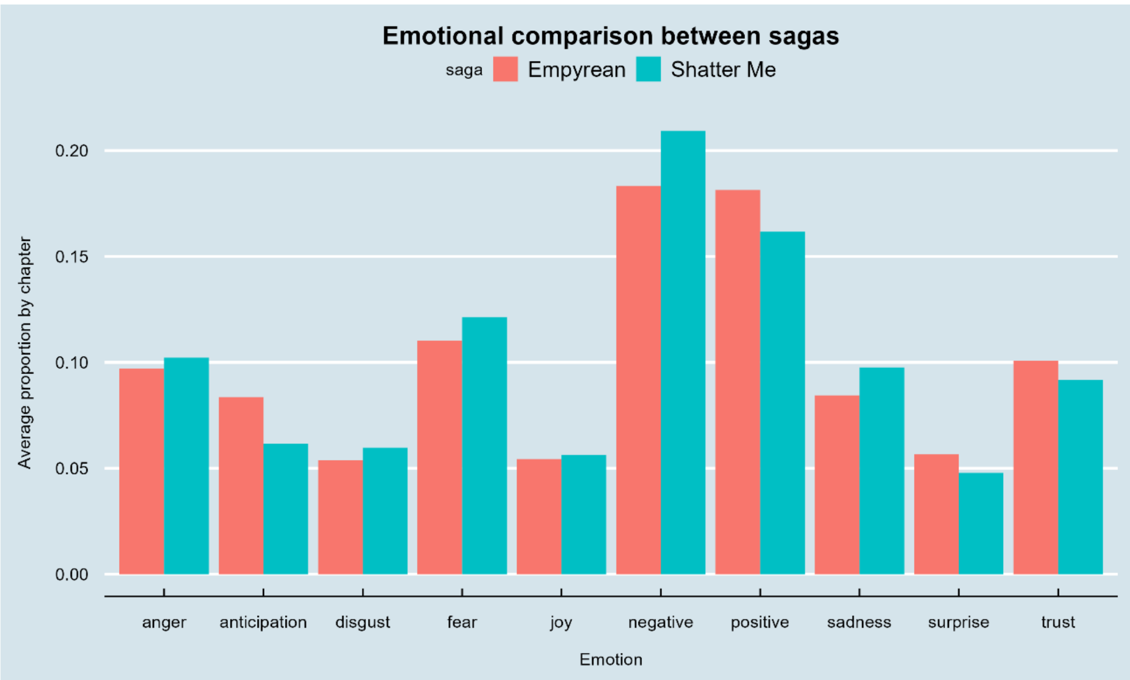


Figure A2. Emotional comparison between sagas

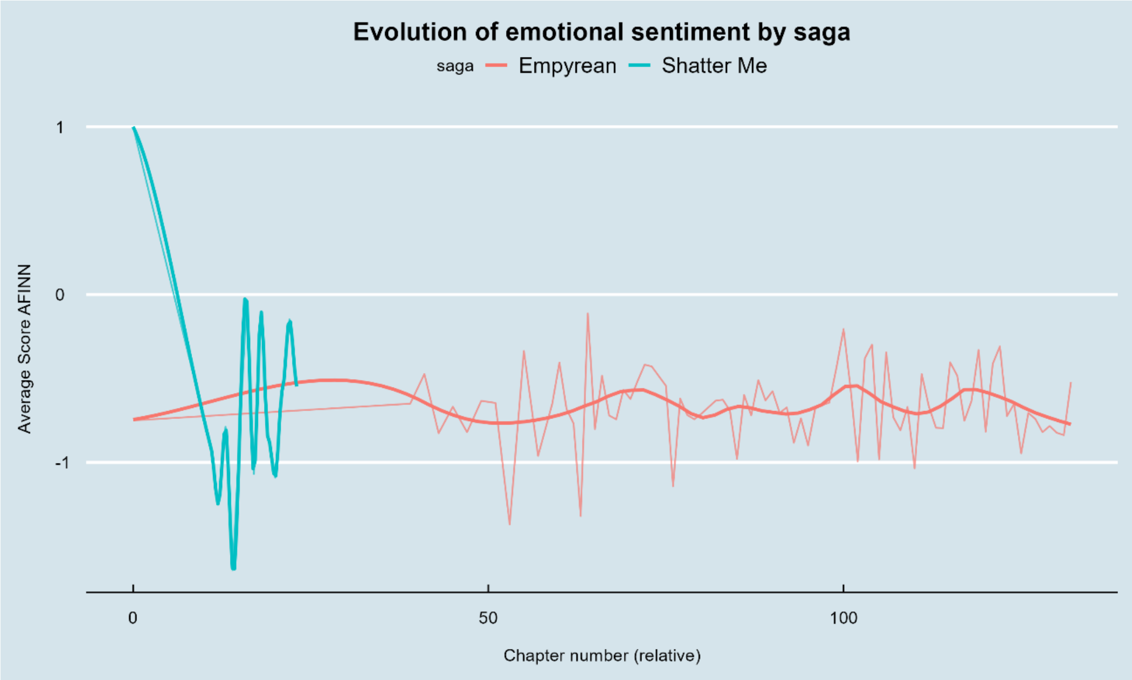


Figure A3. Evolution of emotional sentiment by saga

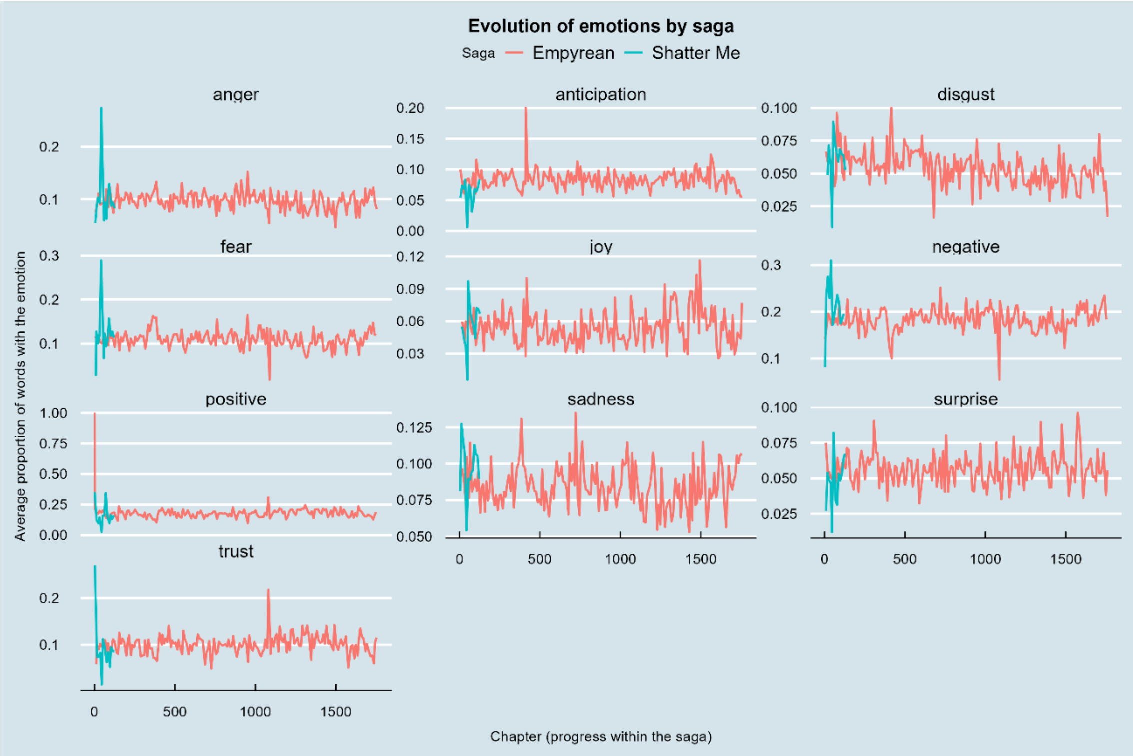


Figure A4. Evolution of emotions by saga

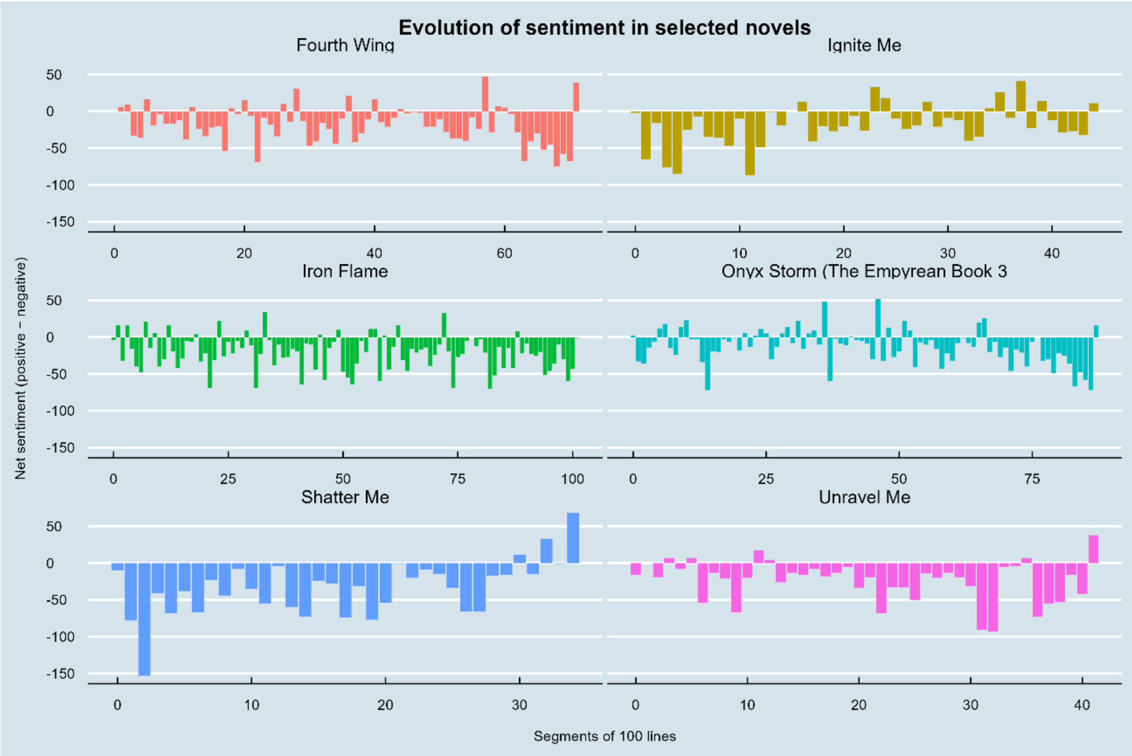


Figure A5. Evolution of sentiment in the Shatter Me and Empyrean sagas

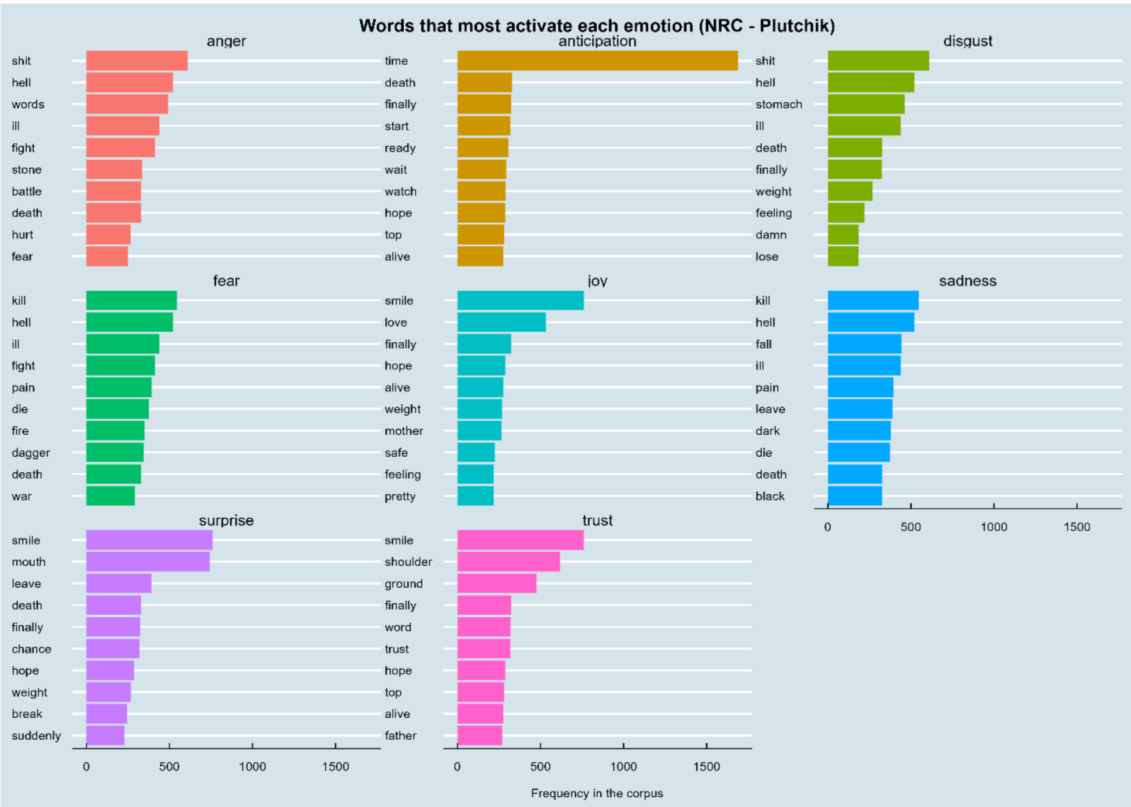


Figure A6. Words that most activate each emotion (NRC – Plutchik)

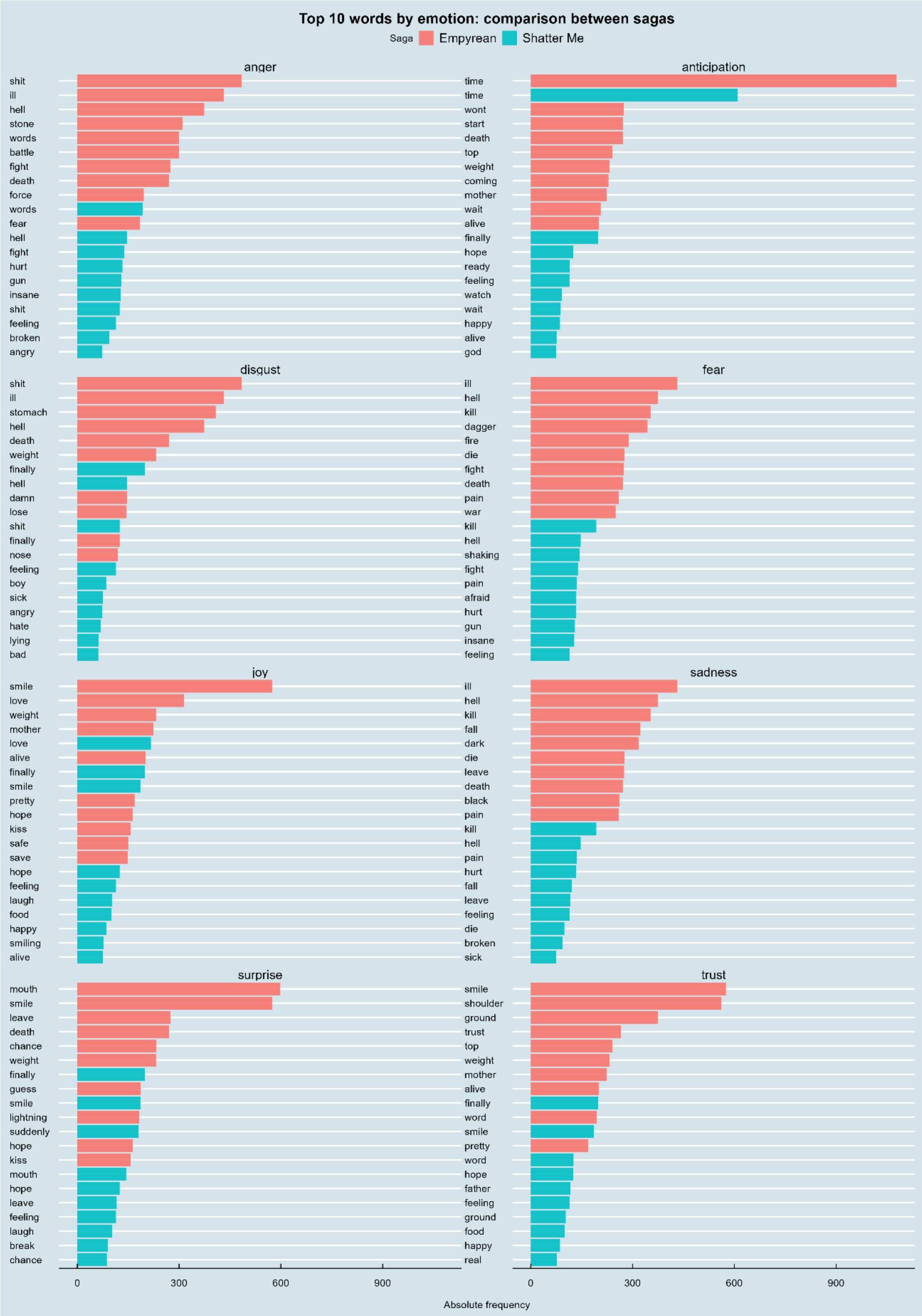


Figure A7. Top 10 words by emotion: comparison between sagas

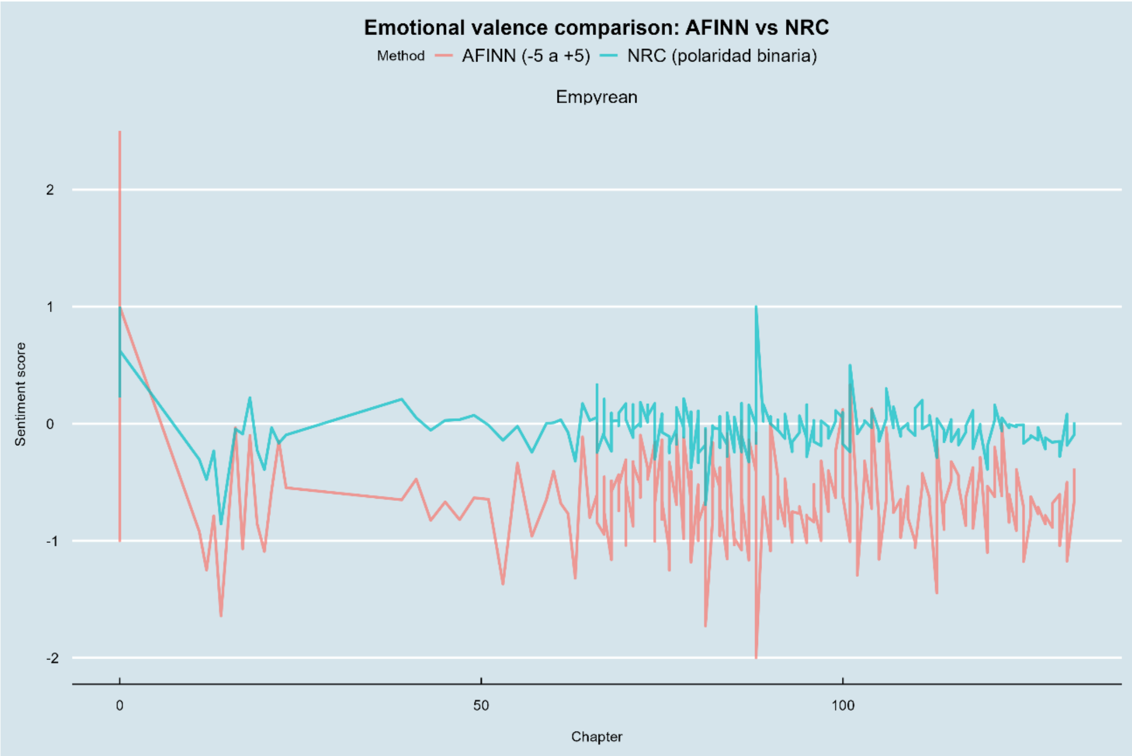


Figure A8. Emotional valence comparison: AFINN vs NRC

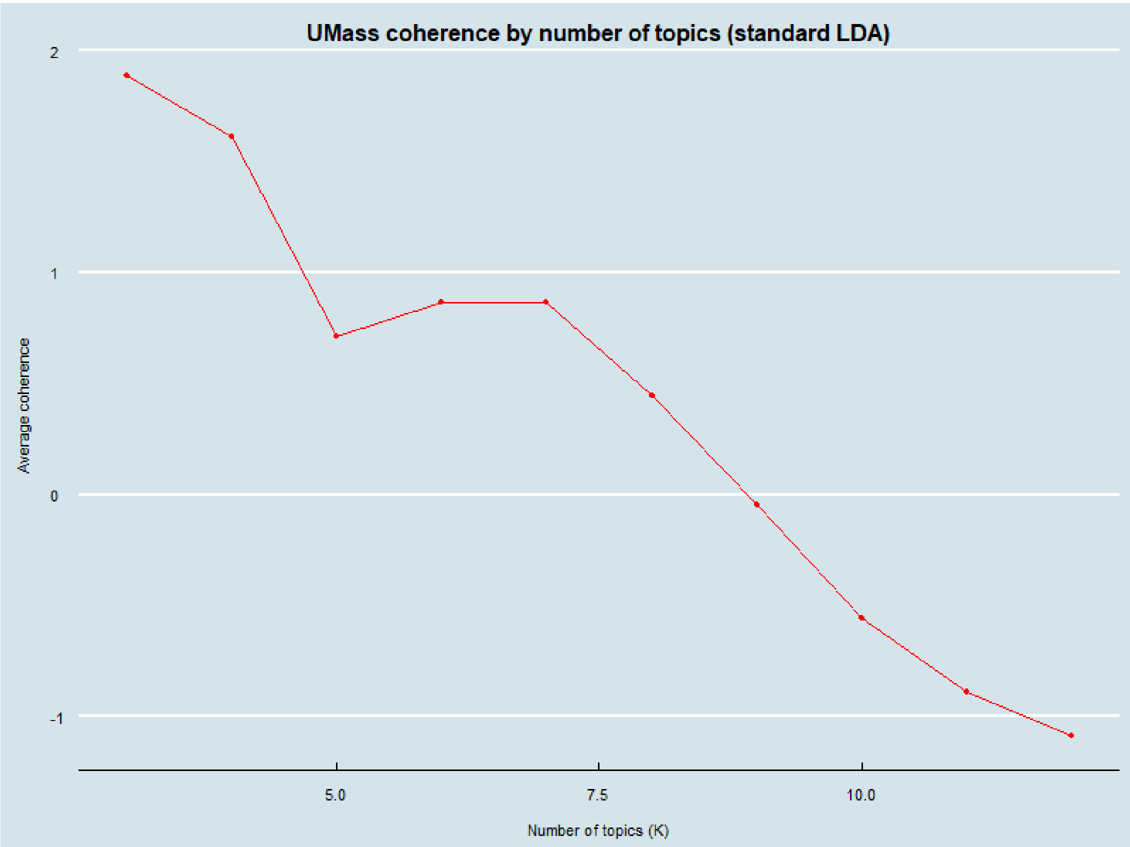
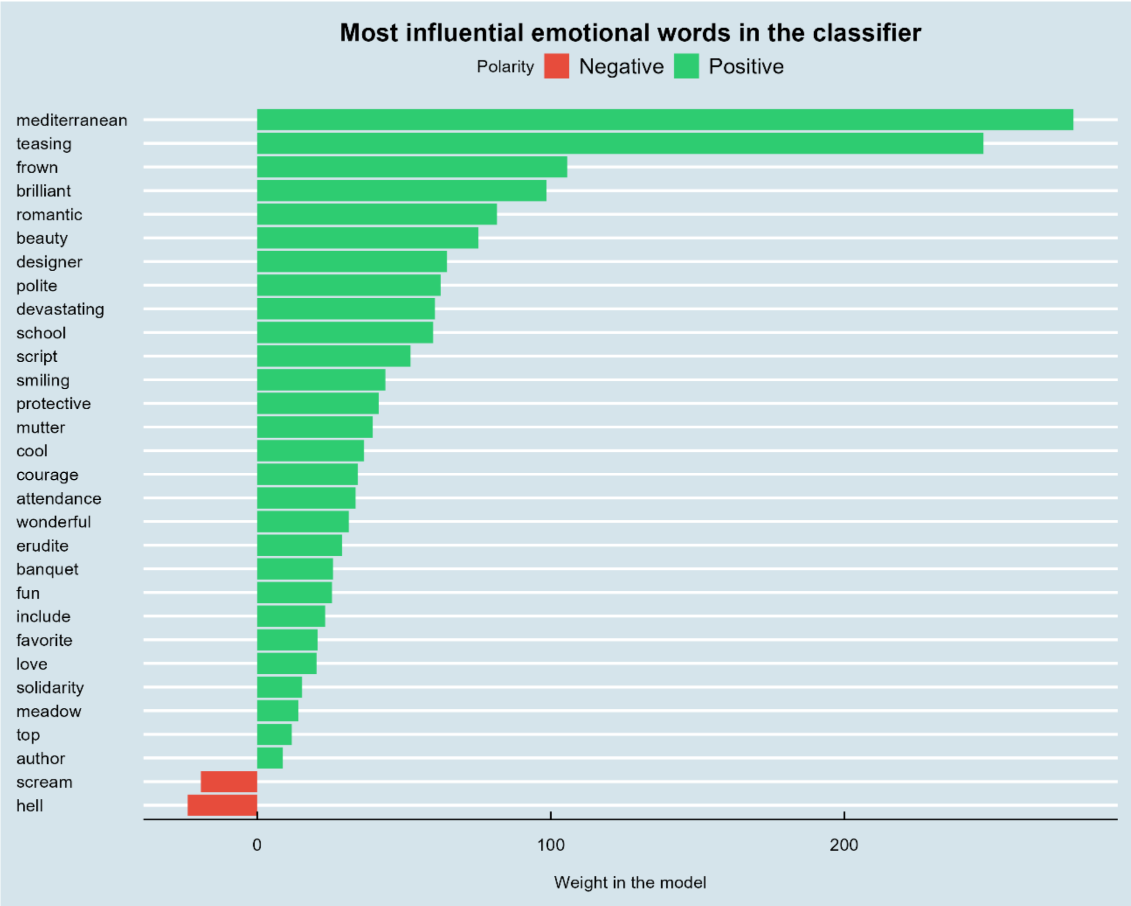


Figure A9. UMass coherence by number of topics (standard LDA)



Figures A10. Most influential emotional words in the classifier

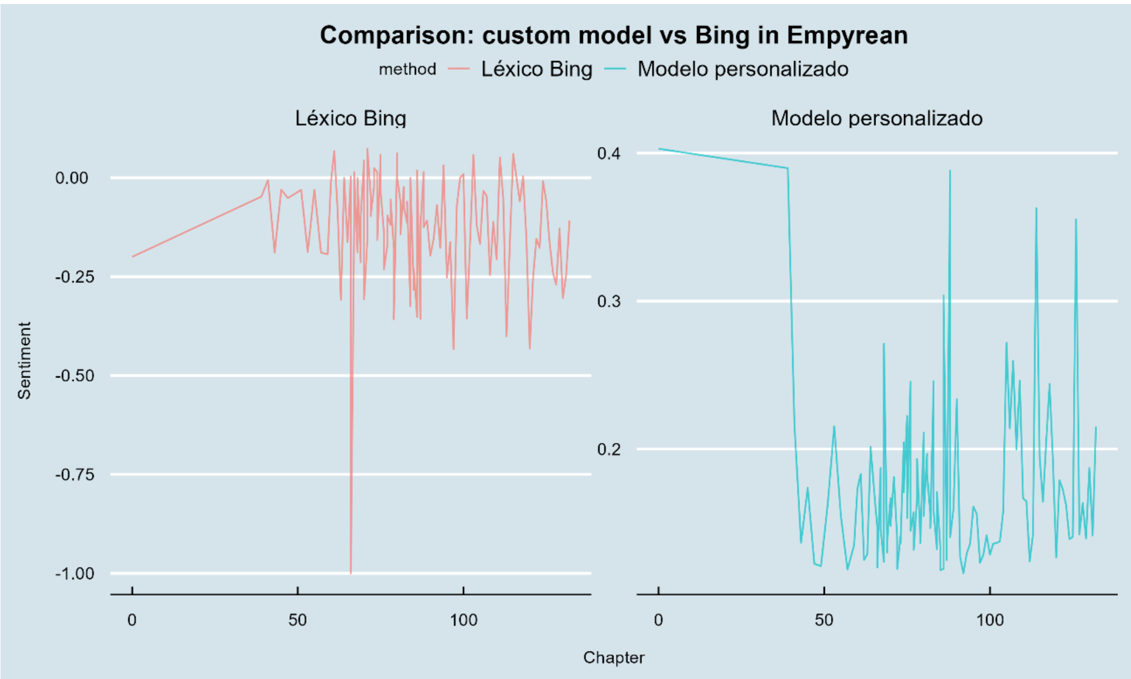


Figure A11. Comparison: custom model vs Bing for Empyrean saga

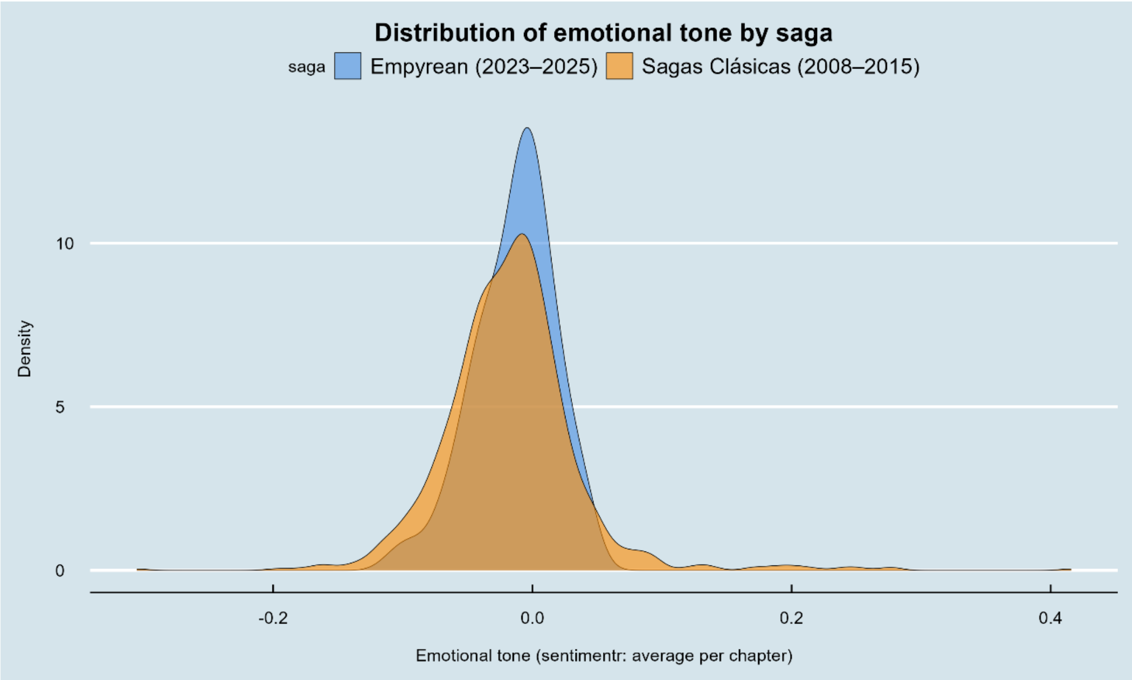


Figure A12. Distribution of emotional tone by saga

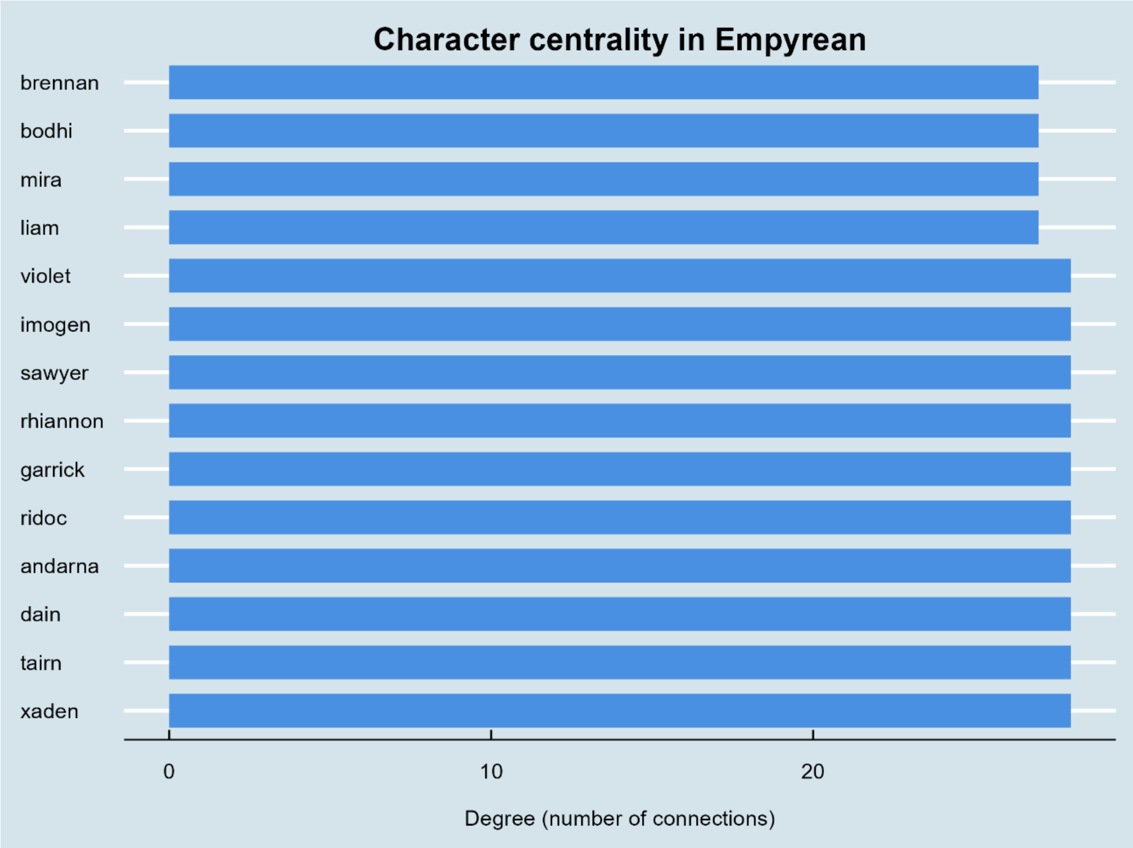


Figure A13. Character centrality in Empyrean

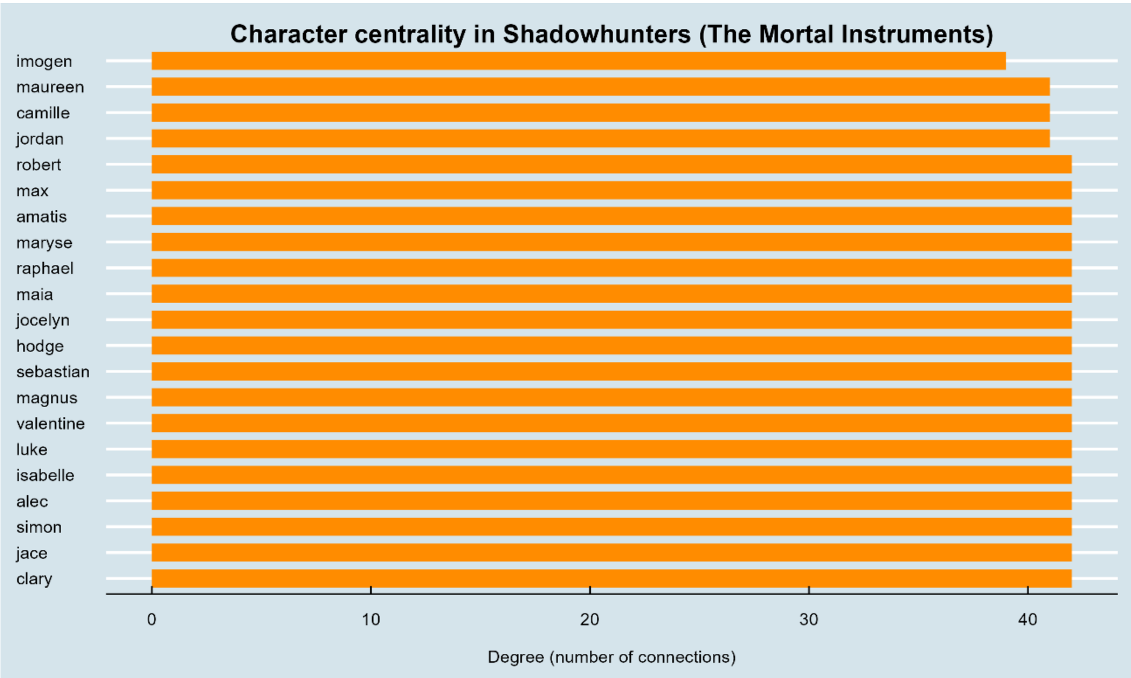


Figure A14. Character centrality in Shadowhunters

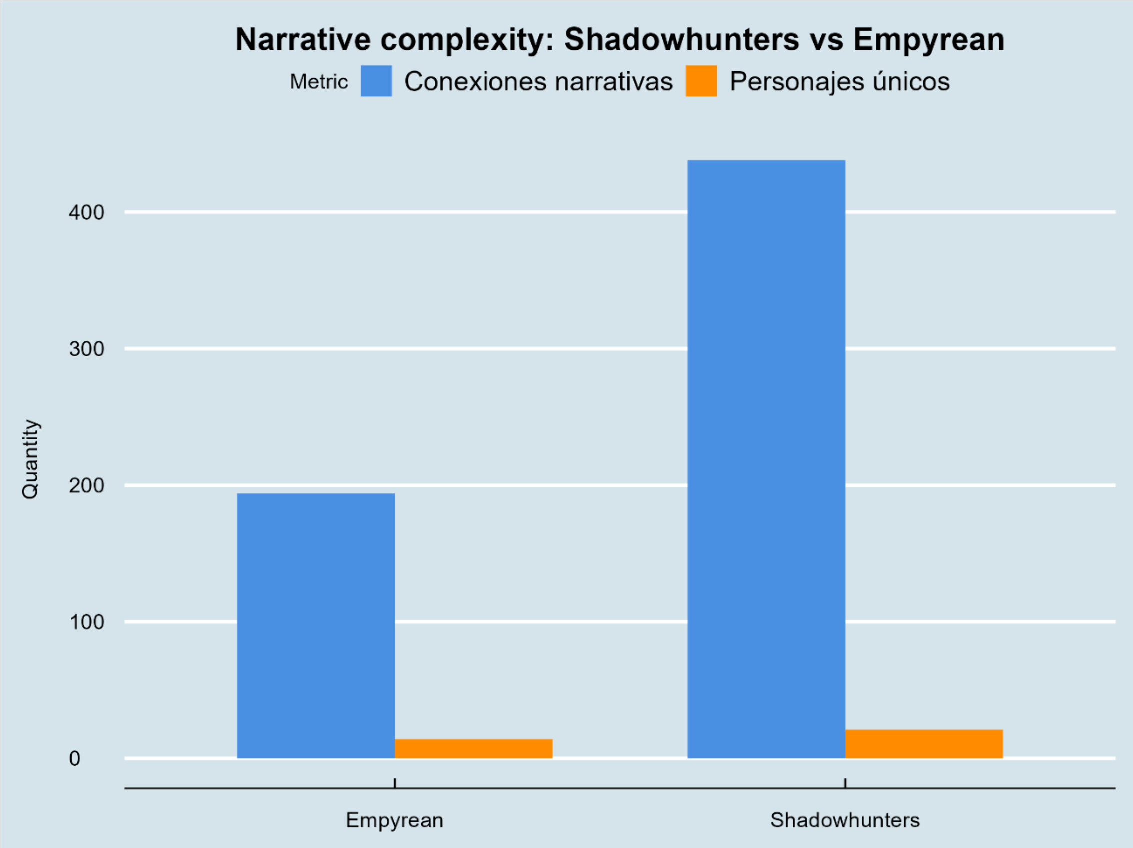


Figure A15. Narrative complexity: Shadowhunters vs Empyrean

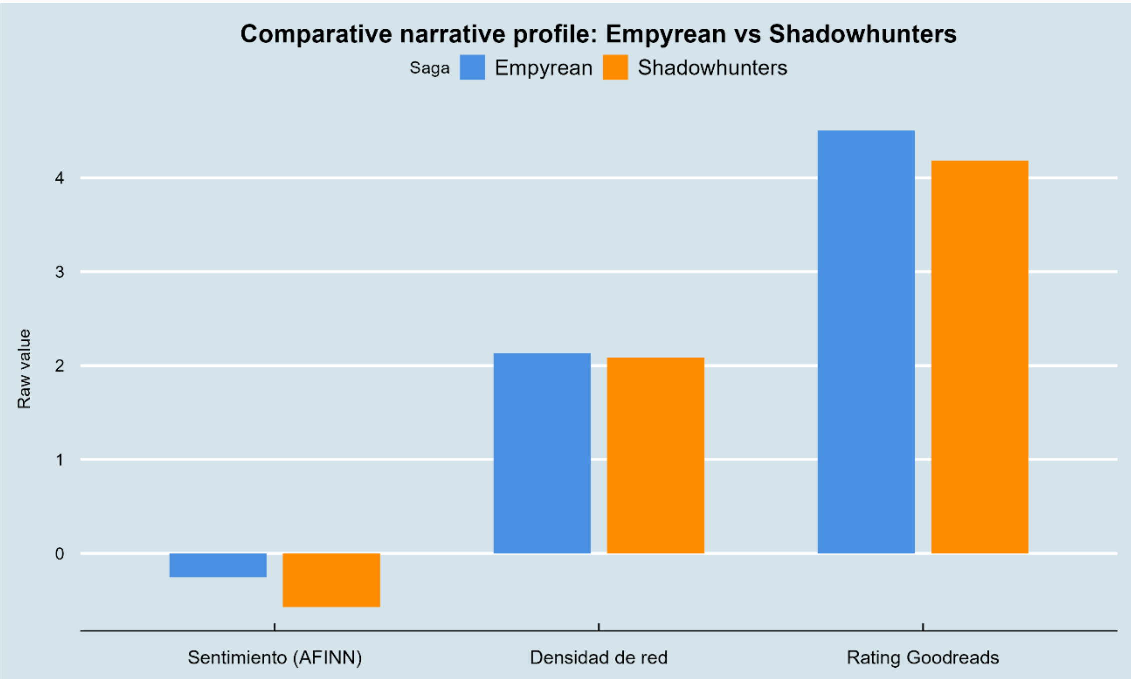


Figure A16. Comparative narrative profile: Empyrean vs Shadowhunters

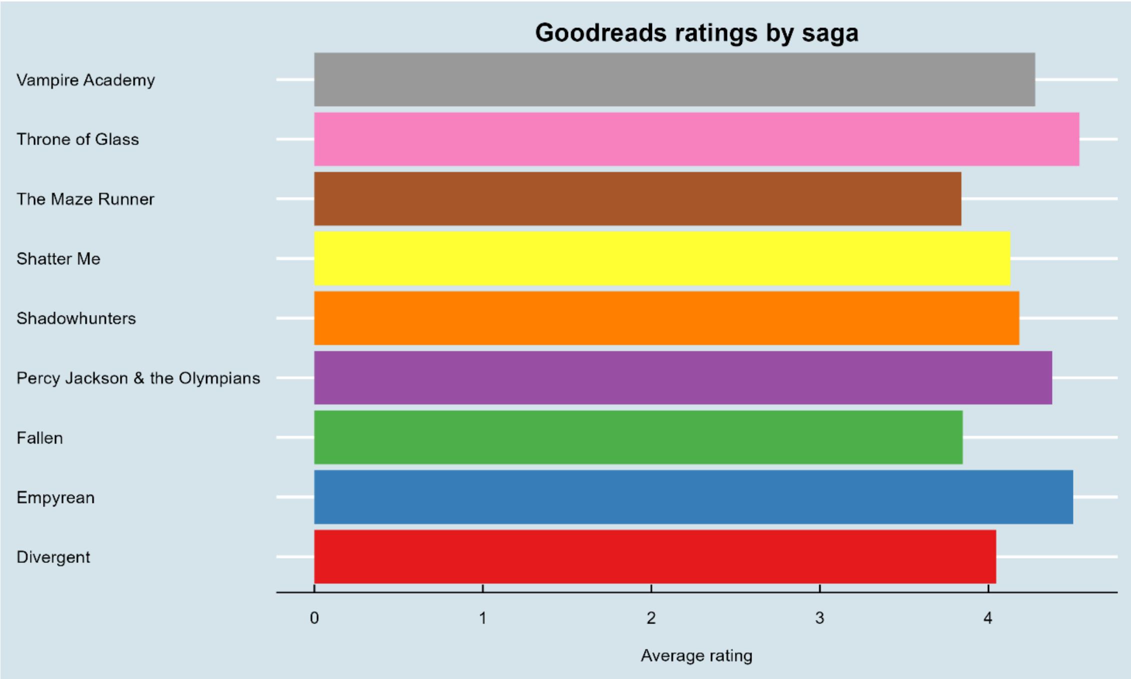


Figure A17. Goodreads rating by saga