



Article

# Gender Stereotypes in Hollywood Movies and Their Evolution over Time: Insights from Network Analysis

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**Abstract:** The present analysis of more than 180,000 sentences from movie plots across the period from 1940 to 2019 emphasizes how gender stereotypes are expressed through the cultural products of society. By applying a network analysis to the word co-occurrence networks of movie plots and using a novel method of identifying story tropes, we demonstrate that gender stereotypes exist in Hollywood movies. An analysis of specific paths in the network and the words reflecting various domains show the dynamic changes in some of these stereotypical associations. Our results suggest that gender stereotypes are complex and dynamic in nature. Specifically, whereas male characters appear to be associated with a diversity of themes in movies, female characters seem predominantly associated with the theme of romance. Although associations of female characters to physical beauty and marriage are declining over time, associations of female characters to sexual relationships and weddings are increasing. Our results demonstrate how the application of cognitive network science methods can enable a more nuanced investigation of gender stereotypes in textual data.



**Citation:** Kumar, A.M.; Goh, J.Y.Q.; Tan, T.H.H.; Siew, C.S.Q. Gender Stereotypes in Hollywood Movies and Their Evolution over Time: Insights from Network Analysis. *Big Data Cogn. Comput.* **2022**, *6*, 50. <https://doi.org/10.3390/bdcc6020050>

Academic Editor: Carson K. Leung

Received: 17 January 2022

Accepted: 13 April 2022

Published: 6 May 2022

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## 1. Introduction

Stereotypes are defined as “cognitive structures that provide knowledge, beliefs and expectations about individuals based on their social group membership” [1]. Being cognitive in nature, stereotypes can affect specific social perceptions of others, such as their personality, behaviour, attitudes, and appearance. For example, stereotypes can lead us into subscribing to the belief that women are communal by nature, which they display through being warm and sensitive to others, and the belief that men are agentic by nature, which they demonstrate by being independent and assertive in the presence of others [2]. It has been shown that the stereotypical categorisation of people into different groups is fluid and dependent on the context of comparisons [3]. However, gender classification seems to evade such fluid categorisation, since it is a primary and salient feature of the perception of other people [4]. Such immediately recognised and chronically salient categorisations contribute to the persistence of gender stereotypes. While stereotypes’ cognitive nature encompasses the beliefs and descriptions that people hold about the members of different groups (e.g., gender), evaluations that follow these implicit or explicit attitudes could involve negative or positive reactions to members of a specific group. In the case of gender stereotypes, they are organised around the importance of the agency of men and the communal nature of women. Therefore, task performance is emphasised for men, whereas social relationships are emphasised for women [5]. Women who violate the prescriptive gender stereotype of being warm and kind in social relationships could potentially face backlash for acting against these prescribed gender norms. Negative evaluations of gender-stereotype violations could result in discriminatory behaviour.

However, much has changed with respect to the roles and expectations of genders in recent years. In the United States, gender employment and pay gaps have reduced

substantially since the enactment of the Equal Pay Act in 1963 [6]. More women are entering science, technology, engineering, and mathematics (STEM) fields, taking on leadership roles, and making key scientific discoveries than before [7]. There have also been four major waves of feminism, with each one marking a specific cultural era and women's involvement with the media [8]. In addition, fewer women are marrying and those who do marry do so at a much older age compared to the past [9].

Social role theory advocates that stereotypes arise from observations of real-life behaviour; in other words, they represent our lived realities. Thus, the changing roles of men and women in society should also influence stereotypes in society [10]. In fact, this is what has been observed across numerous studies and meta-analyses based on questionnaires on implicit and explicit attitudes [11–13]. More recently, Charlesworth and Banaji [14] found decreasing gender stereotypes (male—science/female—arts, male—career/female—family) from measures of implicit and explicit attitudes across a 10-year period from 2007 to 2018. However, these are indicators of subjective individual attitudes in a controlled setting, and may be limited in their representation of implicit attitudes of a society [15]. Cultural products such as movies may complement individual perceptions to offer a richer account of how gender stereotypes prevail in society, especially since they do not exist independently from one another. An individual's perception and acceptance of a stereotype into their schema is influenced by their experiences—including those shaped by the media [16]—while the media products a culture creates are ultimately products of the same perceptions that individuals hold [17]. Therefore, both individual attitudes and cultural products make for apt sources through which to study the evolution of gender stereotypes in society, and ought to supplement each other.

Hence, Durkheim [18] and his proponents argued that the primary materials through which to investigate social stereotypes are the products of a society. This is in contrast to the psychological studies mentioned previously, which typically ask participants to complete questionnaires or take part in laboratory experiments in order to measure the types and strength of gender stereotypes. Durkheim's idea of studying the cultural products of society on a large scale was not feasible during his time, but it is possible today given the drastic increase in computational power along with the accessibility of big data. For example, Stella's paper [19] used textual forma mentis networks (TFMN) to reconstruct large-scale online discourses regarding the gender disparity in STEM fields on the social media platform Twitter, and the researchers found largely positive, gender-stereotype-free perceptions of the gender gap. Other studies used word-embedding models to study gender stereotypes and their dynamic changes across time [7,20]. Word embeddings are machine-learning methods in which the words in a language are represented using high-dimensional vectors. Geometric relationships between the vectors denote semantic relationships between the words. For example, words that are geometrically closer to each other in the vector space are semantically closer to each other [21]. Bhatia and Bhatia [20] used word embeddings to examine a century's worth of shifts and developments in the gender biases expressed in large-scale historical natural-language data, and found that these stereotypes decreased in strength over time. It is important to note that the changes they observed seem to have been driven mainly by changes in stereotypically feminine traits (as opposed to stereotypically masculine ones) and personality-related traits (as opposed to physical traits). Charlesworth et al. [7] analysed the embeddings in more than 65 million words in English-language texts to investigate the presence of gender stereotypes and mainly found that gender stereotypes were pervasive and consistent across different age groups, sources, and time periods. However, they further noted that gender stereotypes that worked to the disadvantage of the different groups were not as prominently displayed in later time periods compared to earlier ones, indicating a trend towards more equitable representations. This meant that more recent corpora included fewer stereotypical gender associations, such as those of 'male-work' and 'female-home', depicting a reduction in the portrayal of women in caregiver roles and signifying a change away from the distinct segregation of traditional roles played by men and women in society.

Despite the usefulness of word embeddings in understanding semantic representations, network science offers unique perspectives in understanding cognitive structures such as semantic memory and the mental lexicon, or in this case, the representation of gender in the media products of a society. Network science can model dynamic changes in systems, as well as enabling the explicit investigation of the underlying structure of a model, something that is more challenging to accomplish with models derived from machine-learning methods [22]. Therefore, network science provides a compelling avenue through which one could represent and model changes in the implicit attitudes of a society. In one article employing a network science approach to studying stereotypes in movies, Xu et al. [23] studied gender stereotypes in 6087 movie synopses from the Internet Movie Database (IMDb) through a network analysis of word co-occurrences. They found that male lead characters were more commonly associated with verbs compared to female lead characters. By using community detection methods, they also showed that the key difference between the roles of leading male and female characters in movies was that women's role in romance is emphasised, whereas men's role in crime is emphasised. However, they did not study how these stereotypes changed or evolved across time. They also restricted their analysis to lead characters in movies.

Another avenue that could be explored is the analysis of narratives through story tropes in movies, which can be facilitated by network analysis. Barthes and Duisit [24] advocated that 'there has never been anywhere, any people without narrative'. A trope is a form of narrative that is viewed as a 'commonly recurring literary and rhetorical devices' [25]. In the case of movies, tropes refer to plot types of plot that audiences would expect a movie to tell, according to its theme or genre. An example would be the trope of 'enemies-to-lovers' in a romance-themed movie, describing a romantic arc whereby a couple who begin their relationship as enemies progressively fall in love. Tropes can also take the form of plot or narrative setups (e.g., a 'groundhog day' loop) or character types (e.g., a supervillain who avenges his parents' tragic death) ("Trope", 2020). In short, they are recognisable storytelling conventions, and can be understood as short, abbreviated, and decontextualised narratives within movies. Identifying tropes and examining how they change over time could thus be an important part of understanding society [26].

Our study builds on the aforementioned work by using a network-science perspective to understand stereotypes and their dynamic evolution in Hollywood movies (i.e., movies produced in North America). Given that our study is confined to Hollywood movies, the findings of our study are limited to stereotypes within a North American context. However, an overarching aim of this paper is to show researchers that the representation of genders and stereotypes could be modelled as a cognitive network. This allows us to add an additional tool to the pre-existing toolkit of methods within natural language processing. A network perspective allows not only the study of specific associations at the level of words, but also the overall structure of a network model. At the level of words, we investigated specific stereotypical associations in Hollywood movies by analysing specific edges within our network. At a broader level of the network model, we analysed stereotypical themes in Hollywood movies using the network's community structures. Additionally, by investigating how gender stereotypes change over time, we were able to examine whether changes in society may be reflected in the changes in stereotypes, which was not explored in the analysis by Xu et al. [23]. In contrast to their study, we also extended our analysis to include both lead and supporting characters in movies, thus providing a more complete picture of gender representations.

In the present study, we first examined the community structure of male and female characters' co-occurrence networks, which were constructed based on a frequency measure similar to that used in the study by Xu et al. [23]. Next, we identified story tropes associated with male and female characters using a novel method of path analysis from co-occurrence networks built using loglikelihood measures. Subsequently, we examined how the significance measures of stereotypical story tropes changed with time. Lastly, we identified the

most significant nouns, verbs, and adjectives in the networks and investigated how their edge weights in the network changed across time.

## 2. Materials and Methods

### 2.1. Description of Data Source

In total, 200 movies were randomly chosen for each year between 1940 and 2019 from Wikipedia's list of Hollywood films by year (e.g., [https://en.wikipedia.org/wiki/List\\_of\\_American\\_films\\_of\\_2000](https://en.wikipedia.org/wiki/List_of_American_films_of_2000), accessed on 9 November 2021). The 'Plot' sections of the Wikipedia entries of the chosen films were scraped using the 'rvest' R library [27]. Unlike Xu et al. [23], who used movie synopses from IMDb to construct their network, we used data from Wikipedia for two main reasons. Firstly, Wikipedia is a community-maintained database free for anyone to edit. Through the process of editing and re-editing by various contributors, the content on its site ultimately reaches an implicit consensus, i.e., when the current state of information is no longer disputed or corrected [28]. Therefore, the data on Wikipedia are typically representative of various voices, making the study of the implicit attitudes of a society viable. Secondly, plots contain more details about movies as compared to synopses, which are more akin to brief summaries of movies.

As mentioned above, for each year between 1940 and 2019, 200 movies were chosen randomly. However, each decade had a varying amount of data because of differences in the number of movies with a plot section, as well as differences in the average number of sentences in each movie plot. To counter the imbalance in the data for each decade and to maximise the available information at the same time, the decade with the least number of sentences was first identified. Next, we used the number of sentences in this decade to randomly sample across the data from each decade. The minimum number of sentences was found in the decade from 1940 to 1949, with 22,638 sentences. Hence, 22,638 sentences were randomly sampled from each decade. This resulted in a total of 181,104 sentences for the analysis, which were randomly selected from all the sentences in 16,000 movies.

The words in this dataset were then tokenised and parsed through natural language processing using the 'spacyR' R library [29] to tag part of speech information (e.g., kill/verb, John/person, etc.). 'SpacyR' is an R wrapper around the Python package called 'spacy', which is an open source library for advanced natural language processing [30]. Subsequently, only character names and the grammatical categories of verbs, nouns, and adjectives were included, prepositions, function words, determiners, and symbols were removed. The 'genderizeR' R package [31] was then used to identify the gender of characters in the dataset. The 'genderizeR' package uses first names to predict gender using a database based on online social media profiles and their associated genders. An advantage of this package is that it is updated every day using information from new social media profiles. This method offers a high degree of accuracy because it is based on real-world data and is not a prediction-based model trained on a data set. For example, as of April 2015, the database contained 212,252 unique names gathered from 2 million social media profiles [32]. Finally, character names were replaced with the general terms 'male/character' and 'female/character' based on their gender, as tagged by the 'genderizeR' R package. An example of the data processing is as follows: "Mary went to meet her father" becomes 'female/character' 'went/verb' 'meet/verb' 'father/noun'.

### 2.2. Network Construction

The graphs in our analysis were constructed using the 'igraph' R package [33] and plotted using the 'visNetwork' R package [34]. Using the processed dataset, we constructed two types of network for our analysis: (i) A raw-frequency-based network to understand the common themes around male and female characters using community detection, and (ii) a log-likelihood-test-based network to more specifically understand the lives of male and female characters in movies using edge weights of words linked to them. More details about the network construction for each of the networks are provided in specific sections below.

### 2.2.1. Common Themes for Male and Female Characters in Movies

To investigate the common themes that emerged in the words surrounding male and female characters, we identified communities in the frequency-based co-occurrence networks for male and female characters separately. Our approach was similar to the one used by Xu et al. [23], who identified community structures in the co-occurrence networks for male and female protagonists in Hollywood movies. However, our analysis was different in that we analysed communities from a network that considered the contexts of all male and female characters in movie synopses and not just the protagonists. First, we separated the dataset for male and female characters by selecting five words before and after the character names for males and females. We employed the same size of word window as Xu et al. [23] so we could standardise and compare the results of our analysis with theirs. The edges in the network were then weighted based on how frequently each pair of words appeared together within the same sentence across the entire corpus. Community detection was performed on this network using the Louvain algorithm [35] for both male and female character networks. The Louvain algorithm is a greedy optimisation method that attempts to optimise modularity when extracting community structures from large networks.

### 2.2.2. The Lives of Male and Female Characters in Movies

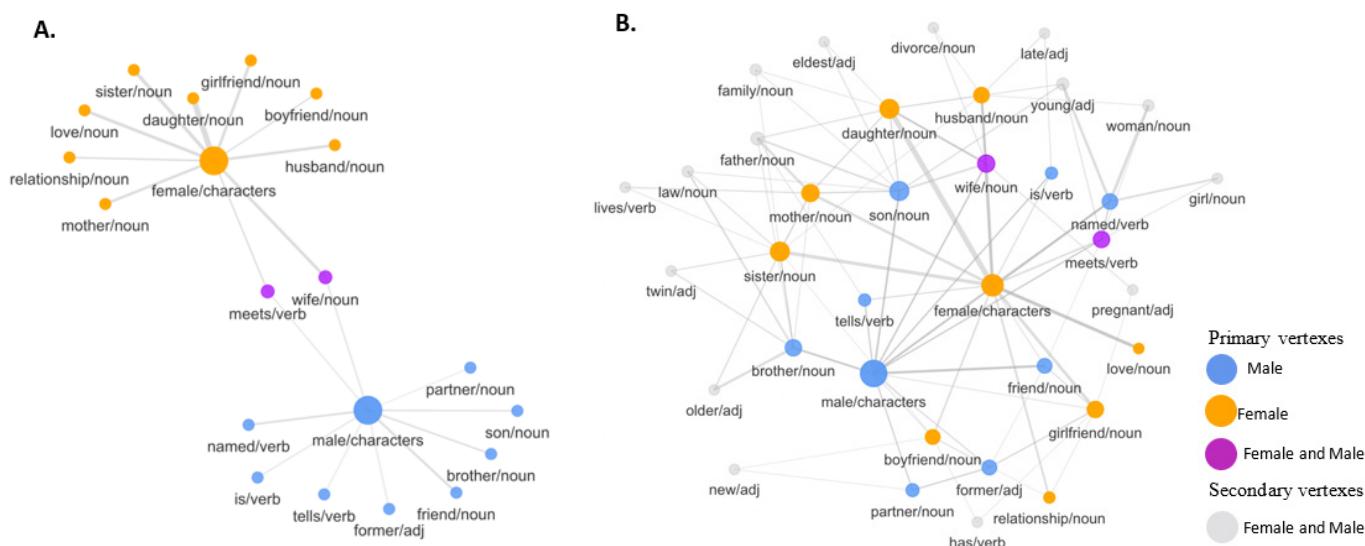
To investigate gender stereotypes in story tropes, we created a network in which the weight of edges was the log-likelihood of co-occurrence rather than frequency of co-occurrence, as used in the previous network. Rankings of most significant word pairs provide an indicator of their co-occurrence in word usage [36]. The log-likelihood test is essentially the use of a generalised likelihood ratio  $\lambda$  to compare two parameterised distributions (binomial in this case). One of the distributions is based on from the independence assumption, and the other from the observed frequencies. Taking  $-2\log\lambda$ , the significance value is obtained, which is  $\chi^2$ -distributed. In their evaluation of the different measures of word similarity, such as baseline frequency, dice, and mutual information, Bordag [36] found that the significance of log-likelihood was the best. Hence, this measure was used in our analysis.

To construct the network, the male and female character vertices (henceforth referred to as gender vertices) were connected to the 20 most significant word associations in the movie plots based on the significance of the log-likelihood ratio of their co-occurrence within the same sentence. These word associations are referred to as primary associations of the gender vertices.

The significance of the log-likelihood ratio of co-occurrence was calculated as described in the Appendix (see Appendix A). Each of these primary associations with character names was then connected to its 20 most significant associations. These are henceforth referred to as secondary associations of the gender vertices. The steps of the network construction are shown in Figure 1 by taking 10 associations as an example, illustrating networks of both primary and secondary co-occurrences for both male and female characters. Vertices with a degree of less than two (i.e., fewer than two edges) were removed for ease of visualisation.

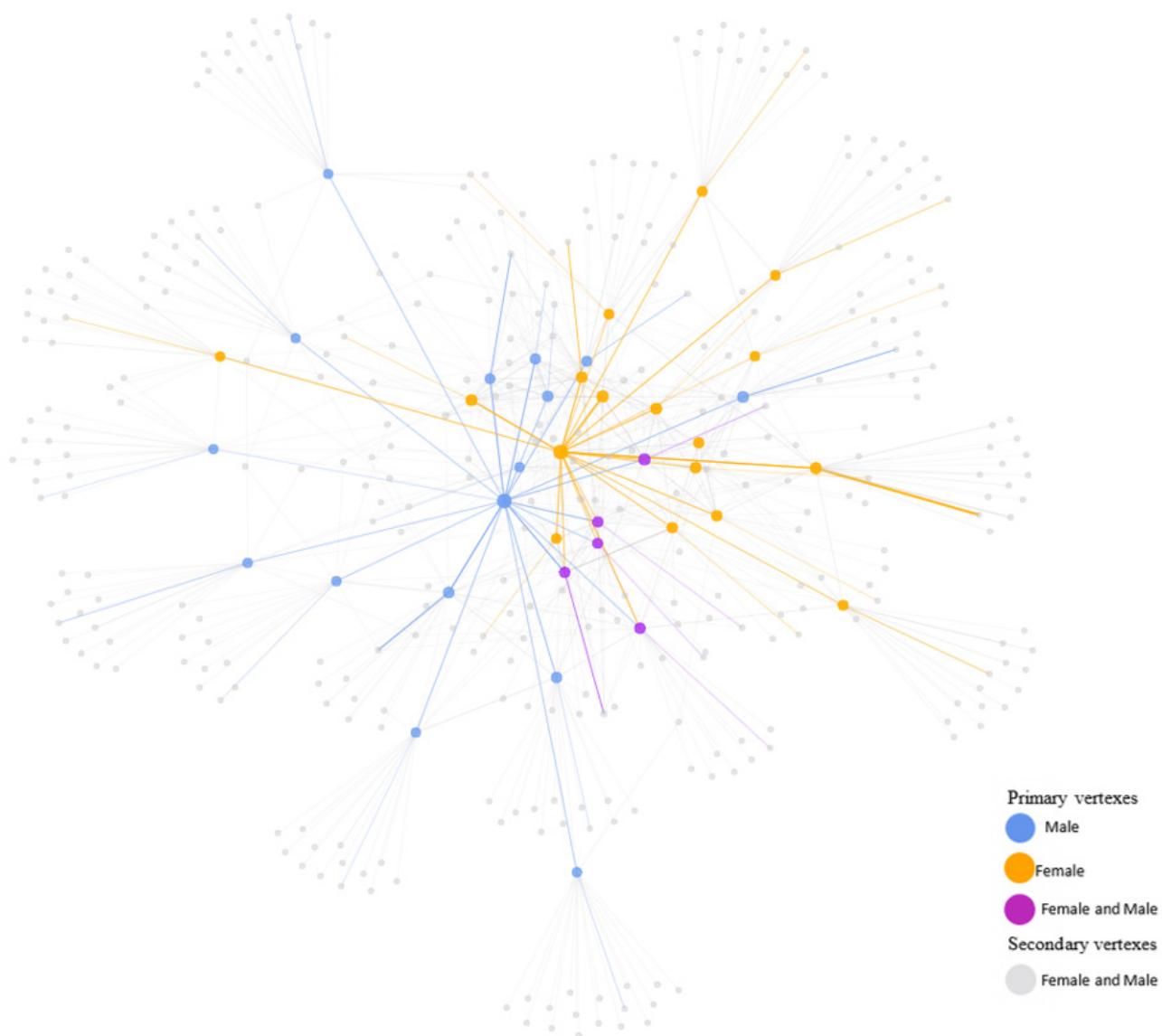
- (a) **Gender-specific story tropes and their evolution.** The main goal of this analysis was to find the most significant story tropes associated with male and female characters across the entire time period of analysis (i.e., from 1940 to 2019). To this end, we used a novel method involving path analysis to identify the most significant story tropes in movies. First, we identified the most significant association of each of the primary vertices. Next, we computed the (weighted) path length from the gender vertices to these secondary vertices, through a path described by: gender vertex–primary vertex–secondary vertex. This resulted in 3-tuples of vertices and their path weights, which showed how significant they were. For example, along the path described by ‘female/characters–love/noun–fell/verb’, the cumulative weight would be the sum of the log-likelihood ratio significances (i.e., the weights) along the path. In other words, it would be the sum of LL (female/characters–love/noun) + LL (love/noun–fell/verb). Rather than simply inferring story tropes from primary vertices alone, the

3-tuples with the addition of secondary vertices provided us with additional context to infer story tropes of each gender. Twenty significant character-specific paths were obtained for each character, one for each of their primary associations. Figure 2 depicts the ten most significant paths for each gender within the co-occurrence network.



**Figure 1.** Details of the network construction. (A) Network with only primary nodes. Blue nodes represent unique associations with male characters, orange nodes represent unique associations with female characters, and purple nodes represent the common associations of both male and female characters. (B) Network with primary and secondary nodes. Secondary nodes are depicted in grey.

After identifying the top 20 tropes for each gender, we identified specific romance- and crime/violence-related tropes from this set, and analysed how their path weights changed across time for each decade from the 1940s to the 2010s, using linear regression. Romance and crime/violence were selected as gender-stereotypical domains worthy of further examination based on Xu et al.'s [23] findings. Xu et al.'s community analysis revealed eight gender-stereotypical themes or domains. Specifically, male characters were associated with crime, career, family, and action, and female characters with romance, career, family, and action. It should be noted that although Xu et al. [23] identified crime as a theme, we subsumed it under the more general theme of crime/violence. This is because an act linked to 'kill' does not necessarily refer to crime-related activities in all instances. For example, a male character could be involved in the killing of a monster rather than the killing of a human being, which does not definitively indicate that the male character has indeed participated in a crime. In Xu et al.'s study, most of the domains overlapped for both genders (i.e., both male and female characters were significantly associated with the career, family, and action stereotypes)—the only differences were that male characters were significantly associated with crime and female characters were not, whereas female characters were significantly associated with romance and male characters were not. As such, the 20 tropes were manually coded to identify specific tropes that fitted into these domains of crime/violence and romance for both genders for subsequent analysis. Importantly, the decision to include an analysis of the violence stereotype in female characters and romance in male characters despite these associations not being present in the communities allowed us to compare the presence and trends of these tropes between the genders across time.



**Figure 2.** A representation of the ten most significant paths in the network for each gender among the whole network. Paths were selected after filtering out paths that crossed through the other gender vertex.

For instance, a 3-tuple that represents a romance trope from the network could be ‘male–girlfriend–proposed’ or ‘female–fall–love’, whereas a crime trope could appear as ‘male–kills–gun’ or ‘female–attacks–robbery’. After the relevant romance- and crime-related tropes were identified, each of their path weights were analysed for changes over time. This analysis enabled us to determine, for example, whether a trope such as ‘male–kills–gun’ became more or less prevalent between the 1940s and the 2010s.

- (b) **Roles, actions, and descriptions of male and female characters and their evolution.** In this part, three network visualisations were created by subsetting the network formed previously based on three word classes: nouns, verbs, and adjectives. The vertices connected to edges of the gender vertices with the highest weight were analysed to find the most common associations for male and female characters. By analysing separate networks of nouns, verbs, and adjectives, we aimed to identify the top 20 most significant roles, actions, and descriptions, respectively, that were associated with male and female characters.

Furthermore, similar to our trope analysis, we sought to understand how stereotypical associations with individual words changed across time. Based on the same pre-identified domains of romance and crime/violence, we coded the individual nouns, verbs, and adjectives from the top 20 words and classified each as a crime/violence-related word or a romance-related word. For example, words such as ‘love’ or ‘dating’ were classified in the romance domain, whereas words such as ‘felony’ or ‘prison’ were classified in the crime/violence domain. After this categorisation, the edge weights of these associations were analysed for changes across decades using linear regression, which enabled us to determine whether a given word became increasingly or decreasingly associated with each gender over time (or whether there was no trend). To illustrate this, the co-occurrence of ‘love’ and female characters from 1940 to 2019 was analysed to determine whether female characters were increasingly associated with the word ‘love’ across that period, or less so. The same would apply to ‘felony’ or ‘prison’ in association with male characters. Ambiguous words that could not be clearly determined as being associated with either category were left out of this analysis.

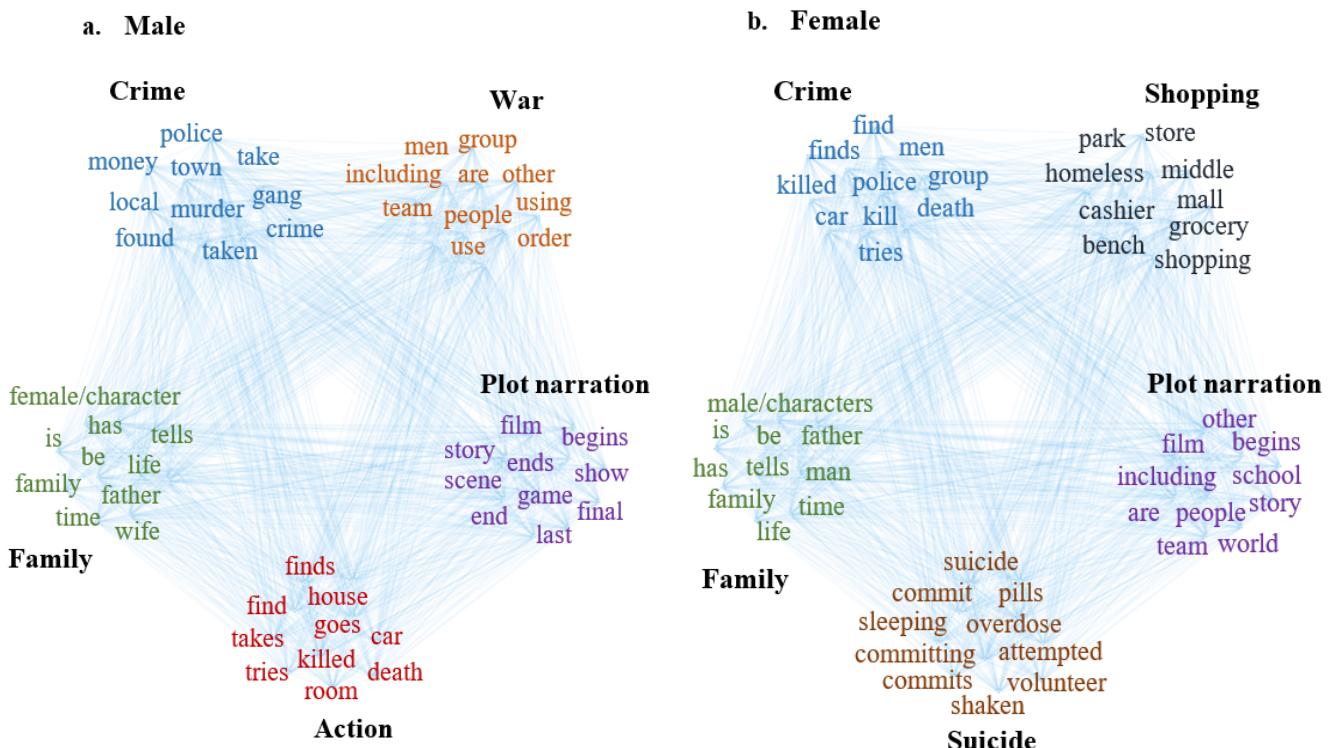
### 3. Results

#### 3.1. Common Themes for Male and Female Characters in Hollywood Movies

Five communities were identified for the male character network and the female character network, each using the Louvain algorithm [35]. The modularity of the female community structure was 0.07, and modularity of the male community structure it was 0.09. The low modularity values indicate that the community structure of these networks was not particularly robust. Using the top twenty vertices with the highest degree within each community (or all the vertices if the community had less than twenty vertices in total), we labelled each community with a specific theme; these are listed in Appendix B. We based our classification on the key words in the top twenty vertices and on the results presented by Xu et al. [23]. For the male network, the communities we identified were: crime, action, family, war, and plot narration. These communities are illustrated in Figure 3. The plot narration community is not an aspect of movies themselves, but instead reflects how movie plots are described on Wikipedia. For the female network, the communities identified were: crime, shopping, family, suicide, and plot narration. The number of vertices in each community is given in Table 1. The themes that are common to the lives of male and female characters in Hollywood movies are ‘crime’ and ‘family’. Male characters differ in that they have the themes of ‘war’ and ‘action’. Female characters differ in that they have the themes of ‘shopping’ and ‘suicide’.

**Table 1.** Communities identified in the network and their total number of vertices.

a. Male Character		b. Female Character	
Community	Number of Vertices	Community	Number of Vertices
family	1465	crime	2876
action	1408	family	2547
war	1405	plot narration	1941
plot narration	1405	shopping	17
crime	524	suicide	12

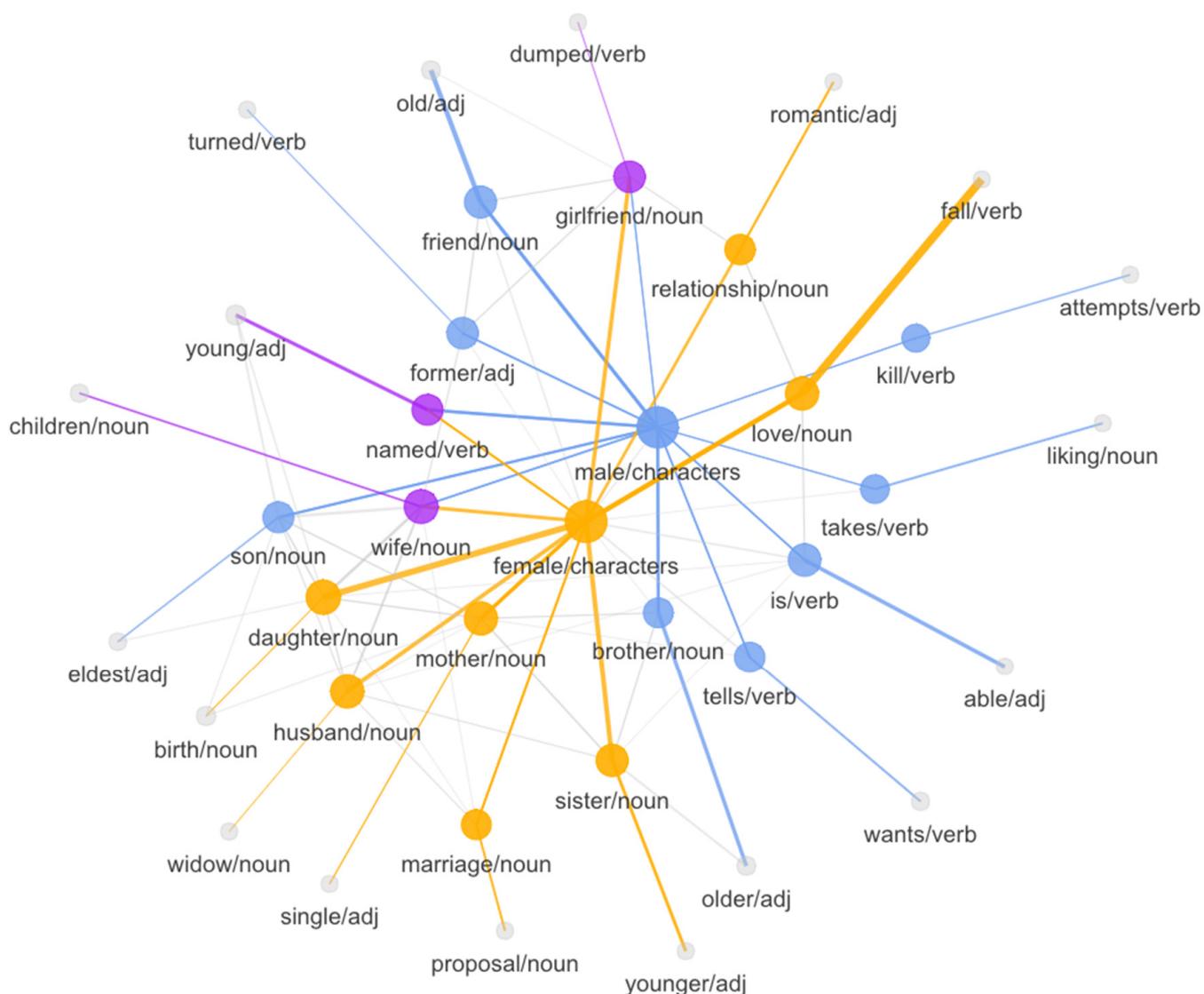


**Figure 3.** Communities identified in the co-occurrence networks. The male network (a) has 5355 vertices (words) and 1,979,829 edges (pairwise combinations of words within the data sample) and the female network (b) has 7393 vertices and 2,403,651 edges. We detected communities in the network using the Louvain algorithm. Five communities emerged in each of the networks, and the top ten vertices in terms of degree are shown.

### 3.2. Gender-Specific Story Tropes and Their Evolution

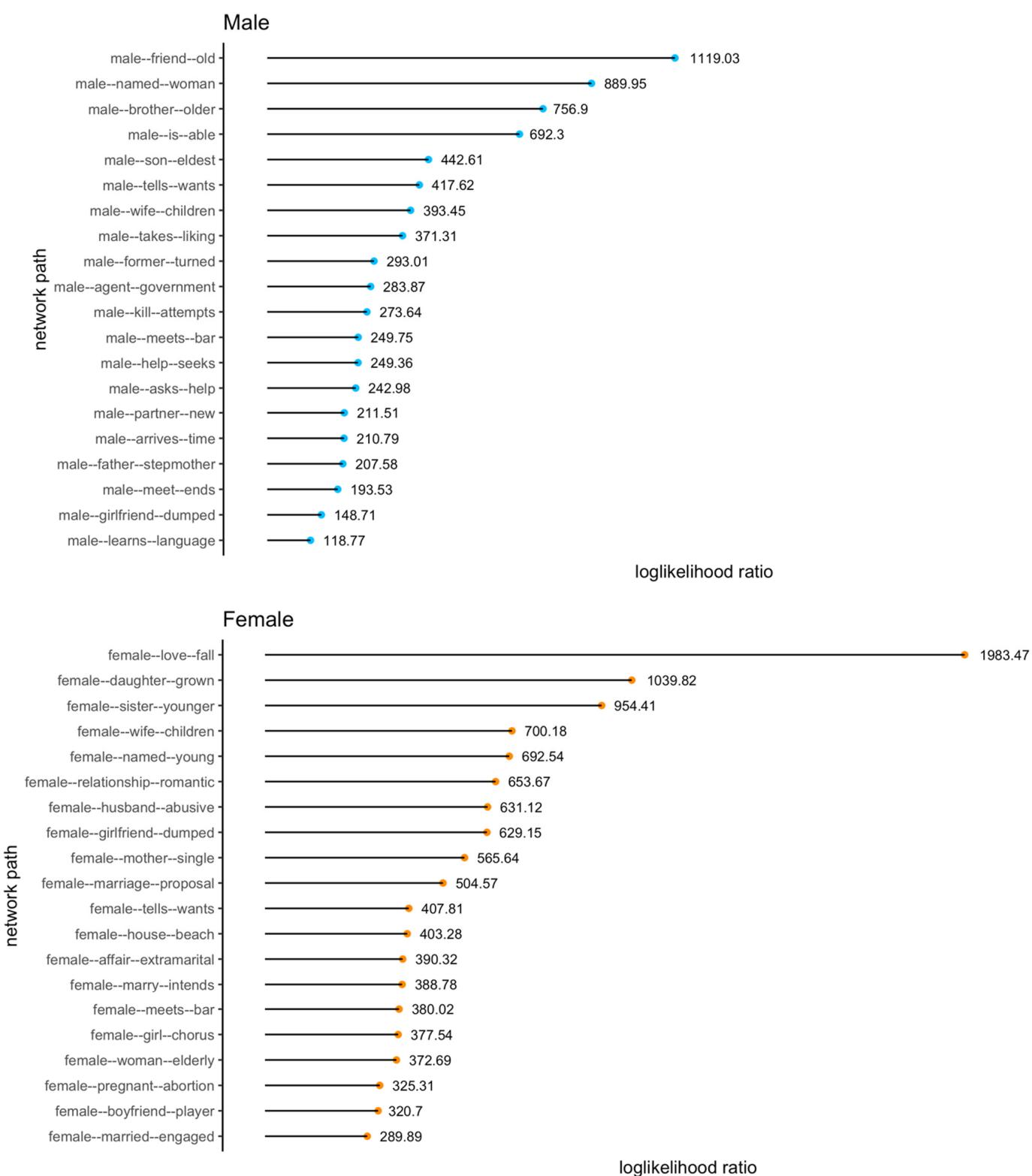
In this section, we describe the story tropes of male and female characters. We determined tropes by identifying significant paths in the network described by the path: ‘character vertex–primary association–secondary association’ (see Figure 4 for a visualisation of tropes in the network). Each 3-tuple of vertices denoted a significant story trope associated with each gender and their primary associations. To identify the most significant story tropes, we computed the path weights of all story tropes and selected the most significant tropes associated with each primary vertex. The top twenty most significant paths for male and female characters can be seen in Figure 5. The major difference between the tropes of male and female characters is that the paths of female characters are dominated by tropes that describe romance and family, whereas, for male characters, the most common tropes include friendship, family, romance, career, and crime/violence. The most significant trope for female characters is described by the path ‘female character–love–fall’. For male characters, the most significant trope is described by the path ‘male character–old–friend’.

**Changes in stereotypical tropes across decades:** We wanted to understand how stereotypical story tropes changed across time. First, we chose the most significant story trope from the two identified stereotypical domains (romance and crime/violence) and measured their path weights across each decade, from 1940 to 2019. For male characters, the most significant crime/violence-related trope was ‘male–kill–attempts’. For female characters, the most significant romance-related trope was ‘female–love–falls’. There were no crime/violence-related tropes in the female network.



**Figure 4.** Most significant story tropes associated with male and female characters described by the path ‘character-primary vertex–secondary vertex’. The thickness of the line represents the significance of the log-likelihood ratio. Blue nodes and lines represent unique associations with male characters; orange nodes represent unique associations with female characters. Purple nodes and lines represent the common associations of both male and female characters.

While the trope of male characters being associated with ‘attempts to kill’ increased in significance ( $R^2 = 0.55$ , beta = 0.40,  $p = 0.03$ ), the association of male characters with the ‘dumps girlfriend’ trope was inconclusive. This was because ‘dumped’ was absent as a secondary co-occurrence of male characters in some of the decades, making the log-likelihood test and comparison across decades impossible. For female characters, the association with the ‘falling in love’ trope decreased in significance  $R^2 = 0.73$ , beta = −3.89,  $p = 0.01$ ) (Table 2; see also Supplementary Materials for figures showing how the path weights of these tropes changed across time).

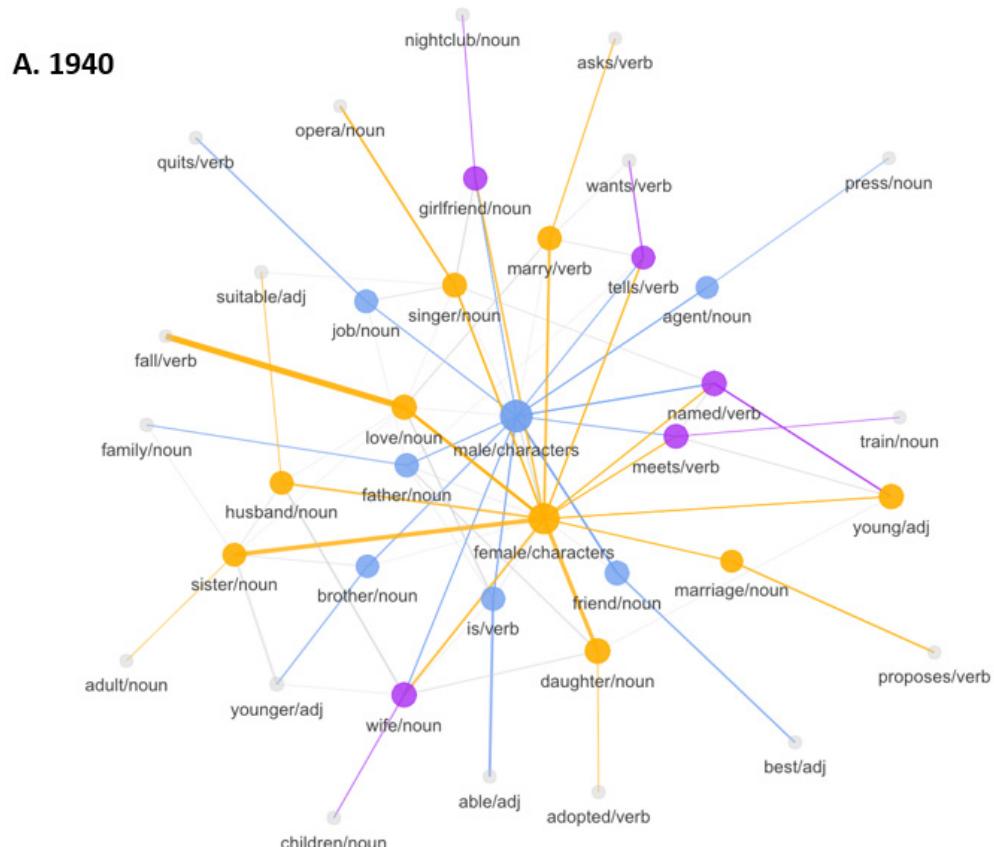


**Figure 5.** Needle plot representing the edge weights of the twenty most significant paths associated with male characters (**top**) and female characters (**bottom**).

**Table 2.** Linear regression analysis of path weight regressed on decade. \*  $p < 0.05$ .

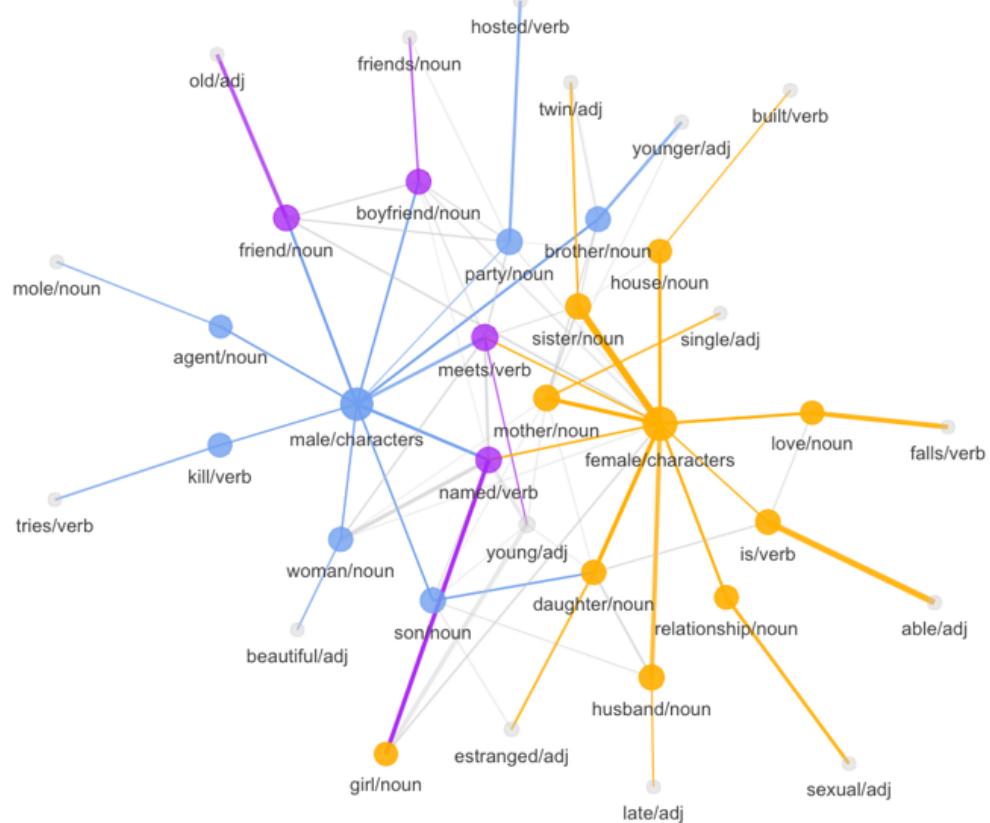
<b>Male</b>	<b>R<sup>2</sup></b>	<b>Slope (Beta)</b>	<b>p</b>
<b>Romance</b>			
Male-girlfriend-dumped	Inconclusive		
<b>Crime/Violence</b>			
Male-kill-attempts * [increasing]	0.55	0.40	0.03
<b>Female</b>	<b>R<sup>2</sup></b>	<b>Slope (Beta)</b>	<b>p</b>
<b>Romance</b>			
Female-fall-love * [decreasing]	0.73	-3.89	0.01
<b>Crime/Violence</b>			
	nil		

In addition to this analysis, two networks were also created specifically for the 1940s and 2010s respectively to provide a visual representation of the changes in the significant character tropes (see Figure 6). There were several key differences between the networks of male and female characters between the 1940s and the 2010s. Firstly, there was an absence of marriage-related tropes in the network of the 2010s. There was a new trope linked to sexual relationships (female–relationship/noun–sexual/adj). However, the trope of falling in love was present in both networks. For male characters, there was a new trope linked to crime/violence (male–kill/verb–tries/verb). This trope was similar to the male–kill–attempts trope that was observed in the overall network (see Figures 4 and 5), which showed a significant increase across time.



**Figure 6.** *Cont.*

B. 2010



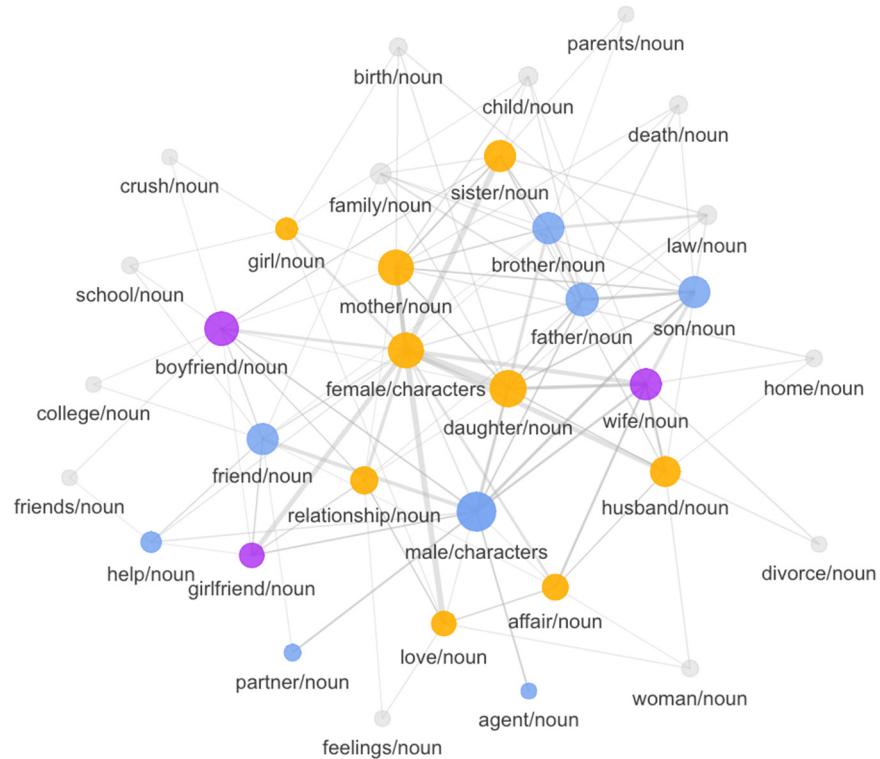
**Figure 6.** A comparison of significant tropes in the 1940s (**A**) and 2010s (**B**). Some key differences between the tropes from these two decades include the disappearance of the marriage trope in the female characters' network between the 1940s and the 2010s, and the new addition of a trope related to sexual relationships. For male characters, while there were no crime-related tropes in the 1940s, there was one in the 2010s.

### *3.3. Roles, Actions, and Descriptions of Male and Female Characters*

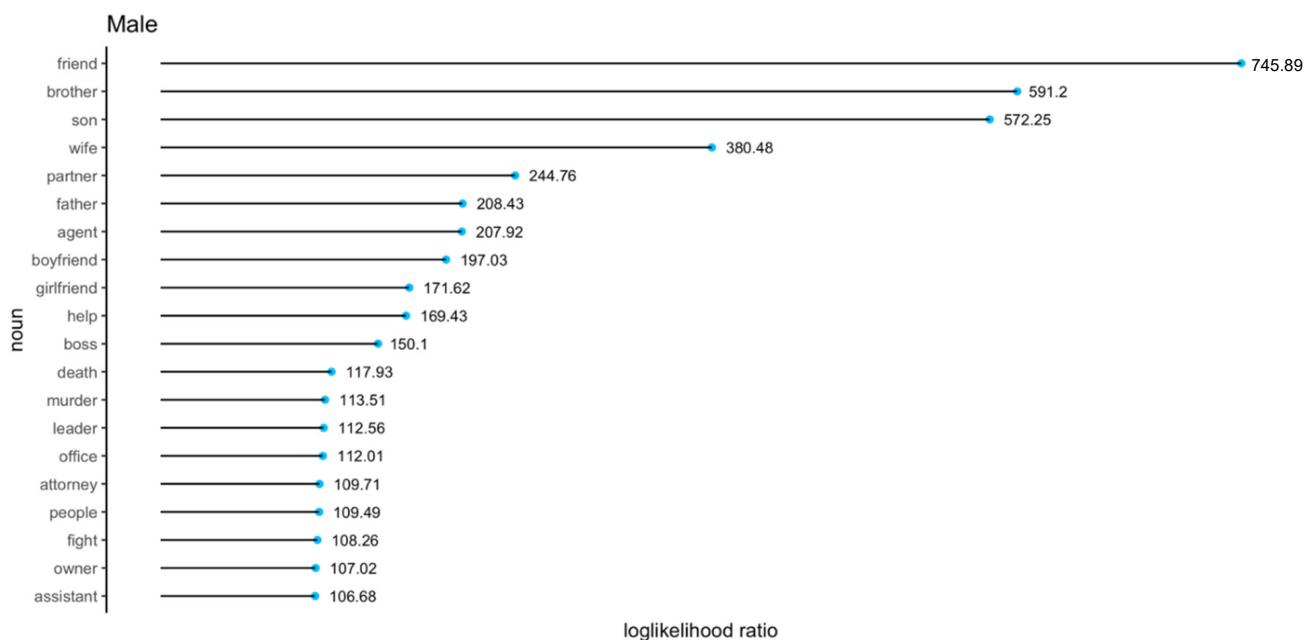
### 3.3.1. Nouns: What Roles Do Male and Female Characters Play?

To understand the most common roles that male and female characters play in Hollywood movies, noun vertices with the highest edge weights in associated with the male and female character vertices were identified. A network with twenty of the most significant associations of each gender is presented in Figure 7. The edge weights for each of these associations are shown in Figure 8. It is evident from Figure 7 that both male and female characters played the role of ‘blood relatives’ in a family.

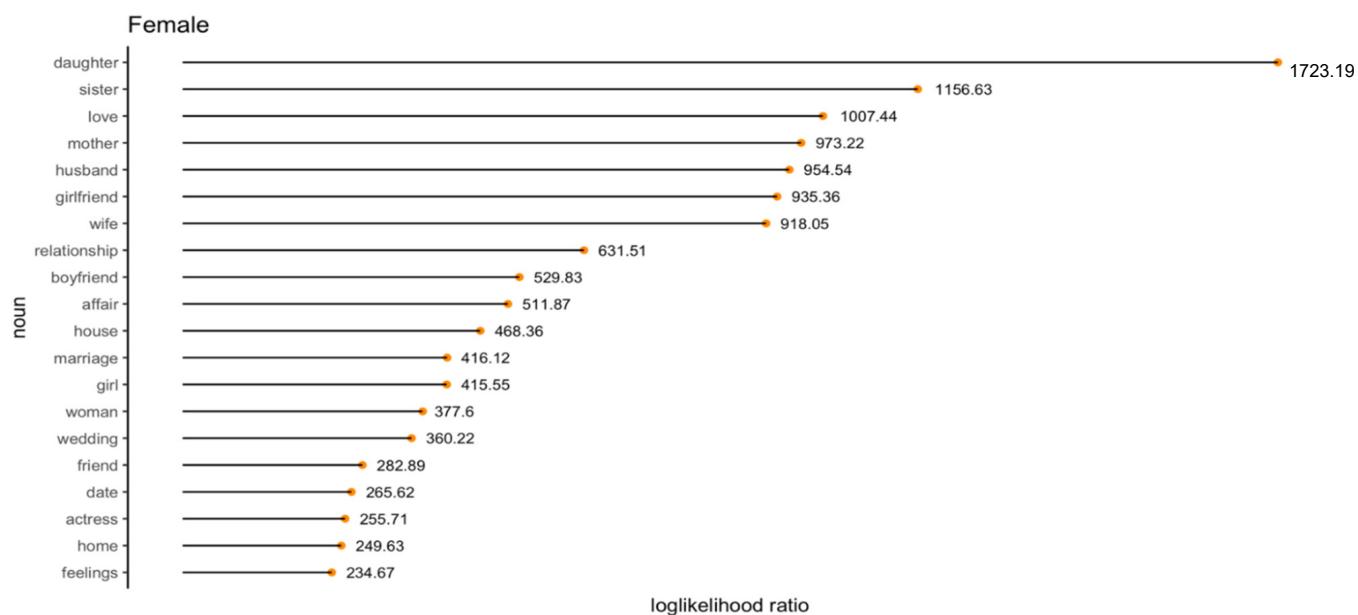
In addition, we identified individual nouns from both male and female character networks that fit the domains of crime/violence (e.g., ‘murder’) and romance (e.g., ‘love’). We then fitted a linear regression model to investigate the changes in their edge weights across time. The results are listed in Table 3 (additional figures depicting the change in edge weights can be found in the Supplementary Materials). For male characters, none of the associations in the domain of crime showed significant changes across time. However, in relation to the domain of romance, the association of male characters with the word ‘wife’ decreased significantly in the same period. For female characters, the associations with ‘love’, ‘wife’, and ‘widow’ in the romance domain showed a significant decline across time, but the associations with ‘relationship’ and ‘wedding’ showed a significant increase across time. There were no nouns found in the female character network that were associated with crime.



**Figure 7.** Most significant primary noun associations with males and females. Nouns found to strongly co-occur with female characters included ‘daughter’ and ‘mother’; for male characters, they included ‘friend’ and ‘father’. Nouns such as ‘boyfriend’, ‘wife’, and ‘girlfriend’ co-occurred strongly with both female and male characters.



**Figure 8. Cont.**



**Figure 8.** Needle plot representing edge weights of the twenty most significant primary noun associations of male characters (**top**) and female characters (**bottom**).

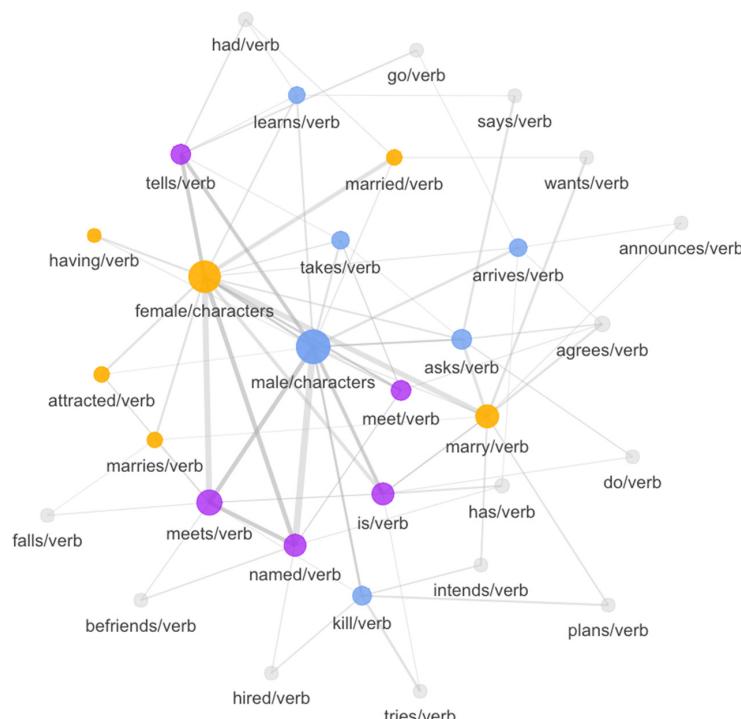
**Table 3.** Linear regression analysis of edge weight regressed on decade for stereotypical nouns.  
\*  $p < 0.05$ , +  $p < 0.10$ .

Male	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
Wife * [decreasing]	0.58	-0.62	0.03
Girlfriend	0.14	-0.09	0.36
Boyfriend	0	0.02	0.91
<b>Crime/Violence</b>			
Death	0.15	0.11	0.34
Murder	0.27	-0.14	0.19
Gun	0.26	-0.14	0.19
Female	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
Love * [decreasing]	0.59	-1.03	0.03
Girlfriend	<0.01	0.03	0.95
Wife *	0.67	-1.15	0.01
Relationship + [increasing]	0.43	0.77	0.08
Affair	0.03	0.16	0.69
Marriage	0.37	-0.41	0.11
Wedding + [increasing]	0.45	0.29	0.07
Widow * [decreasing]	0.63	-0.44	0.02
Crush	<0.01	0.03	0.87
<b>Crime/Violence</b>			
nil			

### 3.3.2. Verbs: What Do Male and Female Characters Do?

To understand the most common actions that male and female characters perform in Hollywood movies, verb vertices with the highest edge weights associated with the male and female gender vertices were identified. A network with twenty of the most significant associations of each gender is presented in Figure 9. The edge weights for each of these

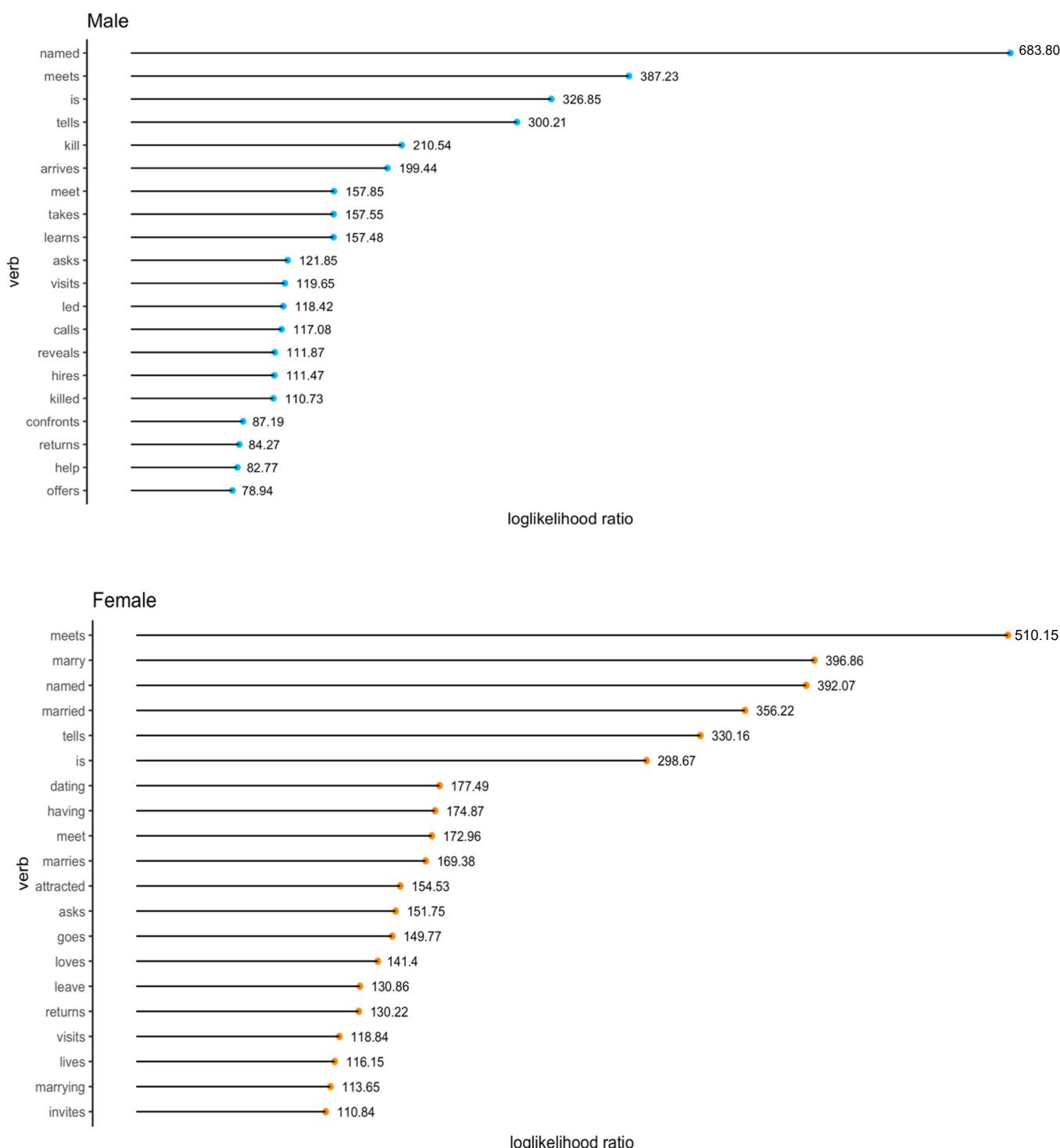
associations are shown in Figure 10. We identified several stereotypical verb associations for each gender based on the domains of crime/violence and romance and fitted a linear regression model to investigate the changes in their edge weights across time. When a word with multiple tenses was identified (e.g., ‘marry’, ‘married’), we used the tense with the largest edge weight for our analysis. These are listed in Table 4 (additional figures depicting the change in edge weights can be found in the Supplementary Materials). For male characters, ‘kill’ (in the domain of crime) showed a significant increase across time. No verbs associated with romance were found in the male network. For female characters, the verb ‘marry’ (in the domain of romance) showed a significant decrease across time. No verbs associated with crime were found in the female character network.



**Figure 9.** Most significant primary verb associations with males and females. Verbs found to strongly co-occur with female characters included ‘marry’ and ‘married’; for male characters, they included ‘kill’ and ‘arrives’. Verbs such as ‘named’ and ‘meets’ co-occurred strongly with both female and male characters.

**Table 4.** Linear regression analysis of edge weight regressed on decade for stereotypical verbs.  
\*\*  $p < 0.01$ , \*  $p < 0.05$ .

Male	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
nil			
Female	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
Marry ** [decreasing]	0.89	-1.15	<0.01
Attracted	0.31	-0.32	0.15
Loves	0.01	0.04	0.84
Dating	0.01	0.03	0.81
<b>Crime/Violence</b>			
nil			

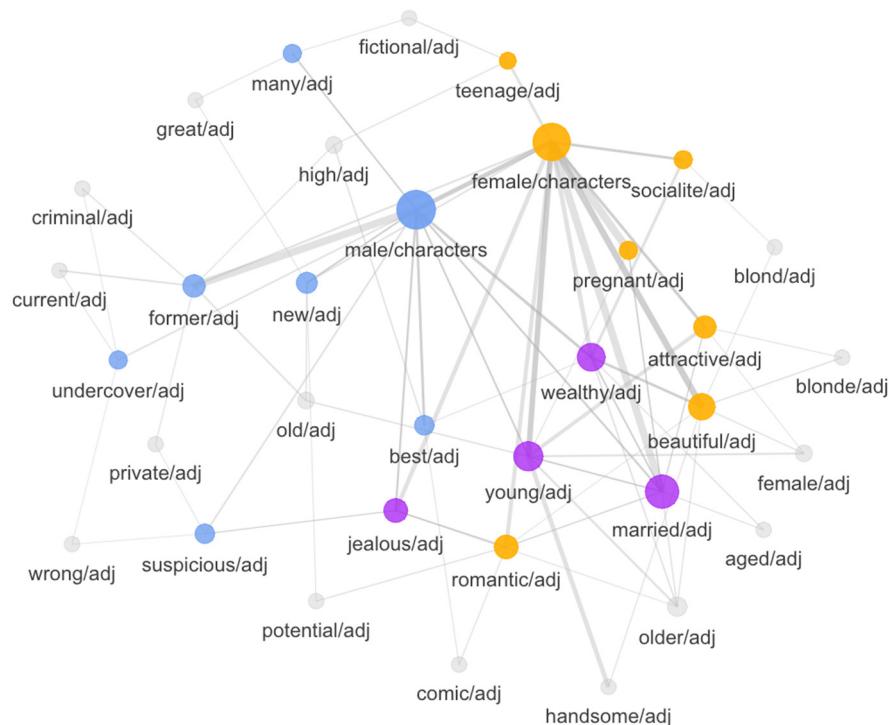


**Figure 10.** Needle plot representing edge weights of the twenty most significant primary verb associations of male characters (**top**) and female characters (**bottom**).

### 3.3.3. Adjectives: How Are Male and Female Characters Described?

To understand the most common descriptions of male and female characters in Hollywood movies, adjective vertices with the highest edge weights associated with male and female characters were identified. A network with twenty of the most significant associations of each gender is presented in Figure 11. The edge weights of these associations are shown in Figure 12. We identified stereotypical adjectives associated with violence/crime and romance for both male and female characters and fitted a linear regression model

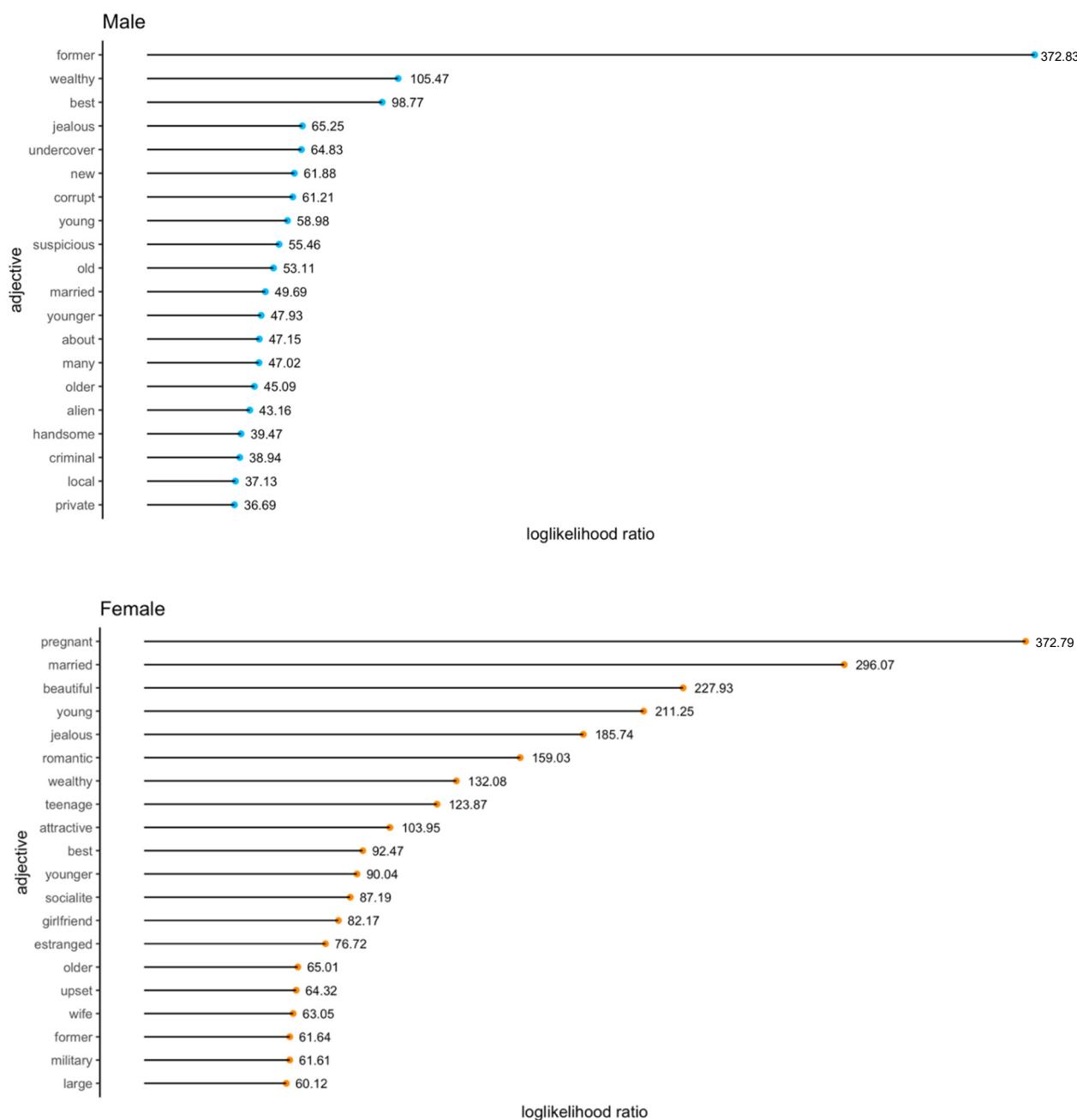
to investigate their changes in edge weight across time. The results are listed in Table 5 (additional figures depicting the change in edge weights can be found in the Supplementary Materials). For male characters, ‘corrupt’ (related to the crime/violence domain) did not demonstrate a significant change across time. ‘Married’ (from the romance domain) did not demonstrate a significant trend either, whereas ‘handsome’ was inconclusive, as it did not co-occurred with male characters in some decades. For female characters, ‘beautiful’ and ‘attractive’ (romance) showed a significant decrease across time. No adjectives related to crime and violence were detected in the female character network.



**Figure 11.** Most significant primary adjective associations with males and females. Adjectives found to strongly co-occur with female characters included ‘pregnant’ and ‘beautiful’; for male characters, they included ‘former’ and ‘best’, among others. Adjectives such as ‘young’ and ‘married’ co-occurred strongly with both female and male characters.

**Table 5.** Linear regression analysis of edge weight regressed on decade for stereotypical adjectives.  
\*  $p < 0.05$ .

Male	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
Married	0.11	0.05	0.42
Handsome		Inconclusive	
<b>Crime/Violence</b>			
Corrupt	0.04	-0.03	0.62
Female	R <sup>2</sup>	Slope (Beta)	p
<b>Romance</b>			
Beautiful * [decreasing]	0.70	-0.37	0.01
Attractive * [decreasing]	0.69	-0.32	0.02
Married	0.24	0.21	0.22
Romantic	0.24	-0.16	0.22
<b>Crime/Violence</b>			
	nil		



**Figure 12.** Needle plot representing edge weights of the twenty most significant primary adjective associations of male characters (**top**) and female characters (**bottom**).

#### 4. Discussion

In this study, we used network analysis to understand the stereotypes associated with male and female characters in Hollywood movies using movie plot data scraped from Wikipedia. We used three different types of network analysis at different levels of the network for the purposes of our investigation. Through a community detection analysis, we aimed to understand the structure of the network at the meso-level and uncover the themes used in the portrayal of men and women. Through our novel approach of understanding tropes using path analysis and the analysis of the edge weights of individual words, we aimed to more specifically understand the lives of male and female characters and how stereotypical representations change with time. Overall, this paper provides empirical evidence that gender stereotypes are expressed through the cultural products of a society. We further demonstrate how the use of network analysis could be a compelling approach

to model the representations of different social groups in the products of society and study their dynamic changes over time. An overview of our findings based on our community analysis, trope analysis, and the analysis of individual nouns, verbs, and adjectives, can be found in Table 6. In the following sections, we discuss the key results of our community analysis, trope analysis, and edge-weight analysis of individual words.

**Table 6.** Summary of quantitative results from different types of analysis conducted. \*\*  $p < 0.01$ , \*  $p < 0.05$ , +  $p < 0.10$ .

Analysis		Findings
Community	Male	<ol style="list-style-type: none"> <li>1. Family (1465 vertices)</li> <li>2. Action (1408 vertices)</li> <li>3. War (1405 vertices)</li> <li>4. Plot narration (1405 vertices)</li> <li>5. Crime (524 vertices)</li> </ol>
	Female	<ol style="list-style-type: none"> <li>1. Crime (2876 vertices)</li> <li>2. Family (2547 vertices)</li> <li>3. Plot narration (1941 vertices)</li> <li>4. Shopping (17 vertices)</li> <li>5. Suicide (12 vertices)</li> </ol>
	Male (top 20)	male–friend–old, male–named–woman, male–brother–older, male–is–able, male–son–eldest, male–tells–wants, male–wife–children, male–takes–liking, male–former–turned, male–agent–government, male–kill–attempts, male–meets–bar, male–help–seeks, male–asks–help, male–partner–new, male–arrives–time, male–father–stepmother, male–meet–ends, male–girlfriend–dumped, male–learns–language
Story trope	Female (top 20)	female–love–fall, female–daughter–grown, female–sister–younger, female–wife–children, female–named–young, female–relationship–romantic, female–husband–abusive, female–girlfriend–dumped, female–mother–single, female–marriage–proposal, female–tells–wants, female–house–beach, female–affair–extramarital, female–marry–intends, female–meets–bar, female–girl–chorus, female–woman–elderly, female–pregnant–abortion, female–boyfriend–player, female–married–engaged
	Male (analysed)	<u><b>Crime/Violence</b></u> male–kill–attempts * [increasing] ( $R^2 = 0.55$ , beta = 0.40, $p = 0.03$ ) <u><b>Romance</b></u> male–girlfriend–dumped
	Female (analysed)	<u><b>Crime/Violence</b></u> nil <u><b>Romance</b></u> female–fall–love * [decreasing] ( $R^2 = 0.73$ , beta = -3.89, $p = 0.01$ )
Noun	Male (top 20)	friend, brother, son, wife, partner, agent, father, girlfriend, boyfriend, help, boss, death, attorney, manager, owner, women, people, murder, gun, office
	Female (top 20)	daughter, sister, love, mother, husband, girlfriend, wife, relationship, boyfriend, affair, house, marriage, girl, woman, wedding, friend, date, actress, home, feelings
	Male (analysed)	<u><b>Crime/Violence</b></u> death, murder, gun <u><b>Romance</b></u> wife * [decreasing] ( $R^2 = 0.58$ , beta = -0.62, $p = 0.03$ ), girlfriend, boyfriend

**Table 6.** Cont.

Analysis		Findings
		<b>Crime/Violence</b> nil <b>Romance</b>
Female (analysed)		love * [decreasing] ( $R^2 = 0.59$ , beta = $-1.03$ , $p = 0.03$ ), girlfriend, wife * [decreasing] ( $R^2 = 0.67$ , beta = $-1.15$ , $p = 0.01$ ), relationship + [increasing] ( $R^2 = 0.43$ , beta = $0.77$ , $p = 0.08$ ), affair, marriage, wedding + [increasing] ( $R^2 = 0.45$ , beta = $0.29$ , $p = 0.07$ ), crush, widow * [decreasing] ( $R^2 = 0.63$ , beta = $-0.44$ , $p = 0.02$ )
Male (top 20)		named, meets, tells, is, arrives, kill, takes, meet, learns, asks, killed, visits, hires, led, returns, kills, suspects, calls, convinces, sends
Female (top 20)		meets, marry, named, married, tells, is, dating, having, meet, marries, attracted, asks, goes, loves, leave, returns, visits, lives, marrying, invites
Verb	Male (analysed)	<b>Crime/Violence</b> kill * [increasing] ( $R^2 = 0.55$ , beta = $0.17$ , $p = 0.03$ ) <b>Romance</b> nil
Female (analysed)		<b>Crime/Violence</b> nil <b>Romance</b> marry ** [decreasing] ( $R^2 = 0.89$ , beta = $-1.15$ , $p < 0.01$ ), attracted, loves, dating
Male (top 20)		former, wealthy, best, jealous, married, suspicious, young, new, undercover, many, old, real, older, younger, private, interested, local, corrupt, about, handsome
Female (top 20)		pregnant, married, beautiful, young, jealous, romantic, wealthy, teenage, attractive, best, younger, socialite, girlfriend, estranged, older, upset, wife, former, military, large
Adjective	Male (analysed)	<b>Crime/Violence</b> corrupt <b>Romance</b> married, handsome
Female (analysed)		<b>Crime/Violence</b> nil <b>Romance</b> beautiful * [decreasing] ( $R^2 = 0.70$ , beta = $-0.37$ , $p = 0.01$ ), attractive * [decreasing] ( $R^2 = 0.69$ , beta = $-0.32$ , $p = 0.02$ ), married, romantic

#### 4.1. Community Analysis

First, we conducted a community analysis of a co-occurrence network based on the words associated with male and female characters to understand the themes associated with these characters. The results of our community analysis have to be interpreted with caution because of the low modularity values, which indicate lack of robust community structure. To the best of our knowledge, only Xu et al. [23] have performed a similar analysis of movies, albeit using movie synopses from IMDb. They identified communities of crime, action, career, and family in association with male characters and the communities of action, romance, career, and family in association with female characters. By contrast, our analysis showed that male characters were associated with the themes of family, crime, action, and war, whereas female characters were associated with family, crime, shopping, and suicide. One possible explanation for these differences is that our present analysis considered both lead and supporting characters, whereas Xu et al. [23] only considered lead characters in movies.

The results of our analysis partly support social role theory, which states that the stereotypes used in a society reflect the gender roles and expectations of that society. For

example, the specific association of war with male characters could be partly attributed to the large number of movies related to World War II in Hollywood [37]. War was often used as a central theme in movies, depicting major social issues such as the post-war readjustment to life of male soldiers. On the other hand, the association of the theme of ‘suicide’ with female characters seems particularly noteworthy. In reality, suicide rates among men are higher than among women, with the US reporting 22.8 male suicides versus 6.2 female suicides per 100,000 people in 2018—a disparity that has remained relatively stable for the past 60 years [38]. It would thus be expected, according to social role theory, that men would be more commonly associated with suicide movies than women in movies, which is contrary to our results. Specifically, suicide is often negatively constructed and stigmatised by many. Often resulting from the need to escape from psychological pain [39], the act of suicide and its ideation are used to emphasise the vulnerability and incompetence of female characters [40]. However, it is worth noting that although men are more likely to commit suicide than women, the trend is reversed for attempted suicides—women are more likely to attempt suicide than men [41]. It is possible that the significant portrayal of suicide in relation to female characters, but not male characters, in movies reflects the general perceptions (including misconceptions) people hold about suicide (i.e., that it is more associated with women than men). It was also surprising to observe that female characters were associated with the theme of crime, as this was primarily a stereotype of male characters in the media, according to our initial literature review.

#### 4.2. Trope Analysis

Next, we identified story tropes in the networks of male and female characters using a novel method of path analysis implemented on the word co-occurrence networks formed using the significance of log-likelihood ratios. Story tropes add a further dimension to the standard single-word associations that have often been used to study stereotypes. Our results showed that the lives of female characters are dominated by the tropes of romance and family. By contrast, the lives of male characters are filled with more diverse aspects of life, including friendship, career, and crime/violence, as well as family and romance. This is not surprising given that the portrayal of female characters as passive love interests has been present in Hollywood movies for a long time, whereas male characters “get in on the action” [42]. To allow gender-based comparisons across time, we focused on crime/violence and romance domains.

Our analysis of the changes in the path weights of the most significant stereotypical tropes for both male and female characters showed that the trope of a male character attempting to kill increased. For females, the trope of falling in love has decreased, and no significant crime/violence-related tropes were found in the network. Even though changes in a few specific tropes would be insufficient for us to conclude that stereotypical associations have changed overall, these results do support the notion that some of the common and stereotypical associations of males and females have in fact changed in movies. Our edge-weight analysis of individual words, discussed below, offers a deeper understanding of the nature of these changes. Specifically, although we saw a general increase in the crime/violence trope in association with male characters, and a decrease in the romance trope in association with female characters, the trends in the associations of individual words within those domains may not necessarily be the same. Within the romance domain, for instance, we could explore trends in discrete words specifically related to marriage, or courtship separately, which portray a richer picture of what comprises these stereotypes.

#### 4.3. Edge-Weight Analysis

Lastly, we studied the edge weights of the most significant crime-related and romance-related noun, verb, and adjective associations of male and female characters. From the overall analysis across the entire time period, we found several interesting trends in how stereotypical domains within the genders evolved over time. For male characters, most

of the words related to crime (i.e., ‘death’, ‘murder’, ‘gun’, ‘corrupt’) did not show any significant change in co-occurrence from the 1940s to the 2010s, except for the specific verb, ‘kills’, which was increasingly associated with male characters in Hollywood movies during this period. For romance-related words, on the other hand, only ‘wife’ demonstrated a significant decrease across time in association with male characters. The words ‘girlfriend’, ‘boyfriend’, and ‘married’ displayed no discernable trends. For female characters, by contrast, we found a mix of increasing, decreasing, and unchanging trends in various romance-related words. The co-occurrence of words such as ‘love’, ‘wife’, ‘widow’, ‘marry’, ‘beautiful’, and ‘attractive’ with female characters decreased over the years, whereas ‘relationship’ and ‘wedding’ increased. The romance words that did not display a significant change in co-occurrence with female characters during this period included ‘affair’, ‘marriage’, ‘crush’, ‘girlfriend’, ‘attracted’, ‘love’, ‘dating’, ‘married’, and ‘romantic’. Interestingly, no crime-related words were detected in the female character networks. Furthermore, there was a general lack of significant romance-related noun, verb, and adjective associations for male characters and a lack of significant associations for female characters in the crime domain. In some instances, no relevant words could be detected and thus analysed (e.g., romance-related nouns for male characters, crime/violence-related nouns, verbs, and adjectives for female characters).

Our edge-weight analysis of the noun, verb, and adjective associations showed that the representation of male characters through crime-related words generally increased over the decades. The analysed words either remained highly associated with male characters or increased significantly, further perpetuating the idea that Hollywood movies continue to portray male characters in relation to crime and violence. This reinforces male characters’ disposition to partake in crimes that could potentially involve violence or some form of dishonesty as a way to display masculine identities and power [43]. Participation in crime is believed to reflect hegemonic masculinity, according to which males regard engagement in crime as an outlet for their aggression, reinforcing their power and prowess [44].

This long-standing stereotype associated with men, crime, also stems from conventions of masculine strength. For example, the act of stalking, which is typically depicted by the media as a gendered crime, involves the “popular image . . . . of a celebrity who is stalked by a crazed fan or a battered woman who has left a physically abusive relationship and is now being stalked by her ex-spouse or ex-lover” [45,46]. Unsurprisingly, in the movie entries that we analysed, there also seemed to be a significant link between the portrayal of men and criminally offensive roles [47]. The aggressive portrayal of men and its contrast with the depictions of women as helpless are also in line with the lack of crime/violence-related words found in the female characters’ noun, verb, and adjective networks. From these findings, it seems that crime remains much more central to the narratives of male characters than to that of female characters.

The depiction of romance in relation to male characters, on the other hand, is generally sparser than that of female characters, as suggested by the smaller number of romance-related nouns, verbs, and adjectives found in the male character network compared with the female character network. However, the significant decrease in the association of male characters with the word ‘wife’ is interesting, possibly suggesting that male characters may be less frequently portrayed as married than they were previously. This could reflect a larger societal trend, in which marriage in the U.S. is declining [48]; however, given the lack of change observed in the use of the adjective ‘married’, this conclusion may be premature. In sum, it seems that romance is not a significant part of the lives of male characters in Hollywood movies as compared with female characters.

However, the results for female characters show a more ambiguous picture. Specific words related to marriage demonstrated both increasing (e.g., ‘wedding’), decreasing (e.g., ‘marry’), and unchanging (e.g., ‘marriage’, ‘married’) trends in relation to female characters in Hollywood movies across time. Traditionally, the role of woman has centred around marriage and the family [49]. In the 1950s, American culture strongly emphasised the creation of nuclear families (or the ‘All-American family’), which reinforced the normative

expectation that women should take on the roles of wife and mother [50]. As expected, these traditional ideas around women and marriage are also evident in movies, such as the early Disney Princess movies, *The Little Mermaid* (1989) and *Aladdin* (1992), and even *Tangled* (2010), all of which conclude their female protagonists' narratives through a romantic, royal marriage, despite the fact that the premise of their individual stories is a search for autonomy and the pursuit of their dreams [51]. Evidently, women and matrimony are strongly associated in both American society and American movies, at least historically.

More recently, some researchers have observed or predicted a waning trend in these stereotypes of marriage. Barber [52] recognised that modern Disney Princess movies have shifted towards starring an independent female lead who is not bound by marriage. Examples include *Brave* (2012), *Frozen* (2014), and *Moana* (2016), all of which feature female protagonists who either actively reject marriage (e.g., Merida in *Brave*) or do not have a romantic arc that culminates in a marriage in their story at all (e.g., Elsa in *Frozen*, Moana in *Moana*). Such changes may be related to the decline in marriage in American society—marriage rates in the US have been steadily falling over the past decades, with around only 50% of American adults being married in 2016 compared to 72% in 1960 [48]. Indeed, the gendered expectation that a woman should marry was largely driven during a time when women were systematically disabled economically and marriage was a means of financial advantage and survival [53]. Such concerns may no longer be as relevant today as American women have higher earning power than before. However, our edge-weight analyses did not support the predictions that marriage would be less frequently depicted in female characters' arcs in more recent movies, as the majority of marriage-related words either remained significantly high or increased in association with female characters between the 1940s and 2010s. This suggests that overall, marriage continues to be a stereotypical trope in the lives of Hollywood's female characters, which is not reflective of trends in social reality.

Apart from matrimony, we also looked at words that emphasise women's romantic roles in general, such as 'wife', 'widow', 'crush', and 'girlfriend'. These nouns describe female characters in relation to their romantic partners, and have either decreased (e.g., 'wife', 'widow') or not changed (e.g., 'crush', 'girlfriend') in their association over time. The decreasing trends could point towards the increasing complexity of female characters, moving beyond the roles of 'wife' or 'widow'. This is in line with past research, which identified that female characters are represented with more complexity, as demonstrated through the increasing representation of the themes of 'self-interest' and 'protection of others' in their narratives in recent times, as compared to the conventional exclusive focus on romantic roles [54]. Perhaps female characters are now being represented through arcs that incorporate multiple social roles, reducing the focus on their relations to their husbands. However, viewed in the context of the lack of change in the associations of 'crush' and 'girlfriend', it is possible that only marriage-related roles are gradually being dropped from female characters' arcs, whereas courtship, or romance roles in general, continue to be represented in movies. Indeed, as marriage numbers have fallen in the U.S., there has been a rise in cohabitation among unmarried couples [55]. Critically, marriage and romance are not synonymous. These results could reflect real-life modernising attitudes and behaviours, in which individuals continue to pursue romance without symbolising it through marriage.

Lastly, an interesting result was the decrease in the associations of the words 'beautiful' and 'attractive' with female characters, which may suggest that women in Hollywood movies are now described through their physical appearance less than they were previously. The depiction of women in the media has long been criticised for pandering to the male gaze, which makes women "a passive object to be looked at" [56]. Accordingly, the camera is likened to the male audience, with its pans and angles over women's bodies and faces representative of the male desire to view women's physicality (which is often related to women's sexuality). In our edge-weight analysis, we found that female characters in Hollywood movies have, in fact, become less likely to be described through their beauty or attractiveness, which may signify a declining trend in the representation of women

in order to fulfil the “male gaze”. Indeed, feminists have long fought against the female consumption of the beauty industry, which is driven, as suggested, by a forced competition for male approval [57]. Possibly, the shift towards a less beauty-oriented stereotypical representation of female characters in Hollywood reflects the increasing recognition or acceptance of these concerns.

#### 4.4. Summary of Results

Summing up, it is clear from the results of our analysis that men and women are represented differently in cinema. We did not lend much weight to the results of the community analysis due to the low modularity value of the network’s community structure. However, based on the other two sets of analyses, our results show that male and female characters are associated with several stereotypes that are commonly observed in real life, and which was in accordance with social role theory. For example, the lives of female characters in movies mainly revolve around romance and relationships, although this is not true for male characters. The roles, actions, and descriptions of female characters are also centred around romance and relationships. By contrast, the lives of male characters are much more diverse. There are aspects of career and crime/violence, but also romance and family, although romance was observed to be less of a relevant domain to male than to female characters. The roles, actions, and descriptions of male characters also reflect this diversity. While we identified both romance- and crime/violence-related words in the male networks, the female networks displayed an absence of crime/violence words.

When comparing networks of word co-occurrences across the entire time period from the 1940s to the 2010s, we observed several differences between the lives of male characters and the lives of female characters. In sum, our results seem to suggest that the stereotypical depiction of an ‘attractive’ and ‘beautiful’ female character who passively ‘falls in love with a male character and marries him’ has decreased. The trope of a female character as an ‘attractive’ and ‘beautiful’, but also a passive, character who ‘falls in love with a male character and marries him’ has decreased. This was inferred from the falling association of female characters with the trope of ‘falling in love’ and also with words such as ‘attractive’, ‘beautiful’, ‘marry’, ‘love’, and ‘widow’. However, this does not quite change the overall stereotypical association of female characters with romance because even as these tropes and associations are in decline, they seem to be replaced by others. For example, associations with ‘wedding’ and ‘relationship’ appear to have increased. We also noticed new tropes that link females to sexual relationships, despite the lack of tropes linked to marriage in the 2010s network. Due to the mixture of trends observed, a more suitable conclusion may be that the ways in which female characters are represented through romance are complex and continually evolving, rather than purely declaring a quantitative rise or fall. As for male characters, the associations seem to be largely stable; however, association with crime seems to have increased in some cases, as inferred from the rising association with the trope of ‘male as a killer’ and the word ‘kill’.

According to social role theory [10], stereotypes mirror societal roles and expectations. Through our examinations of gender stereotypes in Hollywood movies, we showed that in some cases, this is indeed the case, whereas it is not necessarily true in other cases. Therefore, it appears that the stereotypes of a society, as represented in its cultural products, need not actually represent gendered roles and expectations in social reality. That is, social role theory might not always apply to the implicit stereotypes of a society as manifested in its cultural products. An alternative interpretation could be that stereotypes are not absolute categorisations. What is considered a stereotype could consist of a plethora of associations, with each association changing at a different pace. Therefore, although it is helpful to group together specific associations under a single broad categorisation, specific associations should be studied to gain a nuanced understanding of how stereotypes change within society. It may be more meaningful to view gender representations as being subject to constant development and change, and leverage the availability of big

data and computational and quantitative methods to obtain nuanced insights into specific stereotypical associations.

#### 4.5. Real-Life Implications

The harmful effects of stereotypes have been well-documented in psychology. For example, stigmatised populations perform worse when they recognise the negative stereotypes surrounding them and their abilities, such as women and mathematical skills, referred to as the stereotype threat [58]. These effects have been observed in female gamers and women in engineering [59,60]. Furthermore, gender stereotypes in children's books have been found to affect children's cognitive development, potentially negatively skewing their world-views [61]. In light of these findings, we should seek ways to reduce the perpetuation of gender stereotypes, in which the media is largely responsible for perpetuating.

The idea that audiences learn and model content from the media is not new, as explained through social learning theory [62]. Indeed, research has found that gender stereotypes presented in video games (e.g., the aggressive male character versus the sexualised, objectified female character) are mirrored in the perceptions of youth [63]. Exposure to stereotype-confirming information, such as the association between Arab people and terrorist acts, has also been found to prime negative perceptions of the stereotyped group among audiences [64]. Evidently, the media has deep and far-reaching implications for the ways in which people understand, perceive, and behave in the world. Long-term exposure to gender-stereotypical content in the media may potentially result in distorted beliefs about genders. For example, repeated exposure to stereotypically aggressive and criminal male characters may shape unbalanced views of the virtues of the respective genders (e.g., the 'women-are-wonderful' effect; [65]). Repeated exposure to stereotypically romance-oriented female characters may implicitly teach girls what to prioritise in their lives. Based on our study, we broadly confirm that Hollywood movies are one form of media in which gender stereotypes are presented, and there are diverse trends in more specific stereotypes as they rise or fall across time. This knowledge can prompt mass audiences to be more critical of the content they consume, and caution against accepting the stereotypical representations of male and female characters as congruent with reality. For filmmakers, these findings can guide them to be more aware of the ways in which they characterise men and women in cinema, and steer them away from perpetuating damaging stereotypes.

Finally, the framework we used in this study may be of use to researchers interested in documenting and examining stereotypes in other text-based media modalities or forms (e.g., movie scripts, television subtitles, books, and newspapers). There is already an existing evidence base suggesting negative stereotyping of multiple, diverse groups of people in the media, including British Muslims [66] and older adults [67]. As such, research on stereotypes presented through cultural products that was previously conducted with relatively small samples and through researcher-coded content analysis methods may benefit from our network approach, which allows large-scale data to be included in the analysis to obtain more widespread, systematic findings.

#### 5. Limitations

Despite the theoretical, empirical, and methodological advances of our study, it is important to reflect on the limitations of our study as well. The main limitation is that we analysed North American movies, owing to the ease of availability of data on Hollywood movies. We also wished to leverage and build on the vast existing literature on North American society. In addition, a lack of non-binary characters from movies across the decades resulted in a lack of representation of these characters in our analysis. This lack of representation of non-binary characters across decades could be attributed to recent changes in our society; the identification of non-binary genders has only increased over the past few years [68]. The genderizeR package that was used in our analysis of characters and their genders also lacked the data to code non-binary characters. Hence, our results may

not be easily generalised to societies and movies from around the world, especially given the lack of transnormativity in the movies in general. Future studies of movie plots could be conducted to compare the nature of gender representations across different regions (e.g., movie plots from Bollywood or globally recognised movie industries, such as the cinema of Hong Kong). This could then be correlated with indexes on gender equality in the region. Such an analysis would add another level of investigation to the question of whether a society's gender equality status has an influence on the representation of gender in its cultural products.

Second, we were not able to capture words that were semantically similar to each other to understand the changes in the associations of entire concepts. This could be made possible by applying other methods, such as textual forma mentis networks [19]. Future studies could use this approach in addition to the approach we employed here.

Third, we have to acknowledge and accept a certain level of ambiguity when it comes to interpreting stereotypes from word networks. Due to the deconstructive nature of a network, which segments sentences via smaller semantic units such as words, there is an inevitable loss of the context that is expressed through the original, full sentence. As such, given an association such as '[male name]-killed', we cannot confirm if the associated meaning is being 'acted on' or 'received by' the character (i.e., did he kill someone, or was he killed?). Hence, we must recognise that underlying assumptions were made when interpreting the word networks. A possible way to counter this issue in future studies is to extend beyond employing the 3-tuples that were used in the trope analysis. As more words or data are captured in them than single-word associations, they may reflect more of the contextual information behind these specific associations, allowing us to draw more accurate conclusions as to the relationship between a character and their associated words.

Fourth, the 'genderizeR' package uses a constantly updating profile of social media profiles and their associated genders to tag first names as male or female. A shortcoming of this is that the names in the early part of the time period might have been less accurately tagged with gender information, despite the high accuracy of the package's identification of recent names. This is because the older demographic are less likely to use social media than younger segments of the population. Additionally, our entries of movie plots came from Wikipedia. While changelogs of these movie entries are available on Wikipedia, which allows the public to view page histories and make necessary corrections, we acknowledge that given its open-source nature, Wikipedia entries could still be relatively unreliable. Further studies could delve into using sources such as IMDb, where public contributions have to be reviewed by an editing team before they are published [69]. An additional standardised review process by a professional team would ensure that the information posted upholds a certain standard of reliability and accuracy. It is also important to acknowledge that given the reconstructed nature of Wikipedia plots, they are not to be taken as precise or exact representations of movies. In other words, the plot as written by a viewer (or multiple viewers, or editors, on Wikipedia) is an agreed-upon interpretation of the movie from which it is taken, independently of the movie itself. Hence, one must be cautious in interpreting the results of our analyses as completely accurate depictions of stereotypes in movies.

Lastly, to make our analysis tractable, we limited our story trope analysis to a specific path type (i.e., character vertex–primary vertex–secondary vertex). However, other types of paths and features of the network could be analysed using a variety of network science methods to reveal other aspects of the lives of male and female characters.

## 6. Conclusions

Using network analysis, this research investigated the trajectories of various gender stereotypes in movies via word co-occurrences generated from Wikipedia entries of movie plot descriptions. While the literature on gender stereotypes in the media is quite extensive, less research on this topic has been performed using quantitative approaches. Our approach is unique in its application of network analysis to analyse word co-occurrence patterns in

movie plots, coupled with a detailed longitudinal analysis of how such stereotypes evolve and change with time. This approach allowed us to explore gender stereotypes in the media and in society. We explored the idea that movies, as cultural artefacts, may reflect the gender stereotypes of society at large. However, due to the complex and dynamic nature of stereotypes, it seems that movies alone do not accurately capture the evolution of stereotypes in society. Given the dominance of the Hollywood movie industry, which continues to grow in terms of production and consumption (e.g., a record 873 movies were released in the US and Canada in 2018, compared with a mere 371 in 2000 [70]; box office revenue in the US and Canada exceeded 11 billion USD in 2019 versus a mere 1.66 billion USD in 1980 [71]), coupled with the potential of audiences to learn and model media content, developing an understanding of the types of stereotypes that either persist or wane in movies is important for studying how they may impact people's attitudes, emotions, and behaviour on a mass scale. Psychological research has long documented the harmful effects of stereotypes on stereotyped groups (e.g., [72]). Hence, our research provides one approach to the monitoring of the state of gender representation in Hollywood cinema, mapping its relation with changes in the values and norms of North American society. Through this, our approach provides new insights into specific gender stereotypes and their dynamic changes.

**Supplementary Materials:** The following document is available online at <https://www.mdpi.com/article/10.3390/bdcc6020050/s1>, Figure S1: Changes in path weights of stereotypical tropes across decades. (Left) Path weight of 'male–kill–attempts' (representing the crime/violence trope) significantly increased over time ( $R^2 = 0.55$ , beta = 0.40, p = 0.03). (Right) Path weight of 'female–love–fall' (representing the romance trope) significantly decreased over time ( $R^2 = 0.73$ , beta = -3.89, p = 0.01); Figure S2: Linear regression models investigating changes in the edge weights of identified stereotypical primary noun associations of male and female characters. (a) The association of male characters with the noun 'wife' decreased significantly over the years. (b) Associations of male characters with nouns relating to crime did not significantly change across the years. (c) Associations of female characters with certain romance nouns, 'love', 'wife', and 'widow', significantly declined over the years, while associations with 'relationship' and 'wedding' significantly increased; Figure S3: Linear regression models investigating changes in the edge weights of identified stereotypical primary verb associations of male and female characters. (a) The association of male characters with the verb 'kill' significantly increased over the years. (b) Associations of female characters with the verb 'marry' significantly fell over the years, whereas associations with 'attracted', 'loves', and 'dating' did not change significantly; Figure S4: Linear regression models investigating changes in the edge weights of identified stereotypical primary adjective associations of male and female characters. (a) The association of male characters with the adjective 'married' did not significantly change over the years. (b) The association of male characters with the adjective 'corrupt' did not significantly change over the years. (c) Associations of female characters with the adjectives 'beautiful' and 'attractive', relating to romance, significantly fell over the years, whereas associations with 'married' and 'romantic' did not change significantly.

**Author Contributions:** Conceptualisation, A.M.K., J.Y.Q.G. and T.H.H.T.; methodology, A.M.K., J.Y.Q.G. and T.H.H.T.; formal analysis, A.M.K., J.Y.Q.G. and T.H.H.T.; writing—original draft preparation, A.M.K., J.Y.Q.G. and T.H.H.T.; writing—review and editing, A.M.K., J.Y.Q.G., T.H.H.T. and C.S.Q.S.; Visualisation, A.M.K., J.Y.Q.G. and T.H.H.T.; supervision, C.S.Q.S.; funding acquisition, C.S.Q.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** C.S.Q.S. is supported by a Start Up Grant (WBS R-581-000-242-133) provided by the National University of Singapore.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data underlying the results presented in this study are available from the Wikipedia website ([www.wikipedia.com](http://www.wikipedia.com)), accessed on 12 April 2022). All Supplementary Materials, code, and processed data are available from <https://osf.io/5pvj7> (accessed on 12 April 2022) and <https://github.com/arjunkmrm/film-networks> (accessed on 12 April 2022).

**Acknowledgments:** Portions of this research were completed as part of the course requirements for PL4246 Networks in Psychology, a capstone module taught at the Department of Psychology, National University of Singapore. The authors wish to acknowledge Russell Lee and the students of PL4246 for their comments and support.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

A1—Significance of log-likelihood ratio calculation

$$H_0: P(A|B) = P(A|-B)$$

$$H_1: P(A|B) \neq P(A|-B)$$

$$\log \lambda(A, B) = -2 \cdot \log \frac{L(H_0)}{L(H_1)}$$

$$sig(A, B)_{lgI} = -2 \log \lambda$$

$$\begin{aligned} \lambda = [n \log n - & n_A \log n_A - n_B \log n_B + n_{AB} \log n_{AB} \\ & + (n - n_A - n_B + n_{AB}) \cdot \log(n - n_A - n_B + n_{AB}) \\ & + (n_A - n_{AB}) \log(n_A - n_{AB}) + (n_B - n_{AB}) \log(n_B - n_{AB}) \\ & - (n - n_A) \log(n - n_A) - (n - n_B) \log(n - n_B) \end{aligned}$$

## Appendix B

**Table A1.** Classification of each community under a specific theme.

a. Male.				
Family	Crime	Action	War	Plot Narration
female/characters	police/noun	finds/verb	other/adj	movie/noun
is/verb	money/noun	find/verb	men/noun	begins/verb
be/verb	town/noun	house/noun	group/noun	story/noun
has/verb	take/verb	takes/verb	including/verb	ends/verb
family/noun	local/adj	goes/verb	are/verb	show/noun
father/noun	murder/noun	car/noun	using/verb	scene/noun
tells/verb	gang/noun	tries/verb	team/noun	game/noun
time/noun	found/verb	killed/verb	people/noun	final/adj
life/noun	taken/verb	death/noun	order/noun	end/noun
wife/noun	crime/noun	room/noun	use/verb	last/adj
man/noun	arrested/verb	way/noun	ship/noun	making/verb
mother/noun	working/verb	body/noun	city/noun	music/noun
have/verb	case/noun	dead/adj	world/noun	movie/noun
new/adj	prison/noun	kill/verb	several/adj	shows/verb
go/verb	taking/verb	escape/verb	help/noun	band/noun
son/noun	office/noun	leaves/verb	war/noun	play/verb
young/adj	officer/noun	sees/verb	explains/verb	playing/verb
home/noun	evidence/noun	kills/verb	crew/noun	following/verb
friend/noun	place/noun	discovers/verb	small/adj	series/noun
love/noun	stolen/verb	gets/verb	plan/noun	song/noun

b. Female				
Family	Crime	Shopping	Suicide	Plot Narration
male/characters	find/verb	store/noun	suicide/noun	other/adj
is/verb	finds/verb	park/noun	commit/verb	movie/noun
be/verb	men/noun	middle/noun	pills/noun	begins/verb
father/noun	killed/verb	homeless/adj	sleeping/verb	including/verb
has/verb	police/noun	mall/noun	overdose/noun	school/noun
tells/verb	group/noun	shopping/noun	committing/verb	are/verb
man/noun	kill/verb	grocery/noun	attempted/verb	people/noun

**Table A1.** Cont.

family/noun	car/noun	cashier/noun	commits/verb	story/noun
time/noun	death/noun	shopping/verb	volunteer/verb	team/noun
wife/noun	tries/verb	bench/noun	shaken/verb	world/noun
life/noun	way/noun	department/noun	contemplating/verb	same/adj
new/adj	escape/verb	aged/adj	contemplates/verb	women/noun
have/verb	dead/adj	convenience/noun		sees/verb
mother/noun	using/verb	amusement/noun		high/adj
take/verb	room/noun	clearing/verb		made/verb
get/verb	kills/verb	liquor/noun		making/verb
go/verb	discovers/verb	hardware/noun		many/adj
own/adj	killing/verb			ends/verb
friend/noun	body/noun			called/verb
takes/verb	causing/verb			show/noun

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