

Social network analysis of manga: similarities to real-world social networks and trends over decades

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Abstract

Manga, Japanese comics, has been popular on a global scale. Social networks among characters, which are often called character networks, may be a significant contributor to their popularity. We collected data from 162 popular manga that span over 70 years and analyzed their character networks. First, we found that many of static and temporal properties of the character networks are similar to those of real human social networks. Second, the character networks of most manga are protagonist-centered such that a single protagonist interacts with the majority of other characters. Third, the character networks for manga mainly targeting boys have shifted to denser and less protagonist-centered networks and with fewer characters over decades. Manga mainly targeting girls showed the opposite trend except for the downward trend in the number of characters. The present study, which relies on manga data sampled on an unprecedented scale, paves the way for further population studies of character networks and other aspects of comics.

Keywords: manga, character networks, temporal networks

1 Introduction

The global comic market has been rapidly growing. The market size was valued at USD 14.7 billion in 2021 and is expected to expand at a compound annual growth rate of 4.8% from 2022 to 2029 [1]. A driving force underlying the rapid expansion of the market is the widespread availability of e-books, which enables us to easily access comics around the world. The COVID-19 pandemic also helped the growth of the comic market because the lockdown in many countries increased the demand for comics. Manga, Japanese comics, has been especially popular on a global scale. Many manga have been translated into different languages. For example, over 510 million copies of *One Piece* have circulated worldwide; *One Piece* is recorded in the Guinness Book of Records as the best-selling comic in the history [2]. The history of the development of manga culture in Japan, its social background, and its global prevalence have been studied [3–5].

Our social networks are complex but characterized by common properties such as heterogeneity and community structure [6, 7]. Because literally all storylines of manga rely on interactions among characters, social networks among characters, which are often called character networks, may provide a backbone of the story of manga and influence its popularity. More generally, character networks have been analyzed for quantitatively characterizing fiction works [8, 9]. A number of problems can be addressed through analyses of character networks, such as summarization [10, 11], classification [12, 13], and role detection [14, 15]. Character networks have been studied for a variety of fiction such as novels [13, 16–20], plays [21–24], movies [15, 25–27], and TV series [11, 25, 28–30]. However, character networks for comics have been rarely explored except for Marvel comics [31, 32], a graphic novel [33], and a few manga titles [34]. One possible reason for this is the difficulty of automating data collection for comics [8].

In the present study, we analyze character networks of 162 popular Japanese manga that span decades and test the following two hypotheses. First, we expect that popular manga tend to produce realistic social networks. Therefore, we hypothesize that structural and temporal properties of the character networks of manga are similar to those of human social networks. Second, our data enables us to investigate how trends of manga have changed over approximately 70 years. Therefore, we hypothesize that character networks of modern manga and old ones are systematically different. We also examine differences in the network structure between manga mainly targeting boys versus girls.

2 Results

2.1 Similarities to empirical social networks

Our original data are equivalent to a temporal bipartite graph in which the two types of nodes are characters and pages, and the edges connect characters to the pages in which they appear. The pages are ordered in time. We show the degree distribution for the character nodes for *One Piece* and the Poisson distribution with the same mean in Fig. 1A. The coefficient of variation (CV), which is defined as the standard

deviation divided by the average, of the original degree distribution is 1.66. This value is approximately 11.1 times larger than that of the Poisson distribution. Therefore, similar to human social networks [6, 7], the characters in manga have heterogeneous numbers of connections, and there are a small number of characters that appear disproportionately frequently on various pages. We obtained similar results for the other manga (see SI file).

In contrast, the CV of the degree distribution for the page nodes is 0.478 for *One Piece*. The CV for the Poisson distribution with the same mean is 0.592. Therefore, we argue that the characters do not appear uniformly randomly over the pages. As we show in Fig. 1B, there are typically two or three characters on a page in *One Piece*, and pages containing none or just one character are relatively rare. We obtained similar results for the other manga (see SI file). These results suggest that the high heterogeneity of the characters in terms of the frequency of appearance on pages and the tendency of a page typically containing two or three characters are two common properties of manga. Therefore, in the following analyses, we consider the bipartite configuration model, in which the degrees of all character and page nodes are preserved and the edges are otherwise randomly placed, as a null model. Then, we examine properties of character networks that we can explain by the null model versus those we cannot.

We show the weighted character network, which is the projection of the bipartite graph onto the space of character nodes, for *One Piece* in Fig. 2 (see SI Fig. S1 for the networks for all 162 manga). By definition, the edge weight is equal to the number of pages in which the two characters simultaneously appear. The character networks vary widely in size from manga to manga. Specifically, the number of nodes, N , ranges from 8 to 124, with mean $\pm$ standard deviation = 32.6 ± 16.6 . The number of edges, M , ranges from 19 to 950, with mean $\pm$ standard deviation = 156.1 ± 128.9 . We define the protagonist as the node with the largest node strength (i.e., weighted degree) in the character network. The protagonist is the character that appears in the largest number of pages for most manga (97.5%). In fact, the protagonist for *One Piece*, indicated by

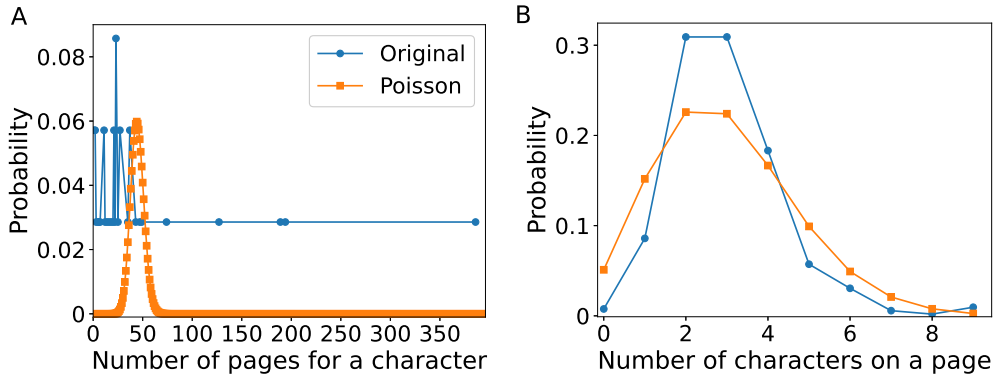


Fig. 1 Degree distribution for the (A) character and (B) page nodes in the bipartite graph for *One Piece*. We also show the Poisson distributions with the same mean.

99 an arrow in Fig 2, is *Monkey D. Luffy*, who is generally known as the most central
 100 character in *One Piece*.

101 We compared various properties of character networks between the empirical char-
 102 acter networks and their randomization obtained by the one-mode projection of the
 103 bipartite network generated by the bipartite configuration model. We first compare
 104 three strength-related indices, i.e., the average strength, $\langle s \rangle$, the CV of the strength,
 105 s_{CV} , and the strength of the protagonist, s_P , of the character networks for all 162
 106 manga between the original and randomized networks in Figs. 3A-C. These figures
 107 suggest that randomized character networks well explain the strength-related indices
 108 of the original character networks.

109 Figure 4A shows the strength distribution for *One Piece*. We find that the strength
 110 obeys a heavy-tailed distribution over some scale. This result is consistent with Fig. 3B,
 111 which shows that the CV of the strength for most manga is substantially larger than
 112 1; the CV for *One Piece* is 1.48. Note that the exponential distribution, which lacks a
 113 heavy tail, yields $CV = 1$. The heavy-tailed strength distributions shown in Fig. 4A
 114 for *One Piece* and implied in Fig. 3B for a majority of manga are consistent with those
 115 for empirical social networks [35, 36].

116 In contrast to the strength-related indices, the randomized character networks do
 117 not explain the degree-related indices of the original character networks. The random-
 118 ized networks tend to overestimate the average degree, $\langle k \rangle$, of the original character
 119 networks (see Fig. 3D). This result suggests that characters tend to repeat inter-
 120 acting with relatively few characters. The CV of the degree, k_{CV} , for the original
 121 networks tends to be larger than that for the randomized networks (see Fig. 3E). The
 122 fraction of the other characters that the protagonist is adjacent to, $k_P/(N - 1)$, is
 123 0.900 ± 0.103 (mean $\pm$ standard deviation based on the 162 manga) and 0.971 ± 0.0413

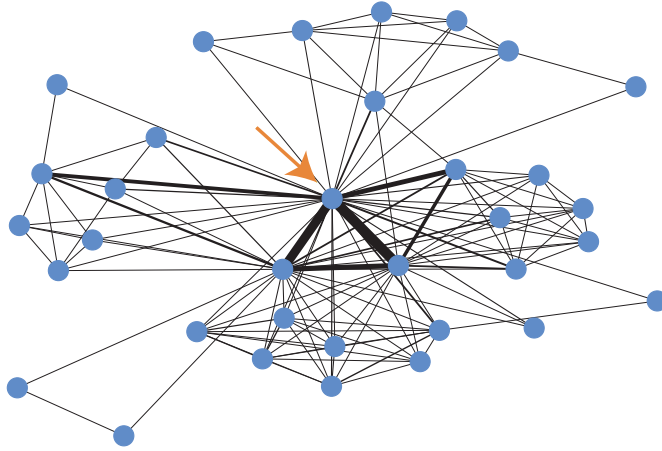


Fig. 2 Character network for *One Piece*. The thickness of an edge is proportional to the weight of the edge. The node with an arrow represents the protagonist, *Monkey D. Luffy*.

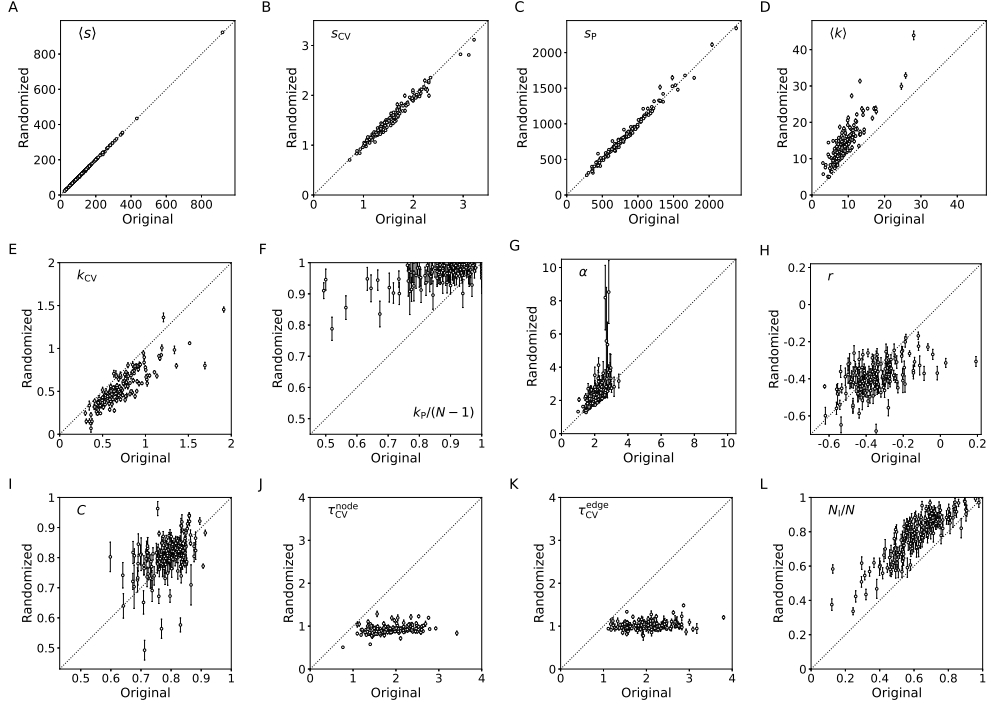


Fig. 3 Comparison between the original and randomized character networks for 162 manga. For the randomized networks, we show the mean and standard deviation on the basis of 1,000 realizations by the circle and error bar, respectively. (A) $\langle s \rangle$: average node strength. (B) s_{CV} : CV of the node strength. (C) s_p : strength of the protagonist. (D) $\langle k \rangle$: average degree. (E) k_{CV} : CV of the degree. (F) $k_p/(N-1)$: normalized degree of the protagonist. (G) α : coefficient in the relationships between the degree and strength, i.e., $s_i \propto k_i^\alpha$. (H) r : degree assortativity coefficient. (I) C : clustering coefficient. (J) τ_{CV}^{node} : CV of IETs on nodes. (K) τ_{CV}^{edge} : CV of IETs on edges. (L) N_I/N : final epidemic size (i.e., fraction of infected nodes at the last time step).

for the original and randomized character networks, respectively (see Fig. 3F). Therefore, the protagonist is adjacent to most of the other characters in both original and randomized networks. Based on these results, we conclude that the character networks are strongly protagonist-centered, in which the protagonist interacts with most of the other characters, while other characters tend to interact only with fewer characters than expected for the randomized networks, but including the protagonist. This interpretation is consistent with the aforementioned observation that $\langle k \rangle$ and k_{CV} are smaller and larger for the original than randomized networks, respectively.

We show the degree distribution for *One Piece* in Fig. 4B. The CV of the degree, k_{CV} , for *One Piece* is 0.77. Figure 3E shows that the CV of the degree for most of the manga is smaller than 1. In fact, this result is consistent with that for empirical social networks with similar number of nodes [37, 38], while large empirical social networks tend to have heavy-tailed degree distributions implying a large CV [39, 40].

137 We found that the strength is super-linearly scaled with the degree, i.e., $s_i \propto k_i^\alpha$
138 with $\alpha > 1$, in the character networks, where $\propto$ indicates “proportional to”. Note that
139 the absence of correlation between the strength and degree would yield $\alpha = 1$ [35].
140 Specifically, in Fig. 4C, we show the relationship between k_i and s_i for *One Piece*.
141 We obtained $\alpha = 1.94$ with the coefficient of determination $R^2 = 0.847$. We obtained
142 similar results for the other manga (see Fig. 3G). These results are consistent with
143 power-law relationships between the strength and degree with $\alpha > 1$, which has been
144 observed in empirical social networks [35, 41]. Note that the randomized character
145 networks also yield $\alpha > 1$ and that α for the original and randomized networks are
146 highly correlated with a small number of exceptions.

147 The character networks are disassortative. The degree assortativity coefficient,
148 denoted by r , of the character network is -0.345 on average. In fact, the values of r
149 for all but two manga are negative (see Fig. 3H). This result is in stark contrast with
150 various observations that social networks are more often than not assortative with positive
151 r [42, 43]. We argue that the character networks are disassortative because they
152 are strongly protagonist-centered. In fact, star graphs are disassortative with large
153 negative values of r [44, 45]. The degree disassortativity is also observed for empirical
154 egocentric social networks [46, 47]. Figure 3H indicates that r is also negative for the
155 randomized character networks although the correlation between r for the original and
156 randomized networks is low. Therefore, we conclude that the degree disassortativity
157 in our character networks is a consequence of the protagonist-centered nature of the
158 original character-page bipartite network.

159 The character networks are highly clustered. The clustering coefficient, denoted by
160 C , over the different manga is 0.790 with the minimum value of 0.598 (see Fig. 3I).
161 This result is consistent with the observations that empirical social networks have
162 high clustering coefficients [48, 49]. In fact, randomized character networks also have
163 similarly large C although the spread is large between the empirical and randomized
164 networks. Therefore, we conclude that a high clustering coefficient is a consequence of
165 one-mode projection of the bipartite graph, which is known [50, 51].

166 We found that heavy-tailed distributions of interevent times (IETs) are simulta-
167 neously present for nodes and edges in the character networks. Copresence of two
168 characters on a page defines a time-stamped event on the edge, where we identify the

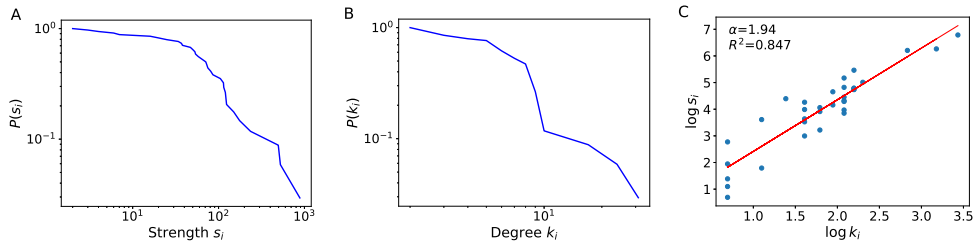


Fig. 4 Strength and degree distributions for the characters in *One Piece*. (A) Strength distribution. (B) Degree distribution. (C) The relationship between the degree and strength. Each circle represents a character. The coefficient α is determined by the linear regression $\log s_i = \alpha \log k_i + b$, where b is an intercept; the solid line shows the linear regression. Variable R^2 represents the coefficient of determination.

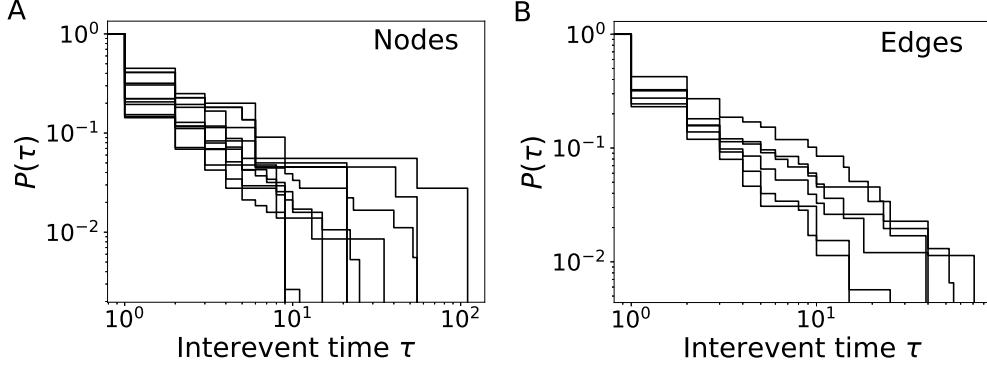


Fig. 5 Survival function, $P(\tau)$, of IETs on (A) nodes and (B) edges for *One Piece*. Each line in (A) and (B) corresponds to a node and an edge, respectively. We only considered nodes that had at least 100 events and edges that had at least 50 events for (A) and (B), respectively.

page number as discrete time. A time-stamped event for a given node is the presence of the character on a page. We show the survival functions of the IETs (i.e., probability that the IET, denoted by τ , is larger than the specified value) for individual nodes and edges in *One Piece* in Figs. 5A and 5B, respectively. The relatively slow decay in Fig. 5 suggests heavy-tailed distributions for both nodes and edges across some scales of τ . The CV values for IETs on nodes and edges for *One Piece* are 1.72 ± 0.697 and 1.92 ± 0.535 , respectively. We obtained similar results for the other manga, as we show in Figs. 3J and 3K. These figures also indicate that the randomization of the bipartite network does not preserve this feature, yielding CV values close to 1 regardless of the CV value for the original temporal character networks. It should be noted that a Poisson process produces an exponential IET distribution, which yields $CV = 1$. These results support that IETs for nodes and edges in the original character networks are non-Poissonian and heterogeneously distributed, which is consistent with properties of empirical social networks [52].

Related to heavy-tailed IET distributions, we found that epidemic spreading occurs more slowly in the temporal character networks than in randomized counterparts. We ran the susceptible-infectious (SI) model. By assumption, an infectious character independently infects each susceptible character coappearing on the same page with probability $\beta = 0.2$. We ran the SI dynamics N times, with the i th character being the only initially infectious one in the i th run. For *One Piece*, we show in Fig. 6 the time course of the fraction of the infectious characters averaged over the N runs. We also show the corresponding averaged time courses for each of the 1,000 randomized temporal networks by the blue lines. Figure 6 indicates that the infection occurs more slowly in the original temporal network than in the randomized temporal networks. We obtained similar results for the other manga (see Fig. 3L). These results are qualitatively the same as those observed for empirical social temporal networks [53, 54].

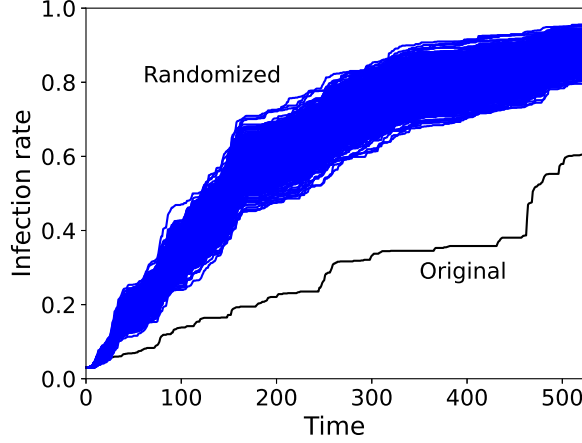


Fig. 6 Time courses of the fraction of infectious characters for the original temporal network and 1,000 randomized temporal networks for *One Piece*. We used the SI model starting from one initially infectious character. Each curve represents the average time course of the fraction of infectious characters over N runs. We set the infection probability per contact event to $\beta = 0.2$.

2.2 Trends of network structure over decades

The 162 manga span nearly 70 years, from *Astro Boy* with the first volume being published in 1952 to *Jujutsu Kaisen* in 2018 (see SI file for detailed information on the 162 manga). The trend of the structure of manga character networks may have changed over the ≈ 70 years, reflecting the transitions of Japanese society including in economics and fashion. In this section, we explore possible existence of such trends.

We first calculated the Pearson correlation coefficient between the year of publication of the first volume, denoted by y , and various indices of network structure on the basis of all 162 manga. We show the correlation coefficients and their 95% confidence intervals (CIs) in Fig. 7A. We find that the number of characters, N , tends to decrease over decades (i.e., negative correlation between N and y). The CV of the node degree, k_{CV} , and that of the node strength, s_{CV} , are negatively correlated with y with moderate effect sizes. In general, these and other network indices may be affected by the number of nodes, N [55]. Therefore, we also examined the partial correlation coefficient between y and each index by partialing out the effect of N . The results of the partial correlation coefficient for k_{CV} and s_{CV} , shown by the lines with squares in Fig. 7A, are consistent with those of the Pearson correlation coefficient, although the partial correlation is closer to 0 than the Pearson correlation. We also find that the average degree, $\langle k \rangle$, is positively correlated with y in terms of the partial correlation. These results suggest that more recent manga tend to be denser and more homogeneous in the node's connectivity, such that various characters, not just the protagonist, tend to have more connections in more recent manga.

How the trend of the character network changes over time may depend on genres of manga. A most major categorization of Japanese manga is the one based on the gender of their main readership [57, 58]. Therefore, we classify the 162 manga into 124 boys' and 38 girls' manga based on the genre section on their Wikipedia pages (see

SI file for the genre of each manga), while their classification is necessarily subjective. We show the Pearson and partial correlation coefficients between each index and y , separately for the boys' and girls' manga in Figs. 7B and 7C, respectively.

We find that there tend to be less characters for more recent manga for both boys' and girls' manga. The boy's and girls' manga are different in the following aspects in terms of the partial correlation coefficients, i.e., when we control for the number of characters. The trends that we identified for all the 162 manga are even more pronounced in the boys' manga. The effect sizes of the partial correlation for $\langle k \rangle$, k_{CV} , and s_{CV} for the boys' manga are larger than those for the 162 manga. In addition, the degree assortativity coefficient, r , is positively correlated with y . Because r is negative for most manga, this result implies that r tends to be closer to 0 for more recent boys' manga. On the other hand, the two protagonist-related indices, i.e., $k_P/(N-1)$ and s_P , are not correlated with y . These results suggest that the character networks in more recent boys' manga tend to be less protagonist-centered, in which non-protagonist characters have more connections among them.

The trend for the girls' manga is opposite to that for the boys' manga except that the downward trend in the number of characters is common. The two indices for which the partial correlation was negative for the boys' manga, i.e., k_{CV} and s_{CV} , are positively correlated with y for the girls' manga in terms of the partial correlation. On the other hand, the two indices for which the partial correlation was positive for the boys' manga, i.e., $\langle k \rangle$ and r , are negatively correlated with y for the girls' manga. Furthermore, the normalized degree of the protagonist, $k_P/(N-1)$, for which we did not confirm a correlation for the boys' manga, is positively correlated with y . Overall, these results indicate that the character networks in the girls' manga have shifted toward more protagonist-centered networks.

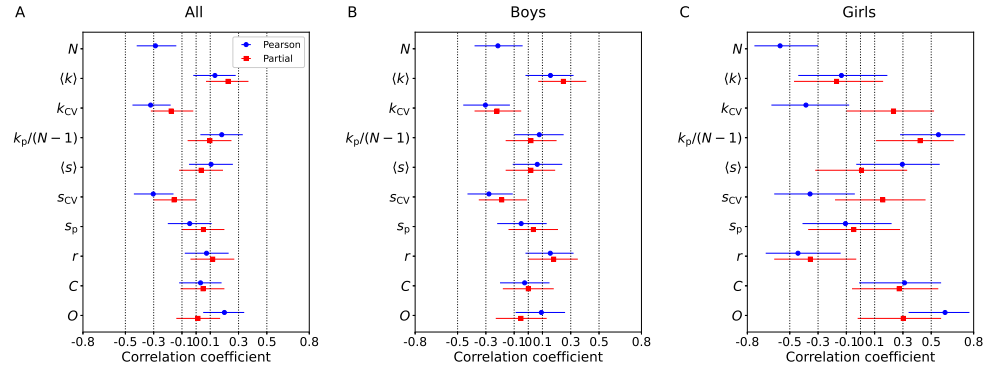


Fig. 7 Correlation between the year of publication of the first volume, y , and indices of network structure. For the partial correlation coefficient, we partial out the influence of the number of nodes. According to a standard, the effect size is said to be large, moderate, or small when the correlation coefficient is > 0.5 , > 0.3 , or > 0.1 , respectively [56]. The horizontal lines indicate 95% confidence intervals. N : number of nodes, $\langle k \rangle$: average degree, k_{CV} : CV of the degree, $k_P/(N-1)$: normalized degree of the protagonist, $\langle s \rangle$: average strength, s_{CV} : CV of strength, s_P : strength of the protagonist, r : degree assortativity coefficient, C : clustering coefficient, and O : temporal correlation coefficient.

3 Discussion

We found that the empirical character networks have various features consistent with empirical social networks. The bipartite configuration model, which is a standard random bipartite graph, has been shown to be reasonably accurate at explaining some features of the empirical character networks including statistics of the node’s strength, α values, disassortativity, and the high clustering coefficients. In contrast, there are other features of the empirical character networks that deviate from the expectation from the bipartite configuration graph. Such features include statistics of the degree, the IET distributions, and speeds of epidemic spreading. We suggested that part of these differences originates from the protagonist-centered nature of the character networks. In other words, the protagonist interacts with most characters, while non-protagonist characters tend to interact only with the protagonist and a smaller number of other characters than expected by the configuration model. There are positive support of protagonist-centered social networks in the real world when the network is egocentric [46, 47].

Similarities between character networks and human social networks have been investigated for some fictions such as Marvel comics [31, 32], a graphic novel [33], Shakespeare’s plays [22], and myths [59]. Our results of the high clustering coefficient and the heavy-tailed distribution of the strength in the character networks are consistent with these previous studies. However, we ascribe the high clustering coefficient to the effect of one-mode projection rather than to similarity to empirical social networks because the randomized character networks also have high clustering. Our results of the disassortativity is also consistent with the results for Marvel comics [32], a graphic novel [33], and myths [59]. Therefore, we infer that the heavy-tailed distribution of the strength and disassortativity in the character networks are common properties for various types of fictions. Although the aforementioned previous studies investigated only the static properties of the character networks, we further revealed temporal properties of the character networks, such as the long-tailed IET distributions, which are in fact consistent with empirical social networks [52–54].

We also found that the trend of the manga character networks has shifted over decades. Specifically, more modern manga tend to have fewer characters, denser and be less protagonist-centered for the boys’ manga, which may reflect a modern change in the society that places more emphasis on diversity and teamwork [60, 61]. In contrast, the character networks in the girls’ manga have shifted toward more protagonist-centered, although the downward trend in the number of characters is common. In general, girls’ manga in Japan tend to revolve around issues of love and friendship with a focus on inner feelings of the protagonist [58, 62]. Our results suggest that more recent girls’ manga may describe the relationships between the protagonist and a few other characters in depth.

There are many future directions of investigation. First, we focused on 162 manga with high circulations. By analyzing manga with low circulation as well, we may be able to discover static and temporal properties of character networks that readers favor, contributing to understanding why some manga are more popular than others. Second, we analyzed only the first three volumes of each manga. Examining all volumes would allow us to understand the narrative structure, which have been analyzed

for novels [20], movies [15], and TV series [25]. For this purpose, a wide variety of time series and temporal network analysis tools, such as change-point detection, temporal centrality, and temporal community structure, may be useful [63–65]. Third, character networks are probably signed in most cases, connecting characters by positive or negative ties. It is worth to deploy sentiment analysis based on text [19] and facial expressions [66] to construct and analyze signed networks of characters in manga. Temporal network analysis of signed character networks may also reveal complicated dynamics of relationships among characters (e.g., an enemy later becomes an ally). Fourth, manga in different genres such as action, adventure, sports, and comedy, may have different structures of character networks. In addition, we have only analyzed the manga that have been published in the paperback pocket edition, which is the most common for the boys’ and girls’ manga in Japan. Analyzing manga of other sizes may help us understand variation of character networks over a wider range of genres. Fifth, studying character networks in comics in countries other than Japan warrants future work. For example, character networks may reflect societal differences from country to country.

In conclusion, to the best of our knowledge, the present study of character networks for 162 manga titles is unprecedented in scale in quantitative studies of comics and has enabled us to discover their general features. We also introduced new tools and views to the analysis of fiction character network data, such as the bipartite configuration model, the concept of protagonist-centeredness, and temporal network analysis. We hope that this study triggers further quantitative studies of character networks in manga and other types of fictions.

4 Methods

4.1 Data collection

We focus on manga of which more than 10 million copies have been published in Japan as of January 2021 [67]. Since the physical size of the manga may affect the number of panels per page and we adopted the page as the unit of analysis, we excluded the manga that had not been published in the paperback pocket edition (112 mm × 174 mm). Note that the paperback pocket edition is the most common for the boys’ and girls’ manga in Japan. As a result, we included 162 manga (see SI file for the list of the 162 manga).

We prepared a data table of time-stamped copresence of characters for each manga as follows. For each manga, we manually examined volumes one through three. All the selected 162 manga had at least three volumes. Then, we first extracted all the characters whose name, blood relation to a named character, or job title that uniquely identifies the character, is known. To ensure the reproducibility of this work, we avoided to use any other information sources (e.g., other volumes of the same manga, the Internet, or anime) to attempt to identify more characters. In practice, such additional information sources would not contribute to identifying many more characters. Second, we recorded the copresence of characters on each page as interaction between the characters. Note that the copresence is the most common definition of interaction in constructing character networks in fictional works [8]. We used copresence on

334 a page rather than in a single panel within a page because it is common that charac-
 335 ters appearing in different panels on the same page have some interactions (e.g., two
 336 characters talk to each other by using alternately occupying successive panels).

337 4.2 Bipartite configuration model

338 The original data from which we construct the temporal and static character networks
 339 are equivalent to a temporal bipartite graph in which the two types of nodes are
 340 characters and pages, and an edge connects a character and a page in which the
 341 character appears. To generate a randomized bipartite network, we choose a pair of
 342 edges in this bipartite graph uniformly at random, denoted by (c, p) and (c', p') , where
 343 c and c' are characters and p and p' are pages. If c and c' are the same or p and p' are
 344 the same, we discard the pairs and redraw them. Then, we rewire the two original edges
 345 to (c, p') and (c', p) . We repeat this procedure 1,000 times excluding the discarded
 346 edge pairs to generate a randomized temporal bipartite network. We construct a static
 347 randomized character network from the generated randomized bipartite graph by one-
 348 mode projection. In other words, we connect two characters by an edge whose weight
 349 is the number of pages on which the two characters are copresent.

350 4.3 SI model

351 We use the SI model [68] to numerically investigate contagion. We assume that just
 352 one character is initially infectious and that the other $N - 1$ characters are initially sus-
 353 ceptible. If a susceptible character co-appears with an infectious character on a page,
 354 the susceptible character becomes infectious with probability β . Different infectious
 355 characters appearing on the same page independently attempt to infect each suscep-
 356 tible character on the page. Once a character contracts infection, it stays infectious
 357 forever. We run the SI dynamics with each of the N characters as the sole character
 358 that is initially infectious.

359 4.4 Temporal correlation coefficient

We quantify the persistence of edges over time by the temporal correlation coefficient
 [69, 70]. First, we calculate the topological overlap for node i at time t by

$$O_{it} = \frac{\sum_{j=1}^N A_{ij}^t A_{ij}^{t+1}}{\sqrt{\sum_{j=1}^N A_{ij}^t \sum_{j=1}^N A_{ij}^{t+1}}}, \quad (1)$$

where A_{ij}^t is the adjacency matrix of an unweighted network at time step t . In other
 words, $A_{ij}^t = 1$ if characters i and j are copresent on page t , and $A_{ij}^t = 0$ otherwise.
 We then define the average topological overlap for node i by

$$O_i = \frac{1}{T-1} \sum_{t=1}^{T-1} O_{it}, \quad (2)$$

where T is the number of pages. The temporal correlation coefficient for the entire temporal network is given by

$$O = \frac{1}{N} \sum_{i=1}^N O_i. \quad (3)$$

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Data availability. The datasets generated during and/or analysed during the current study are available in the GitHub repository, <https://github.com/KS-92/Manga>.

Authors' contributions. N.M. conceived the research; K.S. and N.M. designed the research. K.S. collected and analyzed the data; K.S. and N.M. discussed the results and wrote the paper.

Competing interests. The authors declare no competing financial or non-financial interests.

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