1. Using Shakespeare to Answer Psychological Questions:
2. Complexity and Mental Representability of Character Networks
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## Abstract

1. Theatre plays are a cultural product that can be used to learn about the capacity of human cognition.
2. We argue that Kolmogorov complexity may be suited to operationalize the demand that is put onto a
3. recipient's cognitive system to represent the character system of a play with sufficient detail and
4. accuracy to follow the narrative. We analyse Shakespeare’s plays and European Drama by means of
5. network analysis in four studies: In Study 1, we use Shakespeare's plays to estimate an approximate
6. limit of complexity of character networks that humans can mentally represent. In Study 2, we
7. investigate where the approximated limit lies in relation to the overall distribution of complexity in
8. European plays. In Study 3, we focus on how complexity and the total number of speaking characters
9. in the plays relate in European theatre plays. In Study 4, we analyse the robustness of network
10. complexity across researcher degrees of freedom using Shakespeare’s plays. We show how research
11. on social networks can be conducted in a reproducible, transparent way, especially when relying on
12. cultural products such as literary works.
13. Cultural products can be productively used to learn about the functioning of the human mind and
14. other psychological processes (Baumard et al., 2023; Dunbar, 2005; Gessey-Jones et al., 2020;
15. Graesser et al., 1999; Krems & Dunbar, 2013; Stiller et al., 2003). This idea is not novel, but we see a
16. lot of yet untapped potential for synergies between cultural studies, such as literature analysis, and
17. psychology.
18. Literary works, such as theatre plays, can be seen as closed worlds that result in self-contained
19. datasets, for example, on character networks (Labatut & Bost, 2019). We will show how such data,
20. together with information about their reception, can provide insights into the capacities of human
21. cognition in a transparent and fully reproducible manner. The main inspiration for the current project
22. was Stiller et al. 's (2003) investigation of 10 of Shakespeare’s plays to learn about the upper bound of
23. the human cognitive system when it comes to the representation of social networks from these plays.
24. They suggested that the number of characters, the clustering of the characters, and the average path
25. length properties of the extracted networks can be used to infer the upper bound of humans’ cognitive
26. systems. In this article, we follow this idea and show how information extracted from theatre plays
27. can yield insights into the representability of social networks and the bounds of human cognition.
28. Ideally, we could use a direct measure of the demand put onto a cognitive system to represent a
29. character network in a way that allows a recipient to follow a narrative. We are not aware of any such
30. direct measure. To estimate this demand indirectly, one potential candidate that prior research often
31. employed is the size of the network. The size of social groups, also known as Dunbar's number
32. assumes an upper limit of social actors that one can represent (Dunbar, 2009; Hill & Dunbar, 2003).
33. Researchers have found that the group sizes in Shakespeare’s plays mirror those of real-world social
34. networks (Stiller et al., 2003; Stiller & Hudson, 2005). The theory of Dunbar’s number, however, has
35. been strongly criticised (Lindenfors et al., 2021). Here, we do not focus on the possibility of a general,
36. universal limit of human’s capacity to represent social networks. Instead, we restrict ourselves to the
37. representation of social networks that unfold over the duration of a play, noting that for other types of
38. networks more cognitive resources may be available (e.g., for the representation of one’s own
39. friendship network across life).
40. Kolmogorov complexity (Kolmogorov[, 1965](https://link.springer.com/article/10.3758/s13428-015-0574-3" \l "ref-CR49); Chaitin[, 1966](https://link.springer.com/article/10.3758/s13428-015-0574-3" \l "ref-CR12)), also known as algorithmic complexity,
41. offers an alternative approach to estimate the demand that is put onto a cognitive system to represent a
42. character network. In contrast to, for example, the number of nodes and measures that are closely tied
43. to specific network characteristics (entropy measures; see Morzy et al., 2017; Butts, 2001; Zenil et al.,
44. 2017), Kolmogorov complexity (complexity from now on) offers a more robust and generalised
45. measure by expressing the length of the shortest possible computer program that produces a certain
46. object (e.g., a network matrix) and then halts. Complexity is not directly computable but can be
47. approximated various ways (e.g., Gauvrit et
48. al., 2016; Zenil,

et al., 2018). To our knowledge, complexity has not yet been applied to character networks extracted

1. from theatre plays[[1]](#footnote-1). In our case, we are interested in the complexity of adjacency matrices of undirected
2. and unweighted character networks. In these matrices, the headers of columns and rows represent
3. characters; the cells represent ties.; A a tie between two characters is represented by a 1 and the absence of
4. a tie by a 0. A more complex adjacency matrix would require a longer computer program to be reproduced
5. than a simpler adjacency matrix (for a thorough introduction into complexity, see Gauvrit et al., 2016).
6. In contrast to the operationalization of cognitive capacity and demand in terms of
7. the number of nodes in a network (as in Dunbar’s number), the complexity of character networks allows for
8. the possibility of
9. relatively smaller networks being more demanding (complex) than relatively larger networks. Consider, for
10. example, a play with 20 characters and a mean density of 0.50. Contrast this character network with the one
11. from a play with 350 characters with a mean density of 0.99 and one from a play with 50 characters and a mean
12. density of 1.00 (i.e., all characters form ties). The first network is more complex than the latter two, even though
13. the latter have more characters. Complexity for the first. Complexity also
14. allows for a more fine-grained distinction between networks of equal size.
15. It is, of course, possible that, to follow a narrative, a character network does not need to be
16. represented completely. Our suggested analyses and interpretations nonetheless assume that the
17. complexity of a character network is monotonously and positively related to the demand that is put on
18. a cognitive system to follow the narrative. In support of this assumption, it has been argued that
19. human cognitive systems employ compression algorithms to reduce the amount of information that
20. has to be mentally represented (e.g., Brashears, 2013; Chekaf et al., 2015; Gauvrit et al., 2014;
21. Gauvrit et al., 2016; Planton et al., 2021). Similarly, Butts (2001) suggests that the human brain is an
22. information processor that applies algorithms to store information. The amount of information that
23. needs to be stored, and the demand that is put onto a cognitive system, depends on the complexity of
24. the object. Butts (2001) distinguishes between the complexity of observable social networks and the
25. complexity of the mental representation of social networks. If the goal were to mentally represent an
26. observable social network completely, then the complexity of the representation would match the
27. complexity of the observed network.
28. We base our argument on several key assumptions. First, we assume that the demand on a cognitive
29. system of what someone must represent to follow a play’s narrative is monotonously and positively
30. related to the complexity as quantified by measures of the character networks. In other words, we
31. assume that a play that results in more complex character networks requires greater cognitive capacity
32. to follow the narrative. Second, Labatut & Bost (2019) discuss that the narrative of a play unfolds
33. through the characters, their actions, interactions, and relations. In such modern approaches to
34. literature analysis, character systems are at the core of the narrative. These systems are often
35. represented as character networks in which characters are nodes and their interactions edges. Given
36. this understanding, recipients must be able to represent the character system in a way that allows them
37. to follow the narrative. Third, we assume that plays are more likely to be well-received and popular if
38. they make it possible for recipients to follow the narrative, i.e., represent the character system in a
39. sufficient manner (from now on “representability of character systems”). We do not assume that
40. representable character systems are sufficient or necessary to render a play popular, but we assume
41. that a play being popular is diagnostic for representability. Fourth, we assume that Shakespeare’s
42. plays can be assumed to be relatively popular and well-received and thereby relatively likely to
43. feature character systems that are sufficiently representable to allow for recipients’ following the plot.

## The Present Research

1. This project is divided into four successive studies. The first study will use Shakespeare's plays to
2. approximate a plausible limit to the mental representability of character networks in terms of their
3. complexity. The second study will investigate where the approximated limit lies in relation to a
4. general distribution of complexity in European plays. The third study focuses on the relation of
5. complexity in European theatre plays to the total number of speaking characters in the plays. This will
6. provide us with insights into how the number of characters and the complexity of a character network
7. in a play relate. The fourth study aims to enrich the first and third studies: By constructing the
8. networks for Shakespeare’s plays by several variants we can estimate the impact of researcher degrees
9. of freedom. This leads to estimations about the robustness regarding the results from Study 1 and 3.

## Study 1: Complexity of Sufficiently Representable Character Networks

1. Our first goal is to approximate a plausible limit for the complexity of sufficiently representable
2. character networks. Ideally, we would be able to estimate the upper bound of complexity directly,
3. which is not possible with the current approach. Instead, we intend to select a set of plays for which
4. we can assume that (i) the character networks are sufficiently representable and (ii) representing the
5. character networks and thereby following the narrative is comparatively demanding. As the best
6. candidate for that, we chose Shakespeare's plays. Following our key assumptions, we assume that
7. Shakespeare’s plays are based on their “international, commercial, and critical success for several
8. centuries" (Stiller & Hudson, 2005, p. 60). Thus, they are a valuable starting point for getting a
9. preliminary estimate of the complexity of likely representable character networks (see Stiller et al.,
10. 2003). Importantly, we do not assume that representable character systems are sufficient
11. or necessary, but we assume that a play being popular is diagnostic for representability. By estimating
12. the complexity of each character network of his plays, we extract the distribution of complexity for
13. Shakespeare's plays themself. For a replication of the network characteristics reported in Stiller et al.
14. (2003) and a comparison with estimates derived from the full set of Shakespeare’s plays see
15. Supplementary Material.

## Registered Analysis 1: What is the distribution of complexity in Shakespeare’s plays?

1. We use the data of all 37 existing Shakespeare’s plays from the Shakespeare Drama Corpus
2. (Fischer et al., 2019). This corpus contains pre-processed data with co-occurrence-based character
3. networks (ties are formed between characters who speak in the same text segment—usually a scene;
4. Börner & Trilcke, 2023) and network measures. We will extract the data from <https://dracor.org/> via
5. the “rdracor”-package (Fischer et al., 2019. To calculate complexity, we will use the following approach per character
6. network: We create adjacency matrices with all permutations of nodes (i.e., all orders of characters)
7. for networks with up to 6 nodes and a random sample of unique 1000 permutations for networks with
8. 7 or more nodes. We then extract the lower triangle (excluding the diagonal) for each adjacency
9. matrix (because we use unweighted, undirected networks) and convert these lower triangles to raw
10. strings. To calculate the complexity of these raw strings, we use the memCompress function (from
11. base R) with type = “xz”. The “xz” compression is based on the LZ77 algorithm, which is a modified version of the algorithm used by
12. Butts (2001). Per character network, we will use the lowest complexity (from all calculated
13. permutations). We will describe and visualise the range of complexity in Shakespeare’s plays.

## Study 2: Distribution of Complexities across European Theater Plays

1. Our second goal is to locate where the approximated limit lies in relation to a general distribution of
2. complexity in European plays. Shakespeare is but one of many playwrights. Selecting him as a point
3. of reference was not completely arbitrary, but convincing arguments could be made for many other
4. points of reference. Accordingly, we will now contextualise our first analysis by comparing the
5. distribution of complexities of Shakespeare’s plays with the distribution of complexities across a large
6. corpus of European theatre plays. Our goal is twofold: First, we will describe where Shakespeare’s
7. plays lie in the overall distribution of complexities. Second, we will describe how many plays of the
8. European drama corpus exceed the upper limit of complexity of Shakespeare’s plays.

## Registered Analysis 2: How are the complexities of European theatre plays and Shakespeare’s

1. **plays located to each other?**
2. In addition to the dataset of Shakespeare’s plays above, we extract the complete dataset from the
3. European Drama Corpus (Fischer et al., 2019) via the “rdracor”-package. The entire dataset contains
4. over 3,000 plays. As some plays exist in multiple versions or translations, we will only include the
5. oldest version of each play. We will exclude all librettos (i.e., texts for musical works such as operas,
6. which differ from texts intended for spoken drama in non-trivial ways) and plays with fewer than
7. three speaking characters, for which at most one tie would be possible. Finally, we will only include
8. plays that were segmented based on scenes, i.e., ties were formed within scenes (or equivalent
9. segments). We will extract the co-occurrence-based character networks. We will calculate complexity
10. as described in Study 1.
11. We will visualise the entire complexity distribution and mark the complexity of Shakespeare’s plays.
12. Then, we will calculate the interquartile range of the complexity of Shakespeare’s plays and multiply
13. it by three. We will report how many plays exceed this upper limit. We chose three times the
14. interquartile range, as this is a usual cut-off to detect outliers. Our analysis thus expresses how many
15. plays would be classified as upper outliers when using the complexity of Shakespeare’s plays as a
16. reference. We deem that three times the interquartile range is a liberal criterion that includes the
17. possibility that plays can be more complex than Shakespeare’s plays and still representable. As this
18. analysis is entirely descriptive, we will report a distribution and visualisations.

## Study 3: Number of Characters and Complexity

1. Studies 1 and 2 were purely descriptive and concerned the upper bound of complexity of
2. representability of character systems and the distribution of complexity across plays per se. In study 3,
3. we are interested in how the number of characters in a play relates to the complexity of a play’s
4. network. In Stiller et al. (2003), a particular emphasis was put on Dunbar’s number. The idea behind
5. Dunbar’s number is that there is an upper bound to the number of nodes (here, characters) in social
6. networks imposed by the capacity of human cognitive systems (see above). Whereas it is conceivable
7. that the complexity and the number of nodes are tightly linked, this is by no means necessary. Thus,
8. our goal is to test and understand the relation of the number of characters to the complexity of networks in
9. theatre plays.

## Registered Analysis 3: How does complexity relate to the size of character networks in drama?

1. We will again use the European Drama corpus, applying the same exclusion criteria as described
2. above (see Study 2), but including Shakespeare’s plays. Complexity is the dependent variable, for
3. which we will use two operationalizations:
4. First, we will use the raw complexity as calculated in Study 1. With this operationalization, we stay
5. close to the question regarding the representability of character networks, with the idea being that a
6. more complex network is more difficult to represent. Adding nodes to a network allows for
7. proportionally more ties and greater complexity. Whether playwrights however realize this potentially
8. higher complexity or whether they employ actions that reduce complexity is an open question.
9. We thus explore whether
10. the number of characters positively predicts complexity. The goal is to derive an estimate and
11. recommendations on the often implied link between complexity and the number of nodes, in sort of a

convergent validity perspective.

1. We thus explore whether the number of characters positively predicts complexity. The goal is to derive an
2. estimate and recommendations on the often implied link between complexity and the number of nodes, in
3. sort of a convergent validity perspective. We quantify the relation between complexity and the number of
4. characters by calculating Spearman’s rank correlation coefficient. Spearman’s correlation coefficient
5. measures how well the relationship is captured by a monotonic function based on ranked data. To account
6. for the nested structure of the data (plays nested within authors), we will calculate the multilevel
7. Spearman’s correlation (Makowski et al., 2020). We will calculate the lower border of the 95% CI of this
8. coefficient and compare it to standard benchmarks of test-retest-reliability for the lack of benchmarks for
9. convergent validity (see Allen et al., 2022; Greiff & Allen, 2018). We will interpret the result accordingly:
10. >.90 indicates excellent convergent validity; >.80 indicates good convergent validity; > .70 indicates
11. acceptable convergent validity; and >.60 indicates questionable convergent validity. In addition, we will
12. visually inspect a scatter plot with the number of characters on the x-axis and complexity on the y-axis.
13. Based on this visual inspection, we will further explore, for example, the exact functional form of the
14. relation. We will discuss how the precise pattern (e.g., potential heteroscedasticity) may have affected the
15. correlation.
16. In addition, we will exploratively calculate a standardised complexity by dividing the raw complexity
17. by an approximated maximal complexity given a number of nodes. This standardised measure tells us
18. what proportion of the potential complexity, given a number of nodes, is present in the observed
19. network. The potentially achievable complexity increases with the number of nodes. With this
20. analysis, we investigate possible systematic tendencies to simplify structures with increasing numbers
21. of nodes to counteract the additional demand introduced by adding more nodes.

We will perform the same analyses as for the unstandardized complexity measure.

1. As a further exploration, we investigate what explains the complexity (in both operationalizations)
2. beyond the number of characters. We apply Prediction Rule Ensembles (Fokkema, 2020; Fokkema &
3. Strobl, 2020) to catch more complex relations between the variables. Prediction Rule Ensembles are a
4. machine learning method that results in specific cut-off rules at which a parameter will increase or
5. decrease. We include a range of possible predictors such as the number of time slices, text length, density,
6. average path length, transitivity, as well as contextual information such as year of publication, genre, country, author, and further possible
7. predictors.

## Study 4: Robustness

1. The goal of Study 4 is to estimate how robust results such as the ones from Studies 1 to 3 are to
2. choices that researchers make when they choose a specific route through a garden of forking paths
3. (Gelman & Loken, 2013). The question of whether the results hinge on which route is taken, i.e., how
4. robust the results are, remains to be answered. In the main article, we focus on complexity. In the
5. Supplemental Material, we will extend our analyses to the main topological measures reported in
6. Stiller et al. (2003), thereby replicating and extending some of their key analyses in a reproducible
7. and transparent way.
8. Two researcher degrees of freedom appear particularly crucial in our work: how the play is segmented
9. into time slices, and the criterion for tie-formation. The segmentation of the play into slices, i.e.,
10. discrete temporal units, yields the units in which characters can form ties. How these slices are formed
11. can, therefore, be expected to impact the character networks. Ideally, a slicing method results in units
12. that correspond to the units into which people mentally subdivide the play as it unfolds. Stiller et al.
13. (2003) formed a new time slice "whenever a character was stated or could be inferred to have left the
14. stage" (Stiller et al., 2003, p.399). Since not only exits, but also entrances change the composition of
15. characters on stage, slices may also be formed based on both exits and entrances. A further, arguably
16. more clear and natural way to slice a play may entail simply relying on scenes, as they involve a
17. change of place and time in the play. As Stiller & Hudson (2005) state, a scene “represents a
18. partitioning that is deliberate on the part of the playwright and therefore intended to be perceived as
19. distinct from other observed groupings within the play” (p. 60). Krems & Dunbar (2013) followed
20. such an approach as well when investigating character networks in movies. Please note that slicing a
21. play based on exits and/or entrances automatically results in cuts between scenes. This means that slicing a play by exits and entrances cannot create slices that cross scene-boundaries.
22. A second theoretical decision regards when to form a tie between characters. Stiller et al. (2003) used
23. co-occurrence of speaking characters as a criterion. Importantly, speaking characters were defined by
24. having a line of speech anywhere in the play (not just in the current time slice) which we interpret as a
25. procedure that forms ties regardless of whether a character had already spoken before the current time
26. slice. We will additionally analyse networks for which ties are formed only between characters who
27. speak during a given time slice.
28. The combination of these analytic choices leads to 6 analytic variants listed in Table 1.

# Table 1

1. *Analytic variants.*

|  |  |  |
| --- | --- | --- |
| **Analytic variant** | **Slicing**  **(3 options)** | **Tie formation (2 options)** |
| **1** | Scene | Speech |
| **2** | Scene | Presence |
| **3** | Exit | Speech |
| **4** | Exit | Presence |
| **5** | Exit & entrance | Speech |
| **6** | Exit & entrance | Presence |

1. *Note.* Each analytic variant corresponds to a distinct combination of three factors. The first factor
2. concerns whether time slices are based on (a) on scenes, (b) exits, or (c) exits and entrances of
3. characters. The second factor concerns whether ties during a time-slice are formed based on presence
4. or speech.

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1. The complexity depends on the extraction of a network from a play, and likely varies between the
2. analytic variants in Table 1. We explore how robust the estimation of complexity is with regard to a)
3. the average complexity and b) the order of plays by complexity.

## Registered Analysis 4: How robust are the results with regard to the construction of the

1. **character networks?**
2. As the European Drama Corpus contains pre-processed data, we cannot use it in Study 4. Instead, we
3. construct the character networks of the 37 Shakepeare’s plays ourselves to estimate the influence of
4. analytical variants (see Research Question 3). We extract data from all 37 surviving Shakespeare
5. plays from the English Corpus from https://github.com/severdia/PlayShakespeare.com-XML[2](#_bookmark0).
6. According to their documentation, these texts are based on the First Folio of 1623 (and Quartos where
7. applicable) of Shakespeare's plays.
8. We wrote code for preprocessing Shakespeare’s plays and to construct the networks (see R scripts
9. available at https://osf.io/xunym/ ). In this pre-processing, we decided to drop ties in which “ALL.”
10. characters speak at once, as this does not add information about the complexity of the network. We
11. will calculate the complexity as described in Study 1.
12. To estimate how complexity is affected by researcher decisions about slicing and tie formation, we
13. will inspect two outcome variables for all analytic variants a) the average complexity and b) the order
14. of plays by complexity. To estimate whether the analytic variants affect the average complexity of the
15. 37 plays by Shakespeare we will run an ANOVA with slicing, tie formation, and their interaction as
16. independent variables. If the ANOVA is non-significant, we will interpret the 95% confidence
17. interval for the generalised eta-square. If the 95% confidence interval excludes the upper bound of
18. 0.01 we will deem this as evidence that the analytic variants do not affect average complexity. We

2 We edited two passages in the dataset manually: The file "ps\_henry\_vi\_pt2.xml" had a small error on line 5003. We fixed the error by including the directions on line 5003 on line 5002. We found the same error on line 5418 and fixed it analogously. For the full specification of the XML-encoding see this documentation: https://github.com/severdia/PlayShakespeare.com- XML/blob/master/PlayShakespeare-XML-Specification.pdf

1. chose this effect size, as this is the common interpretation of a small effect, and as we do not have
2. prior information about effects of the analytical variants.
3. To explore how strongly the analytic variants affect the order of the plays by complexity, we will
4. calculate Spearman’s rank correlation coefficients between complexities for all pairs of analytic
5. variants. We will plot and describe the distribution of correlation coefficients. Relatively lower
6. correlation coefficients indicate that the analytic choices exert a larger influence on the order of
7. complexities. A wide range of correlation coefficients would mean that analytic choices have
8. heterogeneous effects on the order of complexities.

## Bias Control

1. We have taken stringent steps to reduce our risk of bias: First, we often report descriptive statistics
2. instead of inferential tests. Second, by employing a battery of reproduction specifications in Study 4,

we conduct a comprehensive robustness test. Third, we have so far only accessed the Shakespeare data and have not calculated complexity for any of the data that will be used for our analyses. In addition, we have not yet accessed the dracor data on which a large part of our analyses will be based.

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# Transparency and Openness

1. We report all data exclusions and all measures in this study. The analytic scripts will be available on
2. the Open Science Framework. Data will be analysed using the R software environment (R Core Team,
3. 2021). The full syntax will be freely accessible on OSF. The current version is available at
4. https://osf.io/xunym/. By providing a computationally reproducible R-Markdown, independent

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researchers can follow each step.

## Table 2

1. Analyses and interpretation of all Research Questions.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Question** | **Sampling plan** | **Analysis Plan** | **Robustness checks** | **Interpretation given different outcomes** | **Theory that could be shown wrong by the outcomes** |
| What is the distribution of complexity in Shakespeare’s plays? | Pre-processed network data for all 37 Shakespeare’s plays from European Drama Corpus | calculate complexity | See Study 4 | Purely descriptive | - |
| How are the complexities of European theatre plays and Shakespeare’s plays located relative to one another? | Network of 37 plays from Shakespeare versus European plays excluding librettos, plays with <3 speaking characters and plays for which ties were not based on scenes | Interquartile Range (IQR) of complexity of Shakespeare’s plays \* 3 vs. complexity of other plays | See Study 4 | Plays within 3\*IQR are similar enough to Shakespeare’s plays in terms of complexity. Plays above 3\*IQR represent outliers of high complexity. We describe the proportions within and outside of 3\*IQR. | - |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| How does complexity relate to the size of character networks in drama? | Networks for European plays including English Shakespeare (same exclusion criteria as above) | 1. Multilevel correlation between raw complexity and number of nodes 2. Prediction Rule Ensembles with    1. raw complexity and    2. standardised complexity as dependent variable and predictors such as the number of time slices, text length, density, average path length, transitivity, as week as contextual information such as year of publication, genre, country, author | We employ  robustness by two  decisions: We  calculate multilevel  Spearman’s  correlation to  account for the  nested structure of  the data; we  calculate the lower  border of the 95%CI  of the coefficient  and interpret this  value. Study 4 adds  further robustness  checks | 1) We compare Spearman’s  correlation to standard  benchmarks of  test-retestst-reliability: >.90  indicates excellent  convergent validity; >.80  indicates good convergent  validity; > .70 indicates  acceptable convergent  validity; and >.60 indicates  questionable convergent  validity (see Allen et al.,  2022; Greiff & Allen, 2018)  2) Interpretation depends on  specific predictor | The often implied link  between the  complexity of a  network and the  number of nodes (see  Dunbar’s number). |
| How robust are the results with regard to the construction of the character networks? | Raw data for Shakespeare’s plays | Networks extracted via 6 analytic variants; ANOVA on  average complexity and Spearman’s  correlation on order of complexity | 6 analytic variants | ANOVA: If the ANOVA is non-significant, we will interpret the 95% confidence interval for the generalised eta- square. If the 95% confidence interval excludes the upper bound of 0.01 we will deem this as evidence that the analytic variants do not affect average complexity.  Spearman’s correlation: In our interpretation, we will consider both the mean of the correlations and the distribution across analytic variants.  In total, if complexity varies by analytic variant, the results from Study 1-3 need to be interpreted with caution, as other arbitrary factors affect them. | - |

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1. Importantly, the current project does not provide empirical answers to the question whether the complexity of character networks is an adequate proxy for the demand that a play puts on recipients’ cognitive systems. Our justification for using complexity rests on the arguments above. [↑](#footnote-ref-1)