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# How network structure shapes languages: disentangling the factors driving variation in communicative agents

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## ABSTRACT

Languages show substantial variability between their speakers, but it is currently unclear how the structure of the communicative network contributes to the patterning of this variability. While previous studies have highlighted the role of network structure in language change, the specific aspects of network structure that shape language variability remain largely unknown. To address this gap, we developed a Bayesian agent-based model of language evolution, contrasting between two distinct scenarios: language change and language emergence. By isolating the relative effects of specific global network metrics across thousands of simulations, we show that global characteristics of network structure play a critical role in shaping inter-individual variation in language, while intra-individual variation is relatively unaffected. We effectively challenge the long-held belief that size and density are the main network structural factors influencing language variation, and show that path length and clustering coefficient are the main factors driving inter-individual variation. In particular, we show that variation is more likely to occur in populations where individuals are not well-connected to each other. Additionally, variation is more likely to emerge in populations that are structured in small communities. Our study provides potentially important insights into the theoretical mechanisms underlying language variation.

## 1. INTRODUCTION

Variation is ubiquitous not only in the natural world, but also in culture. There are intriguing patterns of variation ranging from within to between individuals (in most biological, psychological, cognitive and linguistic characteristics) and groups (most obvious in various aspects of culture). In the language domain, one can think about how two different persons would pronounce the phoneme /r/ in different ways, even if they speak the same language (Sankoff & Blondeau, 2007), or how grammatical constructions vary between English dialects (Trudgill & Chambers, 2017), or even about lexical variation (different use of 'firefly' and 'lightning bug' words in English, for example). Why this variation exists, why it is patterned the

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way it is, and what processes govern its dynamics are extremely important and non-trivial scientific questions.

Language variation arises from divergences in the evolution of linguistic features over time among different populations. It is customary to distinguish the emergence of an innovation (the so-called “initiation”) from the dynamics of its diffusion in the speaker community (“actuation”) (Croft, 2008; Dediu & Moisik, 2019; Solé & Vives, 2012; Stevens & Harrington, 2014; Yu, 2013). Initiation is usually seen as an individual-level process, while actuation is essentially a community-level process involving competing linguistic variants (Blythe & Croft, 2012; Fagyal et al., 2010). These processes can take place in two main scenarios: when the language used by the population is being created *de novo* (language *emergence* scenario, as is arguably the case for emergent sign languages such as Al-Sayyid Bedouin Sign Language and Kaka Kolok; Zeshan & de Vos, 2012), and when a language is already in use and undergoing change (language *change* scenario, by far the most frequent and studies case). The selection of variants during the actuation phase can be influenced by many different factors, such as aspects of the environment (e.g., the effect of environment type on the phonemic inventories of languages; Everett et al., 2015; Maddieson & Coupé, 2015), cultural and historical factors (degree of contact with outsiders, or number of L2 speakers; Lupyan & Dale, 2010), or factors related to the structure of the network of linguistic interaction itself (Wray & Grace, 2007; Trudgill, 2011a). Indeed, interactions between individuals in human societies are embedded in social networks with specific characteristics (Beckner et al., 2009; Newman & Park, 2003), which would constrain the transmission of linguistic features (Chambers, 1995). While all human networks tend to share a few features, such as a small average path length, social network structures exhibit a great diversity across populations (Newman, 2003; Nichols, 1992). Our goal in this paper is to disentangle what characteristics in network structures are instrumental to understand how variation unfolds through evolution.

It is, however, challenging to carefully disentangle the relative effects of network structure from those of the other factors involved, prompting several researchers to introduce experimental, computer modeling and observational paradigms. The rich tradition of sociolinguistic studies uses fine-grained methods that provide insight into the role of network structure (among many other factors) on language change (Labov, 1972, 2001, 2010; Milroy & Milroy, 1985; Yu, 2013). Following a different approach, Raviv et al. (2019, 2020) tackle this question with an experimental approach involving the learning and transmission of an artificial miniature language within a carefully controlled network structure. Network structure was even put forward to have an influence on cultural evolution (Derex & Boyd, 2016; Migliano et al., 2020). These laboratory experiments emphasize the role of population size and network structure on language variability. However, despite their inherent advantages, laboratory experiments are strongly constrained in terms of population size, network structure and aspects of language considered, limiting the direct extrapolation of these results to understanding the dynamics of actual linguistic communities.

Artificial multi-agent models do provide ways to address some of these issues, in particular concerning the number of linguistic agents, the structure of their communicative networks, and the usually long time scale necessary for innovations to spread in large populations. Some studies based on the use of such models highlight the role of population structure in shaping convergence (Lee et al., 2015), the formation of categories (Zubek et al., 2017; Gong et al., 2012), the diffusion of innovations (Ke et al., 2008), and linguistic structure (Reali et al., 2014;

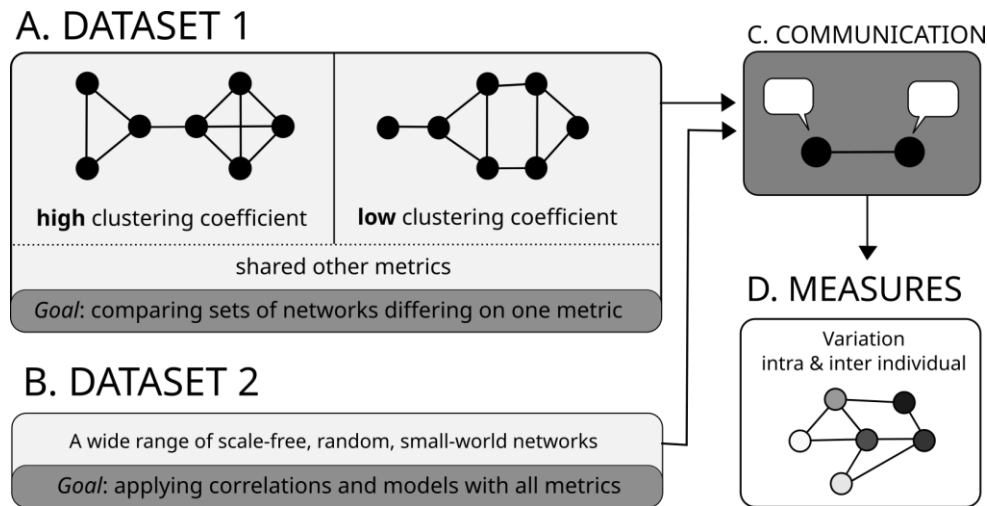
Lou-Magnuson et al., 2018). Despite using different communication algorithms and addressing various aspects of language, these models share a common approach: they all compare different types of pre-existing network structures (such as fully-connected, star, or small-world networks) and then observe whether language evolves differently in these distinct network structures. For example, Lee et al. (2015) examined populations of learners in fully-connected, linear, Neumann lattice, and bridge network structures and showed that these distinct network typologies result in different patterns of grammar convergence. Departing from these pre-existing network structures, in the field of cultural evolution, Kobayashi et al. (2016) aimed to untangle two key metrics: population size and social connectedness. They propose that social connectedness might exert a stronger influence on the level of culture compared to population size. While most of these models address the dynamics of language change and do not specifically explore language variation, Mudd (2022) and Meir et al. (2012) also emphasize the role of social structure on lexical variation in emergent sign languages. Notably, Mudd (2022) developed computational models grounded in observations from the Kata Kolok community, focusing on various aspects of their social structure, such as connectivity and size. To explain why some sign languages witness more lexical variation than others, she proposed that population size is an important factor influencing lexical variability in these languages. However, while it appears that network structure influences language in both scenarios of emergence and change, it remains unclear whether the impact of network structure differs in these two contexts.

Thus, a wide range of approaches strongly suggests that network structure likely influences the evolution of many linguistic features. But what exactly is meant by “network structure”? The networks used in such studies are either networks observed in the real world, or are automatically generated with specific properties (such as, for example, being fully connected, scale-free, or small-world). Any network, whether “natural” or “artificial”, can be described using a set of measures (called *metrics*) that summarize various aspects of the network, varying between the relatively global to the quite local (see Illustration 1). As Raviv et al. (2020) observed, it is very difficult to tease apart the contribution of each network characteristic in real-world observational networks. In other words, comparing real-world populations raises the question of understanding which network structural factors are involved in the actuation of linguistic innovations, and in which manner. In contrast, multi-agent models allow a much finer degree of control over these factors. As a consequence, most agent-based modeling studies to date have investigated the separate role of various characteristics of the communicative network. However, this approach has two main limitations: first, when focusing on specific factors in isolation, it is very difficult to compare their relative influence, and to understand the interactions between them. Secondly, working with automatically generated networks has not led to a fine-grained understanding of which network metrics behind these networks actually affect the dynamics of actuation. Indeed, there are intrinsic relationships between various metrics resulting from the type of network being generated. As an example, if communities structured as scale-free networks produce more stable variation than those structured as small-world networks, is this due to their lower centrality, lower clustering coefficient, or any other metric that intrinsically differs between these two types of networks?

Addressing these questions makes it essential to disentangle and bring a theoretical basis to the question of what aspects of network structure do, in fact, shape language. This has theoretical implications for understanding how languages adapt to fit their social environments and how network structure shapes language. In turn, it will help understand language

differentiation and help explain the great diversity observable in the world's languages. To answer these questions, we introduce here a multi-agent model based on the one in Josserand et al. (2021). The agents use a Bayesian model of language learning in artificially generated static networks where we control various metrics, and, across thousands of runs, we effectively isolated the relative influence of several global metrics (average shortest path length, clustering coefficient, global assortativity, degree distribution, and size) and of local characteristics of the agents (measures of centrality and clustering coefficients). See Illustration 1 for an example. We found that these metrics have different contributions to the evolution of language in this model: while intra-individual variation is not shaped by network structure, inter-individual variation is strongly affected by the path length and the clustering coefficient.

The paper is structured as follows: in the Data and Methods, we present our Bayesian agent-based model, along with the networks used, the metrics under consideration, and the overall procedure of this analysis. In the Results, we investigate whether some of these metrics affect inter- and intra-individual variability in different types of networks. We close by discussing the limitations and implications of our findings, and suggest several future directions of study.



*Illustration 1. A. Dataset 1 comprises sets of networks differing on only one metric (here, clustering coefficient, but we applied it to every metric in Table 1). B. Dataset 2 comprises a wide range of different networks: scale-free, small-world, random networks of different sizes and parameters. C. Throughout our study, agents interact using Bayesian communication for an extended period of time. D. Finally, we investigate the language variability within and between agents in the network. To do so, we compare language variability in networks that differ based on global metrics, using dataset 1. We also explored the networks in dataset 2 by computing the correlations between different metrics and measuring their relative contributions to variability in models. More information about the differences between the two datasets will be presented in Data and Methods section.*

## 2. DATA AND METHODS

Here we develop a Bayesian model of language evolution (Griffiths & Kalish, 2007) based on published work (Josserand et al., 2021), where agents exchange linguistic messages as constrained by a communicative network. Briefly, the network's nodes represent the agents,

which all have an internal representation of language, here reduced to a single feature. The agents that are connected via undirected edges in the network are called “neighbors” and can “talk” to each other. Upon “hearing” their neighbors’ utterances, an agent updates its internal representation of language to take into account the newly “heard” data using Bayes’ rule. We study how the language changes after multiple rounds of such interactions, and, in particular, the manner in which different network structures affect these dynamics in two types of scenarios: language emergence (agents interact without any initial language exposure) and language change (agents interact with an initial language exposure).

## 1.1 The language

The language in our model is a multinomial feature that can take one of  $k$  exclusive possible values. This simple representation is arguably adequate to approximate numerous aspects of human language, such as lexical choices (using one of several words or expressions to describe a given concept), allophony (different actual sounds for the same phoneme as conditioned by the phonetic environment, socio-linguistic/dialectal choices, or in free variation), or morpho-syntactic structures (different ways of organizing the sentence). Here, we call an *utterance* a token drawn from this multinomial distribution. For example, if the feature refers to the possible allophones of “r” in English, the possible utterances include the alveolar trill [r], the approximant [ɹ], and the retroflex approximant [ɻ], among others. Abstractly, we can represent the feature through the vector of its possible utterances  $u = \{u_1, u_2, \dots, u_k\}$ . We fixed the number of utterances  $k$  to 10 here, but simulations ran with different values of  $k$  led to similar conclusions.

While we also generalized our feature to a continuous one (which can represent, for example, very fine-grained measurements of vowel height or voice-onset-time (VoT); presented for the Dataset 1 in the **Supplementary Materials** in Part 3.2.2), we decided to focus here on the case of the discrete valued feature. Indeed, using a continuous representation instead of the discrete one does not alter our conclusions, but presenting both would lead to clutter and unnecessary complexity in the presentation of the results.

## 1.2 How do agents represent language?

Agents are Bayesian learners (Griffiths & Kalish, 2007). In this framework, there is a fixed “universe” of languages,  $U$ , and each possible language  $h$  from this universe ( $h \in U$ ) has a certain probability  $p$  of being “the real one” from the agent’s “subjective” point of view. Before being exposed to any utterance, each agent has an *a priori* “belief” concerning the probabilities of each possible language, denoted  $p(h)$  and known as the *a priori probability distribution* of the languages (or the *prior*). However, each time an agent “hears” an utterance, denoted as  $d$ , it updates its subjective distribution of the probabilities of the languages in light of this data using Bayes’ theorem:  $p(h|d) = \frac{p(d|h)p(h)}{p(d)}$ . Here,  $p(d|h)$  is the likelihood of observing data  $d$  given that the language is  $h$ , while  $p(h|d)$  is the updated belief, or *posterior*, i.e. the probability of the language being  $h$  after both the *prior* and the observed data  $d$  are considered. The denominator  $p(d)$  acts as a normalization factor and is not of immediate concern here. While this mechanism is extremely general, we apply it here in a very particular and relatively simple setting.

More precisely, an agent's internal representation of language is given by a vector  $\mathbf{p} = (p_1, p_2, \dots, p_k)$ , where each component  $p_i$  represents the probability of the  $i^{\text{th}}$  utterance  $u_i$ ; as the utterances are mutually exclusive and exhaust the space of possible utterances for this features,  $\sum_{i=1}^k p_i = 1$ . An agent has an *a priori* distribution that represents its initial belief in the probability of each utterance, which leads naturally to a *multinomial distribution* that represents the likelihood. More precisely, given  $n$  such utterances “heard” independently by an agent, the random variable  $\mathbf{X} = (X_1, X_2, \dots, X_k)$  distributed as *Multinomial*( $n, \mathbf{p}$ ) gives the expected number of times each possible utterance  $u_i$  appears. Here, the multinomial distribution models how frequent any one of the  $k$  possible utterances should be among the  $n$  “heard” independent ones, if their probabilities are given by the vector  $\mathbf{p}$ .

To compute the posterior distribution after having seen the data, it is possible to use the very computationally expensive Markov Chain Monte Carlo technique. However, in particular cases, one may choose specific conjugate priors, which drastically simplify the application of Bayes' theorem. The conjugate prior of a multinomial distribution is given by the *Dirichlet distribution*, which is defined by a vector of  $k$  parameters  $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_k) \in R^k$ . These parameters  $\alpha_i$  are related to the probability  $p_i$  of each utterance  $u_i$ , so that the vector of probabilities  $\mathbf{p} = (p_1, p_2, \dots, p_k)$  is distributed as *Dir*( $\boldsymbol{\alpha}$ ). The prior and posterior distributions of probabilities are modeled by Dirichlet distributions and, thus, characterized by prior (denoted here as  $\boldsymbol{\alpha}$ ) and posterior (denoted here as  $\boldsymbol{\alpha}'$ ) Dirichlet parameters. Using Bayes' theorem, one can update the prior distribution *Dir*( $\boldsymbol{\alpha}$ ) into the posterior distribution *Dir*( $\boldsymbol{\alpha}'$ ) after seeing a number  $n$  of independent utterances (the data,  $d$ ): it reduces to trivial arithmetic:  $\alpha'_i = \alpha_i + X_i$ , where, as above,  $X_i$  gives the number of times utterance  $u_i$  was “heard” in the data  $d$ . Thus, this reduces to a simple model where the parameters of the Dirichlet distribution reflect the number of “heard” utterances and the prior belief. It is important to note that, as expected for Bayesian models, both the prior beliefs and the observed data matter. Seeing enough data should be able to overwhelm even very strong *a priori* beliefs and the order in which the utterances in the data arrive does not matter. This generalizes the prior model studied in (Josserand et al., 2021) by allowing more than two possible utterances (i.e., from a Bayesian model with a binary feature using Binomial/Beta conjugate distributions, to a multinomial feature using Multinomial/Dirichlet conjugate distribution).

### 1.3 The initial language exposure: emergence vs. change

We considered two types of agent populations, differentiated by their “initial language exposure”, which represents the type of scenario (language emergence versus language change). In the populations in a language emergence scenario, the agents are born *without* initial language exposure. Such agents are naïve regarding the language, with all possible utterances having the same probability of occurrence. This is modeled by a Dirichlet distribution with all parameters  $\alpha_i$  being equal,  $\boldsymbol{\alpha} = (1, 1, \dots, 1)$ . It represents the situation where agents are born in a language-less community, but it may as well represent a community with a language where all possible utterances are equally frequent.

In contrast, in the language change scenario, agents are born in a population *with* initial language exposure, i.e. born in a community with a pre-existing language that favors a certain utterance at the expense of the others; say, utterance 4,  $\alpha_4$  is 6 times more frequent than the others (for various reasons, including past internally-motivated language change, language contact, or top-down language policies). This situation is represented by a Dirichlet distribution

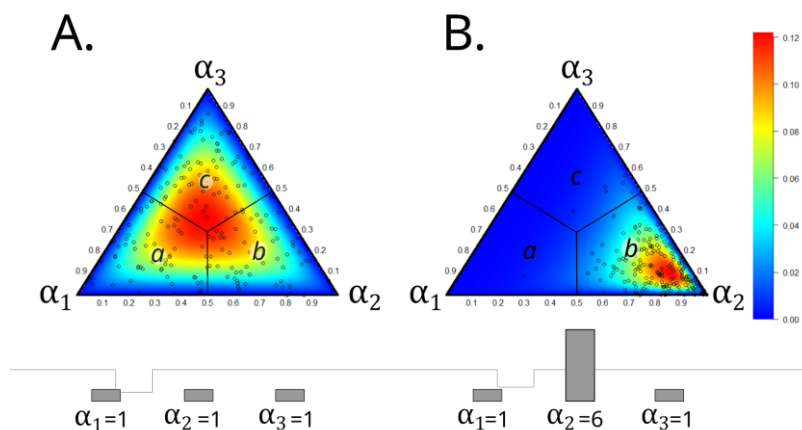
with parameters  $\alpha = \{1, 1, 1, 6, 1, \dots, 1\}$ . Given how the parameters of the Dirichlet distribution reflect the number of “heard” utterances, this can be seen as modeling the fact that agents are expecting, before they engage in communication with other agents, that the utterance  $u_4$  is much more frequent than all the others. A value of 6 is supposed to represent an initial language with a very skewed frequency of the utterances, but not too strong (however, we also investigated the effect of using 21 instead of 6 in the **Supplementary Materials**; see part 3.2.1.8).

## 1.4 The communication process

As described above, the agents are “born” with their initial Dirichlet distribution, which represents their bias concerning the language feature. The simulation happens in discrete timesteps (*rounds*), and in each round, the agents “speak” (i.e., produce utterances) and “hear” (i.e., receive) the utterances produced by their neighbors.

To produce utterances, an agent uses the following procedure: first, it normalises the  $k$  parameters of its Dirichlet distribution,  $\alpha$  to a probability vector  $\mathbf{m} = (m_1, m_2, \dots, m_k)$ , where  $m_i = \frac{\alpha_i}{\sum_j \alpha_j}$ . Then, it draws a single value  $1 \leq j \leq k$  proportional to its probability  $m_j$ , such that each index  $j$  can be chosen depending on its probability relative to the other  $k-1$  indices in  $\mathbf{m}$ . This is equivalent to the use of random multinomial generator,  $j \sim \text{Multinomial}(\mathbf{m})$ , as implemented by, for example, R’s `rmultinom(n, size, prob)`, where `n=1`, `size=1` and `prob=m`, or Stan’s `multinomial_rng(vector theta, int N)`, where `theta` is the simplex vector `theta=m` and `N=1`. Finally, this value  $j$  represents the utterance that is actually produced, namely  $u_j$  (see Illustration 2). So, we use what is known as a sampler (or ‘SAM’) strategy (Griffiths & Kalish, 2007; Josserand et al., 2021) in which the agent picks any of the possible  $k$  utterances proportional to its subjective probability (as given by the agent’s current Dirichlet distribution).

Conversely, upon hearing the utterances produced by its neighbors, the agent updates its current Dirichlet distribution as described above. This update consists of an addition, so that the Dirichlet hyper-parameters become  $\alpha'_i = \alpha_i + X_i$ , where  $X = \{X_1, X_2, \dots, X_k\}$  represents the number of times each utterance appears among those that the agent just heard.





*Illustration 2. Representation of the Dirichlet distribution for an agent without initial language exposure (language emergence, panel A) and for an agent with an initial language exposure towards  $\alpha_2$  (language change, panel B). For visualization purposes, we plotted here  $k=3$  utterances instead of the  $k=10$  actually used in the study. The dots represent the random draws from the Dirichlet distribution: if the random draw occurs in the **a** part, the agent will produce an utterance  $u_1$ ; if it occurs in the **b** part, it will produce an utterance  $u_2$ , and it will produce an utterance  $u_3$  when drawn in the **c** region. In the condition without initial language exposure, random draws happen equally probably for all three utterances, but with initial language exposure, they occur mostly in the **b** region, resulting in many more  $u_2$  utterances. The bar plot below each triangle is an alternative way of representing the values of the Dirichlet distribution. The color gradient reflects the density of random draws, with red denoting high density and blue indicating low density.*

## 1.5 The networks: types and metrics

The agents form the nodes of a network with a static structure, fixed for the duration of a simulation, while the edges between the nodes determine the agents that can talk to each other. Given that we focus on the structure of these networks, our discussion in this section is framed in terms of nodes and edges, instead of agents and their communicative exchanges. Here, we use three classes of network topology: random, small-world, and scale-free networks. The random networks are generated using Erdős & Rényi (1959)'s algorithm, where each node has a fixed probability of connecting with other nodes in the network. We kept only networks without any isolated components. The small-world networks are generated using the Watts-Strogatz algorithm (Watts & Strogatz, 1998): this algorithm starts with a ring of nodes, where each node is connected to a fixed number  $N$  of neighbors on either side, followed by a rewiring with a fixed probability  $p$ . This process leads to the generation of networks with many real-world properties (Kenett et al., 2018; Kitsak et al., 2010), such as the presence of short average path lengths (see Milgram (1967)'s "Six degrees of separation"). The scale-free networks are generated using the preferential attachment algorithm of Barabási et al. (2000), and exhibit a power-law degree distribution: most nodes have a limited number of neighbors, while few nodes have very many (Albert, 2005; Albert et al., 1999), resembling real offline and online social networks. The algorithm gradually adds new nodes to a network such that the probability  $p_i$  that the newly added node is connected to node  $i$  is  $p_i = \frac{d_i}{\sum_j d_j}$  where  $d_i$  is the degree of node  $i$ , and the sum is over all pre-existing nodes  $j$ . We use these different classes of network topology to investigate the effects of specific network metrics (see Table 1).

Name of the global network metric	Short name	Description	Mathematical description	Type of network
Average node degree	Degree	Average number of neighbors for all nodes	$D = \frac{\sum_{i=1}^n k_i}{n}$ where $k$ is the degree of a node $i$ and $n$ is the total number of nodes in the network	Constant for Barabasi-Albert scale-free networks with a fixed size
Network size	Size	Total number of nodes	$n$	All

Average shortest path length	Path length	On average, how close (defined by the number of intermediate nodes) are two random nodes	The mean of the shortest path length between all pairs of nodes: $l_G = \frac{\sum_{i,j} dist(v_i, v_j)}{n(n-1)}$ , where $dist$ is the shortest path length between two nodes	All, since we removed isolated components in random networks
Global assortativity coefficient	Assortativity	Preference for a network's nodes to attach to others that are similar (here, in terms of nodes's degree)	The mean of the local assortativity based on the node degree, where local assortativity is defined as $\rho = \frac{j(j+1)(\overline{m_j} - \mu_d)}{2M\sigma_d^2}$ , where $M$ is the number of edges in the network, $j$ is the excess degree of a particular node and $\overline{m_j}$ is the average excess degree of its neighbors. (The excess degree distribution $j$ is defined as $j(k) = \frac{(k+1)P(k+1)}{D}$ ). Thus, assortativity can vary between -1 (highly disassortative) to 1 (highly assortative).	All
Average clustering coefficient	Clustering	Measure of the degree to which nodes in a network tend to cluster together	The average local clustering coefficient of all nodes (as in Watts & Strogatz, 1998), where the local clustering is defined as: $C_i = \frac{\lambda_G(v)}{\tau_G(v)}$ , where $\lambda_G(v)$ is the number of triangles on $v \in V(G)$ , $V(G)$ being the set of all nodes in the undirected graph $G$ , and $\tau_G(v)$ is the number of triangles on $v \in G$ . The clustering coefficient varies between 0 (the friends of my friends are never connected) and 1 (the friends of my friends are all connected)	Constant in scale-free networks
Degree distribution: the shape of the power law distribution	Degree distribution	Shape of the degree distribution for power-law distributions: how strongly hubs gather all connections	A power-law distribution is defined as $P(k) \sim k^{-\alpha}$ where $\alpha$ is the exponent of the distribution. The larger the exponent, the rarer the large values are. The exponent is estimated by applying "log" to the degree distribution and looking at the slope of the obtained new graph. Exponents in scale-free networks obtained with Barabasi-Albert algorithm usually present some random fluctuations and vary between 2 and 3.	Only networks exhibiting a power-law distribution

In this study, we aim to isolate the effect of the different metrics in order to understand how they may influence language variability. Please note that we focus on these metrics because they capture essential properties of communicative networks that have been claimed, or may arguably contribute to language dynamics within networks. Moreover, some of these metrics are very hard to disentangle and, therefore, their effects might be confounded in most previous studies. To overcome those difficulties, we generated hundreds of thousands of networks, and then selected two sets of networks, each containing 100 networks: for a given metric, we selected the two sets of networks guaranteeing that the averages for the other metrics in the two sets were similar except for the metric under consideration (see Table 2). As significance can be easily attained when it is possible to generate a high number of networks, we ensured that the difference between the two sets was much larger (at least two orders of magnitude) for the metric considered than for the "equalized" metrics. We used scale-free networks to analyze the independent effects of the network size, the path length, the assortativity, and the degree distribution; small-world networks for the clustering coefficient; and random networks for the average degree and path length.

Metric value <sup>1</sup>	Difference between the two sets varying in the network metric (in <b>bold</b> ) <sup>2</sup>					
	Size	Path length <sup>3</sup>	Degree distribution	Assortativity	Clustering	Node degree
<i>Size</i>	(100 / 50) <b>50</b>	(50 / 50) 0	(50 / 50) 0	(50 / 50) 0	(150 - 150) 0	(50 - 50) 0
<i>Path length</i>	(4.49 / 4.50) 0.01	( <b>4.99 / 3.37</b> ) <b>1.62</b>	(4.09 / 4.10) 0.01	(4.02 / 4.01) 0.01	(1.68 - 1.68) 0	(1.78 / 1.79) 0.01
<i>Degree distribution</i>	(2.85 / 2.85) 0.00	(2.79 / 2.80) 0.01	( <b>3.04 / 2.55</b> ) <b>0.49</b>	(2.75 / 2.75) 0	--	--
<i>Assortativity</i>	(-0.29 / -0.30) 0.01	(-0.31 / 0.31) 0	(-0.35 / -0.35) 0.01	( <b>-0.16 / -0.48</b> ) <b>0.32</b>	(-0.01 / -0.01) 0	(0.02 / 0.01) 0.01
<i>Clustering</i>	(0 / 0) 0	(0 / 0) 0	(0 / 0) 0	(0 / 0) 0	( <b>0.58 - 0.32</b> ) <b>0.26</b>	(0.25 / 0.25) 0.01
<i>Degree</i>	(1.98 / 1.96) 0.02	(1.96 / 1.96) 0	(1.96 / 1.96) 0	(1.96 / 1.96) 0	(48 / 48) 0	(12.69 / 11.98) <b>0.71</b>

These metrics reflect the *global* network structure, but there is *local* heterogeneity between nodes, which is captured by node-level metrics. Using the same model, we investigated the influence of *local* network heterogeneity on language change (Fagyal et al., 2010). Specifically, we extended the results from our previous paper (Josserand et al., 2021). In this earlier work, we found that language adapts more to a group of biased agents—namely, those born with a preference for a specific utterance—when these biased agents have higher centrality. While in the prior study, we defined centrality as betweenness centrality, we complemented these results here by exploring whether various other node-level metrics (local clustering coefficient, node degree, eigenvector centrality, and closeness centrality) might exert different influences. These findings, available only in the **Supplementary Materials** (see part 3.4), not only expand upon but also validate the results presented by Josserand et al. (2021).

## Measurements

Previous studies (see Figure 13 in Josserand et al., 2021) have shown that in a type of Bayesian model of language change similar to the ones implemented here but where the linguistic feature was binary, language stabilized before 1000 rounds in all network types (see our **Supplementary Materials** part 3.1 for visualization). Here, we introduced a conservative

<sup>1</sup> Each row shows the absolute difference between the two sets in the appropriate metric given by the names. The parenthesis indicates the mean value for each set of networks (high / low).

<sup>2</sup> Each column refers to the two sets of networks varying only in the shown metric.

<sup>3</sup> For example, the second column shows the differences between the two sets of networks differing by design in path length: these two sets contain 100 networks each, have the same size, clustering coefficient, average degree, and almost the same degree distribution and assortativity, but (as intended) markedly different path length. These numbers should be interpreted with caution, as the strength of a difference of “1” or “0.01” may vary depending on the metric being analyzed.

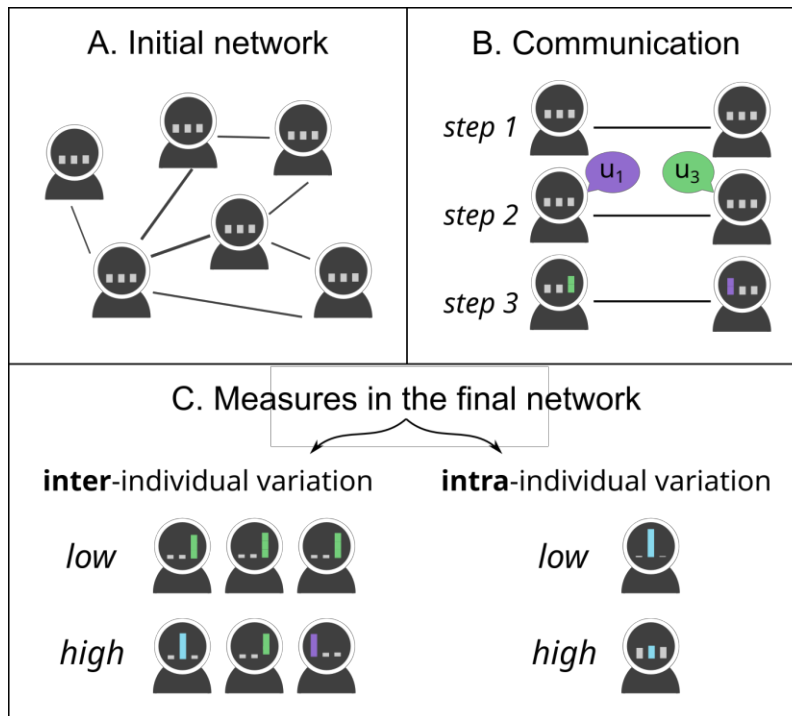
margin and analyzed the inter- and intra-individual variability after 3000 rounds (when all agents had produced 3000 utterances) in order to make sure that language would have stabilized.

First, we define *inter-individual variability* by how different the agents are regarding their internal language representation. For example, if agents tend to use different utterances (some preferentially  $u_4$  while some others preferentially  $u_3$ ), the inter-individual variability will be high. We estimate inter-individual variation using the Kullback-Leibler divergence, which is a measure of the statistical distance between two probability distributions (as coded in the *entropy* package in R; Hausser & Strimmer, 2021). To do so, we computed for all possible pairs of agents the pairwise Kullback-Leibler divergence between their Dirichlet distributions, and then averaged the resulting pairwise Kullback-Leibler divergences to obtain an average measure of the inter-individual variation in the network.

Secondly, *intra-individual variability* captures how consistent an agent is in its own language productions. For example, if an agent uses equally likely two utterances ( $u_2$  and  $u_8$  half of the time each, for example), its intra-individual variability will be high. On the contrary, an agent that always uses the same utterance has a low intra-individual variation. We estimate intra-individual variation as the entropy of an agent's Dirichlet distribution (as coded in the *entropy* package, using Jeffreys prior<sup>4</sup>; Hausser & Strimmer, 2021), which is bounded between 0 and  $\log_2(k)$ , where here  $k=10$ . The *average* of this intra-individual variation across all agents captures their propensity to consistently use the same utterance (a high average indicates that agents switch between different utterances, while a low average suggests that agents tend to use the same utterance consistently), while its *standard deviation* across all agents captures to what degree there are differences between the agents regarding their intra-individual variation (a high standard deviation suggests that while some agents always use the same utterance, others show a high variability, and a low standard deviation suggests that all agents tend to be equally consistent or not in their language production). See Illustration 3 for a visualization of the entire process.

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<sup>4</sup> This ensures that the resulting entropy value is robust and not overly influenced by the specific parameterization of the probability distribution. We also selected other priors, but conclusions were the same.



**Illustration 3.** A schematic representation of the multi-agent model. (A) Agents are “born” embedded in a network with a fixed structure and with given characteristics. Each agent has an internal language representation given by the parameters of the Dirichlet distribution (see gray bar plot in Illustration 2). For visualization purposes, we decided to represent  $k=3$  utterances here instead of the  $k=10$  utterances used in the paper. (B) **Step 1.** Each agent randomly extracts a number from its Dirichlet distribution: here, the probability of picking any of the three utterances is the same. **Step 2.** Each agent produces the chosen utterance (here,  $u_1$  for the agent on the left and  $u_3$  for the one on the right). **Step 3.** Each agent hears the utterance(s) of its neighbor(s) and updates its own Dirichlet distribution accordingly. (C) After each individual talks 3000 times, we measure the inter- and intra-individual variation among the agents in the final network.

## 1.6 The network generation procedure

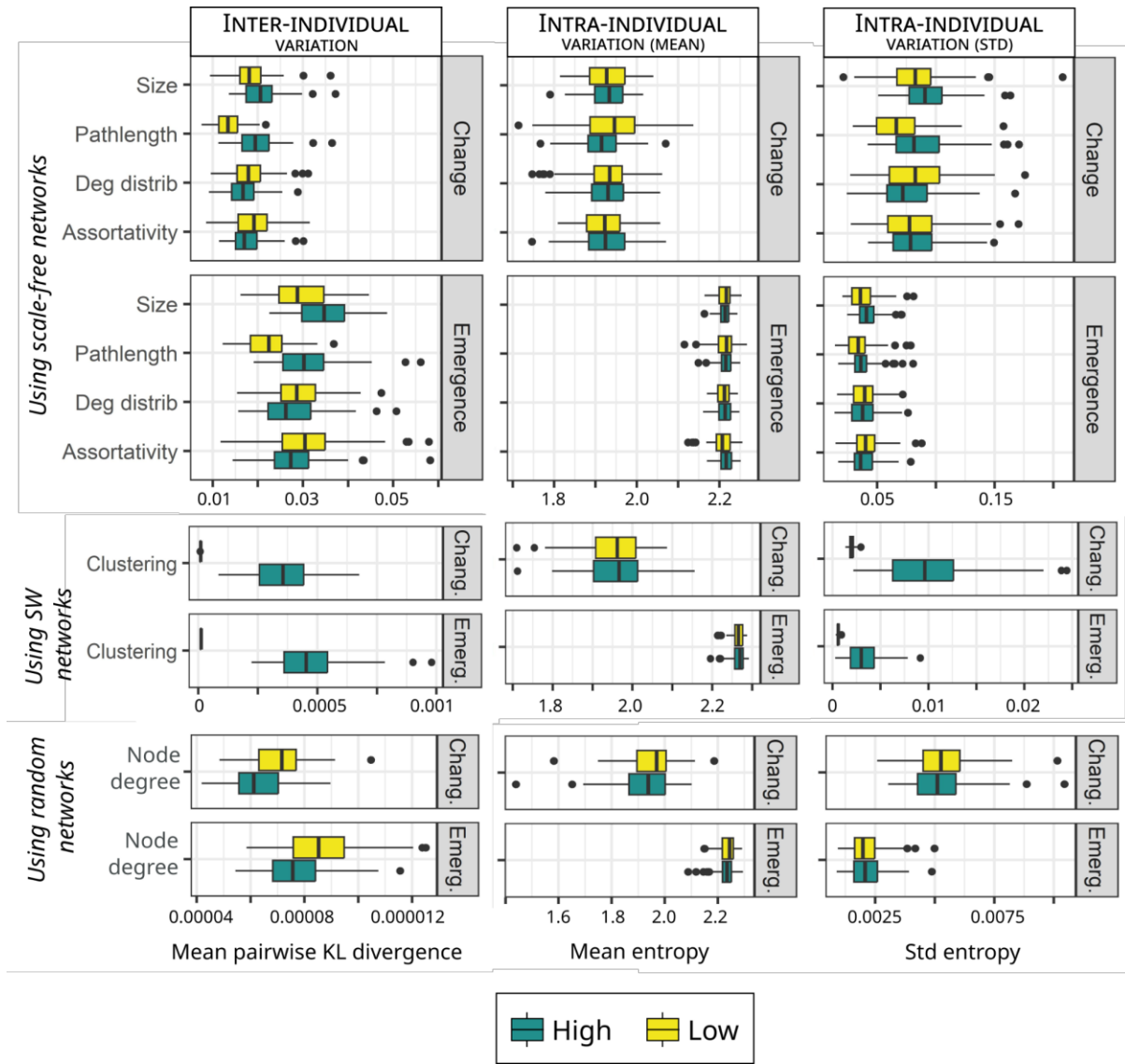
We conducted simulations using Netlogo (version 6.2.2; Wilensky, 1999) and generated two datasets. In the first (which we will call *dataset 1*), we systematically compared two sets of networks differing in exactly one metric, as described above. To achieve this, we first generated 100 networks for each combination of parameters which resulted in 80,000 scale-free networks (with varying sizes), 240,000 random networks (with varying connection probability to control for density and pathlength), and 600 small-world networks (with high and low rewiring probability, to examine the influence of clustering). Detailed information about the specific parameters is available in the **Supplementary Materials** (see Part 2.2.1). Following the generation of these networks, and using graphic visualization, we manually selected sets of networks that differed in only one metric. Subsequently, to compare the amount of variation in the two sets of networks and assess whether the difference was meaningful, we used Cohen’s  $d$ , a statistical metric that measures the difference between two groups. This metric is computed by dividing the difference between the means of the two groups by the pooled standard deviation of the groups.

With dataset 2, we ran a series of simulations with random, scale-free, and small-world networks using a wide range of parameters. For each network type, we generated networks with sizes of 50, 150, and 300. In the case of random networks, we explored connection probabilities ranging from 0.05 to 0.95 in increments of 0.05. For small-world networks, we created networks with varying average numbers of neighbors (4, 8, 16, 48) and different rewiring probabilities (0.1, 0.3, 0.5, 0.7, 0.9). Initially, we examined how the metrics co-varied across a broad range of values using Spearman's and Pearson's correlations. Then, we modeled how these metrics influenced the final variability in the communicative network. We z-scored all the metrics and we predicted inter-individual, mean intra-individual and standard-deviation of intra-individual variation using all our metrics as predictors. To do so, we used three machine learning techniques. First, we measured the predictor importance with *random forests* (using package `randomForest`; Liaw & Wiener, 2002) using an accuracy-based index and a gini-based Index. Second, we used *conditional forests* (using `cforest` function in `partykit` package; Hothorn & Zeileis, 2015) to measure the unconditional predictor importance index. Last, we used *Support Vector Machines* (SVM; `fit` function in `rminer` package; Cortez, 2010) for sensitivity analysis. Additionally, for all of them, we measured the goodness of fit using  $R^2$  and RMSE. To prevent overfitting, we trained the model on 80% of the data (stratified by size) and tested the model on the 20% remaining data using 50 replications. For easier plotting, we z-scored and then aggregated the results for importance by method (accuracy-based, gini-based, unconditional, and sensitivity), by network type, and by predictor. The values for each method and each predictor, as well as additional details on the exact parameters used in the models, are available in the **Supplementary Materials** (see Part 3.3.4).

### 3. RESULTS

#### 3.1 Dataset 1

To produce sets of networks that vary only in one metric, we needed to use multiple types of networks. We used scale-free networks to investigate the influence of assortativity, degree distribution, path length, and size. Small-world networks were used to examine the impact of the clustering coefficient, while random networks were used to investigate the effect of the average node degree. The inter- and intra-individual variation (mean and standard-deviation) values are presented in Figure 1, while Figure 2 indicates the effect sizes and significance for each set.



**Figure 1.** Measure of inter-individual variation (left column), mean of intra-individual variation (column in the middle), and standard deviation of intra-individual variation (right column). Each row shows the results for one metric: for example, the first row shows the results for 100 networks that have a low size on average (in blue), and 100 networks with a high size (in yellow) (see Table 2), in networks where there is an initial language exposure (language change, upper panel) and networks without initial language exposure (language emergence, lower panel). Depending on the network type used to study the metric of interest, the x axis may vary: the x axis of inter-individual variation shows the mean pairwise Kullback-Leibler divergence, while the two other columns show respectively the mean and the standard deviation of the entropy for all agents, computed using the final Dirichlet distribution for each agent. The quantification of the effect size between the two sets is indicated in Figure 2.

**Clustering coefficient.** Both networks in language emergence (Cohen's  $d = 4.2$ ) and language change (Cohen's  $d = 4.2$ ) scenarios exhibit a strong influence of clustering coefficient on inter-individual variability, as shown in Figures 1 and 2. Networks without a clique structure tend to display lower levels of inter-individual variation. Similar to all other network structure metrics, the clustering coefficient has no effect on the mean intra-individual variation. However, higher clustering coefficients lead to more differences among agents in terms of standard deviation of intra-individual variation (with some agents consistently using the same utterance and others switching between several different utterances), which is

observed in networks with language emergence or change scenarios (Cohen's  $d = 2.0$  and Cohen's  $d = 2.2$ , respectively).

**Path length.** The path length strongly affects inter-individual variability, in both emergence (Cohen's  $d = 1.5$ ) and change (Cohen's  $d = 1.5$ ) scenarios. Thus, networks where agents are easily reachable by others are likely to show low levels of inter-individual variation. Path length does not affect the mean amount of intra-individual variation, but it does slightly positively affect the standard deviation of intra-individual variation in networks in language change scenario only (Cohen's  $d = 0.7$ ).

**Size.** The network size also influences language variability, but its effect quickly disappears with higher initial language exposure. Big networks show higher inter-individual variation in networks with language emergence (Cohen's  $d = 0.9$ ) and language change scenarios (Cohen's  $d = 0.5$ ). However, an additional analysis suggests that the stronger the initial language exposure, the less the network size will play a role in shaping inter-individual variation. More specifically, Cohen's  $d$  drops to 0.3 when the initial language exposure is strong (namely, if the initial language is skewed with 21 utterances instead of 6; see **Supplementary Materials** part 3.2.1.8). Thus, the size of the population may only affect inter-individual variation in emergent languages. As for intra-individual variation, size does not appear to have any impact on the amount and standard-deviation of intra-individual variation observed.

**Average node degree.** The average node degree has a discernible but moderate impact on the degree of language variation among individuals, compared to other metrics. In networks with language emergence (Cohen's  $d = 0.7$ ) and language change (Cohen's  $d = 0.7$ ) scenarios, networks with a low average node degree typically exhibit high inter-individual variation. However, the average node degree does not affect any type of intra-individual variation.

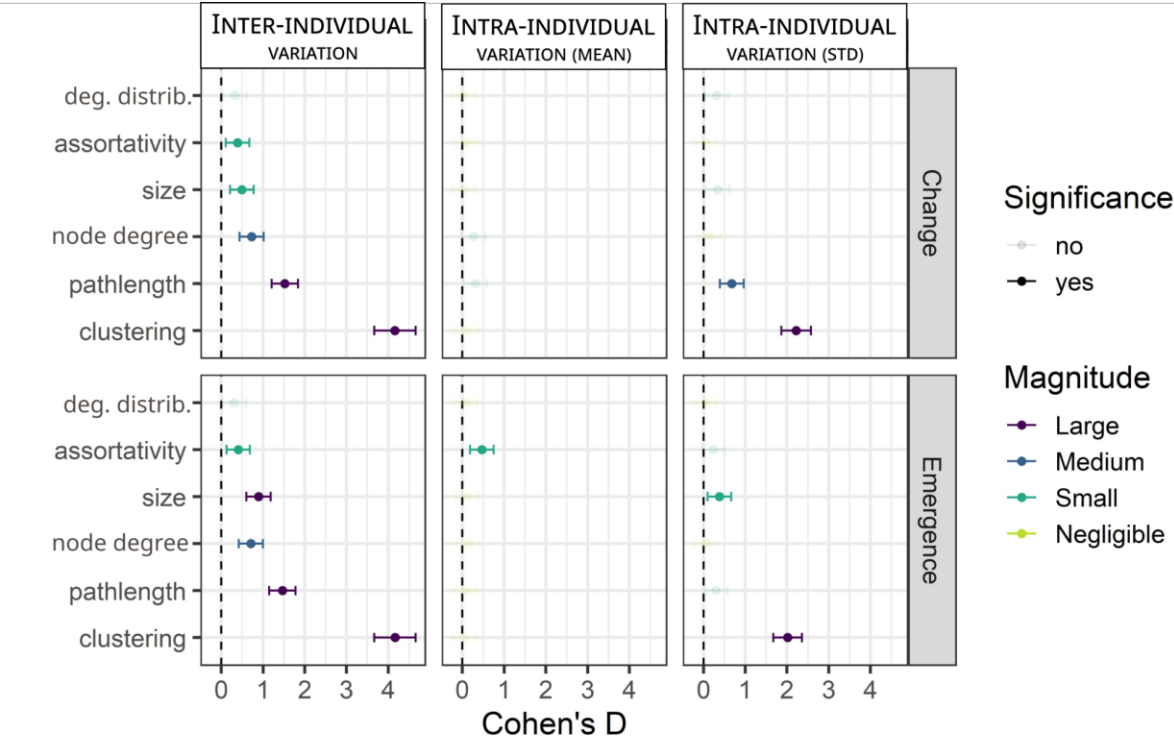
**Assortativity and degree distribution.** Finally, both assortativity and degree distribution have no observable effect on inter-individual nor intra-individual variation. Networks where individuals are preferentially connected to individuals who have a similar degree, and networks with very skewed degree distributions, do not show specific patterns of variation.

**Initial language exposure.** The initial language exposure, which reflects whether agents are born in language emergence or language change scenario, affects both inter- and intra-individual variation. Networks in language emergence scenarios exhibit greater inter- and mean intra- individual variation: as expected, agents communicating in a language change scenario exhibit more consistency (lower entropy on average) than agents involved in a language emergence scenario. Notably, the amount of intra-individual variability is solely affected by the initial language exposure. However, the standard-deviation of intra-individual variation is lower in language emergence scenario.

**Summary.** In summary, our findings indicate that clustering coefficient and path length are the main factors impacting both inter-individual variation and the standard deviation of intra-individual variation. Size and density moderately affect inter-individual variation, specifically in language emergence scenarios. Notably, the mean intra-individual variation remains



unaffected by any of our network structure measures. The initial language exposure, reflecting language change or emergence scenarios, also strongly influences all types of variation.

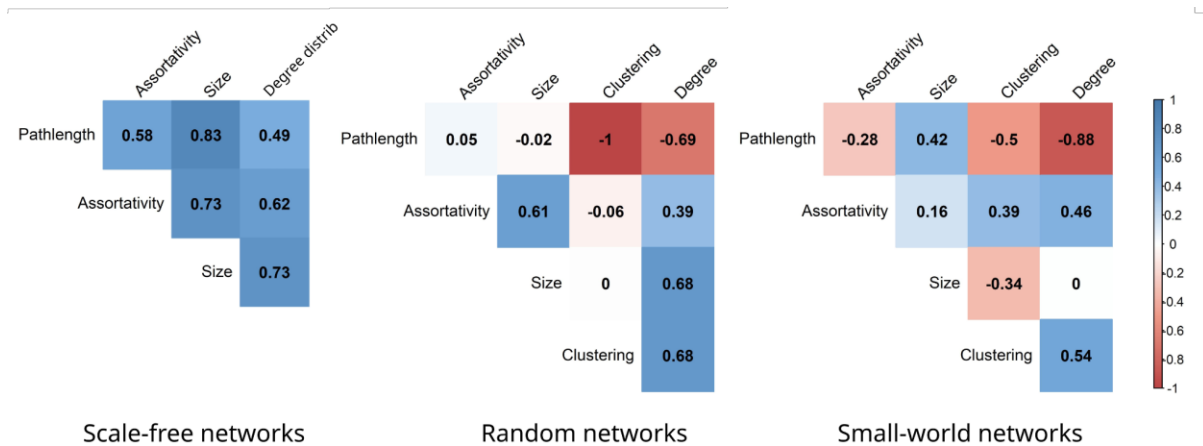


**Figure 2.** Measure of inter-individual variation (left column), mean intra-individual variation (middle column), and standard deviation of intra-individual variation (right column) in networks with initial language exposure (language change; upper panel) and without initial language exposure (language emergence; lower panel). The Cohen's  $d$  index for each predictor indicates the effect size of the difference in variation between the two sets (high and low) for each predictor along with its confidence interval. Gray indicates a non-significant metric, while significant metrics are in shades of color.

### 3.2 Dataset 2

Here, we also use simulations obtained using automatically generated random, small-world, and scale-free networks (all generated networks were kept without any specific selection criteria<sup>5</sup>). We analyzed the Spearman's correlations between the metrics (see Figure 3). The clustering coefficient, the node degree, and the path length are highly correlated with each other. Thus, the more neighbors a given agent has on average, the more likely the friends of this agent will be connected to each other, and the lower the average path length will be in the network. Network size also correlate to the other metrics in scale-free networks: bigger scale-free networks have higher path length and higher assortativity. These results reflect the necessity of the sampling procedure used above to study the effect of the different metrics separately.

<sup>5</sup> We only excluded random networks that possessed isolated component, in order to be able to compute the path length.



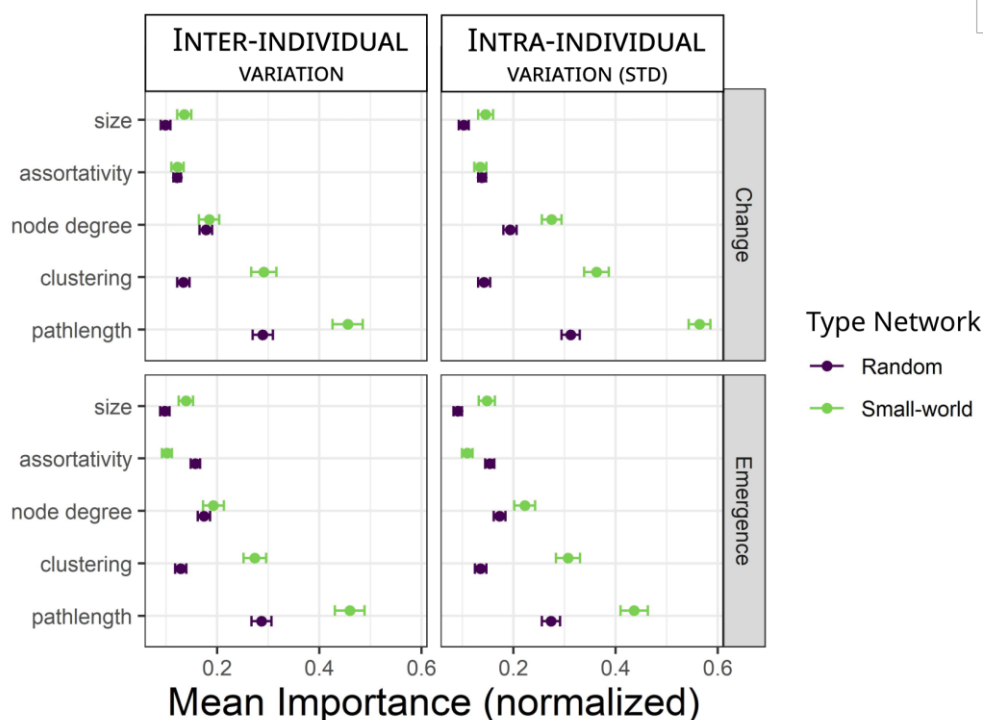
**Figure 3.** Correlation matrix with the different metrics in scale-free (left), small-world (middle), and random (right) networks.

Using this same set of simulations, we applied several machine learning techniques to predict variability in different network types using our metrics as predictors (see Figure 4) in both language emergence and language change scenarios. We observed that the  $R^2$  for the mean intra-individual variation was notably low, with an average  $R^2$  of 35% for language emergence and of 2% in language change scenarios (these means were computed for all methods and all types of networks; please note that there are high differences between the  $R^2$  obtained in the different methods). Furthermore, our predictors in models using scale-free networks poorly predicted any types of variations, with  $R^2$  around 37% for inter-individual variation and 4% for the standard deviation of intra-individual variation. However, in small-world and random networks, and in both language scenarios, our predictors effectively predicted inter-individual variation and the standard deviation of intra-individual variation, with  $R^2$  values for these models around 92% for inter-individual variation and 76% for standard-deviation of intra-individual variation. Thus, we focus our analysis on these two types of networks and types of variation. The exact  $R^2$  and RMSE for each method, network type and type of variation are available in the **Supplementary Materials** (see Part 3.3.4).

**Inter-individual variation.** Encouragingly, these results concur with the previous findings comparing sets of networks. The models consistently indicate that path length and clustering coefficient are the most reliable predictors for inter-individual variation in both language change and emergence scenarios. Notably, in this case, path length emerges as a stronger predictor than the clustering coefficient. Interestingly, the models reveal a substantial impact of average degree on inter-individual variation, particularly in random networks. The effect sizes of the other metrics are very small, corroborating the idea that network size and assortativity are not important for understanding inter-individual variability. There are no big differences between the language change and language emergence scenarios regarding the importance of predictors in both random and small-world networks.

**Mean intra-individual variation.** Similar to our previous observations, strong differences in the mean intra-individual variation were identified between language change and language emergence scenarios. However, our metrics do not contribute significantly to predicting this type of variation, as evidenced by the relatively low  $R^2$ . This aligns with the findings of Dataset 1.

**Standard-deviation of intra-individual variation.** Concerning the standard deviation of intra-individual variation, the importance of the predictors varies based on the type of network and the initial language exposure. In both random and small-world networks, path length emerges as the most crucial predictor. Notably, in small-world networks, it exerts a stronger influence in language change scenarios compared to language emergence scenarios. In small-world networks, the clustering coefficient takes the position of the second most important predictor, followed by node degree. Within random networks, node degree holds the second-highest importance as a predictor, closely followed by clustering coefficient and assortativity. In both cases, assortativity and size exhibit the least importance.



**Figure 3.** Mean importance for inter-individual variation (left column) and standard deviation of intra-individual variation (right column) in language change scenario (upper panel) and language emergence scenario (lower panel). Results for the mean intra-individual variation and for scale-free networks are not presented, as the predictors exhibited poor prediction performance for all types of variation (low  $R^2$ ). This measure of importance was computed by averaging the following z-scored predictor importance measures: accuracy-based and Gini-based (extracted from random forests models), unconditional (extracted from conditional forests), and sensitivity-based (extracted from support vector machines). The dots represent the mean of these four measures, and the line represents the standard error between these four measures. Results for random networks are shown in purple, while results for small-world networks are displayed in green.

## 4. DISCUSSION AND CONCLUSIONS

Understanding the patterns of variability within a language provides important insights into the great diversity observable in the world's languages. While many studies highlight the role of network structure on language change, no differentiation was made between various network characteristics in real world-populations or agent-based models, making it impossible to

disentangle their relative contributions. In this study, we applied several methods using a Bayesian agent-based model of language evolution to understand how specific characteristics of a network affect language in a language emergence and change scenarios.

We found that network structure affects inter-individual language variation in both language emergence and change scenarios. Although most earlier studies focused on grammatical complexity and other aspects of language, rather than linguistic variation per se, previous claims supported the idea that the effect of network structure on language was largely attributed to differences in the *size* and *density* of social networks (Dale & Lupyan, 2012; Trudgill, 2011b; Wray & Grace, 2007; Raviv et al., 2019). However, our results suggest that when considering language change, the size and density of a social network do not appear to be the most important factors. Instead, parameters such as path length and the clustering coefficient seem to be more influential in determining language variability. The confusion between size and density on the one hand, and clustering and path length on the other hand, can be easily understood given that these factors are highly correlated: bigger and well-connected populations tend to have shorter path lengths and higher clustering coefficients. Hampering the transmission of information and promoting the existence of distinct communities within a population will favor the emergence of variation in a language. Also, a population growing in size will not necessarily witness more variation, as long as the transmission of information is effective; this is, in particular, the case in populations with hubs, which facilitate the circulation of information. However, interestingly, in the first dataset and in the language emergence scenario only, it appears that the size of a network has an effect: larger populations tend to exhibit more variation. This emphasizes the intrinsic difference between the two scenarios and underscores the need to consider this factor when studying the evolution of language. Quite consistently, network density has a moderate effect in most analyses, but its exact role remains to be determined.

Additionally, the type of scenario (language change versus emergence) also plays an important role in predicting the amount of inter-individual variation present in a population. Thus, individuals born in a society where there is already a pre-existing language (language change scenario) would be more likely to use homogenous forms of language. In turn, this would explain why emerging sign languages in small remote villages (such as Al Sayyid Bedouin Sign Language sign language in Israel; Jaraisy & Stamp, 2022) usually exhibit more variation than official deaf community sign languages taught at schools, even though these official languages are characterized by sparser and larger populations of signers (Meir et al., 2012; Mudd et al., 2020). We suggest that the pressure for conformity (and more specifically, for using the dominant variant in the population) is the main factor underlying the differences between an established language (language *change* scenario) and an emerging language (language *emergence* scenario). Importantly, the strong influence of the type of scenario suggests that non-structural factors do play a very important role in shaping language variability, and that network structure cannot alone account for all the diversity present in real-world networks. For example, other extrinsic factors such as the role of a shared context (Mudd et al., 2022) and the openness to strangers (Dale & Lupyan, 2012) were not taken into account here, but they might have additional contributions to the effect of network structure.

On the contrary, intra-individual variability is not shaped by the network structure, but only by the type of scenario of the society in which an individual is born. An individual born in a society with low pressure to use a specific form of language (language *emergence* scenario) will use

different types of utterances to refer to the same concept. These findings relate to the study of very recent emergent sign languages, such as Kata Kolok, where high intra-individual variation was observed (Lutzenberger et al., 2021). However, differences between individuals regarding their level of intra-individual variation are affected by the network structure. Here too, a high path length and a high clustering coefficient increase the probability that the population possesses both individuals very confident in their language beliefs and individuals with low confidence in which language form to use. We suggest that both high path length and high clustering coefficients are related to the presence of structural communities (cliques), which then lead to linguistic communities. Individuals bridging these communities are then more likely to possess high intra-individual variation, changing their language according to whom they are speaking to, while individuals inside communities use the language spoken by their group unconditionally.

Together, these results suggest that differences at the global level of network structure, especially for path length and clustering coefficient, influence language inter-individual variability. They also highlight the weak role of network structure on intra-individual variation. However, one potential limitation of our study is that the degree of contrast between the sets of networks generated based on a single metric may not have been strong enough to capture the full extent of the metric's influence. For instance, the magnitude of the difference between the high and low node degree networks may have been insufficient to fully explain the impact of node degree on language variability. Also, our "flat" Bayesian model contrasts with the human capacity to differentiate and track various language varieties depending on the interlocutors and contexts. This highlights the potential for elaborating more complex simulations (such as hierarchical Bayesian models) in future research, and meanwhile, our conclusions should be extrapolated with caution to real-world language networks. Additionally, the model only accounted for static networks, whereas real-world networks are dynamic and evolve through interactions. While interactions are the driving force behind network structure, further research could explore the mechanisms of preferential attachment to gain a deeper understanding of their impact on language variability.

## 5. DATA AVAILABILITY STATEMENT / SUPP MATERIALS

The datasets and the analysis presented in this study can be found in the online repositories [mathjoss/NetworkStructure\\_ABM](https://mathjoss.org/NetworkStructure_ABM).

## 6. AUTHOR CONTRIBUTIONS

BdB, DD, MA-T, and MJ designed the research. MJ performed the research, wrote and ran the simulations. MJ wrote the first draft with substantial contributions from DD and FP. All authors (BdB, DD, MA-T, MJ, and FP) read, contributed to, and approved the manuscript.

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