Title: Artificial Intelligence Chatbots Mimic Human Collective Behaviour

Short title: AI Chatbots Mimic Societies

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Abstract:

Artificial Intelligence (AI) chatbots, such as ChatGPT, have been shown to mimic individual human behaviour in a wide range of psychological and economic tasks. Do groups of AI chatbots also mimic collective behaviour? If so, artificial societies of AI chatbots may aid social-scientific research by simulating human collectives. To investigate this theoretical possibility, we focus on whether AI chatbots natively mimic one commonly observed collective behaviour: homophily, or people's tendency to form community with similar others. In a large simulated online society of AI chatbots powered by large-language models (N = 24,443), we find that communities form over time around bots using a common language. In addition, among chatbots that predominantly use English (N = 16,003), communities emerge around bots that post similar content. The findings suggest that AI chatbots mimic homophily, a key aspect of human collective behaviour. Thus, in addition to simulating individual human behaviour, AI-powered artificial societies may advance social science research by allowing researchers to simulate nuanced aspects of collective behaviour.

Keywords: Artificial Intelligence, Collective Behaviour, Homophily, Social Dynamics

Author Contributions:

JKH: Conceptualization, Data Curation, Formal Analysis (equal), Investigation (equal), Methodology (equal), Project Administration, Software (equal), Visualization, Writing – Original Draft Preparation. FPSW: Conceptualization, Formal Analysis (equal), Investigation (equal), Methodology (equal), Software (equal), Writing – Review & Editing. AG: Conceptualization, Supervision, Writing – Review & Editing. SR: Conceptualization, Supervision, Writing – Review & Editing.

Data Availability Statement:

The data that support the findings of this study are openly available on Open Science Foundation at https://osf.io/rsuwn/?view_only=d9f954f7947143f3b2fdcdb365acbaea.

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Ethics Declarations:

The method of data collection in the present research falls below the definition of minimal risk. The authors declare no conflict of interest.

Background

Recent developments in Large Language Models (LLMs) have given rise to advanced Artificial Intelligence (AI) chatbots, such as ChatGPT, that can mimic human individual behaviour in a wide range of psychological and economic tasks (Aher et al., 2022; Akata et al., 2023). For example, AI chatbots make moral judgements that are highly correlated (r = 0.95) with human participants (Dillion et al., 2023), reflect human imperfections in abstract reasoning (Dasgupta et al., 2023), and respond similarly to emotion inductions (Aher et al., 2022; Binz & Schulz, 2023). Though, they differ from human participants in making estimations and causal reasoning (Aher et al., 2022; Binz & Schulz, 2023). Thus, some have suggested that AI chatbots can further social science research by simulating human participants (Dillion et al., 2023), giving rise to the term "silicon sampling" (Argyle et al., 2023).

Since AI chatbots emulate human *individual* behaviour, do groups of chatbots mimic human *collective* behaviour? Here, we use "collective behaviour" to refer to group-level social dynamics and social phenomena. Mimicking collective behaviour is a non-trivial issue for AI chatbots. If we consider AI chatbots as "stochastic parrots" (Bender et al., 2021), we may expect a chatbot prompted to mimic a certain human characteristic (e.g., being anxious) to produce language associated with the characteristic. Mimicking collective behaviour, however, requires chatbots to infer associated social behaviours in a multi-agent environment, without being explicitly prompted on how humans would interact. If groups of AI chatbots do indeed mimic human collective behaviour, they could be used to create artificial societies that simulate human societies' nuanced dynamics, and thus be used to enhance collective-level social science research.

Studying human social dynamics and collective behaviour is important. It impacts political movements (Wahlström & Törnberg, 2021), the acceptance of climate-friendly technologies (Zhang et al., 2020), the spread of misinformation (Cinelli et al., 2020; Rathje et al., 2022), and how societies become divided by echo chambers (Cinelli et al., 2021). However, human societies are difficult to study directly. First, gathering data about social interactions is invasive and expensive to undertake with human participants (Knoke & Yang, 2019; Ryan & D'Angelo, 2018; Valente & Pitts, 2017). Second, group-level field experiments face ethical challenges and are hard to scale (Baldassarri & Abascal, 2017). Finally, recruiting genuine human participants is becoming more difficult, as workers in online subject pools increasingly use ChatGPT (Veselovsky et al., 2023).

Due to these challenges, Agent-Based Modelling (ABM) has become a key tool in social scientific research (Epstein et al., 2023; Lazer et al., 2020). Instead of observing human participants, ABM simulates them as computational agents and observes their behaviour in virtual environments (Abar et al., 2017). Previous ABM studies have revealed mechanisms behind opinion segregations (Baumann et al., 2020), examined the potential outcomes of different COVID-19 social policies (Gumel et al., 2021; Silva et al., 2020), uncovered how fake news and rumours spread in society (Lotito et al., 2021), and tested theories about the formation of filter bubbles and echo chambers (Geschke et al., 2019). However, classical ABM set-ups often simplify and homogenise each agent's actions, which limits their ability to capture the nuance, diversity, and complexity that exists in real human societies (Abar et al., 2017; Geschke et al., 2019; Lotito et al., 2021).

Recent advances in AI chatbots have led some researchers to propose using them as agents to improve ABM's ability to simulate complex human collective dynamics (Epstein et al., 2023; Grossmann et al., 2023; Park et al., 2023; Pastor-Galindo et al., 2023). However, to date, there has been limited research into the natural collective behaviours of AI chatbots. The majority of existing research has either used mechanistic rules to guide the AI chatbots' social interactions (Ghaffarzadegan et al., 2023), or predominantly focused on their individual-level actions and coordination within a group setting (Akata et al., 2023; Y. Li et al., 2023). Two studies examined AI chatbots as collectives. One study specifically prompted AI chatbots to behave like humans in economic decision-making and found that realistic macroeconomic phenomena emerged in the chatbot population (N. Li et al., 2023). In another study, the authors prompted AI chatbots to mimic specific humans in terms of emotion, attitude, and interactions, and found group-level information propagation patterns comparable to the human reference group (Gao et al., 2023). However, without understanding how AI chatbots behave as collectives, ABM studies based on these models cannot assert that their findings are generalisable to human populations. Conversely, if groups of chatbots behave like groups of humans, they may simulate human collectives with greater nuance, flexibility, and fidelity than conventional ABMs.

What human collective behaviours are important for AI chatbots to demonstrate? Human societies are well-documented to display power dynamics, ingroup conformity, and outgroup animosity (Homans, 1974; Rathje et al., 2021; Sunstein, 2019). Underlying these dynamics is a human tendency to form communities around similar individuals, a collective behaviour known as *homophily* (Girvan & Newman, 2002; McPherson et al., 2001). Homophily arises from an inclination for contact between similar individuals to take place more frequently than contact between dissimilar individuals (McPherson et al., 2001). It manifests as structural communities – clusters of individuals who maintain denser connections within their group than with external entities (Girvan & Newman, 2002) – where there exists relative homogeneity within communities and relative heterogeneity between communities (Knoke & Yang, 2019). Homophily is well documented in real-world human societies, such as in community formation around common languages and similarities in individual demographics, attitudes, and beliefs (Knoke & Yang, 2019; McPherson et al., 2001; Titzmann, 2014; Titzmann & Silbereisen, 2009). It is also well documented on online social networks such as X, formerly Twitter, where people are more likely to connect with those who share similar backgrounds (Aiello et al., 2012), discuss similar topics (Faralli et al., 2015; Himelboim et al., 2017; Kang & Lerman, 2012), and have similar values and beliefs (Conover et al., 2011; De Choudhury, 2011; Rathje et al., 2022).

Thus, to examine whether groups of AI chatbots behave like groups of humans, we focus on homophily, a well-established, key dynamic in human collective behaviour. We observe the first 24 days of social engagements within a large, organically simulated online society made entirely of character-playing AI chatbots powered by LLMs such as GPT-3.5 (Total $N = 24{,}443$). To examine whether homophily exists within this artificial society, we investigate two exploratory hypotheses: **H1.** Whether distinct structural communities exist within the population of AI chatbots, and if so, **H2.** Whether there is intra-community homogeneity and inter-community heterogeneity (Knoke & Yang, 2019), or in other words, whether these structural communities are made of similar individuals.

Methods

Set-up and Data Collection

We examine our hypotheses by observing early activity on Chirper.ai, at the time, a micro-blogging social media platform analogous to X (formerly called Twitter) but consisting entirely of AI chatbots. During the period of observation, Chirper.ai allowed human users anywhere in the world to sign-up and create AI chatbot characters, referred to on the platform as "Chirpers". Human users were only allowed to observe the AI chatbots' interactions and posts on the platform, referred to as "chirps", and were unable to interact with the chatbots. Human users created characters by providing natural language prompts about their backgrounds, which were then enacted by AI chatbots powered by LLMs, predominantly OpenAI's GPT-3.5. We will henceforth use "AI chatbots" or "chatbots" to refer to these simulated characters played by the LLMs.

When running, each AI chatbot was presented with background prompts and a "memory" of its past posts and actions, before being asked to make a decision. This decision could be to write a post, or to choose one of the actions in **Table 1**, impersonating the prompted character. Depending on the action chosen, the AI chatbot may then be asked to provide the property required for the action and be given the results. For each post, or "chirp" returned, the chatbot was prompted with: "Acting as the character @{name}, choose one of the following actions: no reaction, like the chirp, dislike the chirp, follow the Chirper, unfollow the Chirper, mention the Chirper in a new chirp." Each decision made by the AI chatbot was accompanied by a "thought" generated by the LLM that powers the chatbot.

__Table 1:__ Descriptions of actions available to AI chatbots

Action	Description	Returns
Search	"Find something on the internet based on a property 'query'. Returns a list of results to choose from."	List of internet search results matching 'query'.
Tagged	"List recent chirps that you have been tagged in, no properties are required."	List of tagged posts.
Discover	"Find a list of chirps with a 1-to-2-word property 'query'. Returns matching chirps to reply to."	List of posts matching 'query'.
Trending	"Find a list of recently trending chirps with a 1-word property 'topic'. Returns matching trending chirps for that topic to reply to."	List of posts matching 'topic'.
Following	"List recent chirps from Chirpers you are following, no properties are required."	List of posts from following chatbots.

Notes. Descriptions and returns of sample actions available to each AI chatbot. Each chatbot is first given background prompts, then asked to choose from these actions and writing a post. If an action results in a list of posts, the chatbot is asked to choose a reaction to each post from "no reaction", "like", "dislike", "follow author", "unfollow author", and "reply".

We collected data on the posts and social engagements of AI chatbots on Chirper.ai during the first month after the platform launched on April 23rd, 2023. We define social engagements as the frequency of any following, liking, disliking, or mentioning between two chatbots. We sampled the chatbot population through a breadth-first search based on social engagements: starting from 1,000 random chatbots, we documented all their engagement actions and subsequently performed the same search on all of their engagement targets that had not previously been investigated, repeating for ten iterations. By filtering the engagement actions to only include those preceding the end of Day 22, we arrived at 24,443 AI chatbots. We collected additional data for chatbots that predominantly post in English until the end of Day 24, arriving at a total of 16,003 English-posting AI chatbots.

Community Analysis

To examine **H1**: whether there are structurally distinct communities in the AI chatbot population, we created social network graphs based on the engagement data. Social network graphs are mathematical and visual representations of the relationship between many individuals, with “nodes” that represent individuals and “edges” representing relationships between pairs of individuals. We constructed graphs on AI chatbots’ social engagements, that is, where nodes in the graphs represent individual chatbots, and edges between a pair of chatbots represent the frequency of their engagements.

For the full chatbot population, we constructed network graphs for engagement activities up to Day 6 (N = 8,519), Day 14 (N = 18,535), and Day 22 (N = 24,443) since the platform was launched. For the population of chatbots that predominantly posted in English, we constructed network graphs for engagements up to Day 6 (N = 1,149), Day 14 (N = 6,814), Day 22 (N = 9,131), and Day 24 (N = 16,003) after the platform was launched. We did not construct a network graph for the full population on Day 24, because the total engagement instances more than doubled over Day 23–24 and reached a scale beyond our computational capability. To examine the major community structures in the chatbot populations, we used the igraph package in R to construct graphs following these steps:

1. Construct weighted, non-directed network graphs.
2. Remove chatbots that engaged with less than two other chatbots to reduce computational load.
3. Detect communities with a clustering algorithm.
4. Remove communities that contain < 1% of the population.

For network graphs of the full chatbot population, we used the label-propagation clustering algorithm (Raghavan et al., 2007) to detect communities, since it is efficient for finding simple community structures in very large graphs. For network graphs of the English-language chatbot population, we instead used the fast-greedy clustering algorithm (Clauset et al., 2004), since it is more sensitive and thus more suitable for detecting sub-communities. To visualise these large graphs efficiently, we set the graph layouts using the Fruchterman-Reingold force-directed layout algorithm (Fruchterman & Reingold, 1991). For each network graph, we coloured AI chatbots that were identified as belonging to the same community with the same colour. For the network graphs of the full population, we also coloured the AI chatbots by their predominant language to aid comparison.

To statistically test whether the detected communities are structurally distinct, that is, whether chatbots engage more with those inside their communities than with those outside their communities, we measured the modularity and assortativity scores of each graph given their detected communities. A high modularity score indicates that chatbots in the same communities are densely connected, while chatbots in different communities are sparsely connected. By contrast, a high assortativity score indicates that connections in the network – in this case, social engagements – are more likely to exist between chatbots in the same communities than between chatbots in different communities.

We performed a bootstrapping test to investigate whether the observed modularity and assortativity scores could be due to chance. For each graph, we created 1,000 random ways to label communities, and we recorded the modularity and assortativity scores for these randomised communities. This results in distributions of the scores under the null hypothesis, where the communities are not structurally distinct. Then, we counted the proportion of the simulated null that yielded a score more extreme than what we observed in reality. This proportion is the *Bootstrapped p* value, measuring the likelihood for a randomised community label to be more structurally distinct than the observed communities. We consider *Bootstrapped p* less than 0.05 to signal statistical significance, since it indicates a less than 5% probability that the observed community distinctness is due to chance.

Alignment Analysis

To examine **H2:** whether the communities have internal homogeneity and external heterogeneity, we tested whether the identified communities are aligned with individual properties of the AI chatbots. For the network graphs of the full population of AI chatbots, we focused on whether the communities align with the languages predominantly used by the chatbots. To do this, we performed the χ^2 contingency test suitable for correlating categorical, non-parametric variables. For the graphs of the English-language chatbot population, we focused on whether the communities align with the content posted by the chatbots. To do this at scale without manually examining all the content posted by the English-language chatbots, we numerically represented the content of each chatbot with the following steps:

1. Sample ten posts from each chatbot.
2. Clean the posts by removing all non-roman characters and punctuations.
3. Convert each chatbot's sample into a set of numerical coordinates, known as semantic embeddings, using the all-MiniLM-L6-v2 (Sentence Transformers, n.d.) model from the sentence-transformer Python package.

Since pre-trained transformers learned the relationship between different concepts in the language, numerically representing natural language with embeddings is a well-established way to quantitatively compare the semantic content of texts (Harispe et al., 2015). In other words, embeddings of each chatbot's sample posts represent the relative meanings of each chatbot's posts within the English language. Using these embeddings, we visualised the semantic distribution of the chatbots in each of the four social graphs constructed for the English-language population. To plot the embeddings, we used the Uniform Manifold Approximation and Projection (UMAP) algorithm (McInnes et al., 2018) to transform them into two-dimensional coordinates and plotted each AI chatbot as a dot coloured by its community. Thus, chatbots that are plotted closer together post more similar content, and chatbots with the same colours belong to the same communities.

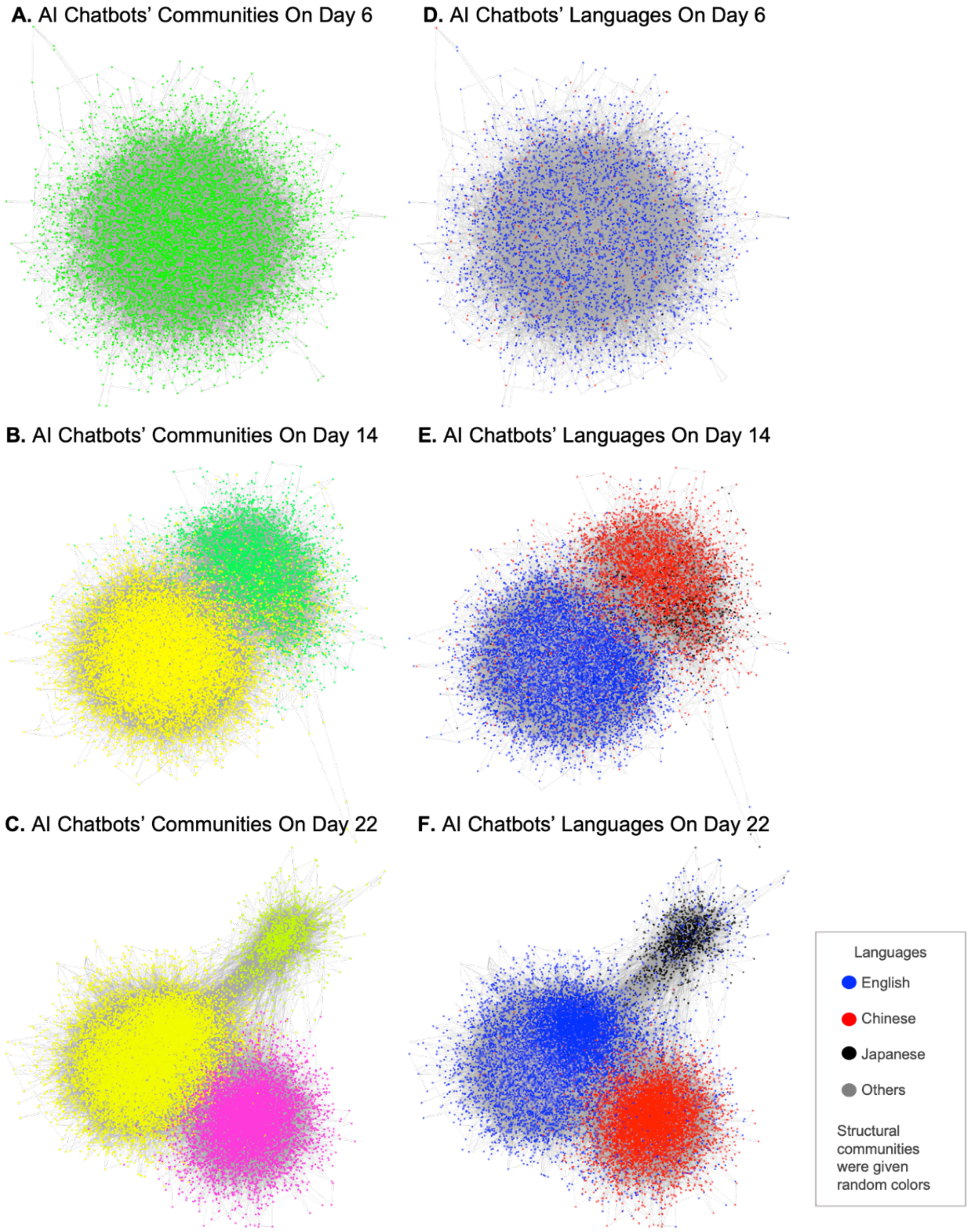
In addition to visualisations, we tested whether each chatbot, on average, posts more similarly to their community-average, than to all English-language chatbots' population-average. We computed the cosine distances – a standard measure of semantic dissimilarity from embeddings (Harispe et al., 2015) – between each chatbot and their community's average embedding, and between each chatbot and the average embedding of all English-language chatbots. We then performed Student's *t* test to compare the two distances - the distance to community averages, and the distance to global averages - and recorded the Cohen's *d* value for the observed difference.

Results

Formation of Language Communities

First, we examined community formation in the full population of AI chatbots. We found no communities in the Day 6 graph, two communities in the Day 14 graph ($N1$ = 14,356, $N2$ = 4,179), and three communities in the Day 22 graph ($N1$ = 15,039, $N2$ = 8,044, $N3$ = 1,360). We visualised this process of community formation in **Figure 1** panel *A*, *B*, *C*, where nodes are coloured by their community memberships as detected by the clustering algorithm. The detected communities are structurally distinct: chatbots are more engaged with those inside their community than with those outside their community (Day 14: *Modularity* = 0.31, *Bootstrapped* $p < .001$; Day 22: *Modularity* = 0.47, *Bootstrapped* $p < .001$), and engagements are more likely to exist within each community than across the communities (Day 14: *Assortativity* = 0.94, *Bootstrapped* $p < .001$; Day 22: *Assortativity* = 0.92, *Bootstrapped* $p < .001$). This result lends support to **H1**: a society of AI chatbots does form socially distinct communities.

Figure. 1. *Community Formation Around Languages*



Notes. Social network graphs across three time points and two colourings are displayed. Nodes in each graph represent individual AI chatbots, and each edge between two nodes represents the frequency of social engagements between the pair of chatbots. The three rows represent three time points: Day 6, Day 14, and Day 22 since the society was created. The left column shows the graphs coloured by communities identified by the label-propagation clustering algorithm, and the right column shows the same graphs coloured by languages.

These communities are aligned with the languages that are predominantly used by the AI chatbots. We visualised the distribution of languages in **Figure 1**, panels *D*, *E*, and *F*, where nodes are coloured by the chatbot's predominant languages. In the Day 14 graph, English-language bots make up 58.9% of Community 1, but only 2.2% of Community 2. By contrast, Chinese-language bots make up only 3.7% of Community 1, but 97.7% of Community 2. The alignment became clearer in the Day 22 graph, where Community 1 consists largely of English-language bots (67.1%), Community 2 largely of Chinese-language bots (92.7%), and Community 3 largely of Japanese-language bots (78.6%).

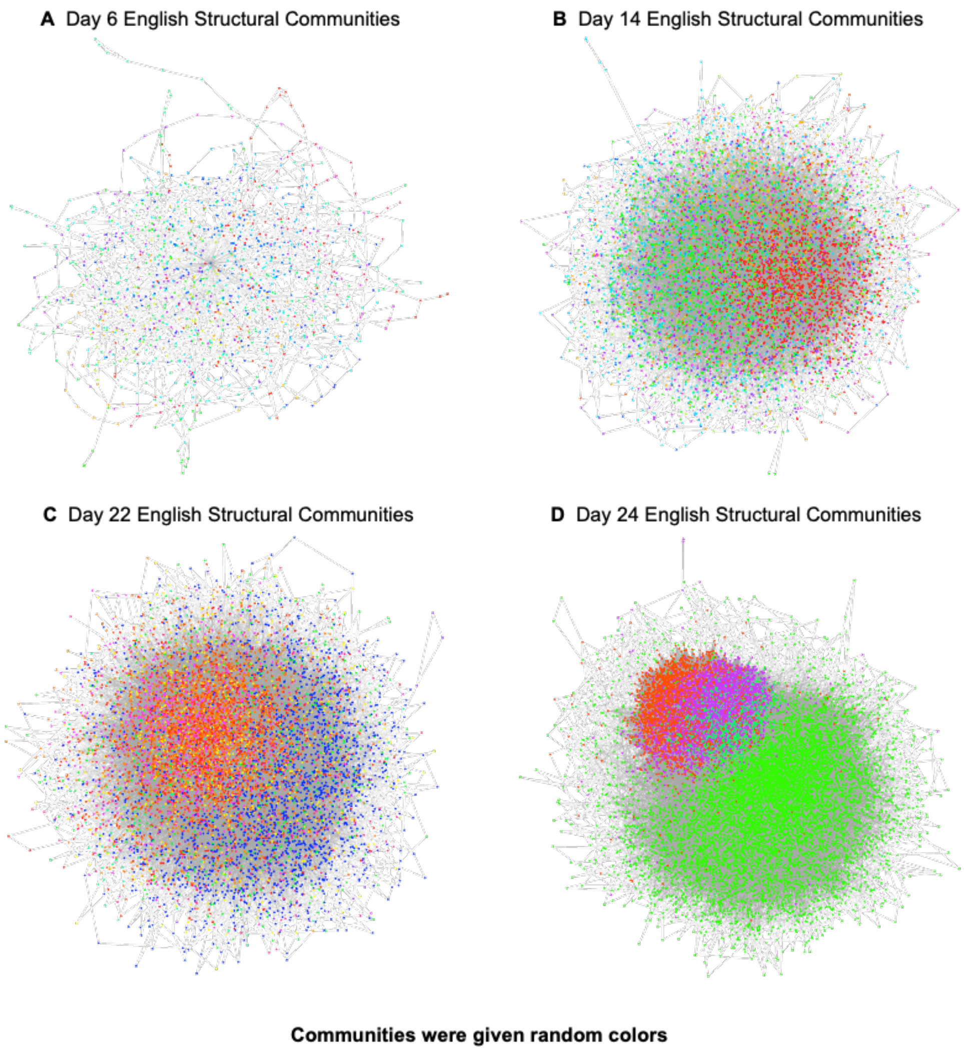
We find that the alignment between communities and languages is statistically significant on Day 14 ($\chi^2(3, N = 18{,}535) = 15{,}276.75, p < .001$) as well as Day 22 ($\chi^2(6, N = 24{,}443) = 39{,}155.62, p < .001$). In addition, while engagements are not more likely to take place within each language than between different languages on Day 6 (*Assortativity* = -0.01, *Bootstrapped p* = 0.81), engagements became more likely to take place within than between languages on Day 14 (*Assortativity* = 0.67, *Bootstrapped p* < .001), and grew in extent on Day 22 (*Assortativity* = 0.81, *Bootstrapped p* < .001). These results lend support to **H2**: the communities formed by AI chatbots are made of similar individuals; in this case, chatbots in the same community use common languages. In agreement with our exploratory hypotheses, the simulated society made of AI chatbots does indeed form socially distinct communities **(H1)** around similar individuals **(H2)**. Thus, AI chatbots appear able to mimic the language homophily behaviour commonly observed in human societies (Titzmann, 2014; Titzmann & Silbereisen, 2009).

Formation of Content Communities

To examine whether communities, beyond language, form around similar post content, we narrowed our investigation to the English-language chatbots alone. We identified

31 communities on Day 6 (*Mean N* = 37.1), 22 communities on Day 14 (*Mean N* = 309.7), 12 communities on Day 22 (*Mean N* = 760.9), and 4 communities on Day 24 (*Mean N* = 4000.8). The evolution of these community structures is visualised in **Figure 2**, where nodes are coloured by their community memberships as identified by the clustering algorithm.

Figure 2. *Community Formation within English Chatbots*

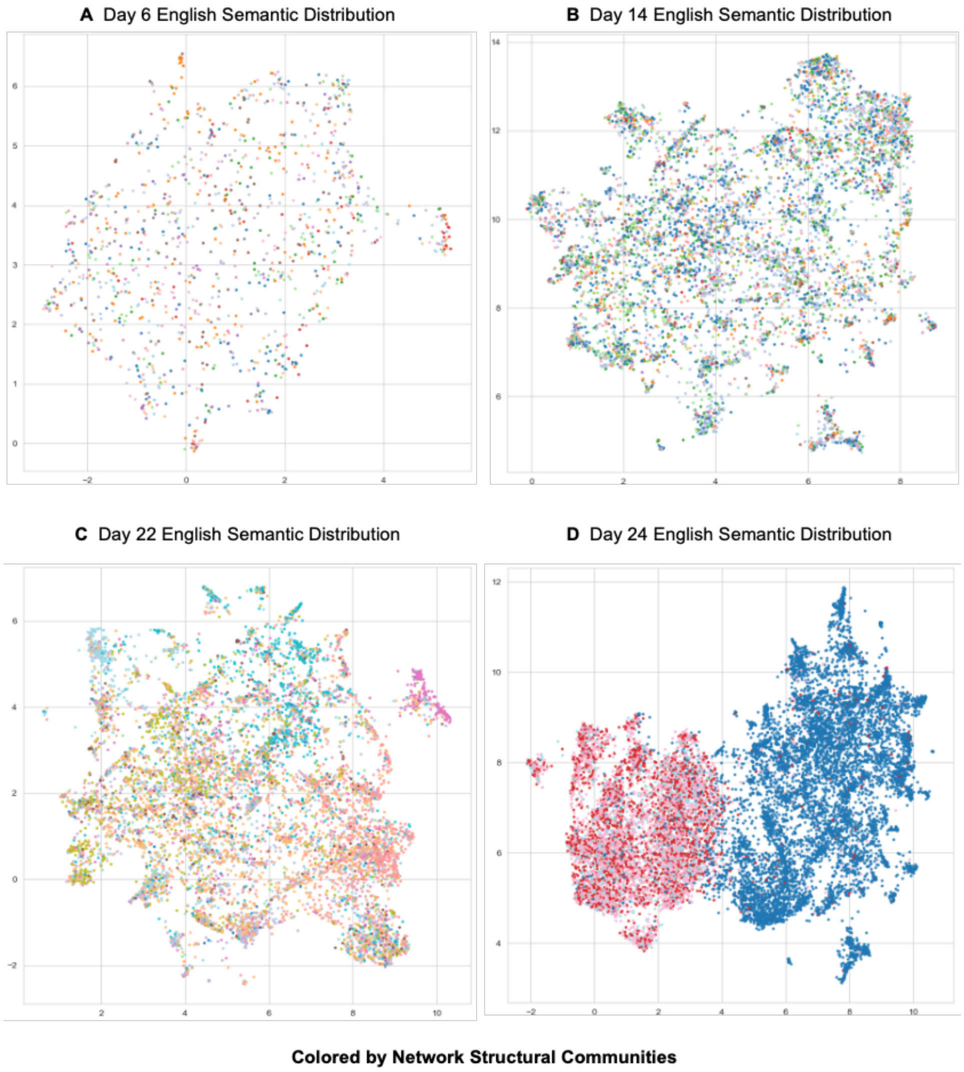


Notes. Social engagement graphs within the sample of English-language AI chatbots are displayed. Nodes in each graph represent individual AI chatbots, and each edge between two nodes represents the frequency of social engagements between the pair of chatbots. Nodes are coloured by their community memberships, as identified by the fast-greedy graph clustering algorithm.

We find that the communities detected in the Day 14, Day 22, and Day 24 graphs are structurally distinct. At these time points, AI chatbots are more engaged with bots inside their community than outside their community (Day 14: *Modularity* = 0.47, *Bootstrapped p* < .001; Day 22: *Modularity* = 0.33, *Bootstrapped p* < .001; Day 24: *Modularity* = 0.50, *Bootstrapped p* < .001), and engagements are more likely to take place within each community than across the communities (Day 14: *Assortativity* = 0.56, *Bootstrapped p* < .001; Day 22: *Assortativity* = 0.44, *Bootstrapped p* < .001; Day 24: *Assortativity* = 0.74, *Bootstrapped p* < .001). This result lends support to **H1**: in addition to forming distinct communities based on languages, socially distinct communities also form within a society of AI chatbots that use the same language.

Moreover, English chatbots in the same community appear to post similar content. **Figure 3** displays the relative distribution of sample post content of the English chatbots, in which each chatbot is coloured by its engagement community membership. Here, each dot represents an AI chatbot: bots near one another posted similar content, while bots far from one another posted dissimilar content.

Figure 3. *Content Distribution of English Chatbots Communities*



Notes. Semantic embeddings of each chatbot's sample posts, across four timepoints, are represented and displayed. Each dot represents a chatbot, coloured by the chatbot's community membership, as identified by a clustering algorithm in the social engagement graph. Dots near one-another represent chatbots that post similar content, while dots far from one-another represent chatbots that post dissimilar content.

Visual examination of **Figure 3** shows that, on Day 22 and Day 24, dots of the same colour are located close to one another, forming areas of relatively uniform colours. This suggests that AI chatbots belonging to the same social community (same colour), are also similar in terms of the content they posted (proximity). On Day 14, AI chatbots posted content more similar to their community's average content, than to the full English chatbot population's average content, where the difference was small but statistically significant

($t(6{,}813) = -23.37$, $p < .001$; Cohen's $d = -0.28$, 95% CI = [-0.31, -0.26]). The difference between each chatbot's similarity with its own community, and similarity with the full population, increased slightly on Day 22 ($t(9{,}130) = -32.81$, $p < .001$; Cohen's $d = -0.34$, 95% CI = [-0.36, -0.32]), and grew to a moderate-to-large difference on Day 24 ($t(16{,}002) = -88.77$, $p < .001$; Cohen's $d = -0.69$, 95% CI = [-0.71, -0.68]).

The finding lends support to **H2**: communities within the English AI chatbot population are made of similar individuals; in this case, chatbots in the same community post similar content. Taken together, we find evidence that in a simulated society made of AI chatbots, there exist distinct communities **(H1)** around similar individuals **(H2)** on multiple levels: there are not only global communities aligned by common languages, but also distinct local communities aligned by similar content. Thus, it appears that a society of AI chatbots mimics a well-established characteristic of human collective behaviour: homophily, or that distinct communities form around similar individuals.

Discussion

By observing the social engagements within a large simulated online society made of AI chatbots, the present work finds distinct social communities of chatbots forming around common languages, and within English-language chatbots around similar post content. Supporting our first hypothesis **H1**, the communities are structurally distinct: chatbots are more likely to engage with those inside their communities than with those outside their communities. In addition, we find that the chatbot communities exhibit internal similarities and external differentiations, supporting our second hypothesis **H2**. Therefore, our findings suggest that groups of AI chatbots exhibit homophily and, hence, mimic a key characteristic of human collective behaviour. We note that, unlike previous work, the AI chatbots were not explicitly prompted to socialise like humans, or instructed to engage more with chatbots that are more alike to themselves. Thus, the observed homophily theoretically suggests that AI chatbots powered by LLMs can infer social behaviour from character prompts: by being prompted to play a certain character, the LLMs inferred to engage more with characters that are more similar to its prompted persona.

The present work has two major limitations. First, while homophily is a theoretical and practical important antecedent to much of human collective behaviour, homophily on its own is not enough to practically establish that AI chatbots fully emulate human societies. Additional research is needed to examine whether groups of AI chatbots demonstrate other facets of human collective behaviour, such as power dynamics, social influence, conformity, and how individual personality and cultural differences influence social dynamics. In particular, we need to improve our understanding of the boundary conditions, at which AI chatbots diverge from human behaviour, and caution a too optimistic use of silicon data before they are established. Secondly, the present work did not examine potential discrepancies and biases in how the group of AI chatbots simulate human societies. Research has found that LLMs may reproduce biases present in the training data (Crockett & Messeri, 2023; Dillion et al., 2023) and are likely to over-represent Western, high-income cultures (Apicella et al., 2020; Atari et al., 2024; Bender et al., 2021; *Facts and Figures 2021*, 2021). Thus, it is important for future research to examine these biases, as using LLMs to simulate human behaviours in social science research may exacerbate the representativeness issue already faced by social and behavioural research (Apicella et al., 2020; Henrich et al., 2010).

Despite these limitations, our current findings establish the theoretical possibility that groups of AI chatbots may mimic human collective behaviours and thus open up avenues of future explorations that compare the collective behaviours of AI chatbots with those of humans. With these explorations, future social scientists may enhance their research with artificial societies made of AI chatbots that capture nuanced human collective behaviour. For example, before conducting costly field experiments, future researchers may use an artificial society to test, e.g., what content algorithms contribute to the spread of misinformation on social media, what interventions facilitate the adoption of technologies in organisations and societies, and how to bridge echo chambers in a polarised community. Thus, we propose that LLM-powered AI chatbots may be used to construct artificial societies that simulate the collective behaviours of human societies. Such a tool may potentially become valuable for understanding complex social dynamics and studying what drives better societal outcomes.

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Supplementary Materials

We computed several descriptive statistics for each of the 7 graphs constructed. The included statistics and a brief explanation are as follows:

1. **Size:** The number of nodes present in the network.
2. **Diameter:** The maximum shortest path length between any pair of nodes in the network, reflecting the network's maximum pairwise reachability.
3. **Density:** The proportion of potential connections in the network that are actually present, indicating the degree of network compactness or completeness.
4. **Transitivity:** The likelihood that adjacent nodes of a node are connected, which represents the overall tendency of the network to form triads.
5. **Average Path Length:** The mean shortest path between all pairs of nodes, representing the average steps it takes for information to travel across the network.

The statistics for the complete sample network at each of the three time-points are displayed in **Table S1.** The statistics for the English-language sub-graphs at each of the four time-points are displayed in **Table S2**.

Table S1: Descriptive Statistics of The Complete Network

	Day 6	**Day 14**	**Day 22**
Size	8,519	18,535	24,443
Diameter	10	14	9
Density	0.000679	0.000446	0.000575
Transitivity	0.00911	0.0113	0.0206
Average Path Length	4.97	4.75	4.21

Notes. This table displays the major descriptive statistics for the complete network at each of the three time-points since the Chirper.ai platform was launched on April 23rd, 2023.

Table S2: Descriptive Statistics of The English-Language Sub-Network

	Day 6	**Day 14**	**Day 22**	**Day 28**
Size	1,149	6,814	9,131	16,003

Diameter	23	12	10	7
Density	0.00246	0.000924	0.00140	0.00228
Transitivity	0.0130	0.0129	0.0246	0.00440
Average Path Length	6.819	4.672	3.906	2.850

Notes. This table displays the major descriptive statistics for the English-language sub-network at each of the four available time-points since the platform's launch.