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Review

Modelling language evolution: Examples and predictions

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Abstract

We survey recent computer modelling research of language evolution, focusing on a rule-based model simulating the lexicon–syntax coevolution and an equation-based model quantifying the language competition dynamics. We discuss four predictions of these models: (a) correlation between domain-general abilities (e.g. sequential learning) and language-specific mechanisms (e.g. word order processing); (b) coevolution of language and relevant competences (e.g. joint attention); (c) effects of cultural transmission and social structure on linguistic understandability; and (d) commonalities between linguistic, biological, and physical phenomena. All these contribute significantly to our understanding of the evolutions of language structures, individual learning mechanisms, and relevant biological and socio-cultural factors. We conclude the survey by highlighting three future directions of modelling studies of language evolution: (a) adopting experimental approaches for model evaluation; (b) consolidating empirical foundations of models; and (c) multi-disciplinary collaboration among modelling, linguistics, and other relevant disciplines.

Keywords: Evolutionary linguistics; Computer modelling; Rule-based model; Equation-based model; Complex adaptive system

1. Computer modelling in evolutionary linguistics

“A basic task of science is to build models – simplified and abstracted descriptions – of natural phenomena” [1, p. 432]. Throughout the history of science, thought experiments have served as the “modelling” approach helping researchers conceive an abstract or poorly-understood domain in terms of a more familiar one [2–4]. Computer modelling dated back to John von Neumann’s universal constructor demonstrating that machines could self-reproduce just like living organisms [5]. As an efficient means to articulate sophisticated theories and address complex phenomena [6], computer modelling has now become pervasive in most traditional as well as newly-founded disciplines [7,8].

Abbreviations: S, subject; V, verb; O, object; *RC*, reliability of cue; *RE*, rule expressivity; RE_{holist}, RE of holistic rules; RE_{comp}, RE of compositional rules; *UR*, understanding rate; UR_{GloOrd}, *UR* of a global order; UR_{LocOrd}, *UR* of a local order; UR_{con}, *UR* become consecutive generations; UR_{ini}, *UR* between the first and later generations; *JA*, joint attention; *CS*, communicative success; *CCrate*, rate of child–child transmission; *ACrate*, rate of adult–child transmission; *PCrate*, rate of parent–child transmission.

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Evolutionary linguistics [9] did not escape the invasion of computer modelling. This resurgent linguistic subfield [10] aims to identify when, where, and how human language originates, changes, and dies out [11]. It studies (a) *origin* (the transition from a pre-linguistic communication system to a communication system with the sort of languages we use today), (b) *change* (the process whereby phonetic, semantic, or syntactic features of one or a group of languages are modified), and (c) *acquisition* (the course while a pre-language infant or an individual who already uses a language acquires a new one exposed to him/her in a socio-ecological environment [12]) of language. These topics address not only particular language(s) but also human *language faculty* (the set of capacities to master and use natural languages [13]) [14].

After more than half a century of modern research in evolutionary linguistics, there remain two issues that still lack decisive answers: (a) how human cognition enables language processing, more precisely, whether language processing abilities are formed by language-specific modules [15,16] or derived from *domain-general* (not language-specific or human-unique) abilities [17–20]; and (b) how biological or socio-cultural factors influence *language universals* (principles of structure or use that hold in most but not necessarily all languages [21]) [22,23] in a socio-ecological environment [22,23].

There exist bifurcating views regarding these issues. For instance, stressing the dissociation of language from other cognitive domains, the nativist view states that humans must have a language faculty that evolved from either a single mutation [24,25] or a series of natural selection [26,27]. In contrast, advocating the intrinsic connections between language and other cognitive functions, the connectionist or emergentist view [9,19,28] states that: (a) language resulted from elaboration of domain-general abilities into language activities and reconfiguration of ancestral systems in evolutionarily novel ways [29–32]; and (b) language processing relies upon not only general systems for expressing objects, actions and their relations, but also socio-cognitive constraints spanning from social interactions, pragmatics, memory, and other processing [33,34]. As for the driving force behind language evolution, the nativist view highlights the roles of biological evolution in forming linguistic abilities [25,35–38], whereas the emergentist view emphasizes the effects of socio-cultural factors on recruiting cognitive mechanisms and shaping language structures [22,23,30, 39–43].

Due to the fact that linguistic behaviours are hard to preserve in fossils [19,44], research in evolutionary linguistics, especially on language origin, remains exploratory to a certain extent, which actually makes it suitable for computer modelling [45,46]. In evolutionary linguistics, *computer modelling* can be viewed as "operational" hypotheses or theories that are expressed by computer programs rather than verbal statements [47]. By running these programs, the simulation results obtained become the empirical predictions derived from the incorporated hypotheses or theories [48]. Unlike the definitions in other academic fields (e.g. psychology or neuroscience), we emphasize modelling as a scientific method to evaluate available theories, suggest new perspectives, and address questions more focused than what theoretical linguists can conceive of [49]. All these aspects help transform evolutionary linguistics from a speculative topic into a scientific domain [50].

According to how components of the target linguistic phenomenon are realised mathematically, available models of language evolution can be classified as rule-based and equation-based models (see [51,52] for other ways of classification). *Rule-based models* define concrete or abstract rules to describe or manipulate linguistic components and relevant behaviours. Correlation of these rules leads to acquisition of language within individuals and socio-cultural evolution of it among individuals. Such models often encode specific language structures and knowledge, simulate interested processing mechanisms, and analyse stochastically effects of these mechanisms on developing those structures or triggering new ones as attested in world languages. In contrast, *equation-based models* tend to transform linguistic and relevant behaviours into mathematical equations. Mathematical analyses on these equations and experimental or empirical confirmations allow equation-based models to reasonably approximate the history of language evolution or predict its future.

Ever since James Hurford designed his rule-based model demonstrating the origin of a coordinated signalling system via iterated communications, many computer models have been proposed to challenge the nativist view that minimizes the role of communication in language evolution [25] (see recent anthologies [47,53–62] and proceedings of the biennial conferences on language evolution [63–68]). For instance, some models ascribe the distributions of phonetic elements (e.g. vowels) to *self-organization* (the process whereby a global pattern of a system emerges from local interactions of its components [69]) during communications [70,71]. Others show that language universals arise naturally via *cultural transmission* (the process whereby information is passed among individuals via social learning such as imitation or language [72]) [39,73] or *language games* (interacting protocols for individuals to develop shared conventions to exchange information) [58,59,74,75].

To avoid a tedious review, we focus on one rule-based and one equation-based model (see [46,76] for reviews of other models). The rule-based model is the lexicon–syntax coevolution model [77,78]. It adopts a *multi-agent system* [79] consisting of a population of interacting agents, and simulates some general learning abilities, a communication scenario, and a socio-cultural environment. It traces a coevolutionary origin of lexical items and simple word orders among agents. The equation-based model is the language competition model [80]. It assigns explicit linguistic meanings to parameters and uses these concrete parameters to address fundamental socio-cultural constraints on language competition. It adapts a biological competition model into the language competition model, and derives a series of mathematical principles from physics, biology, and population dynamics to estimate parameter values in actual cases of language competition.

After briefly describing these models, we discuss their primary contributions. The rule-based model demonstrates the domain-generality of language-specific processing mechanisms for lexical items and simple word orders [77,78]. By incorporating natural and cultural selections, it provides a coevolutionary explanation to the degree differences in language-related mechanisms between humans and non-human primates [81]. By simulating forms of cultural transmission and social structure, it also reveals the effect of cultural transmission on triggering and maintaining a communal language across generations of individuals [82,83] and the correlation between social structure and linguistic understandability within a group of individuals [84].

The equation-based model calculates parameter values from empirical data of population surveys and linguistic questionnaires, which allows reliably replicating and reasonably predicting the dynamics of language competition, especially in cases that lack sufficient competition data. In addition, the model itself and those mathematical principles are derived from well-attested principles in linguistics, biology, physics, and population dynamics, which reveal the intrinsic commonalities among linguistic, physical, and biological phenomena [80]. All these have significantly improved the robustness, applicability, and explanatory power of the language competition model.

We conclude the survey by pointing out three directions for future modelling research in evolutionary linguistics, including designing psycholinguistic experiments to evaluate simulation results concerning human behaviours, referring to language databases to consolidate the empirical bases of computer models, and conducting multi-disciplinary collaborations among relevant disciplines.

2. Behavioural model and its predictions

2.1. Lexicon–syntax coevolution model

This model aims to evaluate the "formulaic" theory of language origin [85,86]. This theory states that: modern languages originated from a holistic protolanguage using holophrastic utterances to encode integrated meanings; and by general learning mechanisms, early hominins segmented holistic expressions to acquire lexical items and relevant grammar. In the model, we simulate a communication system using a holistic protolanguage, define both holistic and compositional linguistic rules, and equip agents with general learning mechanisms to see whether these mechanisms can sufficiently trigger a compositional communal language.

2.1.1. Individuals, artificial language, and linguistic knowledge

In the model, language users are simulated as artificial agents, and the artificial language created and used by them is denoted by *meaning-utterance mappings*. Agents share a semantic space containing a number of *integrated meanings*, such as "run⟨fox⟩" ("a fox is running") or "chase⟨lion, goat⟩" ("a lion is chasing a goat"). These meanings can be encoded by utterances (sentences), each being a string of syllables from a signalling space. An utterance encoding an integrated meaning can be segmented into subparts mapping semantic constituents, and subparts can also combine to encode an integrated meaning.

Agents' linguistic knowledge is denoted by linguistic rules (see [77,78] for examples). For instance, "chase⟨wolf, bear⟩"↔/abcde/ is a *lexical rule* denoting that the meaning "chase⟨wolf, bear⟩" can be encoded by the utterance /abcde/; and /abcde/ can also be interpreted as "chase⟨wolf, bear⟩". This is a *holistic* rule, mapping an integrated meaning onto a sentence. A lexical rule can also be *compositional*, mapping semantic constituent(s) onto a subpart of a sentence (e.g. "wolf"↔/cd/).

When forming sentences using compositional rules, their utterances in sentences are regulated by order rules. An *order rule*, e.g. "Category 1 $\ll$ Category 2", denotes that the utterances of lexical rules from Category 1 (see below) lie before (not necessarily immediately before) those from Category 2. One order rule helps form utterances encoding intransitive meanings like "run⟨wolf⟩", and two or three help construct utterances encoding transitive meanings like "chase⟨wolf, bear⟩".

A *category* contains a number of lexical and order rules. The lexical rules encode constituents having identical *thematic roles* (actions, action instigators, or entities undergoing actions) in integrated meanings, and the order rules specify the orders between the utterances of these lexical rules and the utterances of other lexical rules from other categories. For the sake of simplicity, categories of lexical rules encoding action instigators are also called S(ubject) categories, because without passive voice, action instigators are often subjects in sentences. Similarly, categories of entities undergoing actions are O(bject) categories, and categories of actions V(erb) categories. An order rule between two categories can also be denoted using the *syntactic roles* (S, V, or O) of these categories, e.g. S $\ll$ V, or simply SV. Via categorisation, order rules acquired from some lexical items can be applied productively to others having identical thematic roles.

Each lexical or order rule is assigned a *strength* (within [0.0 1.0]), indicating how often this rule has been applied successfully during communications. A compositional rule also has *association weights* to categories that contain it, indicating how often the order rules in those categories are applied successfully on this rule during communications. Rule strength and association weight enable a strength-based competition in communications and a gradual forgetting of linguistic knowledge.

Using predicate-argument structures to represent semantics, syllables to form utterances, and lexical and grammatical rules to denote linguistic knowledge has been widely adopted in computer models of language evolution (e.g. [39, 71]), though semantic structures of integrated meanings, syntactic structures of exchanged utterances, and linguistic rules remain distinct among models focusing on different aspects of language evolution.

2.1.2. Domain-general learning mechanisms

Agents are equipped with general learning mechanisms to acquire linguistic rules (see [77,78] for details of these mechanisms). Lexical rules are acquired from constituent(s) and syllable(s) that appear repetitively in two or more meaning-utterance mapping. Agents store *previous experiences* (meaning-utterance mappings acquired in previous communications). New mappings, before being stored, are compared with those already existing. For instance, by comparing "hop⟨fox⟩"↔/ab/ and "run⟨fox⟩"↔/acd/, an agent can detect the recurrent pattern "fox" and /a/. If the agent has no rule recording this pattern, it will create a lexical rule "fox" ↔ /a/ for future use.

Categories and order rules are acquired based on thematic roles of lexical rules and sequential relations of their utterances in meaning-utterance mappings. If an agent notices that in some previous experiences, the utterances of two or more lexical rules having the same thematic role are consistently before (or after) the utterance of another lexical rule (or the utterances of another set of lexical rules all having identical thematic roles), the agent can associate these lexical rules into a category having the corresponding syntactic role, create an order rule to record the local order with respect to the other lexical rule(s), and put this order rule to the same category. In this way, the agent can gradually form categories associating different lexical rules and local orders among them.

These item-based learning mechanisms have been traced in language acquisition studies [87]. The categorization process resembles the verb-island hypothesis [30,88]. This hypothesis states that children's early grammar consists of sets of lexically-specific predicate structures (i.e. verb-islands). For instance, a child can use any object that he/she knows has performed kicking as the antecedent to "kick". Then, due to overlap of these object items, the child gradually merges verb-islands surrounding distinct verbs and forms a complete verb category. Until then, the verb-general marking can occur. Such islands are also formed around lexical items other than verbs [89].

2.1.3. Communication scenario

A linguistic communication involves two agents (a speaker and a listener), who perform a number of *sentence exchange*, each proceeding as follows.

In production, the speaker (hereafter as "she") first selects randomly an integrated meaning from the semantic space to produce. She then activates her lexical, order, and category rules to form candidate sets for production, each offering a sentence to encode the meaning. For each set, she calculates the combined strength (see [77,78] for calculation equations), which is the average strength of the lexical rules in this set plus the average product of the association weights of the lexical rules to the categories and the strengths of the order rules in these categories used for regulating the lexical rules. After calculation, she chooses the set having the highest combined strength, builds up the sentence accordingly, and transmits the sentence to the listener. If lacking enough rules to encode the meaning, she occasionally creates a holistic rule to encode the whole meaning and sends the utterance of this rule to the listener. In other words, before sufficient compositional knowledge is available, agents stick to holistic knowledge, which is in line with the "formulaic" theory.

In comprehension, the listener (hereafter as "he") receives the sentence from the speaker and an *environmental cue*. The cue, as non-linguistic information, contains an integrated meaning plus a *cue strength*. Incorporating non-linguistic information into linguistic communications allows evaluating the correlation between the evolutions of language and non-language-specific abilities.

Cues are unreliable (not always containing the speaker's intended meaning), which avoids *explicit meaning transfer* [90] (explicitly transferring meanings encoded in exchanged sentences via non-linguistic cues, thus making linguistic communication unnecessary) as in previous models (e.g. [39,91]). We define *reliability of cue* (*RC*) to denote how often the listener obtains a correct cue in an utterance exchange; otherwise, he receives a wrong cue. The correct cue contains the speaker's intended meaning, whereas the wrong one contains an integrated meaning randomly chosen from the semantic space and distinct from the speaker's intended meaning.

The listener activates his lexical, order and category rules that can interpret the heard sentence as integrated meaning(s). He then compares the cue's meaning with the one(s) comprehended by linguistic rules, and sets up candidate sets for comprehension. If the cue's meaning completely or particularly matches the one interpreted by some linguistic rules, the cue and those rules form a candidate set. Otherwise, the cue itself forms a candidate set. If some linguistic rules can also offer a complete interpretation, they form another set as well.

The listener calculates the combined strength of each set. For a set without a cue, its combined strength is calculated exactly the same as that in production. For a set having a cue, the cue strength is added to the combined strength. After calculation, he chooses the set having the highest combined strength for comprehension. If this combined strength exceeds a confidence threshold, the sentence exchange is deemed successful. In this situation, the listener stores the perceived meaning-utterance mapping as a previous experience, and then, both speaker and listener reward their rules in their chosen sets by adding a fixed amount to their strengths and association weights, and penalize competing ones in other sets by deducting the same amount from their strengths and association weights. Otherwise, the sentence exchange is failed. In this situation, the listener discards the perceived mapping, and both speaker and listener only penalize their rules in their chosen sets.

During a sentence exchange, non-linguistic information assists linguistic comprehension, by clarifying unspecified constituent(s) and enhancing rules that can lead to a similar interpretation to this information. The cue strength equals to the confidence threshold, so that linguistic and non-linguistic information are treated equally. Such multi-information coordination has its neural basis in the human brain [92]. In addition, throughout the sentence exchange, there is no check whether the speaker's encoded meaning matches the listener's decoded one, which allows the model to address whether unreliable cues help trigger fundamental linguistic knowledge. Furthermore, the strength adjustment mechanism leads to conventionalization of linguistic knowledge. Such linear inhabitation mechanism has been used in many rule-based models (e.g. [60,61]), with distinct details.

2.2. Correlation of domain-general abilities and language-specific mechanisms

The learning mechanisms adopted by agents are domain-general. Pattern extraction is to detect or encode isolated or combined items that appear repetitively in linguistic or other types of instances [93]; sequential learning is to detect or encode the sequential orders of discrete elements occurring in a temporal sequence [21]; and categorization is to apply available knowledge in novel, similar conditions [30]. Usage-based and functional linguists [94–96] group these mechanisms as general pattern-finding skills [30].

The model can simulate either a holistic language (via holistic rules) or a compositional one (via compositional, order, and category rules). To evaluate the "formulaic" theory, we test whether agents can develop, via those general mechanisms and iterated communications, a compositional language out of a holistic one. *Linguistic compositionality* refers to the principle on how the meaning of a complex expression is built from its subparts via regulating rules [97]. We divide it into *compositionality* (agents use compositional rules to build sentences encoding integrated meanings) and *regularity* (agents use consistent orders to regulate lexical items in sentences).

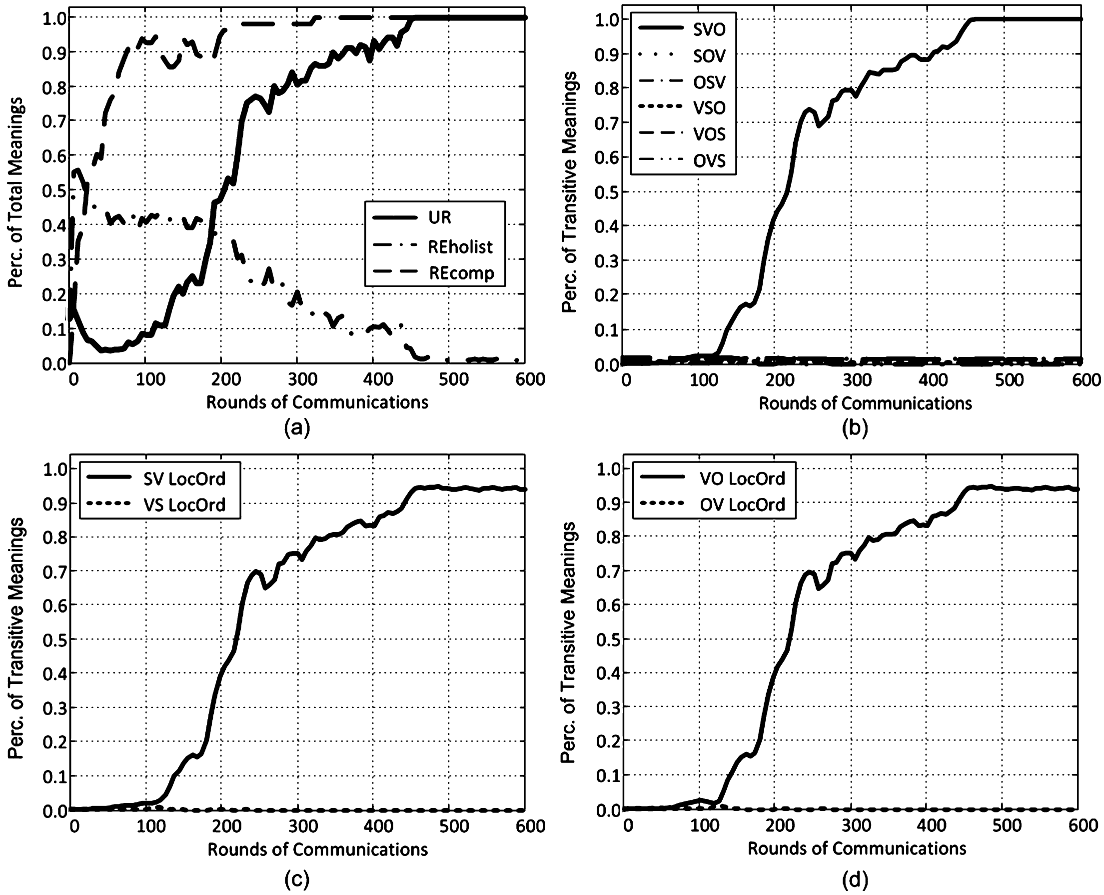

Fig. 1. These figures (adapted from [78]) illustrate that agents gradually develop a common set of compositional rules (high UR_{comp} in (a)) and order rules (high UR_{LocOrd} of SV and VO in (c) and (d)) leading to a consistent global order (high UR_{GloOrd} of SVO in (b)). These rules comprise a communal language capable of accurately exchanging most integrated meanings (high *UR* in (a)).

We define four indices to evaluate simulation results (see [78] for how to calculate them): (a) *rule expressivity* (*RE*), the average percentage of integrated meanings that all agents can produce; (b) *understanding rate* (*UR*), the average percentage of integrated meanings understandable to each pair of agents based on their linguistic knowledge, which evaluates whether the acquired linguistic knowledge helps agents efficiently produce and accurately comprehend integrated meanings; (c) *UR of a local order* (UR_{LocOrd}), the average percentage of transitive meanings understandable using agents' lexical knowledge and a particular local order (SV, VS, SO, OS, VO, or OV); and (d) *UR of a global order* (UR_{GloOrd}), the average percentage of transitive meanings understandable using agents' lexical knowledge and a particular global order (SVO, SOV, OSV, OVS, VSO, or VOS), here, a global order is the combined order of local orders (e.g. local orders SV and VO lead to a global order SVO).

Fig. 1 shows the result of a typical simulation run (under the settings in [78]). In this run, agents initially share only a small number of holistic rules, indicating a holistic language with limited expressivity. Fig. 1(a) traces *RE* of holistic rules (RE_{holist}), *RE* of compositional rules (RE_{comp}), and *UR*. As for *RE*, RE_{holist} first increases slightly, indicating that exchanged sentences are primarily formed by holistic rules. Given more linguistic experiences, recurrent patterns start to appear and get acquired as compositional rules, and a competition occurs between compositional and holistic rules. The combinatorial advantage (a compositional rule, due to combination, can express many meanings involving its encoded constituent(s), whereas a holistic rule only expresses one integrated meaning) makes compositional rules gradually win the competition. With more compositional rules being shared, RE_{holist} drops and RE_{comp} increases and approaches 1.0.

As for *UR*, it first increases with RE_{holist}, indicating that comprehension at this stage relies on holistic rules. With the origin of compositional rules, an explicit drop of *UR* is seen, reflecting the competition between holistic and compositional rules. After compositional rules win the competition, *UR* starts to increase sharply, because sharing one more compositional rule enables agents to accurately exchange many more integrated meanings. With more compositional rules being shared, *UR* approaches 1.0, along with RE_{comp}. The high RE_{comp} and *UR* illustrate the origin of compositionality: agents share a common set of compositional rules to accurately exchange most integrated meanings.

Fig. 1(b) illustrates that along with the origin of compositional rules, UR_{GloOrd} of SVO increases. Figs. 1(c) and 1(d) illustrate that most agents in this run develop SV and VO to interpret transitive meanings, thus leading to SVO. Since V categories associate lexical rules encoding both transitive and intransitive actions, SV also regulates intransitive meanings (see [98] for discussions on relations between semantic structure, emergent global orders, and general learning mechanisms).

Fig. 1 illustrates a coevolutionary origin of compositionality and regularity; the sharp increase in *UR* synchronizes temporarily with that in UR_{GloOrd} or UR_{LocOrd} of the prevalent order(s). The driving forces for this process include mutual understanding, semantic similarity (integrated meanings share constituents having identical thematic roles), and non-linguistic cues (aiding comprehension when linguistic knowledge is insufficient).

These results illustrate the roles of domain-general mechanisms in acquiring lexical items and simple syntax, demonstrate the "formulaic" theory, match the general patterns of language acquisition [12,93,99], and reveal the inseparability of lexicon and syntax in language processing and development [100]. These results also trace a "bottom-up" syntactic development (consistent global order of multiple lexical items results from combination of local orders each between two items), which can trigger reconsideration on the nativist view on syntax and relevant mechanisms. An insightful future work here is to check whether complex syntactic hierarchy can also be triggered in such a "bottom-up" manner.

2.3. *Coevolution between language and relevant abilities*

Although the above simulation and previous studies (e.g. [19]) illustrate that domain-general mechanisms shared by humans and other animals can contribute to the acquisition and development of language, there are degree-differences in these mechanisms between humans and non-human primates [101]. One such mechanism is *joint attention* (*JA*) (establishing common ground in general interactive activities by means of socio-cognitive abilities [102]; e.g. one individual alerts another to an object or event by means of eye-gazing, pointing, or other verbal or non-verbal indications). There is a positive correlation between mother-child *JA* and child's word learning efficiency [103,104], whereas wild or captive non-human primates of different ages exhibit a significantly lower *JA* level than humans [105].

This comparative evidence hints that a fully-formed high *JA* level in humans seems to be a prerequisite for language and communication [101,106–108], but the brain-language/gene-culture coevolution theory [109–111] also suggests that such difference could result from a *coevolution* (a reciprocal or competitive influence between two or more natural species or system components [112]) with language. According to the coevolution theory, early hominins borrowed *JA* from general interactions into linguistic communications to form mutual understanding and acquire basic linguistic knowledge, and once the *JA* level became correlated with linguistic comprehension, *communicative success* (*CS*) could enhance reciprocally the *JA* levels in language users. In other words, the initial *JA* level in early hominins need not be very high.

The rule-based model helps evaluate this coevolutionary scenario. First, the communication in the model involves non-linguistic cues to aid linguistic comprehension, and *RC* reflects the ability of establishing common grounds during communications (obtaining correct cues containing speakers' intended meanings). If we simplify *JA* as availability of topics from non-linguistic information, *RC* can quantify the *JA* level. Second, *CS* of an agent can be reflected by the *UR* of this agent when others talk to it.

We implement a transmission framework that involves both genetic transmission (transmitting *JA* level (*RC*) from adults to offspring during reproduction) and cultural transmission (adult–adult and adult–offspring communications). During reproduction, half of the adults are chosen as parents, each producing two offspring (to keep the population size stable) who initially have no linguistic knowledge but inherit their parents' *RC* with occasional mutation (increasing or decreasing copied *RC* value with a fixed amount). Then, these offspring learn from their parents or other adults as listeners in adult–offspring communications. After that, they become adults, replacing all adults in the previous generation, and conduct adult–adult communications with each other. Then, the next round of reproduction occurs.

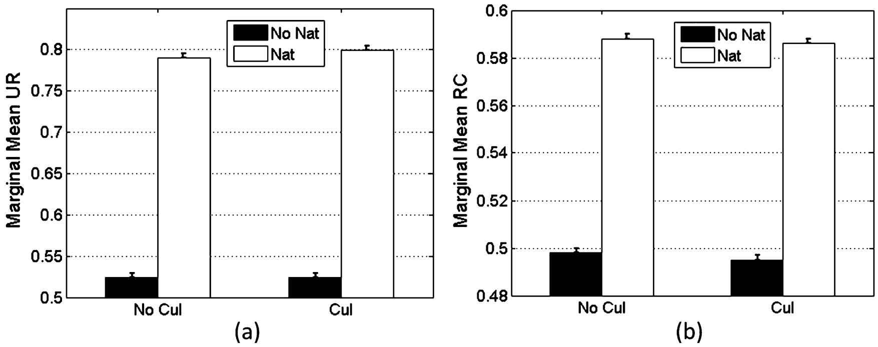

Fig. 2. These figures (adapted from [81]) illustrate the coevolution between language (*UR*) (a) and *JA* level (*RC*) (b) after 1000 rounds of reproduction. Results are obtained from 50 simulation runs in each condition.

Both natural and cultural selections can take effect in this framework. The former selects adults who understand others better (having higher *CS*) as parents to reproduce, and the latter chooses adults having higher *CS* as teachers talking to offspring in adult–offspring communications. We set up four sets of simulation to manipulate these selections. In the sets without natural or cultural selection, parents or teachers are randomly chosen in each generation. In these sets, *RC* values in the first generation are chosen from Gaussian distributions having fixed standard deviations but different means. According to these means, we set up nine *RC* conditions in each of the four sets.

Fig. 2 shows the simulation results (under the settings in [81]). In these simulations, agents initial use a holistic language with limited expressivity. As shown in Fig. 2(a), the mean *UR* (over all *RC* conditions of all simulations) in the sets with natural selection is significantly higher than that in the sets without, whereas the mean *UR* in the sets with cultural selection is similar to that in the sets without. Fig. 2(b) shows a similar effect on the mean *RC*. These results indicate that it is natural selection, rather than cultural selection, that drives the origin of a communal language with good understandability (*UR*) and enhances a low *JA* level (*RC*). Although the coevolution is mainly via natural selection, cultural transmission is inevitable, which serves as a medium for individuals to form their distinct *CS* to be selected by natural selection.

These results illustrate that culturally constituted aspects (e.g. *CS*) can drive the natural selection of predisposed cognitive features (e.g. *JA*) [113], and that genetic assimilation in the context of language evolution helps retain and expand communicatively effective features [33,114]. *JA* exists prior to language and takes effect during general interactive activities. However, once borrowed to aid linguistic comprehension, it could piggyback on language, having its level increased along with language evolution. Apart from *JA*, this coevolutionary scenario may help explain the degree-difference in other language-related competences (e.g. memory capacity or other socio-cognitive abilities), which paves the future work in this line of research.

2.4. Socio-cultural constraints on language evolution

Cultural transmission and social structure determine how individuals communicate with each other. In this way, these two aspects can cast their influence on language evolution. We conduct two studies based on the rule-based model to explore the effects of cultural transmission and social structure on linguistic understandability.

2.4.1. Cultural transmission and language evolution

This study examines the roles of cultural transmission in language origin and change [115]. Three forms of transmissions between two consecutive generations of individuals are considered: (a) *horizontal transmission*, communications between members of the same generation; (b) *vertical transmission*, a member of one generation talks to a biologically-related member of the next; and (c) *oblique transmission*, a member of one generation talks to a biologically-unrelated member of the next.

We implement an acquisition framework. During reproduction, half of the adults are randomly chosen as parents, each producing an offspring (child) who have no linguistic knowledge. Then, these children participate in child–child (horizontal), adult–child (oblique), or parent–child (vertical) transmissions (in each notion, the first part denotes speaker, and the second part listener) to acquire their idiolects. After that, they become adults, replacing their parents,

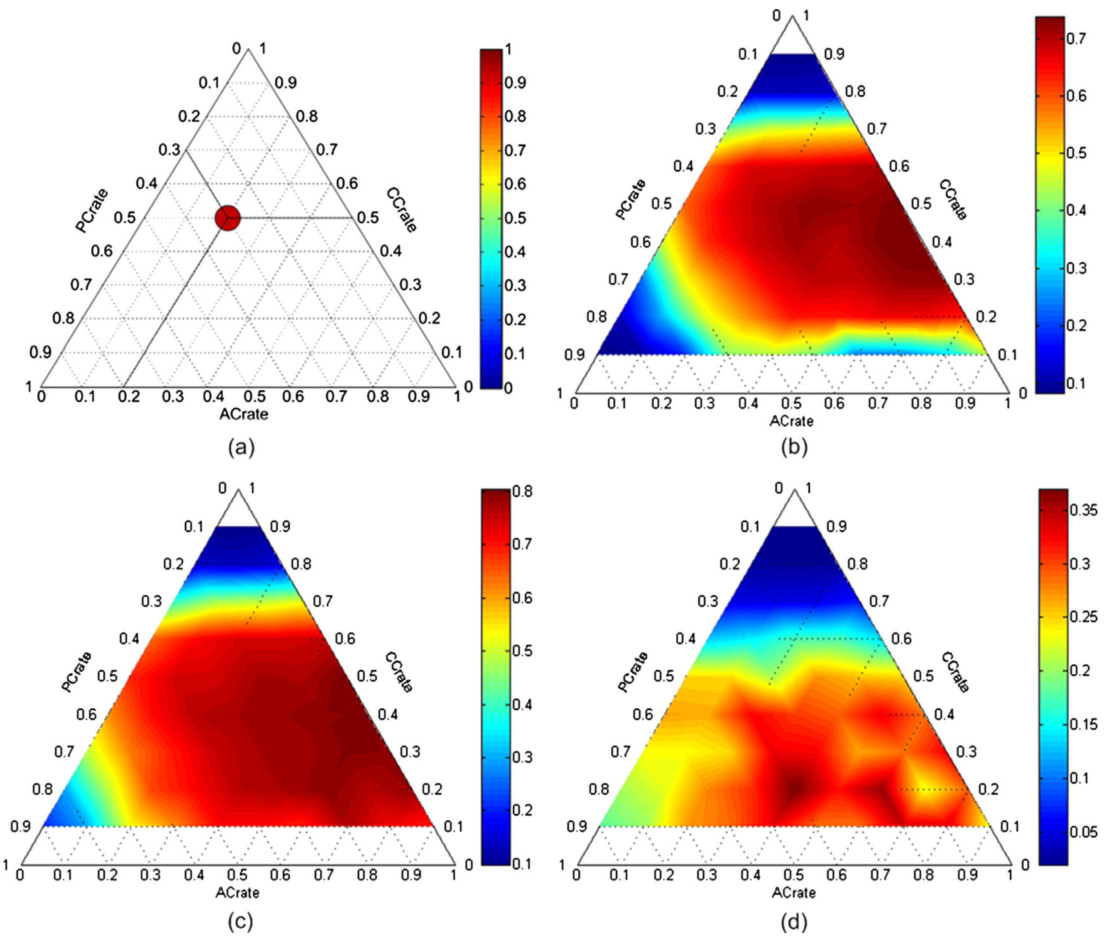

Fig. 3. These figures (adapted from [83]) illustrate that maximum linguistic understandability (UR_{con} in the origin simulations (b), UR_{con} in the change simulations (c), UR_{ini} in the change simulations (d)) can be achieved under non-zero *ACrate*, *CCrate* and *PCrate*. Results are obtained after 100 rounds of reproduction, and averaged over 20 simulations runs in each case. In (a), the patch marks the case $CCrate = 0.5$, $PCrate = 0.3$, $ACrate = 0.2$, and the colour map clarifies the value obtained in this case.

and the next round of reproduction occurs. At children's acquisition stage, all three forms of transmissions are interwoven randomly, whose rates in the total transmissions are denoted respectively by *CCrate*, *ACrate* and *PCrate*, the sum of which is 1.0.

We conduct *origin simulations*, in which adults in the first generation share only a small number of holistic rules, and *change simulations*, in which adults in the first generation share a compositional language capable of expressing all integrated meanings in the semantic space. The purpose of designing change simulations is to test whether the initial communal language can be sufficiently transmitted across generations under different combinations of the three forms of transmissions. However, in reality, individuals may not have such complete linguistic knowledge.

Fig. 3 shows the simulation results (under the setting in [83]). We evaluate *UR* between adults in consecutive generation (i and $i + 1$) (UR_{con}) and *UR* between the first and later generations (UR_{ini}). In the origin simulations, too many horizontal transmissions (top angle in Fig. 3(b)) or too many vertical transmissions (left angle in Fig. 3(b)) fail to trigger a communal language with high *UR*; instead, a combination of all three forms of transmissions can efficiently trigger and largely maintain a communal language with high *UR* across consecutive generations (central area in Fig. 3(b)). In the change simulations, non-zero *CCrate*, *ACrate* and *PCrate* can largely preserve a communal language across consecutive (Fig. 3(c)) and many generations (Fig. 3(d)) (see [83] for discussions of respective and collective roles of these transmissions).

Figs. 3(c) and 3(d) also show that although a high UR_{con} is maintained in certain cases, after many generations, UR_{ini} drops inevitably in those cases. This reflects the dynamics of language change: although agents from consecutive generations understand each other very well, the communal language changes inevitably in the long run (see [83] for discussions).

Apart from these forms, the acquisition framework can incorporate transmissions spanning three consecutive generations (e.g. grandparent–child, parent/adult–child, and child–child transmissions). Examining their roles in linguistic understandability serves as a future work for this line of research [116].

2.4.2. Social structure and language evolution

Agents in the previous simulations have uniform probabilities to take part in communications. In reality, social structures can break down such uniformity by allowing individuals of various social ranks to participate in more or fewer communications. Social rank is subject to many factors (e.g. economic condition, friendship, political influence, etc.).

One way to describe social structures is via network, treating each individual in the community as a *node*, and communications or connections among them as *edges* linking nodes. The number of edges a node has is its *degree*, and the probability distribution of these degrees over the network is the *degree distribution*. Using the network approach, empirical studies [117] have discovered that many social structures formed by language-related activities tend to exhibit a *power-law* degree distribution, and its λ value (quantifying the power relation between the two quantities in the distribution) is usually around 2.0 [118]. For instance, in the telephone call network, the ranks of phone numbers and the numbers of calls made or received via these phone numbers have a power relation, whose λ is 2.1. In the email network, the ranks of email addresses and the numbers of emails exchanged via these addresses have a power relation, whose λ is 2.0.

It is worth exploring whether this particular social organization can facilitate language evolution, in terms of triggering or preserving a communal language with high *UR*. We define a power-law *social popularity* (the probability for an agent to communicate with others) (Eq. (1), where r denotes agent's rank from 1 to N (population size) (the agent having the highest probability to communicate with others has rank 1, the one having the second highest probability has rank 2, and so on), $p(r)$ calculates the social probability for an agent of rank r to communicate with others, and c is a normalizing factor ensuring the sum of all probabilities as 1.0):

$$p(r) = cr^{-\lambda} \tag{1}$$

Defining social popularity allows us to manipulate (via λ) communications among agents at the population level, without specifying actual connections among agents. If we assume that the rank of an agent (node) is reversely accumulative with the number of agents that have more edges than this one (i.e. if the rank of a node is r, it means that there are $N - r$ nodes having equal or smaller degrees than this node), then, the λ in power-law social popularity is mathematically related to the λ' (to distinguish it from λ in power-law social popularity) in power-law degree distribution (Eq. (2), see [119] for proof), which enables a quantitative comparison between simulation results obtained under different λ and empirical data classified by λ'.

$$\lambda' = 1 + \frac{1}{\lambda} \tag{2}$$

Via the origin and change simulations (similar to those in the study of cultural transmission, but without reproduction) under various N (50, 100, 150, 200, 300, 400, and 500) and λ (0.0 (the case of random communication), 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0), we study the effect of social popularity on *UR*.

Fig. 4 shows the simulation results. In the origin simulations (Fig. 4(a)), only if λ is 0.0 (solid lines), 0.5 (dash lines) or 1.0 (dot lines) can *UR* reach a high value after 600 rounds of communications in all populations. When λ is 1.0, the increase in *UR* from its initially-low value occurs the earliest among all λ values, and the shapes of *UR* curves do not change much across populations. In the change simulations (Fig. 4(b)), if λ is smaller than 1.0, a high *UR* is preserved in all populations, whereas for other λ values, *UR* drops with the increase in N.

These findings are not limited to the rule-based model [119]. They reveal an *optimal λ value* (1.0) of power-law social popularity: under it, emergent conventions can diffuse to preserve a high *UR*, even in bigger populations; whereas below or above it, with the increase in population size, language origin becomes less efficient.

The change simulations seem exceptional to this general tendency. In these simulations, agents initially share a set of linguistic knowledge. When λ is smaller than 1.0, every agent has sufficient chances to communicate with others, so that their shared knowledge is frequently used. However, individuals in reality may not share all linguistic knowledge,

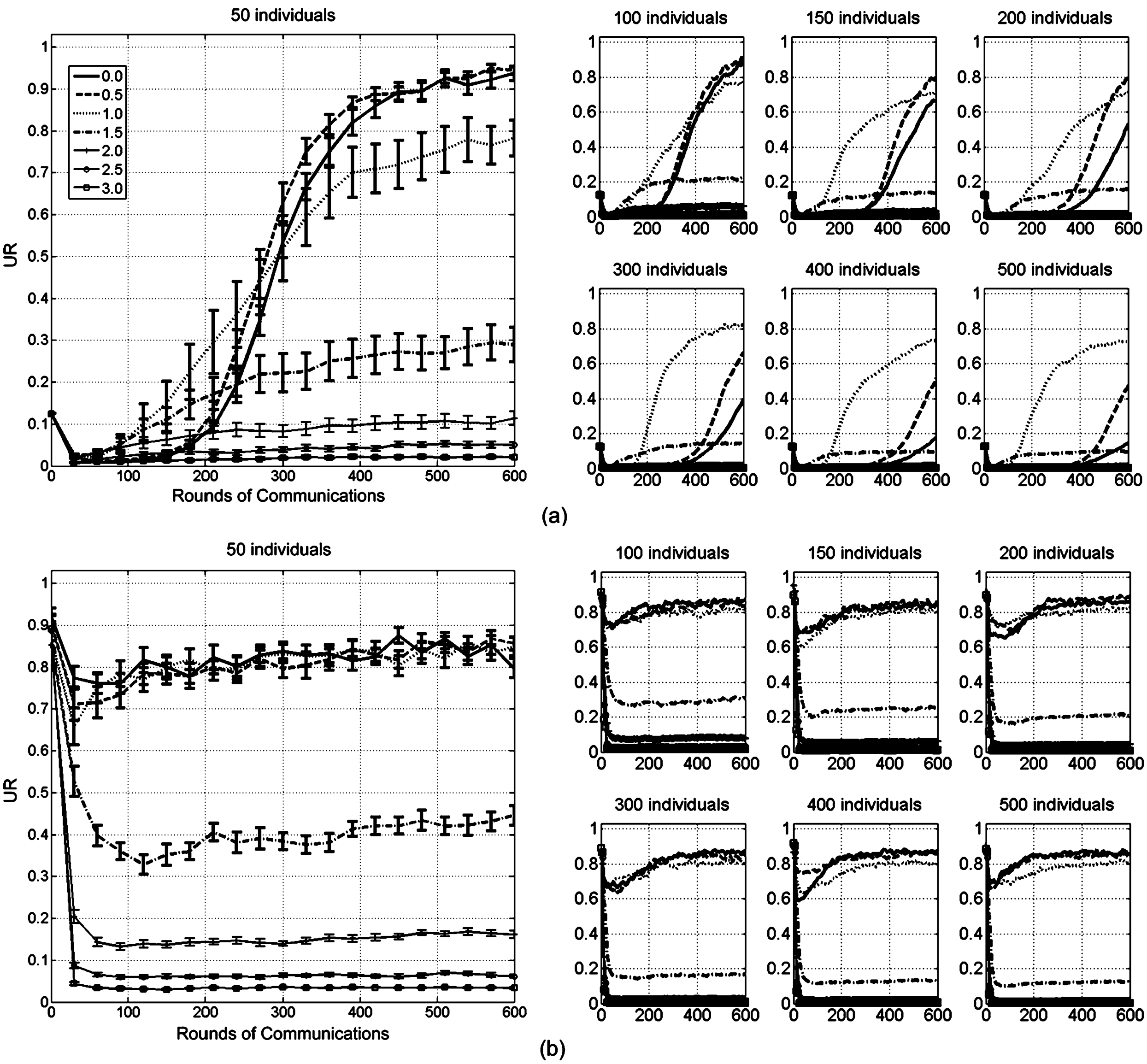

Fig. 4. These figures (adapted from [119]) illustrate that particular social popularity ($\lambda = 1.0$) can efficiently trigger and largely preserve a high *UR* in different populations in both the origin (a) and change (b) simulations. Each line shows the average *UR* over 20 simulation runs under a particular λ value. Error bars denote standard errors.

and shared knowledge has to be gradually developed during language origin. Therefore, even though λ as 0.0, 0.5 or 1.0 may have similar effects on maintaining common knowledge, as for development of common knowledge, only the power-law social popularity with λ as 1.0 has the best performance.

Following Eq. (2), the optimal λ (1.0) in power-law social popularity equals to the frequently-observed λ' (2.0) in power-law degree distribution of social structures formed by language-related activities. This offers the empirical support for the simulation results. These results not only reflect a close correlation between language and social structure in the human group, but also indicate that a human group tends to organize in such a way to efficiently trigger a communal language with a high *UR*. In other words, language is an *emergent group-level trait* [120,121], whose evolution not only concerns individual behaviours, but also helps shape and gets shaped by group structures. Apart from this structure, modelling studies have touched upon many other structures within and/or across groups [122–124].

The two studies on cultural transmission and social structure reveal the effects of socio-cultural constraints on developing and maintaining communal languages with good understandability. Other theoretical and empirical studies [22,23,39,58,59] advocate that the socio-cultural evolution of language is a much more powerful process than the genetic evolution of language in shaping particular language structures. More studied by means of computer modelling or other approaches are needed to better understand the effects of socio-cultural factors on language evolution.

3. Equation-based model and its predictions

3.1. The language competition model

3.1.1. The AS model

The most influential model studying the dynamics of competition between two languages (say, X and Y) is the AS model, proposed by Abrams and Strogatz [125]. It transforms the population conversation from using X to using Y and vice versa into differential equations (Eq. (3), the other equation can be obtained by swapping relevant components):

$$\frac{dx}{dt} = (1-x)P_{YX} - xP_{XY}, \quad \text{where } P_{YX} = cx^{\lambda}s \text{ and } P_{XY} = c(1-x)^{\lambda}(1-s) \tag{3}$$

Seen from Eq. (3), the transition in the proportion of speakers of X in the population per unit time is calculated as the proportion of speakers who convert from speaking Y to speaking X minus the proportion of speakers who convert from X to Y. These two values are calculated as the proportions of $Y(1-x)$ and $X(x)$ at time t multiplying the conversion rates P_{YX} and P_{YX}. P_{YX} (conversion rate from Y to X) is determined by the proportion of $X(x)$ (having a power relation; λ is claimed fixed across cultures) and the prestige of $X(s)$ with respect to Y. Mathematically speaking, Eq. (3) has two stable fixed points ($x = 0$ and $x = 1$), indicating that one language will eventually drive the other to extinction. Later extensions, also adopting the parameter of prestige, have incorporated additional elements into the model, such as the bilingual state and socio-cultural factors [126–129].

The beauty of the AS model and its extensions is that the competition dynamics (e.g. who will become the extinct language and how fast the extinction will proceed) is solely determined by prestige. The *prestige* of a language can be defined as the socio-economic status of the speakers of this language. Rather than explicitly estimating prestige from socio-economic factors, the AS model directly uses empirical data to tune its values in different cases. Under tuned prestige, the AS model reports well-fitted transition curves of proportions of speakers of competing languages to the historical data of English–Welsh, English–Gaelic, and other competitions.

Despite these good results, the parameter of prestige has an obscure link with actual socio-cultural conditions; prestige alone fails to address many fundamental factors that can affect language competition (e.g. population sizes of competing languages and distributions of speakers of different languages in the competing region [130–133]). Lacking such empirical foundations makes curve-fitting the only option to estimate prestige in reality, which makes these models dependent on the empirical data to be studied and restricts them from studying cases that lack sufficient data for parameter tuning. All these significantly reduce the explanatory power of these models. A more powerful model should define concrete parameters to directly address socio-cultural constraints on language competition, and use specific principles to estimate parameter values in actual cases of language competition.

3.1.2. Our language competition model

Considering the limitations of the AS model and its extensions, we propose two concrete parameters to address those socio-cultural constraints.

The first parameter is the *impact* of a language (σ), reflecting the influence of other language(s) on it (or vice versa) after it diffuses into the competing region. People are language carriers and language diffuses along with population diffusion from the centre of a language to elsewhere. Accordingly, the impact of a language is proportional to the population size of this language in the competing region.

The second parameter is the *inheritance rate* of a language (r), indicating its inheriting capacity during acquisition. In a mixed language population, a language with a high inheritance rate tends to be largely learned and used by people, whereas one with a low r is less preferred. The distribution of monolingual or bilingual speakers of different languages in the competing region affects the inheritance rate of a language.

Language competition can be viewed as a process whereby competing languages plunder speakers, which resembles species competition in biology. Language inheritance also resembles biological reproduction. Therefore, we adapt the well-attested Lotka–Volterra competition model [134,135] in evolutionary biology to define our language competition model. This biological model also involves similar parameters of impacts and inheritance rates of competing species.

The transition functions in our language competition model are derived from the differential equations in the Lotka–Volterra competition model (Eq. (4), where n_X and n_Y are the numbers of speakers of X and Y in a region and at time t, r_X is the inheritance rate of X, N_X is the maximum monolingual population of X in this region, N_Y is the maximum monolingual population of Y, σ_X is the impact of Y on X; the other equation can be obtained by swapping relevant components):

$$\frac{dn_X}{dt} = r_X n_X \left(1 - \frac{n_X}{N_X} - \sigma_X \frac{n_Y}{N_Y}\right) \tag{4}$$

Seen from Eq. (4), the transition in the number of speakers of X per unit time is determined by three factors: (a) $r_X n_X$, the potential number of local people who newly inherit X; (b) $(1 - \frac{n_X}{N_X})$, the retarding effect casted by speakers of X, if a large proportion of local people already speak X, it would be hard to further increase speakers of X; and (c) $(-\sigma_X \frac{n_Y}{N_Y})$, the retarding effect casted by speakers of Y, which concerns both the ratio of available speakers of Y among local people and the impact of Y on $X (\sigma_X)$.

The competition dynamics in our model is determined by both impacts and inheritance rates of competing languages. We propose three principles to estimate the values of these critical parameters in actual cases of language competition.

We propose *the population diffusion principle* to calculate the impact of a language by estimating its population in the competing region. Generally speaking, the centre of a language has the maximum population density of this language, and this density drops along with the increase in the distance to the centre. Without geographical, social, or political constraints, people may diffuse in all directions at similar rates, and such diffusion resembles heat conduction in physics, though with distinct rates.

Noting these, the population diffusion principle adopts the Fourier's law of heat conduction to estimate population diffusion (Eq. (5), where d is the Euclidean distance between the population centre $(0, 0)$ and the competing region (x, y), Q is the population at $(0, 0)$, and C calculates the population ratio between (x, y) and $(0, 0)$) (see [80] for derivation), and calculates the impacts of competing languages as the ratios between their populations in the competing region (Eq. (6), where d_X is the distance from (x, y) to the centre of X, d_Y is the distance from (x, y) to the centre of Y; σ_Y is calculated by swapping relevant components).

$$C(d, t) = \frac{Q}{(4\pi)^{\frac{3}{2}}} e^{-\frac{d^2}{4}} \tag{5}$$

$$\sigma_X = \frac{Q_Y}{Q_X} e^{\frac{d_X^2 - d_Y^2}{4}} \tag{6}$$

Noting the similarity between language inheritance and biological reproduction, we adapt the Hardy–Weinberg genetic inheritance principle [136] (i.e. without disturbing influences, both allele and genotype frequencies in a population remain constant across generations) into *the language inheritance principle I*. Our language inheritance principle states that: populations speaking different languages remain constant across consecutive generations, if these populations are sufficiently large, people in the new generation sample these languages randomly, and there is no sudden change of language or selective pressure for or against any of these languages (see [80] for derivation).

Following this principle, we can estimate the occurring probabilities of competing languages from empirical questionnaires of language choices (Eq. (7), where n_X, n_{XY}, and n_Y are numbers of monolingual speakers of X, bilingual speakers, and monolingual speakers of Y, respectively, $p(XX)$, $p(XY)$, and $p(YY)$ calculate the type frequencies of X, bilinguals, and Y, respectively), and use these probabilities to calculate the inheritance rates (Eq. (8)).

$$p(XX) = \frac{n_X}{n_X + n_{XY} + n_Y}, \qquad p(XY) = \frac{n_{XY}}{n_X + n_{XY} + n_Y}, \qquad p(YY) = \frac{n_Y}{n_X + n_{XY} + n_Y} \tag{7}$$

$$r_X = p(X) = p(XX) + 0.5p(XY), \qquad r_Y = p(Y) = p(YY) + 0.5p(XY) \tag{8}$$

As for cases lacking sufficient data of language choice, we propose *the language inheritance principle II* to estimate inheritance rate. It is inspired by the lexical diffusion dynamics [137,138], where the logistic function [139] is adopted to describe change in population using one of the two lexical forms. As for language competition, inheritance rates of competing languages resemble the fractions of population using two lexical forms. Accordingly, we borrow the logistic function in the lexical diffusion dynamics to estimate inheritance rate (Eq. (9), where α adjusts the competition speed, since population size affects competition, we use Eq. (5) to estimate α). Then, suppose that competing languages were brought to the competing region at $t = 0$, their inheritance rates can be estimated as in Eq. (10), where ε is set to 0.1.

$$r(t) = \frac{\varepsilon e^{\alpha t}}{1 + \varepsilon(e^{\alpha t} - 1)} \quad \text{and} \quad \alpha = C = \frac{Q}{(4\pi)^{\frac{3}{2}}} e^{-\frac{d^2}{4}} \tag{9}$$

$$r_1 = r_A(1) = \frac{\varepsilon e^{\alpha_A}}{1 + \varepsilon(e^{\alpha_A} - 1)} \quad \text{and} \quad r_2 = r_B(1) = \frac{\varepsilon e^{\alpha_B}}{1 + \varepsilon(e^{\alpha_B} - 1)} \tag{10}$$

3.2. Applicability, robustness, and explanatory power of the model

We use two cases to test our model whose parameters are estimated from the three principles.

The first case is the English–Welsh competition that happened around the 20th century in Wales, UK [140]. This case, also referred to by the AS model, contains sufficient data of monolingual and bilingual populations of English and Welsh from 1901 to 2001 [141]. Following the population diffusion principle and the language inheritance principle I, we can explicitly calculate the impacts and inheritance rates of English and Welsh in 1901, and let the model predict the monolingual populations at later time points (see [80] for details). Fig. 5(a) shows that the predicted data of the model reliably replicate the historical data.

Apart from year 1901, if we choose other years as the initial time points of the model, calculate the parameters according to the data at those time points, and let the model predict the monolingual populations at later time points, we can still obtain a good match between the predicted data and the historical data (see [80] for details).

We can also use the language inheritance principle II to estimate inheritance rates. Fig. 5(b) shows that the predicted data under thus-obtained inheritance rates also reliably match the historical data. The inheritance rates calculated by these two inheritance principles are not the same, because the rates calculated by the language inheritance principle II may not match exactly the data at a particular time point. Nonetheless, the fact that the model under either set of inheritance rates can replicate the historical data reflects the consistency of these two inheritance principles.

The second case is the Mandarin–Malay competition in Singapore. There are only four data points tracing this on-going competition [142]. Both Mandarin and Malay were brought to Singapore by immigrants. When calculating their impacts, we have to consider the distance between Singapore and the centre of Mandarin and that between Singapore and the centre of Malay. We also need the population data in those centres. These data are also required in calculation of inheritance rates using the language inheritance principle II. We can obtain this relevant information from other reliable sources than this limited set of historical data, and still explicitly calculate the parameter values in this case (see [80] for details). Fig. 5(c) shows that the predicted data of our model with thus-estimated parameters still match this limited set of historical data.

If we apply the AS model to this case, several uncertainties are involved. For instance, the calculation of this model is restricted to this limited set of historical data, which cannot reflect the migration history of different speakers in Singapore. Apart from the Mandarin–Malay competition, other competitions are on-going in Singapore (e.g. English–Mandarin competition, see [80] for the study of this competition based on our model), but the AS model assumes that the whole population consists of only monolinguals of two languages. Moreover, a large proportion of Singapore people are bilingual or even trilingual and these people play important roles in language competition, but the AS model cannot address these roles. Although some extensions (e.g. [126,128]) of the AS model incorporate the bilingual state, due to the limited set of historical data, the tuned prestige values of monolinguals and bilinguals remain less reliable.

These two cases illustrate that our equation-based model has a wide scope of applicability, not limited to cases with sufficient competition data. The model is also robust, less dependent on initial conditions. Moreover, the three mathematical principles assign explicit meanings to the critical parameters of this model, make the model independent of the empirical data to be studied, and allow reasonably estimating their values in various cases of language competition. All these give the model a much better explanatory power than the AS model and its extensions.

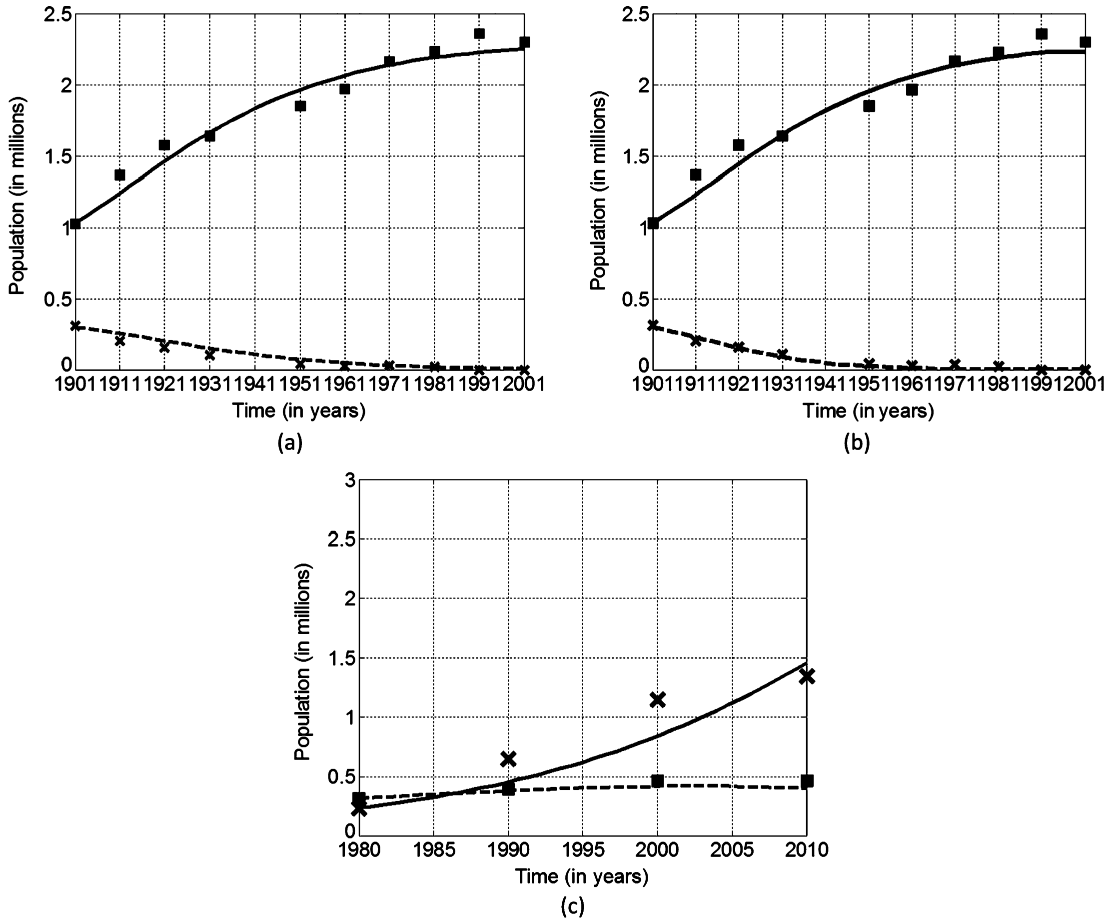

Fig. 5. These figures ((a) and (c) are extracted from [80]) illustrate that the predicted data of our language competition model match the historical data of English–Welsh (a) (b) and Mandarin–Malay (c) competitions. Predicted data are shown in solid (English or Mandarin) or dash (Welsh or Malay) lines, and historical data are shown in dots (English or Malay) or crossings (Welsh or Mandarin). Predicted data in (a) are obtained based on the inheritance rates calculated by the language inheritance principle I, and those in (b) are obtained based on the inheritance rates calculated by the language inheritance principle II.

3.3. Similarities and differences among linguistic, biological, and physical phenomena

The equation-based model and its underlying principles reveal intrinsic commonalities between language competition and biological or physical phenomena. First, competition among species resembles competition among languages (e.g. both are shown by changes in population sizes, and both proceed via plundering resources, such as members of a species or speakers of a language). Factors affecting biological dynamics also have their linguistic correspondences (e.g. inheritance rate of a species during reproduction corresponds to preference for a language during learning) and cast similar effects on linguistic dynamics.

Second, lexical diffusion and language inheritance also resemble each other (e.g. speaking a language is similar to using one type of lexical forms). Both dynamics are subject to similar constraints (e.g. the exponential factor adjusts the changing rates of lexical items and the inheritance rates of languages). The language inheritance principle II also uses the general logistic curve, also adopted in lexical diffusion dynamics and population dynamics, to estimate inheritance rate.

Third, the language diffusion principle adopts heat conduction equations to calculate population diffusion, which reveals the commonalities between molecule diffusion and population diffusion.

Apart from these cross-domain similarities, the proposed principles also highlight particular factors in language competition. For instance, the language inheritance principle I incorporates bilinguals into the calculation of language impacts. Only in this way can the model successfully replicate the English–Welsh competition, because bilinguals in this case used to take up a sufficiently large proportion in the total population. In addition, both the population diffusion principle and the language inheritance principle II take into account the geographical distance, whose roles in language competition have been recently discovered and analysed in empirical and simulation studies [143–145].

These intrinsic similarities and critical aspects can shed important lights on our understanding of language competition and the design of future models of language competition as well as other linguistic or socio-cultural phenomena.

4. Future directions of computer modelling of language evolution

Recent theoretical and empirical research in evolutionary and general linguistics suggests that language is a *complex adaptive system* (CAS) [146,147]. For instance, language structures are formed by partially-separable components that are organized in a hierarchical way and interact closely during language processing [101]. Linguistic behaviours and language contact outcome are subject to many competing factors from individual perceptual mechanisms, linguistic experiences, and socio-cultural aspects [147].

Computer modelling serves as an efficient means to address such a CAS as language. For instance, by equipping agents with concrete mechanisms, our rule-based model evaluates whether and how these domain-general mechanisms can shape linguistic structures and affect language evolution. By quantifying correlations between language and socio-cultural factors, our equation-based model quantifies the effect of these factors on language competition. By adjusting simulated behaviours and parameter settings, our rule-based model conducts a thorough search in a much larger hypothesis space than what laboratory experiments can cover, which illustrates the possible coevolution between language and other abilities and the collective effect of cultural transmission on language evolution.

Despite these significant contributions, computer models tend to concentrate on particular aspects of language evolution and disregard other linguistic, processing, or environmental factors. For instance, our rule-based model focuses on word order regularity and neglects other grammatical structures. With the emphasis on socio-cultural factors, our equation-based model treats competing languages as monolithic wholes and ignores the components of these languages and the possible effects of these components on language competition. Such simplicity and specificity [46] make computer models only show what could happen, not necessarily what must have happened [114]. In other words, what models simulate or illustrate may not reliably reflect the reality. Therefore, additional evaluations on models are necessary, which lead to three immediate needs for future modelling studies of language evolution.

4.1. Incorporating additional experimental approaches for model evaluation

Two experimental approaches in psychology or psycholinguistics can be recruited to further evaluate simulated human behaviours and their outcomes.

The first approach is *experimental semiotics*, investigating experimentally the novel forms of human communication system [148,149]. Assuming that the origin of novel communication systems in a laboratory does not differ greatly from that in a more natural context, this approach recruits human participants and puts them in a situation where no communication systems are in place or available linguistic communications are disallowed. Then, it observes whether these participants can develop a communication system from scratch via some forms of intentional interactions [150]. By tracing the emerging process and analysing the characteristics of the emergent system, experimental semiotics can replicate the trajectory of language origin to a certain extent, and bring forth knowledge about: (a) what are the universal structural features in general communication systems; (b) how these features originate via human interactions; and (c) what are the roles of individual behaviours and socio-cultural settings in the evolution of such systems. These questions are in line with those in computer modelling studies.

Some experimental semiotics studies [151–153] show that signals in an emergent communication system must be arbitrary, easy to distinguish, and tolerable to variations. Linguistic signals possess all these characteristics. In line with explorations using computer models, some experimental studies [154,155] set up a similar iterated learning framework as in previous models [39,91], and trace the origin of compositionality in a chain of human participants. By adjusting interactions among participants, other studies discuss the effects of cultural transmission on the origin of compositionality [156]. Different socio-cultural settings in these studies can also guide the design of relevant frameworks in computer models. Apart from these studies that focus on language-like communications, another study

[157] explores how humans handle non-linguistic signals (e.g. colours or movements of items) and recruit a set of novel signals (e.g. movement patterns of items) for communicative purpose.

The second approach is *artificial language learning* [158]. It assumes that certain mechanisms are manifest in both artificial and natural language processing [159]. In a typical study, during the training phase, human participants are exposed to training utterances formed by arbitrary sounds or syllables and following specific structures as in natural languages. Then, during the subsequent testing phase, participants are asked to judge whether exposed testing utterances have the same underlying structures as in training utterances [160]. Some testing utterances are identical to the training ones, but others are novel, in terms of surface syllables and/or underlying structures.

Artificial language learning experiments have several advantages over natural language learning studies. For instance, using artificial languages allows precisely controlling the initial familiarity for exposed items [161] and generating a sufficiently large number of possible utterances to test participants' generalising ability beyond the limited input [160]. In addition, these experiments can test hypotheses on linguistic or language-like properties or structures that are hard to examine in a naturalistic condition, and help identify common properties in mechanisms that process structural regularities in linguistic and non-linguistic tasks [162–165].

By studying word segmentation [166], sequencing regularities [167], nonadjacent dependencies [168], and recursive structures [169], artificial language learning and relevant non-linguistic experiments have revitalized the research on language processing, acquisition, and evolution [158,159]. These experiments resemble rule-based models of language acquisition, though these experiments deal with real humans. Findings in these experiments are also informative to models studying specific mechanisms for particular language structures. For instance, a mismatch between the results and dynamics shown in these experiments and those shown in computer models may direct us to incorporate additional behaviours into models.

4.2. Consolidating the empirical foundations for modelling studies of language evolution

Comparing simulation results with empirical data is the most direct way of evaluating a computer model of language evolution. The empirical data are not limited to linguistic data, but extendable to non-linguistic data (e.g. population surveys or geographical distances), especially for discussing the effects of population, ecological or socio-cultural factors on language evolution. In addition, the available diachronic data covering a few years or centuries and synchronic data of world language characteristics also help propose general theories of language evolution and evaluate models that incorporate these theories. For instance, based on the diachronic data of language competition, our equation-based model illustrates the effects of population size and geographical distance on language competition. Based on the synchronic data of social networks, our rule-based model illustrate that the common structure formed by language-related activities can facilitate language evolution.

Modelling studies can also make use of well-established, large-scale databases in historical linguistics, typology, and psychology, such as Ethnologue [170], World Atlas of Language Structures (WALS) [171], World Colour Survey (WCS) [172], and Child Language Data Exchange Systems (CHILDES, childes.psy.cmu.edu). The abundant information contained in these databases can serve as inputs to models of language evolution or empirical observations for verifying their incorporated theories. For instance, based on Ethnologue and WALS, some models examine the effect of cultural transmission on word order bias [43] and the monogenesis of languages out of Africa [173]. Based on WCS, some models reveal the correlation between human perceptual constraint and universal colour categorization patterns in world languages [174–176]. Based on CHILDES, some models examine how children form basic linguistic categories in different languages (e.g. [177]).

4.3. Collaboration between modelling, linguistics, and other disciplines

Due to simplicity and specificity, computer models may not accurately predict the time spans of different evolutionary stages, reconstruct the full socio-ecological environment of early hominins, or reveal the whole story of the evolutions of different language faculty components. For instance, our rule-based model says nothing about when those domain-general mechanisms were first recruited for language processing and how long it takes for the degrees of relevant socio-cognitive abilities to reach stable levels.

Research in animal behaviours, anthropology, archaeology, neuroscience, genetics, sociology, and statistical physics helps clarify these issues. For instance, animal behaviour studies can provide knowledge about the characteristics of animal communication systems and mechanisms involved (e.g. [18,19,101]). Archaeology and anthropology research can discover evidence about the time span of language origin (e.g. [178]) and the presence or absence of certain abilities in early hominins (e.g. [101,179,180]). Neuroscience experiments can reveal the neural bases of language-related abilities and illustrate the activation patterns between humans and other animals in linguistic and non-linguistic tasks (e.g. [181–183]). Genetic evidence can provide hints on the possibility of genetically encoding language components (e.g. [184–186]). Sociology research can collect rich information about the characteristics of social structures formed by human behaviours and the distinct ratios of cultural transmissions in different communities (e.g. [117,187]). As evident in our equation-based model and other studies (e.g. [188]), adopting well-attested theories or methods from statistical physics, evolutionary biology, population genetics, and bioinformatics into linguistics research is an efficient way to obtain better understanding of linguistic phenomena.

Just like computer models, these approaches from other disciplines also have their limitations and difficulties [14,45,189]. For instance, uncertainty is inevitable when interpreting motivations and details of animal behaviours based on our own thoughts. Deficiency in archaeological or anthropological evidence often results in contradictory theories. Complex mappings between behaviours and genes or neural activities add difficulties in locating the genetic or neural bases of relevant behaviours behind language processing.

Noting these, we have to bring these numerous approaches together to tackle problems of language evolution. Only in this way can we obtain a biologically plausible, computationally feasible, and behaviourally adequate understanding of language evolution [45,57]. This multi-disciplinary perspective toward evolutionary linguistics has been advocated in many recent monographs (e.g. [19,101,190]). To modellers, this perspective requires paying sufficient attention to findings or approaches in other disciplines that help evaluate their models and results. To interested scholars in other fields, this perspective encourages them to contribute to evolutionary linguistics based on their expertise. To traditional linguists, this perspective appeals to exchange not only between linguists from different persuasions but also among scholars from a number of disciplines [45].

5. Conclusion

Base on two computer models of language evolution, we discuss: (a) what insights we can gain from these models and their simulation results on the evolutions of language structures, individual learning mechanisms, and relevant socio-ecological environment; and (b) how other approaches and empirical data help verify computer models and their incorporated theories of language evolution. All these call for a multi-disciplinary collaboration among modellers, linguists, and scholars from relevant disciplines, which can not only enhance the empirical foundations of computer models, but also continuously bring forth significant contributions to evolutionary linguistics.

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