Journal of Experimental Psychology: Learning, Memory, and Cognition

Phonological Networks and Systematicity in Early Lexical Acquisition

--Manuscript Draft--

Manuscript Number:	XLM-2023-2867R1
Full Title:	Phonological Networks and Systematicity in Early Lexical Acquisition
Abstract:	Infants' early words tend to be phonologically similar. This may reflect a systematic approach to early production, as they adapt newly-acquired forms to fit familiar structures in the output. This 'rich-get-richer' approach to phonological acquisition, known as *preferential attachment* in network science, proposes that new words cluster together with existing phonologically-similar words in the lexicon (or network). This contrasts with recent work (e.g. Fourtassi et al., 2020) showing that the learning environment is the key predictor in learning (*preferential acquisition*). This study expands on previous analyses of vocabulary norm data to analyse naturalistic data, namely phonetic transcriptions of nine infants' word productions, from word onset to age 2;6. Network growth models test whether 1) acquisition is best modeled through preferential attachment or preferential acquisition, 2) the trajectory of network growth changes over time, and 3) there are any differences in network growth of adult target forms vs. infants' actual productions. Results show that preferential attachment predicts acquisition of new words more convincingly than preferential acquisition: newly-acquired words are phonologically similar to existing words in the network. Furthermore, systematicity becomes increasingly apparent over the course of acquisition, and infants produce their early words more systematically than we would expect from looking at target forms alone.
Article Type:	Article
Keywords:	systematicity; phonological development; preferential attachment; networks analysis
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	Michael Frank Stanford University mcfrank@stanford.edu Leader in L1 word learning research
	Cynthia Siew National University of Singapore psyssqc@nus.edu.sg Has published on network growth models in first language acquisition - the paper is based on her analysis approach with older children.
Order of Authors:	Catherine Laing, PhD
Manuscript Classifications:	30: Age of acquisition; 180: Child development; 190: Child language; 840: Phonology; 1200: Speech production

Funding Information:	
Additional Information:	
Question	Response
I have stated whether data are available and, if so, where to access them. In both the Author Note and at the end of the Method section, I have either specified where the data will be available or noted the legal or ethical reasons for not doing so.	Yes
In both the Author Note and at the end of the Method section, I have stated whether study materials are available and, if so, where to access them.	No
For submissions with quantitative or simulation analytic methods, in both the Author Note and at the end of the Method section, I have stated whether the study analysis code is available, and, if so, where to access it.	Yes
I have stated whether or not any work was preregistered and, if so, where to access the preregistration. If any aspect of the study is preregistered, I have included the registry link in the Method section and the Author Note. For example: This study's design was preregistered; see [STABLE LINK OR DOI]; This study's design and hypotheses were preregistered; see [STABLE LINK OR DOI]; or This study was not preregistered.	Yes
Please disclose any changes in authorship (inclusions/exclusions/order of authors) in the revised version of your manuscript. Have any changes been made?	No, there aren't any changes
If your paper is accepted, do you have any disclosures that would need to be listed on the Full Disclosure of Interests form? This includes any interests or activities that might be seen as influencing the research (e.g., financial interests in a test or procedure, funding by pharmaceutical companies for research).	No, I have no disclosures to report.

12th March 2024

Dear Professor Benjamin,

Please find enclosed a revised version of the manuscript “Phonological Networks and Systematicity in Early Lexical Acquisition”, re-submitted for consideration in *Journal of Experimental Psychology: Learning, Memory, and Cognition*. I believe this paper will be of interest to your readership due to its theoretical and methodological contributions. I draw on network growth models to compute phonological distance between each word and each other word in nine infants’ vocabularies, from first word production to age 2 and a half.

I have revised the paper in line with the three reviewers’ comments, and those of the Associate Editor. I hope the reviewers and the editorial team will find these revisions satisfactory; I welcome any further comments on the paper.

Yours faithfully,

Catherine Laing

Dear Dr. Slevc,

I am very grateful to you and the reviewers for your constructive and thoughtful comments on this manuscript. I found the criticism to be insightful and I have done my best to address each comment thoroughly. Below you will find a copy of the editor and reviewer comments in green, followed by my responses in black, with newly added text *italicized*, where relevant.

Sincerely,

Catherine Laing

Dear Dr Laing,

Thank you very much for submitting your manuscript "Phonological Networks and Systematicity in Early Lexical Acquisition" for review and consideration for publication in Journal of Experimental Psychology: Learning, Memory, and Cognition. I sincerely appreciate the opportunity to review the manuscript. I have now received three expert reviews of your manuscript (appended below) and have read the paper myself. We all agree that this is an interesting and useful contribution, but the reviewers note a number of concerns with the manuscript in its current form. Many of these involve issues of clarification or some additional issues to consider/discuss, which I think can all be feasibly addressed. I thus invite you to revise your manuscript taking these comments into account.

Thank you for your kind remarks about the paper being interesting and useful; I'm glad for the opportunity to strengthen the manuscript further.

Please note that I have made a couple of general changes to the paper (based on reviewer comments) that I would like to flag up here:

- PAT/PAQ values are now termed INT/EXT, respectively, to more clearly mark the distinction between the two;
- I have slightly changed the model structure in both logistic regression models and GAMMs. Following reviewer comments I added a new variable (age of acquisition from comprehensive vocabulary norms) and amended an existing one (using a more general input frequency measure), and to avoid multicollinearity in the data, this led me to remove two of the fixed effects that were included in the initial model (n tokens and vocabulary size).

If you decide to revise the work, please include a cover letter that details your response to each point raised by the Editor and the reviewers in this letter.

To submit a revision, go to https://www.editorialmanager.com/xlm/ and log in as an Author. You will see a menu item call Submission Needing Revision. You will find your submission record there.

Sincerely,
L. Robert Slevc, PhD
Associate Editor
Journal of Experimental Psychology: Learning, Memory, and Cognition

Reviewers' comments:

Reviewer #1: * Review of XLM-2023-2867

Phonological Networks and Systematicity in Early Lexical Acquisition

* Summary and overall assessment

This manuscript adopted the network science framework to study systematicity in the early productive lexicons of very young children. It represents a much needed extension of the comparison between two key network growth models of preferential attachment and preferential acquisition to naturalistic data of infants' actual productions - that has not been done in previous work that used vocabulary norms, as the author rightly points out. The author finds support for the preferential attachment model, in line with research on early production showing that children rely on the word forms that they can produce to guide future learning (what is rich in the lexicon, gets richer), and found stronger effects of PAT over time in contrast to previous literature on this topic. Overall, I have a really positive view of this work - the method and analytic approach are clearly described and presented, the approach of working with naturalistic data is a positive, and the results are important for research in early language acquisition. It is a neat showcase of how network analysis can provide a powerful, quantitative framework to ask theoretical questions about the way that young children build their lexicons. Below are some questions and comments for the author to consider.

Thank you for this positive feedback – I'm really glad R1 found the work clear and saw value in this approach! As a general first comment, please note that, following another reviewer's request, I have re-labelled PAT/PAQ values as INT/EXT values, respectively.

* Specific comments and questions

p. 6 - I know that the Lure of the Associates model is not considered here, but it has been mentioned a couple of times in the Introduction that it may warrant a brief explanation either in-text or in the footnote. Although it is true that previous studies did not find strong evidence for this model, there is some other evidence for it by Holly Storkel and colleagues. They found that nonwords that had more "lures" to the words in the existing lexicon are better acquired - which is conceptually what is predicted by the Lures model.

Storkel, H. L., Armbrüster, J., & Hogan, T. P. (2006). Differentiating phonotactic probability and neighborhood density in adult word learning. Journal of Speech, Language, and Hearing Research.

I agree that it makes sense to add a brief definition of this model, which I have added to the footnote on p.5:

"*A third model - Lure of the Associates - predicts that new words will be learned that are similar to the highest number of already-known words in the network. This model has been considered in some studies (Hills et al., 2009; Siew & Vitevitch, 2020) but will not be considered here as there is no conclusive evidence for this model in the development literature, though note that there is evidence for this model in adult word learning (e.g. Stamer & Vitevitch, 2012; Storkel, Armbrüster, & Hogan, 2006).*"

p. 6 - Below are a couple of more recent references that also looked at the preferential attachment/acquisition network growth models in language acquisition - those would be relevant in the literature review of previous work.

Luef, E. M. (2022). Growth algorithms in the phonological networks of second language learners: A replication of Siew and Vitevitch (2020a). Journal of Experimental Psychology: General, 151(12), e26-e44. https://doi.org/10.1037/xge0001248

Ciaglia, F., Stella, M., & Kennington, C. (2023). Investigating preferential acquisition and attachment in early word learning through cognitive, visual and latent multiplex lexical networks. Physica A: Statistical Mechanics and Its Applications, 612, 128468. https://doi.org/10.1016/j.physa.2023.128468

Thank you for these suggestions; these have been added to the literature review on pp.6-7:

"*Ciaglia, Stella and Kennington (2023) analysed complex multiplex networks (including phonological, semantic, sensorimotor and visual associations) to find evidence for both EXT and INT in word learning, though evidence was stronger for EXT..*"

"*A replication of this study using data from adult second-language learners of English found consistent results (Luef, 2022).*"

p. 10 - How many words were excluded on the basis of not being in the CDIs?

I have now added this data to the Methods section on p.12:

"*Altogether, 5483 words were excluded from the data due to not appearing on the French or American English CDIs (2224 in French and 3259 in English).*"

Note that, in addressing this point, I found that ~200 tokens that were CDI words had not been correctly coded in the data, and thus were excluded as being non-CDI words. I have now re-coded these and so the new data sample is slightly larger than that of the initial submission (3096 word types instead of 3013 word types).

p. 11 - Could a concrete example of how the phonological feature approach was used to compute distance? It might also help to explain how this computation was done /without/ the vowels ("in the present analysis only consonants were included"), which was something I did not quite understand. For instance, does this mean that it is not possible to compute the distance between two words that differ by a vowel - like "cat" and "cot"? Some additional explanation for this section would be very helpful.

First to clarify, in this analysis, words that differ only by a vowel, as in "cat" and "cot" would have a distance of 0. To my mind, this is not an issue for infant production, since if the infant was producing both words as, say, /kɛt/, accuracy would be high in both cases (in such cases it would be interesting to test whether different vowels were used to discriminate minimally different words, but that is not within the scope of the current study!).

To clarify my approach, I have added two tables to the SI (Tables 1 & 2) that shows the distances between 3 target words in the dataset, each with a different phonological structure (*baby* compared with *balloon* and *sky*). The tables presented here are adapted from Monaghan et al. (2010), as I found their approach very clear and indeed used it to generate my own phonological distance measures in this paper.

I have also clarified this approach in the main text on p.11:

"*This means that two words that differ only in their vowel segments are coded as the same in the current analysis. Words were aligned by syllable nucleus: onset consonants were* *compared with other onset consonants, and codas were compared with codas. Full criteria for establishing distance, alongside tabulated examples, are included in the Supplementary Information, S1."*

And added the following explanation in the Supplementary Materials, along with examples in two tables, to illustrate:

"*Phonological distance was established following Monaghan, Christiansen, Farmer and Fitneva's (2010) approach, with some adaptations. Note that in their study, only monosyllabic words are included, and so their approach is adapted here to include multisyllabic words. Following their method, each word was first divided into a series of 'slots', according to its phonological structure. For example, the word baby was separated into five slots: /b-e-i-b-i/. Because vowels were not accounted for, the nucleus of each syllable - both monophthongs and diphthongs - was then replaced by a generic V slot, i.e. /b-V-b-V/. Words were then aligned by nucleus to generate a phonological distance measure between each possible word pair. All consonants at word onset and final syllables were aligned, regardless of syllable number, such that the final /d/ of bed would be aligned with the final /n/ of balloon. This is because infants may have a tendency to produce only certain consonants word-finally, and so this approach would capture such systematicity. For the English data, the maximal word structure considered in the analysis is C-C-C-V-C-C-|C-C-C-V-|C-C-C-V-|C-C-C, where syllable boundaries are marked with a |. This accounts for complex clusters at word onset (e.g. splash /splæʃ/, C-C-C-V-C), coda (plant /plænt/, C-C-V-C-C), and across syllable boundaries (pumpkin /pʌmpkɪn/, C-V-C-C-|C-V-C). In French the maximal structure was C-C-C-V-C-C-|C-C-C-V-|C-C-C-V-C|C-C-C-V-C|C-C-C-V-|C-C-C-C. This accounted for multisyllabic target words such as hélicoptère ("helicopter" /elɪkɔptɛʁ/, V-|C-V-|C-V-C-|C-V-C) and appareil photo ("camera" /apaʁɛjfɔto/, V-|C-V-|C-V-C-|C-V-|C-V), and complex codas as in arbre ("tree" /aʁbʁ/, V-C-|C-C). For vowel-initial words, the C1 slot in word-initial position is empty, but all other alignments remain the same. This maximal structure is required in an analysis of infant word production, to account for unexpected complexities such as, production of French mettre "to put" as [mɛʁstʁ] and étoile "star" as [ɛstwal]. In the infant data, it was not always easy to determine exactly where a syllable boundary should occur in complex productions, in part because this was not predictable based on the target form due to the variability in production, so would have to be done on a word-by-word basis, and in part because the syllable boundary of some productions could not be clearly established from its phonetic transcription. Instead, consonants were always assigned to the syllable-initial cluster, rather than assigning part of the cluster to the coda of the previous syllable (e.g. for the examples above, the infant production of mettre was coded as C-V-|C-C-C-C and étoile as V-|C-C-C-V-C).*"

p. 12 - Because I don't know how phonological distance was calculated specifically it makes it hard to understand what 0.25 means - presumably these are standardized in some way before deciding on the cut off. Some clarification and confirmation that the edges in the network are indeed unweighted, undirected edges would be good. A related question I had was how are the results robust if different thresholds were used to decide which words to connect up? Would the 111 hermit words (on p. 13) have phonological edges if a different threshold were used?

I have addressed this question in full in S2, which I have not copied here in order to save space. To clarify in brief here, the distance values were standardised within-subject, and so 0.25 reflects the bottom quartile of connectivity across each child's dataset. I have explored the validity of using this threshold in two different ways: first, I have produced figures to show the AoP~degree correlation across 1000 different thresholds, from 0.01 to 0.99 (this approach is adapted from that of Amatuni & Bergelson, 2017). Figure 1 in the SI shows spearman's correlations across these different threshold values, and how a threshold of 0.25 compares in relation to all other options. I have also added density plots to show the distribution of different phonological distances between all words in the dataset (SI Figure 2). Second, I re-ran the GLMER models to test whether results would differ across 7 different thresholds (mean connectivity in the network, the lowest and highest viable thresholds according to the correlation plots generated above, and then the lowest quartile of each of the French and English Target and Actual data). The effect of INT on the data remained consistent across all thresholds, while EXT was found to be significant at the lowest viable threshold of 0.15, but not for any of the six higher thresholds. This further supports the robustness of INT as a predictor of network growth for this dataset.

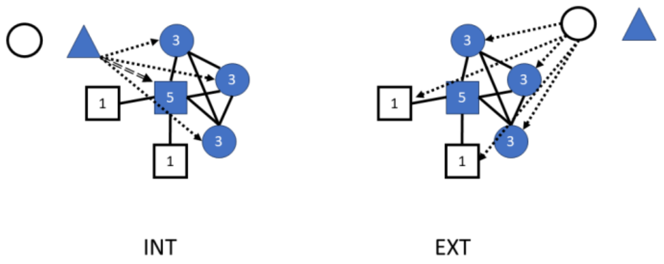
To address the final query in this point, the 111 words that did not form any edges would indeed have edges under different thresholds. This is now shown in Tables 3-4 (S2). However, in re-generating this data I realised that my original point about the 111 unconnected words was not entirely transparent, as this total was generated from Actual and Target data combined. I now show these separately across the two tables and report it more clearly in the main paper on p.14:

"*as both INT and EXT values are established through connectivity in the network (i.e. only words that form an edge with another word are represented), the words included in each network differs slightly; 54 words did not connect to any other word at a threshold of 0.25 in the Actual data, and 63 words in the Target data.*"

Tables 3 and 4 (S2) clarify how the networks would differ under different connectivity thresholds, alongside Spearman's correlation coefficients, and model coefficients with 95% confidence intervals and p values from the GLMERs.

For the methods section, I would suggest including a couple of figures that a provide a visualization of the preferential attachment and preferential acquisition models, as well as to explain the "flow" of network construction and analysis from the "raw" data to the network representation. I believe this would make the study design more accessible to readers who are unfamiliar with network analysis.

I have now added this to the manuscript on p.39, and have copied the figure here for convenience.



"*Figure 1. Visualisation of INT and EXT models of network growth. Shapes represent nodes* *in the network and filled lines represent edges between nodes. The two images demonstrate the likelihood of two new nodes - a filled triangle or an open circle - being added to the network under conditions of INT- and EXT-like network growth. In each case, the node that would be acquired is added to the network, and new edges are shown with dashed arrows. The double-dashed arrow in the INT model shows the new edge formed with the most highly-connected node in the existing network."*

On a final note, I agree with the authors' argument that vocabulary norms represent the "average" out of many infants, which may explain why analyses of such norms are biased toward a PAQ growth model - I am curious to know if there is evidence from the current data analyses to conclude if there are individual differences in the growth patterns, that is, do children show greater or lesser extents of the preferential attachment pattern in their lexical acquisition?

This is a very interesting question and I have been grappling how best to address it. To some extent, the clear variability in the correlations shown in S3 can address this as the data clearly shows that connectivity varies across the nine infants' networks, to the extent that two infants' networks do not change predictably as vocabulary size grows (i.e. there is no correlation between age of production and degree; for one infant this is marginal, but for Anais the rho value is close to 0). This suggests that, at least for CDI words, acquisition is driven by factors other than INT or EXT (since both assume that connectivity and age should correlate negatively) for these infants.

To inspect this further, I have re-generated Figure 4 with a by-speaker grid, shown in S6, which shows the trajectory of each infant's INT values over time. Here we can see differences in the extent to which INT-like network growth drives learning across the infants, accompanied by the following text:

"*Between-child differences are well established in the phonological development literature (Maekawa & Storkel, 2006; Vihman, Ferguson, & Elbert, 1986). There is thus reason to expect that the nine infants in the current dataset may have differential paths to word production, and so results may be variable when considered across speakers. Figure 4 below shows a by-infant breakdown of the INT value trajectories visualised in Figure 4 of the main paper. Descriptively, in Anais, Nathan and Alex's data, INT values increase exponentially over time, suggesting that INT is an increasingly influential factor in their early production. On the other hand, INT values plateau relatively early in the data for William, Naima and Lily, suggesting that other factors may have a stronger influence in these infants' word production and acquisition after a certain time-point.*"

Reviewer #2: The author considers whether infant and early child spoken word production can best be predicted by high similarity to preexisting produced forms (if you know pat, bat is highly likely to be learned) as opposed to high connectivity to a variety of words in the language. The former is called preferential attachment (PAT) in the nomenclature of network science, the latter preferential acquisition (PAQ).

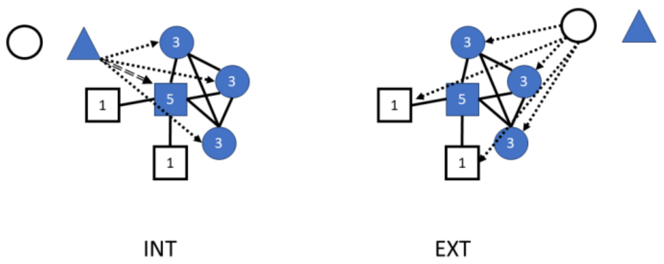
The author finds strong evidence for PAT, that is, producing more words that sound like already-produced words. This is true both of network relationships between target word forms (child is trying to produce pat, patch, panda) and network relationships between actual productions (child says "pa" when trying to produce pat, patch, panda). There is little evidence for PAQ. They argue that previous findings showing strong PAQ evidence may reflect general trends in children's acquisition (they reflect norms of data, not individual children) which would tend to obscure phonological patterning.

I am convinced by most of the material presented here. I'm especially convinced by arguments that normative data (such as 10% of kids know "bat" at age 13 months) obscures the course of individual children's production patterns. I'm still confused by exactly what PAQ is in the phonological context: I think it means something like contextual diversity (similarity to a lot of other words in the language in general, but not similarity to stuff in the child's productions), but it's not quite clear. Am I correct that there are *two* differences between PAT and PAQ, one being whether connections are within the child-specific network (PAT) or general network (PAQ), and the other whether there are connections to "popular" nodes (PAT) vs. lots of different nodes (PAQ)? If both of these are the case, how do we know which one is more important? Some network illustrations and/or concrete examples might help readers understand this better.

I am glad to know that R2 found the work convincing and relevant in the context of the related literature! As a general first comment, please note that, following R2's recommendation below, I have re-labelled PAT/PAQ values as INT/EXT values, respectively.

To return to this first comment, R2's understanding of the two differences between EXT vs. INT is correct, though note that the "general network" referred to here is limited to the data being analysed – that is, the global network only includes words we know are eventually produced in the data, so ultimately all words included in the analysis of EXT will eventually be considered in the INT models, and vice versa. However, this difference is indeed crucial in the models: in EXT, the connectivity of the eventually-acquired network should predict learning (i.e. nodes with the highest number of edges in the end-state network are acquired earliest), whereas in INT, the state of the network at the given timepoint should predict learning (i.e. the most densely-connected nodes drive learning of new nodes that will connect to them).

To clarify the difference in predictions made by the two models, and following a request from R1 as well, I have added an explanatory figure to p.39 of the manuscript, which I have copied here for convenience.



"Figure 1. Visualisation of INT and EXT models of network growth. Shapes represent nodes in the network and filled lines represent edges between nodes. The two images demonstrate the likelihood of two new nodes - a filled triangle or an open circle - being added to the network under conditions of INT- and EXT-like network growth. In each case, the node that would be acquired is added to the network, and new edges are shown with dashed arrows. The double-dashed arrow in the INT model shows the new edge formed with the most highly-connected node in the existing network."

I have also expanded on the explanation in the paper with some examples, on p.5:

"*EXT-like growth assumes that forms that connect to (i.e. share properties with) a higher number of different nodes in the target network will be acquired first. EXT models of network growth thus assume that external factors in the learning environment influence acquisition – that is, forms that are most well-connected within the target language will be acquired earlier. In phonological terms, this would mean that early productions would constitute the distribution of segments and structures that co-occur most frequently in the input, thus leading early forms to resemble the statistical properties of the ambient language more closely, rather than a 'pattern force' driven by dominant features of the existing lexicon. For example, given an existing lexicon that included the forms pat and bat, an INT model would predict that a highly phonologically-similar form such as pit or bit might be acquired next, whereas EXT would predict that more variable forms would be acquired, such as /p/-initial or /t/-final words, which have high phonotactic probability in English and thus connect to a wider range of different forms.*"

In terms of the importance of the two differences outlined in this comment, I don't think there is necessarily a need to weight one above the other in general terms, though the difference in what each model predicts is of course relevant to this paper. The difference between child-specific and general network construction is a difference that is inherent in what the models each expect: one predicts that learning will be bottom-up, driven by what the child already knows; the other predicts top-down learning, driven by the linguistic environment.

Other than that, I have a few remaining questions, and some suggestions to connect the work better to language processing and language development literatures.

Remaining questions—the first two are the most important.

1. Is it possible that some of the changes in connectivity with vocabulary size are inevitable? What about some 'random word' models—if you select random sets of tokens from the full dataset and grow a vocabulary network from that, does connectivity increase/decrease the more words you have? The current data would be more convincing if random networks showed very different properties than the ones based on real data.

Thank you for this interesting suggestion, which I hadn't considered in the initial submission but I agree would strengthen the argument in the paper. I have added a short section to the first part of the Results, copied below from p.16. I have opted for what is a simpler but I think equally representative solution, by randomising AoPs in the original dataset, and then generating degrees from this. If connectivity increases with vocabulary size, as proposed in this comment, then we would expect the same outcome as is assumed by both EXT/INT models: that later-acquired words are less well-connected (i.e. negative AoP~degree correlation). However, this was not the case for the randomised data, which was in fact found to have an AoP~Degree correlation of 0.01.

"*To ascertain that this negative relationship between AoP and connectivity is not simply a given in vocabulary-based networks that increase in size over time, this analysis was re-run on an identical dataset that was randomized by AoP, such that new words were added to the French and English networks at random ages, and then the degree of each word in this random network was calculated. Across the data, there was no correlation between AoP and degree (r=0.01; p=.678); evidence for INT/EXT-like growth in the real data is thus not an inevitable outcome of vocabulary growth.*"

2. How does this finding relate to comprehension? This seems important for fully characterizing language development. Are children limited (or swayed) in their comprehension to forms they can more easily produce? Or are they simply refusing to say words they easily recognize because they are hard to produce?

One way to address this in the analysis – albeit an imperfect measure – is to include age of acquisition norms for comprehensive vocabulary in the models, which is introduced on pp.16-17 as follows:

"*As well as INT and EXT growth values, each model also included target word length in phonemes, reported age of acquisition for each item in the comprehensive vocabulary according to vocabulary checklists (CDIs; see below), input frequency in child-directed speech, word category (based on CDI word categories), and corpus (English vs. French) as fixed effects. Infant was specified as a random effect with a by-infant random slope for the effect of age. Input frequency for each word was derived from Braginsky et al.'s (2019) frequency estimates, which includes a unigram count for every word produced in adult speech in all CHILDES corpora for the respective language. Normed comprehensive vocabulary data for English and French CDI words was taken from WordBank (Frank et al., 2017); again following Braginsky and colleagues (2019), age of acquisition (AoA) was taken as the month in which >50% of children were reported to understand a given word. As comprehensive vocabulary norms are only available up to ages 16/18 months for French/US English data, respectively, 1470 total tokens did not include this measure (603 word types actoss all infants), either due to the word being acquired after the cut-off for the CDI checklist (i.e. it was included on the checklist but fewer than 50% of infants understood the word by 16/18 months), or due to it not being included on the checklist in the first place (i.e. it is included on the productive vocabulary checklist only).*"

This measure significantly predicted learning in both the Target and Actual data ($b=-.22$, $p<.001$); words that are typically acquired earlier in comprehensive vocabulary norms were acquired earlier in this data. To address this comment more directly, I don't think there is any reason to expect that infants' comprehension would be determined by their production, given the clear evidence to suggest that infants understand words at 6 months, long before they can produce them (e.g., Bergleson & Swingley, 2012). However, I hadn't considered the second point and I agree that this would be a really valuable addition to the findings presented here. I have reflected on this in the Discussion on p.27:

"*Finally, it would have been valuable to have data on these infants' comprehensive vocabularies over the course of the analysis. While comprehensive vocabulary norm data was included in the models, this is a wide step away from the expectation posited throughout this paper that individual trajectories shape learning. Comprehensive vocabulary data would allow an analysis of the extent to which known (but not yet produced) words "fit" existing segments and structures in the child's productive repertoire; in this way, models could be devised that predict which words in the comprehensive vocabulary are most likely to appear next in the productive vocabulary.*"

3. Is it possible that characterization of children's language is a little inaccurate in the sense that they may produce a form at (say) age 1 year that they later stop producing? Thus, carrying forward a previously-produced word assumes some structure that is not there?

This is a good point and is definitely a possibility in this dataset. The fact that the average word type has 24 different tokens produced across the dataset suggests that this is unlikely to be the case for a substantial proportion of words; however, it was easy to test for this.

I've now added some text to the methods that considers the number of different word tokens produced across the data, by-word, and then added a column to Table 1 that shows total token production by child. The new text is on p.12 and copied below:

"*On average, there were 32 tokens of each word type (SD = 144); 3 words occurred only once in the data, and on average each word type was produced across 6 different months (SD = 8), which supports the (admittedly imperfect) assumption made here that the first production of a word in the dataset indicates its acquisition in the infant's lexicon.*"

4. Euclidean vs. edit distance: I think the distinction the author is making is more between features and phonemes. You could calculate edit distance over features, which would be a city-block metric but still better than phoneme-based edit distance. Still, I agree that feature-based seems like a more fine-grained characterization of similarity than phoneme-based.

Thank you for this point, which I had not considered. I have briefly clarified this in the manuscript on p.11 by referring to "*Levenshtein distance in phonemes*" and "*edit distance (in phonemes)*".

Suggestion for discussion
It would be fruitful to connect this to the neighborhood structure vs. phonotactic probability literature, both in child learners and adults (children: Dollaghan, Coady and Aslin, Luce and Charles-Luce, Storkel; adults: Luce, Magnuson among others). The findings here seem to suggest that high-neighborhood words are easier to acquire (despite phonological competition?), though in practice it's hard to pull apart these influences. I was surprised not to see that any of that work referenced here. It would certainly increase the relevance of the manuscript.

Thank you for this suggestion. I have now introduced the link between phonological networks and phonological neighbourhood density in the literature review on p.5 ("*In phonological development terms, this model implies that the lexicon will constitute clusters of similar-sounding words (i.e. denser phonological neighbourhoods)*"), and have added a section to the Discussion exploring the link between the findings in this paper and those of the existing work on neighbourhood density and phonotactic probability (pp.25-26). It makes sense to me that higher PND and phonotactic probability in early development (and its facilitative effect in word learning as seen in experimental studies, e.g. Zamuner, 2009; Zamuner et al., 2014) may result from an early bias towards the acquisition of words that a child can produce (word selection). I have therefore proposed that this may be the case in the Discussion, copied below, but I welcome R2's further input on this.

"*These results align with and expand on previous work observing phonological neighbourhood density (PND) and phonotactic probability in early word learning. Both have been found to positively influence new word acquisition earlier on in development (Coady & Aslin, 2003; Dollaghan, 1994; Storkel, 2004), though for older children (Charles-Luce & Luce, 1990) and adults (Gordon & Kurczek, 2014; Vitevitch & Luce, 1999), low neighbourhood density appears to be more beneficial in learning and remembering novel words. The present findings suggest that, at least in early development, high PND (i.e. phonologically more similar words in the lexicon) may in part be derived from systematicity in production. That is, if infants are selecting new words that match their output capacity in* *early development, then we would expect a higher number of phonological neighbours in the Target and Actual forms, as observed here, and consistent with the PND literature. On the other hand, the fact that INT predicts acquisition in both Target and Actual forms may be due to the increased learnability of words that belong to denser neighbourhoods, leading infants to produce these earlier on – the fact that they are also phonotactically similar (due to PND and phonotactic probability being correlated, Vitevitch & Luce, 1999) would no doubt support their early production as infants need to draw on fewer resources to produce a number of new words. Results in this study lend preference to the first explanation (i.e. that higher PND is motivated by production, rather than the other way around): we see a continuous increase in Actual INT values over time as new words are adapted to fit existing well-rehearsed segments and structures (i.e. existing dense neighbourhoods attract phonologically similar words for acquisition), which is significantly higher than Target INT values over the same period (see Figure 5). If higher PND was motivated by learning, we would expect to see no difference in acquisition of Actual and Target forms, since infants would be learning words that clustered together just as densely in the Target network as in the Actual network, i.e. they wouldn't be systematically adapting words to fit the dominant patterns and structures in their existing lexicon."*

Clarifications and line edits

PAT and PAQ are rather abstract. And phonologically similar, so it's hard to remember which is which (even though I can produce both ϑ). Possible to rename them something like "highly connected" vs. "contextual diversity" or something like that?

I agree with this suggestion, as I have had issues with the phonological similarity (!) of these two terms myself when presenting this work at conferences. Following recent similar work in this area (e.g. Kalinowski et al., submitted) I have opted to refer to the two networks as INT (PAT; an internally-driven network) and EXT (PAQ; an externally-driven network). I have clarified this terminology in the paper on pp.4-5:

"*Network growth models analyse changes within a system over time, and two key models1 of development have been proposed for lexical acquisition: preferential attachment (hereafter INT due to the assumption that network growth is internally-driven in this model; note that some studies refer to this model as PATT) and preferential acquisition (hereafter EXT, due to the assumption that network growth is externally-driven in this model, note that this model is otherwise known as PAQ Hills et al., 2009; see also Steyvers & Tenenbaum, 2005).*"

And I have otherwise INT/EXT have replaced all instances of PAT/PAQ.

p. 6: "Mak and Twitchell's (2020) work with paired-association learning in adults shows that participants were better at remembering word pairs when items had been paired with highly-connected cue words in semantic space"
highly connected to the target word, or highly connected to a lot of other words? If the latter, doesn't that support PAQ more than PAT?

Thank you, I agree this is confusing! I have double-checked the paper to ensure I have interpreted the findings correctly, and re-phrased this sentence as follows (p.7):

"*Mak and Twitchell's (2020) work with paired-association learning in adults shows that* *participants were better at remembering word pairs when items had been paired with cue words in semantic space that had a higher degree (i.e. were connected to a larger number of semantically-similar words)."*

Top of p. 7: This is a really good argument: vocabulary norming data abstracts away from the individual differences expected in early phonological development … To better understand the role of systematicity in early word production, it is essential to consider infants' actual productions of their early word forms...

Thank you for the positive feedback; I'm glad R2 finds this perspective convincing!

p. 12: "multiple tokens of a given word type in that session were 'averaged out' to one unique value for each word"
Does that mean there was a different connectivity for each token, and connectivity for the word type was the average of token values? I thought only a single form was used for each word type. So then how do you get different connectivity values?

It was not plausible to derive a connectivity for each token in the dataset, as the number of tokens was so big (n=159,043 tokens). The distinctive features for each token were averaged out (so, all sonorant values, all nasal values, etc) to create one "average" word type, and then connectivity between this word type and all other word types was established. I admit that this is not a perfect measure – I initially included only the first token of a given word in the dataset, but I prefer this option as it better represents variability in the data; results are consistent with both approaches, though. I have now clarified this on p.13 as follows:

"*multiple tokens of a given word type in that session were 'averaged out' to one unique set of distinctive feature values for each word, from which connectivity with all other word types was then derived.*"

p. 14, Age of production ~ connectivity correlations. Is there any other way this could have turned out? That is, is it possible that, given an increasing vocabulary, later items will necessarily be less well connected?
I included this component of the analysis because this is typically the first step taken in the analyses of the previous work I drew on here (Hills et al., 2009; Fourtassi et al., 2020; Amatuni & Bergelson, 2017), and to my mind it is a sensible first-step validity check of the data. However I agree that it seems almost a given that a negative correlation would be identified in vocabulary acquisition data. To check this, I randomized my dataset by AoP (age of production), re-generated connectivity values across the data, and then re-ran the correlations on this random sample. The correlation was non-significant, and this time the direction was positive. This reassures me that the overall network structure is indeed in line with assumptions made by INT/EXT, and not just an artefact of the data.

I have re-worded some of this paragraph, and added the additional results, on p.15:

"*First, to assess the broader assumption that connectivity in the network will change systematically over time, regardless of whether that is through INT- or EXT-like changes, the relationship between age of production (AoP) and connectivity (degree) in the static network was considered. Both INT and EXT models of network growth assume that later-acquired words will be less well-connected in the network. Across all infants, there was a mean AoP~degree correlation of r=-0.21 (Spearman's, SD=0.09; English: r=-0.26, SD =0.04; French: r=-0.15, SD=0.11); overall, later-learned words were less well-connected in the* *networks. Negative correlations were found in all children's data; these were all significant at p<.05 except Anais (French corpus). See Table S3 and Figure S3. This is consistent with previous similar work showing that earlier-learned words are more highly-connected in the network (Fourtassi et al., 2020; Hills et al., 2009), and replicates these findings with a naturalistic sample of infant production data. To ascertain that this negative relationship between AoP and connectivity is not simply a given in vocabulary-based networks that increase in size over time, this analysis was re-run on an identical dataset that was randomized by AoP, such that new words were added to the French and English networks at random ages, and then the degree of each word in this random network was calculated. Across the data, there was no correlation between AoP and degree (r=0.01; p=.678); evidence for INT/EXT-like growth in the real data is thus not an inevitable outcome of vocabulary growth."*

p. 15 (not really a question for this page as much as a general one): were to-be-learned words just selected out of the total word types in the sample, or some larger dictionary of English or French word types?

These were selected out of all words in the sample. I have now clarified this on p.13:

"*an as-yet-unknown word (i.e. all the words in the global network - that is, all words produced in a given child's data up to and including age 2;6 - that had not yet been produced)"*

p. 16: "less frequent words were more likely to be learned, as were words with a higher token count"
Higher token count makes sense, but less frequent words doesn't. Is there some sort of interaction/suppression going on between token count and word frequency? Where did the word frequency information come from? Oh, I see—token count in the CHILD's speech, not the mother's speech. It would be a lot clearer to keep this bit of info present, for example, n tokens (child), n tokens (mother) or something like that. It still doesn't make sense to me why the mother's speech effects would go in the directions they do, though. Or is frequency calculated across all mothers rather than being specific to each child's mother?

To avoid confusion, I have re-labelled 'Word frequency' as 'Input frequency' throughout the paper. I have also removed the token count variable from the models, as, due to the addition of comprehensive AoA into the model, both n tokens and vocabulary size were removed to avoid multicollinearity.

Multiple reviewers queried the direction of the input frequency result, and so I opted to use a more robust measure of word frequency across the dataset. The initial measure drew on token counts of each child word produced in their own mothers' speech – while I think there is real value in using such a child-specific measure, because the dataset was filtered to include CDI words only, there were ~125 word types in the data that did not appear in mothers' speech and were coded as 0. There was also high variability in the number of words produced across corpora and infants.

Instead, I now include an input frequency measured developed and used by Braginsky and colleagues (2019), which incorporates token counts from all adult speech in the given language on CHILDES. This measure has been applied in a number of previous studies, including Fourtassi et al. (2020), which I draw on heavily in this paper. This measure includes an input frequency count for every word in my dataset.

As shown in Table 3 on p.37, this measure of frequency significantly predicts learning in the expected direction: more frequent words were acquired earlier (Actual: b=.17, p=.001, CI: [0.07,0.27]; Target: b=.19 p<.001, CI: [0.09,0.29]).

Braginsky, M., Yurovsky, D., Marchman, V. A., & Frank, M. C. (2019). Consistency and variability in children's word learning across languages. *Open Mind*, 3, 52-67.

Reviewer #3: The manuscript is well-written and the project makes a strong contribution to an existing literature modeling word acquisition using network growth models. In particular, it shows that when individual children's actual productions are analyzed (as opposed to analyzing target form productions of aggregated parent-reported vocabulary), systematicity between new words and words already in the child's productive repertoire is clearly apparent.

I am glad that R3 found the paper well-written, and sees the value in its contribution! As a general first comment, please note that, following another reviewer's request, I have re-labelled PAT/PAQ values as INT/EXT values, respectively.

There are several places where I think the paper could be clearer and I have a few questions about how particular modeling decisions might have affected the results:

Abstract: The statement "systematicity is most apparent in early acquisition" doesn't seem to me to match the results. Rather, systematicity increases over the age range included in this study.

I have now changed this statement in the Abstract to "*systematicity becomes increasingly apparent over the course of acquisition*".

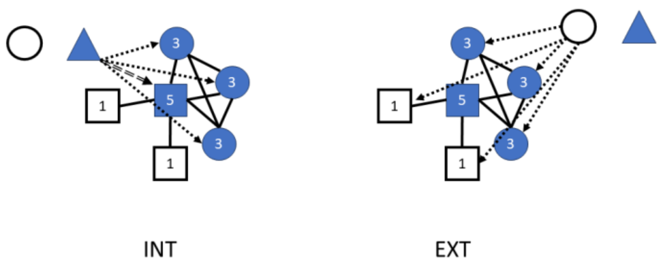
Intro., p. 5: I wasn't following how PAQ necessarily implies dominance of external factors. In general, couldn't the motivation to maximize diversity of connections to a new node potentially be entirely internally driven? I can see the logic of assuming PAQ represents a less internal-motor-constraints-driven mechanism, in the current project, so my suggestion is just to be a little clearer about the logic behind that assumption here in the intro.

My understanding is that EXT/PAQ models of network growth are defined as being driven by external factors in the learning environment (as set out in Hills et al., 2009; Fourtassi et al., 2020). I see R3's point about the potential for EXT-like growth to be internally-driven, but as I understand it this would have different theoretical implications to those of EXT/PAQ.

That being said, all three reviewers have asked for a clearer explanation of EXT models in particular. I have therefore expanded on the explanation in the paper with some examples, on p.5:

"*EXT-like growth assumes that forms that connect to (i.e. share properties with) a higher number of different nodes in the target network will be acquired first. EXT models of network growth thus assume that external factors in the learning environment influence acquisition – that is, forms that are most well-connected within the target language will be acquired earlier. In phonological terms, this would mean that early productions would constitute the distribution of segments and structures that co-occur most frequently in the input, thus leading early forms to resemble the statistical properties of the ambient language more closely, rather than a 'pattern force' driven by dominant features of the existing lexicon. For example, given an existing lexicon that included the forms pat and bat, an INT model would predict that a highly phonologically-similar form such as pit or bit might be acquired next,* *whereas EXT would predict that more variable forms would be acquired, such as /p/-initial or /t/-final words, which have high phonotactic probability in English and thus connect to a wider range of different forms.*"

Intro./Methods: A schematic illustration to help the reader understand PAQ and PAT network growth models as applied to the current domain might enhance the paper.
All three reviewers have requested an illustration of the two models. I have added an explanatory figure to p.39 of the manuscript, which I have copied here for convenience.



"Figure 1. Visualisation of INT and EXT models of network growth. Shapes represent nodes in the network and filled lines represent edges between nodes. The two images demonstrate the likelihood of two new nodes - a filled triangle or an open circle - being added to the network under conditions of INT- and EXT-like network growth. In each case, the node that would be acquired is added to the network, and new edges are shown with dashed arrows. The double-dashed arrow in the INT model shows the new edge formed with the most highly-connected node in the existing network."

p. 8: "PAQ thus assumes that Actual and Target networks do not differ": PAQ as a general approach seems agnostic to whether Actual and Target networks are the same or different. It's conceivable that PAT would best fit Actual data and PAQ would best fit Target data. So for the theory that Actual and Target data both grow in a PAQ fashion, perhaps some other descriptive term(s) could be used.

I see your point here and agree that the statement quoted above is not fully in line with expectations regarding INT and EXT. I have re-phrased this statement as follows:

"*the question of differences between Actual and Target forms is thus not of central theoretical interest for EXT models in this analysis*" (p.8)

p. 11, top paragraph: How was syllable structure factored into phonological distance? Also, a table of examples of pairs plus their phonetic features and phonological distance scores would be helpful to make the methods clearer.

This query aligns with a similar question from another reviewer, who also requested a table showing how phonological distance between word pairs was calculated. I have thus copied my previous response here:

I have added two tables to the SI that shows the distances between 3 target words in the dataset, each with a different phonological structure (*baby* compared with *balloon* and *sky*).

The table presented here is adapted from Monaghan et al. (2010), on which my own phonological distance measures were based when writing this paper.

I have also clarified this approach in the main text on pp.11-12:

"*This means that two words that differ only in their vowel segments are coded as the same in the current analysis. Words were aligned by syllable nucleus: onset consonants were compared with other onset consonants,, and codas were compared with codas. Full criteria for establishing distance, alongside tabulated examples, are included in the Supplementary Information, S1."*

And added the following explanation in the Supplementary Materials:

"Phonological distance was established following Monaghan, Christiansen, Farmer and Fitneva's (2010) approach, with some adaptations. Note that in their study, only monosyllabic words are included, and so their approach is adapted here to include multisyllabic words. Following their method, each word was first divided into a series of 'slots', according to its phonological structure. For example, the word baby was separated into five slots: /b-e-i-b-i/. Because vowels were not accounted for, the nucleus of each syllable - both monophthongs and diphthongs - was then replaced by a generic V slot, i.e. /b-V-b-V/. Words were then aligned by nucleus to generate a phonological distance measure between each possible word pair. All consonants at word onset and final syllables were aligned, regardless of syllable number, such that the final /d/ of bed would be aligned with the final /n/ of balloon. This is because infants may have a tendency to produce only certain consonants word-finally, and so this approach would capture such systematicity. For the English data, the maximal word structure considered in the analysis is C-C-C-V-C-C-|C-C-C-V-|C-C-C-V-|C-C-C, where syllable boundaries are marked with a |. This accounts for complex clusters at word onset (e.g. splash /splæʃ/, C-C-C-V-C), coda (plant /plænt/, C-C-V-C-C), and across syllable boundaries (pumpkin /pʌmpkɪn/, C-V-C-C-|C-V-C). In French the maximal structure was C-C-C-V-C-C-|C-C-C-V-|C-C-C-V-C|C-C-C-V-C|C-C-C-V-|C-C-C-C. This accounted for multisyllabic target words such as hélicoptère ("helicopter" /elɪkɔptɛʁ/, V-|C-V-|C-V-C-|C-V-C) and appareil photo ("camera" /apaʁɛjfɔto/, V-|C-V-|C-V-C-|C-V-|C-V), and complex codas as in arbre ("tree" /aʁbʁ/, V-C-|C-C). For vowel-initial words, the C1 slot in word-initial position is empty, but all other alignments remain the same. This maximal structure is required in an analysis of infant word production, to account for unexpected complexities such as, production of French mettre "to put" as [mɛʁstʁ] and étoile "star" as [ɛstwal]. In the infant data, it was not always easy to determine exactly where a syllable boundary should occur in complex productions, in part because this was not predictable based on the target form due to the variability in production, so would have to be done on a word-by-word basis, and in part because the syllable boundary of some productions could not be clearly established from its phonetic transcription. Instead, consonants were always assigned to the syllable-initial cluster, rather than assigning part of the cluster to the coda of the previous syllable (e.g. for the examples above, the infant production of mettre was coded as C-V-|C-C-C-C and étoile as V-|C-C-C-V-C)."

p. 11, bottom paragraph: An alternative to analyzing Target forms of all words produced lol by 2;6 would be to analyze the adult productions from the same sessions. Some mention of alternative ways of representing external targets and rationale for the current approach rather than alternatives would be nice to see added.

I'm not sure if I've fully understood this comment, since the Target forms essentially are the "adult" forms, though granted not the words that the caregiver necessarily produce. By using the Target forms, the analysis essentially replicates that of previous work that has drawn exclusively on vocabulary norm data, with actual production age, rather than normed AoA data, as an index of developmental time.

However, I agree that the rationale for making this decision would be valuable in the Discussion, and so I have added the following on p.23:

"*It may also be the case that the representation of the Target network was not sufficiently aligned with the reality of the end-state network that the infants will acquire. Analysing the Target network on a larger scale – for example, including all words produced in the infants' inputs across their recordings, and building a network based on which of these words infants produce in the dataset – might better represent the role of EXT-like growth on early word learning. This is an avenue that could plausibly be considered in future work.*"

p. 12: It seems a limitation that semantic info. is not included in these models. Can that be added to the Discussion as a limitation?

I have added a sentence to the Discussion on p.27 to consider how future studies could build on this one to consider semantic networks:

"*The influence of semantic networks on acquisition has also not been considered here - further studies may want to analyse similar naturalistic data to consider semantic network growth within infants' actual productions, or even combine indices of semantic connectivity with that of phonological networks to observe how/whether the two interact in early development.*"

p. 16, top paragraph: Confidence intervals on the estimates could potentially provide evidence that PAQ is significantly less predictive than PAT. Currently, the conclusion rests, technically, on (over-)interpretation of a null result. The chi sq. values are very different, so I would bet the difference is significant. Moreover, confidence intervals could potentially show that even though PAQ and PAT are both predictive for Actual data, PAT is a better predictor that PAQ for Actual data as well.

I have now added confidence intervals to the model summaries in Table 3, as well as to the relevant tables in the SI.

p. 16, middle paragraph: The result that "less frequent words were more likely to be learned" is very counter-intuitive. I imagine this is related to the way the model is set up, but I'm having a hard time reasoning beyond that. Can you provide some possible explanations?

Thank you for flagging this up; R2 also had a similar query. For convenience, I have copied my response to their comment below:

Multiple reviewers queried the direction of the input frequency result, and so I opted to use a more robust measure of word frequency across the dataset. The initial measure drew on token counts of each child word produced in their own mothers' speech – while I think there is real value in using such a child-specific measure, because the dataset was filtered to include CDI words only, there were ~125 word types in the data that did not appear in mothers' speech and were coded as 0. There was also high variability in the number of words produced across corpora and infants.

Instead, I now include an input frequency measured developed and used by Braginsky and colleagues (2019), which incorporates token counts from all adult speech in the given language on CHILDES. This measure has been applied in a number of previous studies, including Fourtassi et al. (2020), which I draw on heavily in this paper. This measure includes an input frequency count for every word in my dataset.

As shown in Table 3 on p.37, this measure of frequency significantly predicts learning in the expected direction: more frequent words were acquired earlier (Actual: b=.17, p=.001, CI: [0.07,0.27]; Target: b=.19 p<.001, CI: [0.09,0.29]).

Braginsky, M., Yurovsky, D., Marchman, V. A., & Frank, M. C. (2019). Consistency and variability in children's word learning across languages. *Open Mind*, 3, 52-67.

p. 17, top paragraph, "the direction of this effect is not as expected: in the Actual data, PAT values of newly-learned words are lower earlier on in development, while they are higher in the Target data": What are some potential explanations and implications of this? It would be good to add some elaboration to the Discussion section about this.

Following other reviewer comments, I have changed the model structure slightly to include comprehensive age of acquisition from vocabulary norms, and the new input frequency measure from Braginsky et al (2019), and have removed vocabulary size and token frequency owing to multicollinearity. As a result, only the Age*INT interaction is significant in the Actual data, which again is positive. The Age*EXT interaction remains negative, according to model estimates, but is now non-significant. I have consequently removed this section from the analysis.

p. 17: For the GAMM analysis, was the unit of analysis words learned at a given age point? Or all unlearned words at an age point? Or something else?

I have reworded the text on p.19 as follows:

"*The data was subsetted to include only INT values at the time-point immediately prior to the word's production as the dependent variable in the model (i.e. for a word produced at 17 months, its INT value at 16 months was analysed); higher INT values are expected to predict that a word would be learned in the next month.*"

p. 18, top paragraph, "the data was subsetted such that only the PAT values at the time-point immediately prior were analysed": Was this also done for the linear age models presented earlier? If not, why not?

This approach wasn't taken on the GLMER models because the dependent variable was whether or not a word was learned at the next time-point based on the INT/EXT values; all time-points were thus included for each target word. In contrast, the GAMM models are testing how the INT values change over time for learned words, as vocabulary grows. Sub-setting the data in this way for the GLMERs would require a full change of the model and all predictions.

I have clarified this in a short addition to the text on p.19:

"*To explore these results further, GAMMs were run using the mgcv() package in R (Wood, 2011), to observe how INT values changed over time as new words were learned.*"

p. 19, middle paragraph, "in both Actual and Target data, earlier-acquired words tended to have lower PAT values, while later-acquired words had higher PAT values": Could it be because of vocabulary size limiting the number of connections between words? What if that were somehow accounted for in network construction, e.g. by choosing the phonetic similarity threshold so as to always have a consistent proportion connectivity?

To address the first point, and following Hills et al. (2009), I have now scaled the INT and EXT values in the GLMER models not only by speaker but also by age. This accounts for the changing network size over the course of the analysis. I have clarified this on p.17:

"*INT/EXT values were scaled by speaker and age to account for the effect that increased vocabulary size at each month has on INT/EXT values (i.e. when the network is bigger, a newly-acquired word has the opportunity to connect to a higher number of different words by default).*"

The significant positive Age*INT interaction continues to be significant in the Actual but not the target data, even when changes in vocabulary size are controlled for (see Table 3).

p. 22, bottom paragraph: "it appears that infants are selectively acquiring forms that match their own production preferences": I think it should also be noted that parents may be selectively eliciting/highlighting words they think their child is capable of producing.

While I absolutely agree with this point, I don't think it would explain the fact that infants' words are phonologically similar to one another. However, I agree that the fact that the words could well be elicited in some way – whether explicitly or implicitly – is relevant to the claims being made in this paper, so I have added a note to the methods section acknowledging this possibility:

"*Note that while interactions were naturalistic and thus not at all directed by the original researchers, the data was not coded for infant productions that were imitated from or prompted by the caregiver, and so data includes both spontaneous and non-spontaneous infant productions.*"

p. 23: It could also be nice in the future to consider babbling forms within the network analysis.

Thank you for this suggestion, which I completely agree with. I am about to start data collection on a longitudinal sample that would incorporate babble, with the intention of doing just that. For now, the kind of data required for this sort of analysis is not easily available.

p. 23, last paragraph, first line: Please change "within a networks account" to "within a phonological networks account".

This has been amended in the text.

p. 34 (Table 4): Why is there PAQ for Actual when PAQ only applied to 2;6 Target forms?

This is the analysis of the Actual network (i.e. the connectivity of all words based on their Actual form) using EXT values that were generated based on connectivity of the Target form. EXT values are generated from Target forms because they represent the final network that the child is moving towards, but given that connectivity differed between Actual and Target networks I analysed both for completeness. I have clarified this on p.14:

"*As EXT-like growth is assumed to represent the connectivity of words in the ambient language, global networks were established with Target forms only, since the way infants produce words in the existing network is not relevant to this model. However, given that connectivity differs across Target and Actual networks (i.e., the known words in the Actual network at month n may be different from the known words in the Target network in the* *same month), both Actual and Target network structure will be tested in the analysis.*"

p. 35 (Figure 1): Please add a color legend. When printed grayscale, I can't tell which is red and which is blue.
The legend was already in colour so I imagine the issue is with the rendering within the manuscript submission system. I have changed the line types in the figure so that hopefully these are more easily differentiated in greyscale.

p. 36 (Figure 2): I thought PAQ was only done on Target data, not Actual data? I think the text mentioned that both were plotted for exploratory purposes, but I think a little more detailed explanation could help, for understanding this as well as Table 4.

As per the comment about Table 4 above, I have now clarified this in the Methods section.

Phonological Networks and Systematicity in Early Lexical Acquisition

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Author Note

All code and associated data for this manuscript can be found on the project's OSF page at https://osf.io/uzrsy/?view_only=340858d2084245d087fc00fcca41b679. This study was not pre-registered.

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Abstract

Infants' early words tend to be phonologically similar. This may reflect a systematic approach to early production, as they adapt newly-acquired forms to fit familiar structures in the output. This 'rich-get-richer' approach to phonological acquisition, known as *preferential attachment* in network science, proposes that new words cluster together with existing phonologically-similar words in the lexicon (or network). This contrasts with recent work (e.g. Fourtassi et al., 2020) showing that the learning environment is the key predictor in learning (*preferential acquisition*). This study expands on previous analyses of vocabulary norm data to analyse naturalistic data, namely phonetic transcriptions of nine infants' word productions, from word onset to age 2;6. Network growth models test whether 1) acquisition is best modeled through preferential attachment or preferential acquisition, 2) the trajectory of network growth changes over time, and 3) there are any differences in network growth of adult target forms vs. infants' actual productions. Results show that preferential attachment predicts acquisition of new words more convincingly than preferential acquisition: newly-acquired words are phonologically similar to existing words in the network. Furthermore, systematicity becomes increasingly apparent over the course of acquisition, and infants produce their early words more systematically than we would expect from looking at target forms alone.

Keywords: systematicity, phonological development, preferential attachment, networks analysis

Phonological Networks and Systematicity in Early Lexical Acquisition

Decades of work on phonological development has documented the systematic nature of infants' earliest words. Studies of phonetic (McCune & Vihman, 2001) and phonological structures (Vihman, 2016) show that many of a child's first word forms share similar properties. Infants draw on what they know: when articulatory, memory and planning capacities are simultaneously limited, a "phonic core of remembered lexical items and articulations" (Ferguson & Farwell, 1975, p. 112) may help them deal with the challenge of developing an early lexicon. Vihman (2019, p. 263) describes the early lexicon as "an emergent network of related forms" that develops systematically, in line with the well-rehearsed segments and structures already in the infant's inventory. A networks approach to phonological development offers one way of identifying and quantifying this systematicity. In this study, I present a longitudinal analysis of nine infants' lexical development to identify systematicity in the first three years of word production. I consider the phonological characteristics of the developing lexicon using network analysis to demonstrate how early systematicity may support infants to acquire the requisite capacity for flexible and automatic word production.

In early development, the combined challenges of articulation, memory and planning mean that the constraints on infants' production are high, and so they draw on a limited set of vocal outputs that represent a growing number of target words. According to Vihman (2014, 2019), word production begins with a small lexicon of phonologically-simple and accurately-produced forms, which are 'selected' for their ease of production, as well as their perceptual salience. As the lexicon grows, target forms that do not necessarily fit these structures are 'adapted' so that they do. Selection of and adaption to accessible phonological structures indicate the presence of systematicity within the developing lexicon. Essentially, the new target form is allocated to one of a small number of accessible or well-rehearsed motoric categories, and as these categories increase in size they become increasingly entrenched (Thelen & Smith, 1996). In data from their bilingual (English-Spanish) daughter's early word acquisition, Deuchar and Quay (2000) show that 13 of her first 20 words are produced with a CV structure, and many are phonologically identical: she produces *car*, *clock*, *casa* 'house' and *cat* as [ka], and *papa* 'daddy', *pájaro* 'bird' and *panda* as [pa]. This demonstrates a 'pattern force', whereby production is driven by a small number of well-rehearsed structures. This tendency to acquire similar-sounding forms may continue throughout development: Mitchell, Tsui and Byers-Heinlein (2022) show that French-English bilingual infants are more likely to acquire translation equivalents that are similar in phonological form (cognates, e.g. *banana* and *banane*) than non-cognate word pairs (e.g. *dog* and *chien*) upto age 27 months. Systematicity in phonological acquisition may thus support lexical development over the first three years.

One way of interrogating systematicity in early phonological productions is through network analysis, which offers a quantitative perspective on the organization and development of the lexicon. Developmental research in this area centres around the words that children target in production to establish connectivity on phonological (e.g. Siew & Vitevitch, 2020) and semantic (e.g. Hills, Maouene, Maouene, Sheya, & Smith, 2009) planes. That is, how similar target words are to one another in form or meaning, and what this might mean for acquisition. However, as yet there is no work looking at the way children *produce* those words; that is, whether or not children are drawing on systematicity in the output. Given the extensive background research that suggests a systematic approach to early word *production*, expanding network analysis to this area is a natural next step for language development networks.

The term *network* refers to a web of forms (or *nodes*, in network terms) that are interconnected based on shared properties. Here these are phonological properties, but could also be semantic, or indeed non-linguistic properties such as genetic information, social connections or location (see Bell et al., 2017, for a review). Network growth models analyse changes within a system over time, and two key models[1] of development have been proposed for lexical acquisition: preferential attachment (hereafter **INT** due to the assumption that network growth is internally-driven in this model; note that some studies refer to this model as PATT) and preferential acquisition (hereafter **EXT**, due to the assumption that network growth is externally-driven in this model, note that this model is otherwise known as PAQ, Hills et al., 2009; see also Steyvers & Tenenbaum, 2005). INT models of network growth propose a rich-get-richer scenario, whereby the most highly-connected nodes (nodes with more *edges*) in the network are most likely to attract new nodes. In phonological development terms, this model implies that the lexicon will constitute clusters of similar-sounding words (i.e. denser phonological neighbourhoods), and that a child is more likely to acquire new words that attach to these dense clusters: infants' production of newly-acquired words will be similar to their production of existing words in the lexicon. INT-like growth is therefore driven by the *internal* linguistic system. On the other hand, EXT-like growth assumes that forms that connect to (i.e. share properties with) a higher number of *different* nodes in the target network will be acquired first. EXT models of network growth thus assume that *external* factors in the learning environment influence acquisition – that is, forms that are most well-connected within the target language will be acquired earlier. In phonological terms, this would mean that early productions would constitute the distribution of segments and structures that co-occur most frequently in the input, thus leading early forms to resemble the statistical properties of the ambient language more closely, rather than a 'pattern force' driven by dominant features of the existing lexicon. For example, given an existing lexicon that included the forms *pat* and *bat*, an INT model would predict that a highly phonologically-similar form such as *pit* or *bit* might be acquired

[1] A third model - Lure of the Associates - predicts that new words will be learned that are similar to the highest number of already-known words in the network. This model has been considered in some studies (Hills et al., 2009; Siew & Vitevitch, 2020) but will not be considered here as there is no conclusive evidence for this model in the development literature, though note that there is evidence for this model in adult word learning (e.g. Stamer & Vitevitch, 2012; Storkel, Armbrüster, & Hogan, 2006).

next, whereas EXT would predict that more variable forms would be acquired, such as /p/-initial or /t/-final words, which have high phonotactic probability in English and thus connect to a wider range of different forms.

Existing studies show mixed evidence for INT- and EXT-like growth[2] in lexical development. Hills and colleagues' (2009) study of semantic networks showed evidence for EXT, but not INT, in associative networks of normed vocabulary acquisition data. Amatuni and Bergelson (2017) support this with an analysis of a large-scale corpus of input data combined with normed productive vocabulary data derived from WordBank (Frank, Braginsky, Yurovsky, & Marchman, 2017). These same approaches have also been applied to phonological data: Fourtassi, Bian and Frank (2020) analyse both phonological and semantic network growth from vocabulary norms (receptive and productive) in 10 languages to find consistent evidence in support of EXT-like growth, for both phonological and semantic networks, receptive and productive vocabularies, and across the 10 languages included in their analysis. Ciaglia, Stella and Kennington (2023) analysed complex multiplex networks (including phonological, semantic, sensorimotor and visual associations) to find evidence for both EXT and INT in word learning, though evidence was stronger for EXT. In contrast, Siew and Vitevitch (2020) tested phonological networks in acquisition of older Dutch- and English-learning children (age 3-9 years), again using vocabulary norms to indicate age of acquisition for each word. Their analysis revealed contrasting findings for English compared with Dutch, as well as an age effect: INT-like network growth predicted acquisition in English and Dutch, and both EXT and a third model (Lure of the Associates, see note above) predicted word learning in Dutch. INT was a better predictor of acquisition earlier on in development (i.e. earlier-acquired words were likely to attach to densely-connected clusters of similar forms); later on, the opposite was found, whereby later-acquired words tended to be phonologically more distinct (i.e. less similar to existing words in the network). A

[2] Note that these are not mutually exclusive.

replication of this study using data from adult second-language learners of English found consistent results (Luef, 2022). Evidence in favour of INT has also been found in adult word-learning experiments: for example, Mak and Twitchell's (2020) work with paired-association learning in adults shows that participants were better at remembering word pairs when items had been paired with cue words in semantic space that had a higher degree (i.e. were connected to a larger number of semantically-similar words). The authors propose that these highly-connected words may support learning due to the fact that they tend to be used more flexibly, and thus occur in a more diverse set of linguistic contexts. In infancy, this relates back to Ferguson and Farwell's "phonic core of remembered lexical items and articulations" (1975, p. 112), as infants apply the same well-rehearsed phonological form flexibly and systematically to new items in the lexicon.

These studies present an intersection of evidence for the role of INT and EXT network growth in phonological development. However, two key aspects of these existing approaches should be expanded further. First, the consideration of acquisition in terms of only target forms provides no view of systematicity in *production*, which is where systematicity has been most well-documented in naturalistic data. Second, vocabulary norming data abstracts away from the individual differences expected in early phonological development (e.g. Vihman, Kay, Boysson-Bardies, Durand, & Sundberg, 1994); by drawing on data that generalises across hundreds (or even thousands) of children, it may not be possible to capture developing systematicity due to individual differences in the words and sounds that are acquired first. This makes it difficult to test which model of network growth (INT or EXT) is most cogent. To better understand the role of systematicity in early word production, it is essential to consider infants' *actual productions* of their early word forms, in terms of both *how* and *when* they produce them. In this paper, I analyse phonological networks of both *target* and *actual forms* (that is, the words children produce, and the way they produce them) produced in naturalistic data from two languages, in order to consider phonological systematicity within the individual development trajectories of nine infants.

Hypotheses

Drawing on naturalistic data, this study uses network growth models to capture phonological connectivity (taken here as an index of systematicity) within the individual lexicons of nine infants. Two sets of networks will be established for each infant: one tracing connections between infants' *actual* word productions, the other between the *target* productions of these forms. Network analysis will quantify systematicity in the developing lexicon via two key network growth frameworks: INT and EXT. I will draw on approaches outlined in previous studies (Amatuni & Bergelson, 2017; Fourtassi et al., 2020; Siew & Vitevitch, 2020) to test whether naturalistic data reveals evidence of systematicity in infants' output forms, such that language development is shaped by existing production knowledge. Specifically, I predict that:

H1) Developing phonological networks will show stronger evidence of an INT-like model of growth over an EXT-like model, based on evidence from the phonological development literature that shows phonological similarity across individual infants' lexicons (e.g. Vihman & Keren-Portnoy, 2013).

H2) INT-like growth will be most evident earlier on in development, as infants select and then adapt words to fit their production capacity (Vihman, 2019). Later, more variability is expected as phonological capacity develops. This would also align with previous evidence for INT-like growth in toddlers (Siew & Vitevitch, 2020) and novel word learning in adults (Mak & Twitchell, 2020).

H3) If INT-like growth is supported in the data, then this should be more convincing for Actual than Target productions, given that we expect infants to adapt target words to fit the motor routines that are most accessible to them in production. This difference is not expected for an EXT-like model of network growth, which assumes that network growth reflects connectivity in the input; the question of differences between Actual and Target forms is thus not of central theoretical interest for EXT models in this analysis.

To test these hypotheses, phonological networks will be established for nine infants acquiring American English or French. Phonological distance will be calculated between each word and each other word in each infant's network to establish connectivity within the network. Logistic regression models and Generalized Additive Mixed Models (GAMMs) will determine whether acquisition of *Actual* and *Target* forms reflects INT- or EXT-like growth in early phonological development, and how these networks change over time.

Methods

This analysis follows approaches taken by Hills and colleagues (2009) and Siew and Vitevitch (2020), by establishing network growth values for each word in each child's lexicon. Logistic regression models will be used to test whether INT or EXT growth values can best predict word learning. This is followed with the use of Generalized Additive Mixed Models (GAMMs) to analyse the trajectory of network growth values over time.

Data and Materials

Data for this study was extracted from CHILDES (Child Language Data Exchange System, MacWhinney, 2000) using Phon (Hedlund & Rose, 2020). Two corpora were selected for the analysis: American English (Providence corpus, Demuth, Culbertson, & Alter, 2006) and French (Lyon corpus, Demuth & Tremblay, 2008). These corpora were selected due to their parallel data collection and transcription methods. The English data includes five infants (including two boys[3]) and four from the French corpus (two boys). Both corpora

[3] The Providence corpus (Demuth et al., 2006) includes six children (three boys). One child was later diagnosed with a developmental disorder and so is omitted from this analysis. The Lyon corpus (Demuth & Tremblay, 2008) includes five children (two boys) but one of the datasets (Marilyn) is not fully transcribed and is therefore excluded from this analysis.

include spontaneous[4] interactions between child and caregiver, recorded in the home for one hour every two weeks from the onset of first words. The original corpora were orthographically transcribed, and then phonetically transcribed and checked by trained coders. See Demuth et al. (2006) and Demuth and Tremblay (2008) for full details of data collection and annotation.

Transcripts were extracted from the first session in the dataset (the first session in which the child produced a word) until age 2;6. Data was analysed on a month-by-month basis, such that all new word types produced in each month were aggregated to give a rolling monthly network of all words produced by each child. The session in which a word first occurred was considered the session in which it was 'acquired', and was included in that month's list of newly-acquired words. Later productions of the same word were not included in the dataset. Two of the American infants (Naima and Lily) had denser data taken at weekly intervals during some periods of data collection, but this is not considered to be an issue as no between-child comparisons will be conducted, and subject will be coded as a random effect in all statistical models. The total network of words at any given month amounts to all the unique words produced up to and including that month. All tokens of each newly-acquired word produced by each infant in each session were extracted (*Actual* forms, i.e., the phonological form as produced by the child) alongside their target transcription (*Target* forms).

Only words included on the US English and French communicative development inventories (CDIs, Fenson et al., 1994; Kern & Gayraud, 2010) were analysed. Following Jones and Brandt (2019), every unique word was considered, though plurals were categorised with their singular nouns. For example, *fall*, *fell* and *falling* were considered as unique words

[4] Note that while interactions were naturalistic and thus not at all directed by the original researchers, the data was not coded for infant productions that were imitated from or prompted by the caregiver, and so data includes both spontaneous and non-spontaneous infant productions.

(coded under the CDI 'basic level' *fall*), while *bananas* was categorised with its singular form *banana* and *children* with *child*. In the French data, this rule was also applied to masculine/feminine forms: *animaux* was categorised with the singular *animal*, and feminine *petite* was categorised with masculine *petit*. Words with the same basic level form that were orthographically different but phonologically indistinguishable (e.g. verb forms in French, such as *aime* and *aiment* from the infinitive *aimer* 'to love') were categorised together. This approach was taken in order to account for developmental changes in infants' word production (i.e. the production of more complex morphological forms) while also avoiding coding two words as different that share almost identical forms and meanings (e.g. plural nouns). To generate networks of Actual and Target forms, phonological distance was calculated between every word and every other word in the cumulative network at each month, following Monaghan, Christiansen, Farmer and Fitneva's (2010) approach. This is based on phonological features, following Harm and Seidenberg (1999) and based on Chomsky and Halle's (1968) theory of government phonology. This was considered to be the most appropriate measure of phonological distance, as oppose to other established measures such as Levenshtein distance in phonemes (e.g. Fourtassi et al., 2020; Siew & Vitevitch, 2020): distinctive features allow us to consider distance on a phonologically-appropriate gradient, whereby the difference between words such as *bat* and *pat* is smaller than the difference between *bat* and *rat*. Using edit distance (in phonemes) as a measure, *pat*, *bat* and *rat* would be equidistant, thereby equating all phonemes as articulatorily similar, which does not reflect the reality of phonological development: /p/ and /b/ are among the earliest consonants to be acquired, whereas /r/ is not typically acquired until around age 5 (cf. McLeod & Crowe, 2018). Note that in the present analysis only consonants were included, given that vowels are highly variable in production until around age 3, and notoriously difficult to transcribe from child speech (Donegan, 2013; Kent & Rountrey, 2020). This means that two words that differ only in their vowel segments are coded as the same in the current analysis. Words were aligned by syllable nucleus: onset consonants were compared with other onset consonants, and codas were compared with codas. Full criteria for establishing distance, alongside tabulated examples, are included in the Supplementary Information, S1. When multiple tokens of the same word type were produced in a single session, the values derived from the distinctive feature matrix were averaged across tokens to create a mean phonological representation for each word type. While this is not a perfect measure, it captures a metric of both variability and similarity within and between each word type.

Altogether, 5483 words were excluded from the data due to not appearing on the French or American English CDIs (2224 in French and 3259 in English). The final dataset includes 3096 word types overall, aggregated across infants (English=1933, French=1163). On average, there were 32 tokens of each word type (SD = 144); 3 words occurred only once in the data, and on average each word type was produced across 6 different months (SD = 8), which supports the (admittedly imperfect) assumption made here that the first production of a word in the dataset indicates its acquisition in the infant's lexicon. See Table 1 for a breakdown of the data by corpus and child. All but 10 tokens (all French) in the data had three syllables or fewer in the target form, with 1 syllable on average in the English data (SD = 0.50) and 1.53 in the French data (SD = 0.66).

Network Analysis

For each child, two kinds of network were generated: 1) a *global network*, which represents the final network, i.e. all words produced in the data by 2;6. This network includes the Target production of all individual word types produced in the dataset, coded for age of first production. The global network is taken to reflect the learning environment, or the input, which is why only Target forms are included; this will be used to establish EXT growth values for each word in the data (see below), and also serves as a proxy for the 'end-state' towards which each child's phonological development is directed. 2) A series of 'known' networks representing the lexicon at each month. Each monthly known network includes all the words produced up to and including the given month, in either Actual (the infants' realization) or Target (the target realization) form. This series of networks is used to generate INT values for each word in the data. As a reminder, for both kinds of networks, a given word type was included from the first session in which it occurred, and multiple tokens of a given word type in that session were 'averaged out' to one unique set of distinctive feature values for each word, from which connectivity with all other word types was then derived. Connectivity was established between all words in the global network, and all words in each monthly network; two nodes were considered to be connected (i.e., formed an edge) if they had a scaled phonological distance of 0.25 or less; this value was established by standardizing all phonological distance values for each infant, and then selecting the the value that captured the first quartile of connectivity within the dataset. The first quartile of connectivity across individual corpora (English and French) and data types (Actual and Target) ranged from a scaled distance of0.18 to 0.24 (see S2 and S3 for further details); the threshold of 0.25 thus represents the upper limit of the total variability across the four subsets of data. All edges in the networks were unweighted and undirected.

Once networks were established, INT and EXT values were calculated for each word. Following Siew and Vitevitch's (2020) approach, these values were generated by computing, for each month, the likelihood that an as-yet-unknown word (i.e. all the words in the global network - that is, all words produced in a given child's data up to and including age 2;6 - that had not yet been produced) would form an edge with known words in the existing network (i.e. the words produced up to and including a given month). The INT value of a given yet-to-be-learned word represents the median degree of all the words it would connect to (i.e. those with a phonological distance of 0.25 or less) if it were learned in the following month. For example, a word with an INT value of 5.6 would connect to a set of words in the following month that, on average, connected to 5.6 other words each. Given that INT assumes that newly-acquired words will connect to already-well-connected words in the existing network, higher INT values predict learning in the following month: new words will connect to words with higher median degrees. INT networks were generated with both Actual and Target forms. EXT values reflect the degree of a given word in the global network of all words produced by 2;6. So a word with an EXT value of 87 connects to 87 other words in the global network. See Figure 1 for a visualization of these two models of acquisition. Again, as EXT predicts that well-connected words in the global network would be acquired earlier, higher EXT values predict earlier learning; in each month, we would expect that as-yet-unknown words with the highest EXT values will be acquired in the following month. As EXT-like growth is assumed to represent the connectivity of words in the ambient language, global networks were established with Target forms only, since the way infants produce words in the existing network is not relevant to this model. However, given that connectivity differs across Target and Actual networks (i.e., the known words in the Actual network at month n may be different from the known words in the Target network in the same month), both Actual and Target network structure will be tested in the analysis. To clarify, as both INT and EXT values are established through connectivity in the network (i.e. only words that form an edge with another word are represented), the words included in each network differs slightly; 54 words did not connect to any other word at a threshold of 0.25 in the Actual data, and 63 words in the Target data. For the same reason, the size of Actual (n = 3266) and Target (n = 3257) networks differs, as some forms connected at a threshold of 0.25 in their Actual, but not their Target, forms.

Data Analysis

Network growth models. Network growth models will be used to address the first two hypotheses. Network growth models are logistic regression models that predict whether or not a word is learned in the following month; the dependent variable is whether or not a word was learned in month n+1 (learned vs. not learned). The key predictors of acquisition are INT/EXT growth values for each word at each month. The models test the assumption that higher growth values predict earlier learning, such that words with higher INT/EXT values at month *n* are more likely to be learned at month *n*+1. Following predictions set out in H1, model comparisons should show INT values to be a better predictor of word learning than EXT values. H2 predicts age-related changes in the effect of INT; an INT x Age interaction is expected to show INT to be a better predictor of learning at earlier time-points.

GAMMs. It is also a possibility that any age-related changes will be non-linear. To address this, Generalized Additive Mixed Models (GAMMs) will be used to test H2, following Wieling (2018) and Sóskuthy (2017). GAMMs allow analysis of dynamically varying data (i.e. change over time), without assuming change to be linear. Since there is no clear expectation as to whether any age-related changes would be linear or not, testing H2 using both logistic regression and GAMMs will account for both possibilities. Non-linearity in the data is analysed in the model through the inclusion of *smooth terms* and *random smooths*, which capture the non-linearity of fixed and random effects, respectively, alongside parametric terms. The dependent variable in these models will be INT and EXT values (tested as predictors in the network growth models outlined above); if predictions set out in H2 are borne out in the data, then we would expect to see a significant effect for age on INT/EXT values as a smooth in the model. H3 will also be tested using GAMMs, given that any differences between Actual and Target data may change over time. Here, we would expect to see a significant effect for Data type as a parametric term. These effects will be identified through nested model comparison and inspection of smooth plots. Full model details are provided below.

All code for data preparation and analysis can be found on the project's OSF page at https://osf.io/uzrsy/?view_only=340858d2084245d087fc00fcca41b679. This study was not pre-registered.

Results

Age of production (AoP) ~ connectivity. First, to assess the broader assumption that connectivity in the network will change systematically over time, regardless of whether that is through INT- or EXT-like changes, the relationship between age of production (AoP) and connectivity (degree) in the static network was considered. Both INT and EXT models of network growth assume that later-acquired words will be less well-connected in the network. Across all infants, there was a mean AoP~degree correlation of r=-0.21 (Spearman's, SD=0.09; English: r=-0.26, SD =0.04; French: r=-0.15, SD=0.11); overall, later-learned words were less well-connected in the networks. Negative correlations were found in all children's data except Anais, and these were all significant at $p<.05$ except Anais and Nathan (French corpus). See S3. This is consistent with previous similar work showing that earlier-learned words are more highly-connected in the network (Fourtassi et al., 2020; Hills et al., 2009), and replicates these findings with a naturalistic sample of infant production data. To ascertain that this negative relationship between AoP and connectivity is not simply a given in vocabulary-based networks that increase in size over time, this analysis was re-run on an identical dataset that was randomized by AoP, such that new words were added to the French and English networks at random ages, and then the degree of each word in this random network was calculated. Across the data, there was no correlation between AoP and degree (r=0.01; p=.678); evidence for INT/EXT-like growth in the real data is thus not an inevitable outcome of vocabulary growth.

Network growth models. Next, network growth models were generated to test whether INT and EXT values predicted which words were produced in the following month. As a reminder, models of both INT- and EXT-like acquisition predict that, for each month, the as-yet-unknown words with the highest INT/EXT values should be learned in the following month. Logistic mixed effects regression models included a binomial dependent variable (coded as 0 or 1) indexing whether, for each as-yet-unknown word at month n, it was acquired in month $n+1$. As well as INT and EXT growth values, each model also included target word length in phonemes, reported age of acquisition for each item in the comprehensive vocabulary according to vocabulary checklists (CDIs; see below), input frequency in child-directed speech, word category (based on CDI word categories), and corpus (English vs. French) as fixed effects. Infant was specified as a random effect with a by-infant random slope for the effect of age. Input frequency for each word was derived from Braginsky et al.'s (2019) frequency estimates, which includes a unigram count for every word produced in adult speech in all CHILDES corpora for the respective language. Normed comprehensive vocabulary data for English and French CDI words was taken from WordBank (Frank et al., 2017); again following Braginsky and colleagues (2019), age of acquisition (AoA) was taken as the month in which >50% of children were reported to understand a given word. As comprehensive vocabulary norms are only available up to ages 16/18 months for French/US English data, respectively, in total 1470 tokens did not include this measure (603 word types across all infants), either due to the word being acquired after the cut-off age for the CDI checklist (i.e. it was included on the checklist but fewer than 50% of infants understood the word by 16/18 months), or due to it not being included on the checklist in the first place (i.e. it is included on the productive vocabulary checklist only). All relevant variables were scaled and centered; INT/EXT values were scaled by speaker and age to account for the effect that increased vocabulary size at each month has on INT/EXT values (i.e. when the network is bigger, a newly-acquired word has the opportunity to connect to a higher number of different words by default). In each case interactions were included between Word length x Age, Word frequency x Age, AoA x Age and INT/EXT values x Age. P-values were established through nested model comparisons. Analysis of Actual/Target data includes INT values for the Actual/Target network, respectively. EXT values always represent connectivity in the Target network (i.e. to simulate the adult production of a given word in the input), but models were run on both Actual and Target data since connectivity in these data sets differed due to words generally being more highly connected at a threshold of 0.25 in the Actual data than the Target data, as explained above. These models were run using the *lme4()* package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Core Team, 2020).

Following Siew and Vitevitch (2020), the first step was to construct three models: a null model (model 0) with word length, input frequency, comprehensive AoA, word category, corpus, and age included as predictors of word learning, and then two additional models with INT (model 1) and EXT (model 2) growth values included as additional predictors, respectively. Models 1 and 2 were then compared against model 0 to test for the effects of INT and EXT values individually. A third model (model 3) was then constructed that included both INT and EXT values as predictors. Data type (Actual and Target) was modeled separately in each case. The full model specification for model 3 is as follows:

Model 3: Learned next ~ EXT value * Age + INT value * Age + Word length * Age + Input frequency * Age + AoA (comprehension) * Age + Category + Corpus + (1 + Age|Speaker)

In the Actual and Target data, INT values improved model fit over and above the effects of input frequency, comprehensive age of acquisition, word length, category, corpus, and age, whereas EXT values did not. See Table 2. When EXT values were added to the model testing just INT values, model fit was not improved over and above the effects of INT alone, but when INT values were added to the model testing only EXT values, model fit improved in both Actual and Target data. INT thus appears to be a predictor of acquisition in both Actual and Target data, while EXT does not appear to predict learning.

Model outputs are shown in Table 3. In both Actual and Target data, higher INT values predicted acquisition (Actual data: b=0.88, $p < .001$; Target data: b=0.47, $p < .001$), providing support for H1. Alongside INT values, age, input frequency and comprehensive AoA were all significant predictors of acquisition in both Actual and Target data: unsurprisingly, words were more likely to be acquired at higher ages, and words with a lower comprehensive AoA (according to vocabulary norms for each language) were more likely to be learned, as were words that were more frequent in caregiver speech. Word length and corpus were also significant in the Target data only: words were more likely to be acquired in the following month in the English data, likely because the English corpus was larger than the French corpus (see Table 1), and as we might expect, shorter words were more likely to be learned. Category has been removed the Table 3 for ease of reading, but is shown in the full model output in the SI (S4). AoA interacted significantly with age in both Actual and Target data: as one might expect, words with lower comprehensive AoA norms were typically learned at earlier timepoints, and vice versa. The INT x Age interaction was significant in the Actual data only; contrary to predictions, INT values increased over time. This was not dependent on increasing vocabulary size as increasing network size was controlled for in the scaled INT variable.

INT-like growth over time. H2 predicted a change in INT-like growth over time, such that INT values should predict learning more effectively in earlier acquisition than later acquisition. That is, earlier words should have higher INT values relative to vocabulary size than later-acquired words. As reported above, a significant INT x Age interaction was observed in only the Actual data, and the effect of age on phonological systematicity is not as expected: INT values of newly-learned words are lower earlier on in development (see Table 3).

To explore these results further, GAMMs were run using the *mgcv()* package in R (Wood, 2011), to observe how INT values changed over time as new words were learned. The data was subsetted to include only INT values at the time-point immediately prior to the word's production as the dependent variable in the model (i.e. for a word produced at 17 months, its INT value at 16 months was analysed); higher INT values are expected to predict that a word would be learned in the next month. This left 2766 data points for the Actual data, and 2702 for the Target data. EXT values for the same month were included as a fixed effect. This time, INT/EXT values were scaled only by speaker, not by age, in order to more clearly visualize the data, though note that results were consistent when the values from the previous models were included (see S6). Otherwise, models incorporated the same fixed effects and interactions as in the mixed-effects regression models above. By-infant and by-corpus random smooths were included in the model for the effect of age; these control for by-infant and by-corpus differences in the data over time. To account for the fact that adjacent values (i.e. INT values at month *n* and month *n+1*) were likely correlated, an autocorrelation parameter was included, which was derived from an initial full model. The start point for each infant's dataset (i.e. their first recording session) was also indexed in the model. To test for the effect of age, model comparisons were run using the *compareML()* function from the *itsadug()* package (Rij, Wieling, Baayen, & Rijn, 2022): the full model included the effect of age as a smooth term, as well as interactions between age and EXT values, input frequency, word length, and AoA. This was compared to another model that did not include the effect of age in either smooth terms or interactions. Because model summaries for GAMM smooths may be non-conservative (Sóskuthy, 2017), any significant effects in the initial model comparisons will be assessed using smooth plots of the models. To continue to explore the independent roles of INT- and EXT-like growth in the data, the same models will also be run with EXT values as the dependent variable (and INT values as a fixed effect). This component of the analysis will be exploratory given that we have no expectation as to how EXT values will affect learning over time, and given that EXT values did not significantly predict learning. As above, Actual and Target data were modeled separately.

Outputs from model comparisons are shown in Table 4 (rows 1-2). Consistent with findings from the logistic regression models above, age had a significant effect on INT values in the Actual data, and not in the Target data. While results from model comparisons are to be treated with caution for GAMMs, model smooths for INT show a convincing linear change in INT values with age. See Figure 2. Consistent with the regression model coefficients above, and again contrary to the expectations set out in H2, in both the Actual and Target data, INT values were lower in earlier acquisition, and increased over time. Model smooths for the EXT values are shown in Figure 3 for comparison purposes, where we see a moderate decrease in EXT values over time.

Data type comparisons. H3 predicted that systematicity would be stronger in Actual, compared to Target, data. We would therefore expect INT values to be higher in Actual data overall, indicating more connectivity. This analysis only applies to INT, given that the global network used to determine EXT-like growth is generated from Target forms anyway; the expected substantial overlap in the two data types is shown in Figure 3. To test for an effect of Data type, GAMMs were used to account for any non-linearity in the data over time. Model structure was almost identical to that reported above, except that 1) Data type was included as a parametric term, with a difference smooth[5] and a by-Data type random smooth for the effect of age; 2) the full dataset, incorporating Actual and Target forms together, was tested.

Results from a nested model comparison are shown in Table 4 (row 3). Data type had a significant effect on INT values. A summary of the full model reveals that INT values were significantly lower in the Target data than the Actual data (b=-0.66, $p<$ .001), thereby supporting H3.

The difference of the two smooths is shown in Figure 4. The red line indicates periods where the two trajectories differed significantly from one another - from ~15 months until the final time-point in the analysis. For clarity, the two smooths are visualised in Figure 5 where the difference between the two trajectories is apparent. A visualization of how the data differs across infants is shown in S6.

Discussion

This study tested two established frameworks of network growth in the context of early phonological development: preferential attachment (INT) and preferential acquisition (EXT)

[5] Difference smooths account for the fact that the different levels of the smooth might differ in their non-linearity; in this instance, the by-Data type difference smooth accounts for the possibility that Actual and Target data may have different trajectories.

(Fourtassi et al., 2020; Hills et al., 2009; Siew & Vitevitch, 2020). Using naturalistic data to observe infants' realization of words, it was possible to establish similarity (or connectedness) across the phonological properties of infants' early words, and map how this changes over time. Based on previous analyses showing that infants' early productions tend to share phonological properties (e.g. Vihman, 2016; Waterson, 1971; see also Vihman & Keren-Portnoy, 2013), it was hypothesised that the early vocabulary would grow in an INT-like manner (H1) – that is, it should constitute dense clusters of similar-sounding forms – and that acquisition should be most systematic earlier on in development (H2). Expanding on two key studies in this area (Fourtassi et al., 2020; Siew & Vitevitch, 2020), it was also predicted that a network consisting of infants' actual productions (that is, the child's *realization* of the target forms) should demonstrate more typical INT-like growth than an equivalent network constituting just the target forms (H3). Two of these three hypotheses were supported by the data.

First, in support of H1, network growth models showed strong evidence for INT-like growth in both Actual and Target data; newly-acquired words were produced in a similar way to existing words in the network, such that, in a given month, as-yet-unknown words that would connect to the most densely-clustered known words were more likely to be acquired in the next month. EXT-like growth did not predict learning in any of the models. H2 predicted that INT-like network growth would be stronger in earlier development, based on previous analyses that show infants' earliest words to be phonologically similar or even identical (e.g. Deuchar & Quay, 2000). However, the opposite was true in this data set: in both Actual and Target data, earlier-acquired words tended to have *lower* INT values, while later-acquired words had higher INT values. Finally, in support of H3, INT-like growth was more convincing for the Actual than the Target data: analysis of GAMM smooths revealed that Data type (Actual versus Target) accounted for significant variance in INT values, whereby Target data had significantly lower INT values than Actual data from early on in the data (15 months).

It was surprising to find no evidence for EXT across the analyses, given that previous studies show more convincing evidence for EXT overall, and given that INT and EXT are not mutually exclusive models of network growth. Amatuni and Bergelson (2017) propose that INT and EXT could work together, such that EXT may "[supplement] INT by providing a structured sampling space for new word selection" (p.5). That is, a combination of INT and EXT would provide both internal (output-driven) and external (input-driven) roles in development. Indeed, acquisition is a dynamic and interactive process (Thelen & Smith, 1996), with ample evidence showing the effects of the input on early word learning (Ambridge, Kidd, Rowland, & Theakston, 2015; Rowe, 2012); it is to be expected that both models would be at work simultaneously during acquisition. It may be that this was not shown in the current data due to the fact that the regression models controlled for many external factors known to affect word learning – input frequency, word length, word category, etc. – which together could have accounted for much of the variability that otherwise would have been captured by EXT growth values in this corpus. It may also be the case that the representation of the Target network was not sufficiently aligned with the reality of the end-state network that the infants will acquire. Analysing the Target network on a larger scale – for example, including all words produced in the infants' inputs across their recordings, and building a network based on which of these words infants produce in the dataset – might better represent the role of EXT-like growth on early word learning. This is an avenue that could plausibly be considered in future work.

The present analysis sheds new light on systematicity in early language acquisition, specifically regarding the role of INT- and EXT-like models of phonological development. Previous studies have drawn on age of acquisition data, using the target form as the index of production (Fourtassi et al., 2020; Siew & Vitevitch, 2020). This has allowed study of vocabulary growth across a large sample, and findings have presented a new perspective on the role of phonological neighbourhoods in early acquisition. However, these analyses have not interrogated the role of *production*. By considering networks in relation to the way infants produce their early-acquired words, it has been possible to consider phonological network growth from a novel perspective. The findings presented here reveal a systematic approach to early phonological development, as infants exploit their existing production capacity to produce new words with familiar articulatory routines. These results support many previous studies that show lexical development to take place via the implementation of systematic structures and templates (Vihman, 2019; Vihman & Keren-Portnoy, 2013; Waterson, 1971), and also model a new way of analysing phonological systematicity in infants' early productions, which can be extended to larger samples and applied to a wider variety of languages.

Given that Fourtassi and colleagues (2020) analysed data from children of similar ages using the same subset of words (i.e. CDI words), we would expect the current findings to map on to their results, particularly in the analysis of Target data. However, their study consistently reveals stronger evidence for EXT and so our results do not align. This may reflect direct differences in the type of data used: in the present study, the order of acquisition (and thereby the model of network growth) reflects the chronological order of individual children's production. Month-by-month acquisition norms taken from thousands of children's CDIs model an 'average' order of acquisition, whereby words that *tend to* appear earlier in the developing lexicon are biased towards an earlier age of acquisition. Frank and colleagues (2021) report the first 10 words of infants acquiring American English, which (for stop consonants only) contain two instances of /m/, three each of /n/ and /d/, five /b/ and one /g/. In naturalistic production, however, a word's phonological form may prime the acquisition of other similar-sounding words: production of *baby* may be shortly followed by *bib* and *ball* (cf. McCune & Vihman, 2001), while in vocabulary norms, acquisition of *baby*, *bib* and *ball* is represented at the group level. Vocabulary norming data thus represents an 'averaging out' of phonological connectedness across thousands of infants, creating a bias towards EXT-like growth. Previous similar studies perhaps represent a more general, one-size-fits-all trajectory to lexical development, whereas these results capture individual clusters of connectivity as children acquire words that match the phonological characteristics of existing words in the lexicon.

Indeed, studies of infants' early words show that, on a word-by-word basis, early-acquired forms tend to consist of the same set of consonants, in both target and actual forms. This reflects the child's 'selection' of early words to match their own consonant repertoire (McCune & Vihman, 2001; Stoel-Gammon & Cooper, 1984; Vihman, 2019). Given that these results show evidence for INT-like growth in both Actual and Target data, it appears that infants are selectively acquiring forms that match their own production preferences, and are either producing these forms accurately (*selected*, in Vihman's terms) or *adapting* them to match their preferred output patterns. Within Vihman's framework, phonological development involves the selection or adaption of lexical units to fit a set of easily-accessible articulatory categories. That is, an infant systematically acts upon new understanding (i.e. acquired receptive vocabulary items) within the limitations of their development, selecting existing categories to deal with challenges presented in production. These are 'well-worn paths' that represent the stable and well-rehearsed production routines that drive selection, and later adaption, of infants' early word forms. In producing forms that are accessible and familiar to the child, they can 'rehearse' particular segments and structures, easing up memory and planning capacity for more flexible and variable production further down the line.

These results align with and expand on previous work observing phonological neighbourhood density (PND) and phonotactic probability in early word learning. Both have been found to positively influence new word acquisition earlier on in development (Coady & Aslin, 2003; Dollaghan, 1994; Storkel, 2004), though for older children (Charles-Luce & Luce, 1990) and adults (Gordon & Kurczek, 2014; Vitevitch & Luce, 1999), low neighbourhood density appears to be more beneficial in learning and remembering novel words. The present findings suggest that, at least in early development, high PND (i.e. phonologically more similar words in the lexicon) may in part be derived from systematicity in production. That is, if infants are selecting new words that match their output capacity in early development, then we would expect a higher number of phonological neighbours in the Target and Actual forms, as observed here, and as consistent with the PND literature. On the other hand, the fact that INT predicts acquisition in both Target and Actual forms may be due to the increased learnability of words that belong to denser neighbourhoods, leading infants to produce these earlier on – the fact that they are also phonotactically similar (due to PND and phonotactic probability being correlated, Vitevitch & Luce, 1999) would no doubt support their early production as infants need to draw on fewer resources to produce a number of new words. Results in this study lend preference to the first explanation (i.e. that higher PND is motivated by production, rather than the other way around): we see a continuous increase in Actual INT values over time as new words are adapted to fit existing well-rehearsed segments and structures (i.e. existing dense neighbourhoods attract phonologically similar words for acquisition), which is significantly higher than Target INT values over the same period (see Figure 5). If higher PND was motivated by learning, we would expect to see no difference in acquisition of Actual and Target forms, since infants would be learning words that clustered together just as densely in the Target network as in the Actual network, i.e. they wouldn't be systematically adapting words to fit the dominant patterns and structures in their existing lexicon.

This study raises new questions for future analyses into systematicity in phonological development. While efforts were made to fully characterise the phonological content of infants' early productions – through using distinctive features with Euclidean, rather than Levenshtein, distance, and observing Actual productions alongside Target forms – still it was not possible to capture the full extent of systematicity, i.e. the presence of prosodic structures or templates (Vihman, 2019). Future work in this area should expand the analyses to consider the development and systematic implementation of templates. Furthermore, this analysis considers only two languages; it would be valuable to extend the approach to a wider variety of languages. Systematicity has been demonstrated across languages (Arnon & Clark, 2011; Khattab & Al-Tamimi, 2013; Szreder, 2013), and so it should be possible to find cross-linguistic commonalities in network growth. Typological differences in network growth would raise questions about the cognitive reality of systematicity in phonological development. The influence of semantic networks on acquisition has also not been considered here - further studies may want to analyse similar naturalistic data to consider semantic network growth within infants' actual productions, or even combine indices of semantic connectivity with that of phonological networks to observe how/whether the two interact in early development. Finally, it would have been valuable to have data on these infants' comprehensive vocabularies over the course of the analysis. While comprehensive vocabulary norm data was included in the models, this is a wide step away from the expectation posited throughout this paper that individual trajectories shape learning. Comprehensive vocabulary data would allow an analysis of the extent to which known (but not yet produced) words "fit" existing segments and structures in the child's productive repertoire; in this way, models could be devised that predict which words in the comprehensive vocabulary are most likely to appear next in the productive vocabulary.

Conclusion

When naturalistic data is considered within a phonological networks account, we find evidence for INT-like network growth, but not EXT-like growth. English- and French-learning infants acquired words that would connect to the most highly-connected nodes in the existing network (INT-like growth), and this became increasingly systematic over time. When we look at the target form of the words infants acquire and how they produce them, in both cases we see evidence to show that early acquisition is driven – at least in part – by preferences in the output. That is, infants acquire words that cluster together phonologically, and produce them systematically such that early production represents clusters of similar-sounding forms.

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\end{longtable}

Table 1

Age (months) at first session, number of sessions and number of distinct word types and tokens produced by each child in the dataset. Means and SDs for each corpus are shown in bold.

Speaker	Corpus	Min. age	n Sessions	Types	n Tokens
Anais	French	12	17	283	7169
Marie	French	12	14	258	5677
Nathan	French	12	17	162	4814
Tim	French	11	17	460	11489
Mean	**French**	**12**	**16**	**291**	**7287**
SD	**French**	**0**	**2**	**124**	**2965**
Alex	English	16	14	272	5253
Lily	English	13	16	456	8221
Naima	English	11	19	550	8107
Violet	English	14	14	385	6604
William	English	16	13	270	2888
Mean	**English**	**14**	**15**	**387**	**6215**
SD	**English**	**2**	**2**	**121**	**2222**
Mean	**All**	**13**	**16**	**344**	**6691**
SD	**All**	**2**	**2**	**125**	**2467**

Table 2

Outputs from nested model comparisons comparing logistic regression models predicting acquisition of words in each month according to INT- and EXT-like growth structures.

	Actual			Target		
Model	Df	Chi Sq	p	Df	Chi Sq	p
null vs. INT	2	395.48	<0.001	2	84.18	<0.001
null vs. EXT	2	1.00	0.608	2	2.87	0.238
INT vs. INT+EXT	2	0.35	0.841	2	0.33	0.848
EXT vs. INT+EXT	2	394.83	<0.001	2	81.64	<0.001

Table 3

Results from maximal logistic regression model (model 3) testing the effects of network growth values, corpus (English as baseline), input frequency, comprehensive AoA, word category and word length to predict word acquisition. All variables were scaled and centred. Category has been removed for ease of interpretation but this is shown in the full model output in S4.

	Actual					Target				
Effect	beta	SE	z	p	95% CI	beta	SE	z	p	95% CI
Intercept	-3.28	0.27	-12.25	<0.001	[-3.81,-2.76]	-2.96	0.38	-7.79	<0.001	[-3.71,-2.22]
INT value	0.88	0.07	12.59	<0.001	[0.74,1.02]	0.47	0.06	8.08	<0.001	[0.35,0.58]
EXT value	0.01	0.05	0.27	0.787	[-0.09,0.11]	0.00	0.05	0.04	0.964	[-0.1,0.1]
Age	0.94	0.14	6.66	<0.001	[0.66,1.21]	1.25	0.13	9.77	<0.001	[1,1.5]
AoA	-0.23	0.04	-6.22	<0.001	[-0.3,-0.15]	-0.21	0.04	-5.79	<0.001	[-0.29,-0.14]
Length	-0.08	0.06	-1.46	0.144	[-0.2,0.03]	-0.14	0.06	-2.32	0.021	[-0.25,-0.02]
Input freq	0.17	0.05	3.30	0.001	[0.07,0.27]	0.19	0.05	3.71	<0.001	[0.09,0.29]
Corpus	0.43	0.31	1.37	0.172	[-0.18,1.03]	0.93	0.47	1.99	0.047	[0.01,1.84]
Age x INT	0.16	0.05	2.96	0.003	[0.05,0.27]	-0.07	0.04	-1.62	0.106	[-0.16,0.01]
Age x EXT	-0.03	0.04	-0.58	0.561	[-0.11,0.06]	-0.03	0.05	-0.56	0.575	[-0.12,0.06]
Age x AoA	0.12	0.03	3.97	<0.001	[0.06,0.17]	0.10	0.03	3.28	0.001	[0.04,0.16]
Age x Length	0.03	0.05	0.72	0.474	[-0.06,0.13]	0.01	0.05	0.22	0.825	[-0.09,0.11]
Age x Input freq	-0.06	0.03	-1.90	0.057	[-0.12,0]	-0.06	0.03	-1.92	0.055	[-0.13,0]

Table 4

Outputs from nested model comparisons of GAMMs testing the effect of age on INT and EXT values in Actual and Target data (Models 1 and 2), and the effect of Data type on INT values (Model 3). Model comparisons compared full models against those without parametric and smooth terms that included the variable being tested.

		Actual			Target		
	Model	Df	Chi Sq	p	Df	Chi Sq	p
1	INT:Age	14.000	17.886	0.001	14.000	33.594	<.001
2	EXT:Age	14.000	6.088	0.592	14.000	10.084	0.125
3	INT:Data type	7.000	496.560	<.001			

Images/INT-EXT.png

Figure 1. Visualisation of INT and EXT models of network growth. Shapes represent nodes in the network and filled lines represent edges between nodes. Numbers show the degree of each existing node in the network. The two images demonstrate the likelihood of two new nodes - a filled triangle or an open circle - being added to the network under conditions of INT- and EXT-like network growth. In each case, the node that would be acquired is added to the network, and new edges are shown with dashed arrows. The double-dashed arrow in the INT model shows the new edge formed with the most highly-connected node in the existing network.

PhonNetworksProj-revised_files/figure-latex/figure-GAMM

Figure 2. INT values over time in Actual and Target data. Red filled line represents Actual values, blue dashed line represents Target values; coloured bands represent 95% CIs.

PhonNetworksProj-revised_files/figure-latex/figure-GAMM

Figure 3. EXT values over time in Actual and Target data. Red filled line represents Actual values, blue dashed line represents Target values; coloured bands represent 95% CIs. Both smooths are shown here for exploratory purposes.

PhonNetworksProj-revised_files/figure-latex/difference-

Figure 4. Difference smooth plot showing difference between scaled INT values in Actual vs. Target forms from the GAMM model specified above. Shaded area shows 95% confidence intervals, red line along x-axis indicates months in which the difference between Actual and Target forms was significant.

PhonNetworksProj-revised_files/figure-latex/plotted-smo

Figure 5. Smooth plot showing scaled INT values in Actual vs. Target forms. Shaded areas show 95% confidence intervals, lines indicate mean trajectories over time, coloured circles represent individual datapoints, jittered for visual clarity.

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\calc@Ccount=\count291
\calc@Cskip=\skip81
) (c:/TeXLive/2022/texmf-dist/tex/generic/babel/babel.sty
Package: babel 2023/02/13 3.86 The Babel package
\babel@savecnt=\count292
\U@D=\dimen184
\l@unhyphenated=\language87
(c:/TeXLive/2022/texmf-dist/tex/generic/babel/txtbabel.def)
\bbl@readstream=\read2
\bbl@dirlevel=\count293
Package babel Info: You haven't specified a language as a class or
package
```

```
(babel)             option. I'll load 'nil'. Reported on input line 4422.
(c:/TeXLive/2022/texmf-dist/tex/generic/babel/nil.ldf
Language: nil 2023/02/13 3.86 Nil language
\l@nil=\language88
))
\everypar=\toks27
(c:/TeXLive/2022/texmf-dist/tex/generic/babel/locale/en/babel-
english.tex)
Package babel Info: Importing data for english
(babel)             from babel-en.ini. Reported on input line 93.
(c:/TeXLive/2022/texmf-dist/tex/latex/was/upgreek.sty
Package: upgreek 2003/02/12 v2.0 (WaS)
Package upgreek Info: Using Euler Roman for upright Greek on input line
31.
\symugrf@m=\mathgroup9
LaTeX Font Info:    Overwriting symbol font `ugrf@m' in version `bold'
(Font)                  U/eur/m/n --> U/eur/b/n on input line 38.
) (c:/TeXLive/2022/texmf-dist/tex/latex/tools/longtable.sty
Package: longtable 2021-09-01 v4.17 Multi-page Table package (DPC)
\LTleft=\skip82
\LTright=\skip83
\LTpre=\skip84
\LTpost=\skip85
\LTchunksize=\count294
\LTcapwidth=\dimen185
\LT@head=\box56
\LT@firsthead=\box57
\LT@foot=\box58
\LT@lastfoot=\box59
\LT@gbox=\box60
\LT@cols=\count295
\LT@rows=\count296
\c@LT@tables=\count297
\c@LT@chunks=\count298
\LT@p@ftn=\toks28
) (c:/TeXLive/2022/texmf-dist/tex/latex/graphics/lscape.sty
Package: lscape 2020/05/28 v3.02 Landscape Pages (DPC)
) (c:/TeXLive/2022/texmf-dist/tex/latex/multirow/multirow.sty
Package: multirow 2021/03/15 v2.8 Span multiple rows of a table
\multirow@colwidth=\skip86
\multirow@cntb=\count299
\multirow@dima=\skip87
\bigstrutjot=\dimen186
) (c:/TeXLive/2022/texmf-dist/tex/latex/tools/tabularx.sty
Package: tabularx 2020/01/15 v2.11c `tabularx' package (DPC)
(c:/TeXLive/2022/texmf-dist/tex/latex/tools/array.sty
Package: array 2022/09/04 v2.5g Tabular extension package (FMi)
\col@sep=\dimen187
\ar@mcellbox=\box61
\extrarowheight=\dimen188
\NC@list=\toks29
\extratabsurround=\skip88
\backup@length=\skip89
\ar@cellbox=\box62
```

```
)
\TX@col@width=\dimen189
\TX@old@table=\dimen190
\TX@old@col=\dimen191
\TX@target=\dimen192
\TX@delta=\dimen193
\TX@cols=\count300
\TX@ftn=\toks30
) (c:/TeXLive/2022/texmf-
dist/tex/latex/threeparttablex/threeparttablex.sty
Package: threeparttablex 2013/07/23 v0.3 by daleif
(c:/TeXLive/2022/texmf-dist/tex/latex/environ/environ.sty
Package: environ 2014/05/04 v0.3 A new way to define environments
(c:/TeXLive/2022/texmf-dist/tex/latex/trimspaces/trimspaces.sty
Package: trimspaces 2009/09/17 v1.1 Trim spaces around a token list
))
\TPTL@width=\skip90
)
\longtablewidth=\skip91
(c:/TeXLive/2022/texmf-dist/tex/latex/xpatch/xpatch.sty
(c:/TeXLive/2022/texmf-
dist/tex/latex/l3kernel/expl3.sty
Package: expl3 2023-02-22 L3 programming layer (loader)
(c:/TeXLive/2022/texmf-dist/tex/latex/l3backend/l3backend-pdftex.def
File: l3backend-pdftex.def 2023-01-16 L3 backend support: PDF output
(pdfTeX)
\l__color_backend_stack_int=\count301
\l__pdf_internal_box=\box63
))
Package: xpatch 2020/03/25 v0.3a Extending etoolbox patching commands
(c:/TeXLive/2022/texmf-dist/tex/latex/l3packages/xparse/xparse.sty
Package: xparse 2023-02-02 L3 Experimental document command parser
)) (c:/TeXLive/2022/texmf-dist/tex/latex/csquotes/csquotes.sty
Package: csquotes 2022-09-14 v5.2n context-sensitive quotations (JAW)
\csq@reset=\count302
\csq@gtype=\count303
\csq@glevel=\count304
\csq@qlevel=\count305
\csq@maxlvl=\count306
\csq@tshold=\count307
\csq@ltx@everypar=\toks31
(c:/TeXLive/2022/texmf-dist/tex/latex/csquotes/csquotes.def
File: csquotes.def 2022-09-14 v5.2n csquotes generic definitions (JAW)
)
Package csquotes Info: Trying to load configuration file
'csquotes.cfg'...
Package csquotes Info: ... configuration file loaded successfully.
(c:/TeXLive/2022/texmf-dist/tex/latex/csquotes/csquotes.cfg
File: csquotes.cfg
)) (c:/TeXLive/2022/texmf-dist/tex/latex/tocloft/tocloft.sty
Package: tocloft 2017/08/31 v2.3i parameterised ToC, etc., typesetting
Package tocloft Info: The document has section divisions on input line
51.
\cftparskip=\skip92
```

```
\cftbeforetoctitleskip=\skip93
\cftaftertoctitleskip=\skip94
\cftbeforepartskip=\skip95
\cftpartnumwidth=\skip96
\cftpartindent=\skip97
\cftbeforesecskip=\skip98
\cftsecindent=\skip99
\cftsecnumwidth=\skip100
\cftbeforesubsecskip=\skip101
\cftsubsecindent=\skip102
\cftsubsecnumwidth=\skip103
\cftbeforesubsubsecskip=\skip104
\cftsubsubsecindent=\skip105
\cftsubsubsecnumwidth=\skip106
\cftbeforeparaskip=\skip107
\cftparaindent=\skip108
\cftparanumwidth=\skip109
\cftbeforesubparaskip=\skip110
\cftsubparaindent=\skip111
\cftsubparanumwidth=\skip112
\cftbeforeloftitleskip=\skip113
\cftafterloftitleskip=\skip114
\cftbeforefigskip=\skip115
\cftfigindent=\skip116
\cftfignumwidth=\skip117
\c@lofdepth=\count308
\c@lotdepth=\count309
\cftbeforelottitleskip=\skip118
\cftafterlottitleskip=\skip119
\cftbeforetabskip=\skip120
\cfttabindent=\skip121
\cfttabnumwidth=\skip122

Package tocloft Warning: \@starttoc has already been redefined; tocloft
bailing
 out. on input line 1156.

) (c:/TeXLive/2022/texmf-dist/tex/latex/tipa/tipa.sty
Package: tipa 2002/08/08 TIPA version 1.1
(c:/TeXLive/2022/texmf-dist/tex/latex/base/fontenc.sty
Package: fontenc 2021/04/29 v2.0v Standard LaTeX package
(c:/TeXLive/2022/texmf-dist/tex/latex/tipa/t3enc.def
File: t3enc.def 2001/12/31 T3 encoding
Now handling font encoding T3 ...
... no UTF-8 mapping file for font encoding T3
LaTeX Font Info:    Trying to load font information for T1+lmss on input
line 3
57.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/t1lmss.fd
File: t1lmss.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)))) (c:/TeXLive/2022/texmf-dist/tex/latex/bookmark/bookmark.sty
Package: bookmark 2020-11-06 v1.29 PDF bookmarks (HO)
(c:/TeXLive/2022/texmf-dist/tex/latex/hyperref/hyperref.sty
Package: hyperref 2023-02-07 v7.00v Hypertext links for LaTeX
```

```
(c:/TeXLive/2022/texmf-dist/tex/generic/pdftexcmds/pdftexcmds.sty
Package: pdftexcmds 2020-06-27 v0.33 Utility functions of pdfTeX for
LuaTeX (HO
)
(c:/TeXLive/2022/texmf-dist/tex/generic/infwarerr/infwarerr.sty
Package: infwarerr 2019/12/03 v1.5 Providing info/warning/error messages
(HO)
)
Package pdftexcmds Info: \pdf@primitive is available.
Package pdftexcmds Info: \pdf@ifprimitive is available.
Package pdftexcmds Info: \pdfdraftmode found.
) (c:/TeXLive/2022/texmf-dist/tex/generic/kvdefinekeys/kvdefinekeys.sty
Package: kvdefinekeys 2019-12-19 v1.6 Define keys (HO)
) (c:/TeXLive/2022/texmf-dist/tex/generic/pdfescape/pdfescape.sty
Package: pdfescape 2019/12/09 v1.15 Implements pdfTeX's escape features
(HO)
) (c:/TeXLive/2022/texmf-dist/tex/latex/hycolor/hycolor.sty
Package: hycolor 2020-01-27 v1.10 Color options for hyperref/bookmark
(HO)
) (c:/TeXLive/2022/texmf-dist/tex/latex/letltxmacro/letltxmacro.sty
Package: letltxmacro 2019/12/03 v1.6 Let assignment for LaTeX macros (HO)
) (c:/TeXLive/2022/texmf-dist/tex/latex/auxhook/auxhook.sty
Package: auxhook 2019-12-17 v1.6 Hooks for auxiliary files (HO)
) (c:/TeXLive/2022/texmf-dist/tex/latex/hyperref/nameref.sty
Package: nameref 2022-05-17 v2.50 Cross-referencing by name of section
(c:/TeXLive/2022/texmf-dist/tex/latex/refcount/refcount.sty
Package: refcount 2019/12/15 v3.6 Data extraction from label references
(HO)
) (c:/TeXLive/2022/texmf-
dist/tex/generic/gettitlestring/gettitlestring.sty
Package: gettitlestring 2019/12/15 v1.6 Cleanup title references (HO)
)
\c@section@level=\count310
)
\@linkdim=\dimen194
\Hy@linkcounter=\count311
\Hy@pagecounter=\count312
(c:/TeXLive/2022/texmf-dist/tex/latex/hyperref/pd1enc.def
File: pd1enc.def 2023-02-07 v7.00v Hyperref: PDFDocEncoding definition
(HO)
Now handling font encoding PD1 ...
... no UTF-8 mapping file for font encoding PD1
) (c:/TeXLive/2022/texmf-dist/tex/generic/intcalc/intcalc.sty
Package: intcalc 2019/12/15 v1.3 Expandable calculations with integers
(HO)
) (c:/TeXLive/2022/texmf-dist/tex/generic/etexcmds/etexcmds.sty
Package: etexcmds 2019/12/15 v1.7 Avoid name clashes with e-TeX commands
(HO)
)
\Hy@SavedSpaceFactor=\count313
(c:/TeXLive/2022/texmf-dist/tex/latex/hyperref/puenc.def
File: puenc.def 2023-02-07 v7.00v Hyperref: PDF Unicode definition (HO)
Now handling font encoding PU ...
... no UTF-8 mapping file for font encoding PU
```

```
)
Package hyperref Info: Option `unicode' set `true' on input line 4060.
Package hyperref Info: Hyper figures OFF on input line 4177.
Package hyperref Info: Link nesting OFF on input line 4182.
Package hyperref Info: Hyper index ON on input line 4185.
Package hyperref Info: Plain pages OFF on input line 4192.
Package hyperref Info: Backreferencing OFF on input line 4197.
Package hyperref Info: Implicit mode ON; LaTeX internals redefined.
Package hyperref Info: Bookmarks ON on input line 4425.
\c@Hy@tempcnt=\count314
(c:/TeXLive/2022/texmf-dist/tex/latex/url/url.sty
\Urlmuskip=\muskip17
Package: url 2013/09/16  ver 3.4  Verb mode for urls, etc.
)
LaTeX Info: Redefining \url on input line 4763.
\XeTeXLinkMargin=\dimen195
(c:/TeXLive/2022/texmf-dist/tex/generic/bitset/bitset.sty
Package: bitset 2019/12/09 v1.3 Handle bit-vector datatype (HO)
(c:/TeXLive/2022/texmf-dist/tex/generic/bigintcalc/bigintcalc.sty
Package: bigintcalc 2019/12/15 v1.5 Expandable calculations on big
integers (HO
)
))
\Fld@menulength=\count315
\Field@Width=\dimen196
\Fld@charsize=\dimen197
Package hyperref Info: Hyper figures OFF on input line 6042.
Package hyperref Info: Link nesting OFF on input line 6047.
Package hyperref Info: Hyper index ON on input line 6050.
Package hyperref Info: backreferencing OFF on input line 6057.
Package hyperref Info: Link coloring OFF on input line 6062.
Package hyperref Info: Link coloring with OCG OFF on input line 6067.
Package hyperref Info: PDF/A mode OFF on input line 6072.
(c:/TeXLive/2022/texmf-dist/tex/latex/base/atbegshi-ltx.sty
Package: atbegshi-ltx 2021/01/10 v1.0c Emulation of the original atbegshi
package with kernel methods
)
\Hy@abspage=\count316
\c@Item=\count317
\c@Hfootnote=\count318
)
Package hyperref Info: Driver (autodetected): hpdftex.
(c:/TeXLive/2022/texmf-dist/tex/latex/hyperref/hpdftex.def
File: hpdftex.def 2023-02-07 v7.00v Hyperref driver for pdfTeX
(c:/TeXLive/2022/texmf-dist/tex/latex/base/atveryend-ltx.sty
Package: atveryend-ltx 2020/08/19 v1.0a Emulation of the original
atveryend pac
kage
with kernel methods
)
\Fld@listcount=\count319
\c@bookmark@seq@number=\count320
(c:/TeXLive/2022/texmf-dist/tex/latex/rerunfilecheck/rerunfilecheck.sty
```

```
Package: rerunfilecheck 2022-07-10 v1.10 Rerun checks for auxiliary files
(HO)
(c:/TeXLive/2022/texmf-dist/tex/generic/uniquecounter/uniquecounter.sty
Package: uniquecounter 2019/12/15 v1.4 Provide unlimited unique counter
(HO)
)
Package uniquecounter Info: New unique counter `rerunfilecheck' on input
line 2
85.
)
\Hy@SectionHShift=\skip123
) (c:/TeXLive/2022/texmf-dist/tex/latex/bookmark/bkm-pdftex.def
File: bkm-pdftex.def 2020-11-06 v1.29 bookmark driver for pdfTeX (HO)
\BKM@id=\count321
)) (c:/TeXLive/2022/texmf-dist/tex/latex/xurl/xurl.sty
Package: xurl 2022/01/09 v 0.10 modify URL breaks
)
Package csquotes Info: Checking for multilingual support...
Package csquotes Info: ... found 'babel' package.
Package csquotes Info: Adjusting default style.
Package csquotes Info: Redefining alias 'default' -> 'english'.
(./PhonNetworksProj-revised.aux)
\openout1 = `PhonNetworksProj-revised.aux'.

LaTeX Font Info:    Checking defaults for OML/cmm/m/it on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for OMS/cmsy/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for OT1/cmr/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for T1/cmr/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for TS1/cmr/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for OMX/cmex/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for U/cmr/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for T3/cmr/m/n on input line 215.
LaTeX Font Info:    Trying to load font information for T3+cmr on input
line 21
5.
(c:/TeXLive/2022/texmf-dist/tex/latex/tipa/t3cmr.fd
File: t3cmr.fd 2001/12/31 TIPA font definitions
)
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for PD1/pdf/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
LaTeX Font Info:    Checking defaults for PU/pdf/m/n on input line 215.
LaTeX Font Info:    ... okay on input line 215.
*geometry* driver: auto-detecting
*geometry* detected driver: pdftex
*geometry* verbose mode - [ preamble ] result:
* driver: pdftex
```

```
* paper: <default>
* layout: <same size as paper>
* layoutoffset:(h,v)=(0.0pt,0.0pt)
* modes: twoside
* h-part:(L,W,R)=(72.26999pt, 469.75502pt, 72.26999pt)
* v-part:(T,H,B)=(72.26999pt, 650.43001pt, 72.26999pt)
* \paperwidth=614.295pt
* \paperheight=794.96999pt
* \textwidth=469.75502pt
* \textheight=650.43001pt
* \oddsidemargin=0.0pt
* \evensidemargin=0.0pt
* \topmargin=-37.0pt
* \headheight=15.2pt
* \headsep=25.0pt
* \topskip=12.0pt
* \footskip=30.0pt
* \marginparwidth=95.0pt
* \marginparsep=10.0pt
* \columnsep=10.0pt
* \skip\footins=10.8pt plus 4.0pt minus 2.0pt
* \hoffset=0.0pt
* \voffset=0.0pt
* \mag=1000
* \@twocolumnfalse
* \@twosidetrue
* \@mparswitchtrue
* \@reversemarginfalse
* (1in=72.27pt=25.4mm, 1cm=28.453pt)

(c:/TeXLive/2022/texmf-dist/tex/context/base/mkii/supp-pdf.mkii
[Loading MPS to PDF converter (version 2006.09.02).]
\scratchcounter=\count322
\scratchdimen=\dimen198
\scratchbox=\box64
\nofMPsegments=\count323
\nofMParguments=\count324
\everyMPshowfont=\toks32
\MPscratchCnt=\count325
\MPscratchDim=\dimen199
\MPnumerator=\count326
\makeMPintoPDFobject=\count327
\everyMPtoPDFconversion=\toks33
) (c:/TeXLive/2022/texmf-dist/tex/latex/epstopdf-pkg/epstopdf-base.sty
Package: epstopdf-base 2020-01-24 v2.11 Base part for package epstopdf
Package epstopdf-base Info: Redefining graphics rule for `.eps' on input
line 4
85.
(c:/TeXLive/2022/texmf-dist/tex/latex/latexconfig/epstopdf-sys.cfg
File: epstopdf-sys.cfg 2010/07/13 v1.3 Configuration of (r)epstopdf for
TeX Liv
e
)) (c:/TeXLive/2022/texmf-dist/tex/latex/apa6/config/APAamerican.txt
```

```
File: APAamerican.txt 2012/02/23 v1.25 apa6 configuration for American
English
)
Package caption Info: Begin \AtBeginDocument code.
Package caption Info: hyperref package is loaded.
Package caption Info: longtable package is loaded.
(c:/TeXLive/2022/texmf-dist/tex/latex/caption/ltcaption.sty
Package: ltcaption 2021/01/08 v1.4c longtable captions (AR)
)
Package caption Info: End \AtBeginDocument code.
LaTeX Info: Redefining \microtypecontext on input line 215.
Package microtype Info: Applying patch `item' on input line 215.
Package microtype Info: Applying patch `toc' on input line 215.
Package microtype Info: Applying patch `eqnum' on input line 215.
Package microtype Info: Applying patch `footnote' on input line 215.
Package microtype Info: Applying patch `verbatim' on input line 215.
Package microtype Info: Generating PDF output.
Package microtype Info: Character protrusion enabled (level 2).
Package microtype Info: Using protrusion set `basicmath'.
Package microtype Info: Automatic font expansion enabled (level 2),
(microtype)             stretch: 20, shrink: 20, step: 1, non-selected.
Package microtype Info: Using default expansion set `alltext-nott'.
LaTeX Info: Redefining \showhyphens on input line 215.
Package microtype Info: No adjustment of tracking.
Package microtype Info: No adjustment of interword spacing.
Package microtype Info: No adjustment of character kerning.
(c:/TeXLive/2022/texmf-dist/tex/latex/microtype/mt-cmr.cfg
File: mt-cmr.cfg 2013/05/19 v2.2 microtype config. file: Computer Modern
Roman
(RS)
)
Package hyperref Info: Link coloring OFF on input line 215.
LaTeX Font Info:    Trying to load font information for OT1+lmr on input
line 2
17.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/ot1lmr.fd
File: ot1lmr.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)
LaTeX Font Info:    Trying to load font information for OML+lmm on input
line 2
17.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/omllmm.fd
File: omllmm.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)
LaTeX Font Info:    Trying to load font information for OMS+lmsy on input
line
217.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/omslmsy.fd
File: omslmsy.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)
LaTeX Font Info:    Trying to load font information for OMX+lmex on input
line
217.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/omxlmex.fd
```

```
File: omxlmex.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <12> on input line 217.
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <8> on input line 217.
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <6> on input line 217.
LaTeX Font Info:    Trying to load font information for U+msa on input
line 217
.
(c:/TeXLive/2022/texmf-dist/tex/latex/amsfonts/umsa.fd
File: umsa.fd 2013/01/14 v3.01 AMS symbols A
) (c:/TeXLive/2022/texmf-dist/tex/latex/microtype/mt-msa.cfg
File: mt-msa.cfg 2006/02/04 v1.1 microtype config. file: AMS symbols (a)
(RS)
)
LaTeX Font Info:    Trying to load font information for U+msb on input
line 217
.
(c:/TeXLive/2022/texmf-dist/tex/latex/amsfonts/umsb.fd
File: umsb.fd 2013/01/14 v3.01 AMS symbols B
) (c:/TeXLive/2022/texmf-dist/tex/latex/microtype/mt-msb.cfg
File: mt-msb.cfg 2005/06/01 v1.0 microtype config. file: AMS symbols (b)
(RS)
) (c:/TeXLive/2022/texmf-dist/tex/latex/microtype/mt-eur.cfg
File: mt-eur.cfg 2006/07/31 v1.1 microtype config. file: AMS Euler Roman
(RS)
) [1{c:/TeXLive/2022/texmf-var/fonts/map/pdftex/updmap/pdftex.map}

] [2]
Underfull \vbox (badness 4954) has occurred while \output is active []

[3]
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <10> on input line 224.
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <7> on input line 224.
LaTeX Font Info:    External font `lmex10' loaded for size
(Font)              <5> on input line 224.

Underfull \vbox (badness 4752) has occurred while \output is active []

[4] [5]
Underfull \vbox (badness 4254) has occurred while \output is active []

[6] [7] [8] [9]
Underfull \vbox (badness 1117) has occurred while \output is active []

[10]
Underfull \vbox (badness 10000) has occurred while \output is active []

[11]
\openout3 = `PhonNetworksProj-revised.ttt'.
```

```
(PhonNetworksProj-revised.ttt) [12]
\openout4 = `PhonNetworksProj-revised.fff'.

(PhonNetworksProj-revised.fff) [13] [14] [15]
Underfull \vbox (badness 10000) has occurred while \output is active []

[16] [17] [18] [19]
Underfull \vbox (badness 10000) has occurred while \output is active []

[20] [21] [22] [23] [24]
Underfull \vbox (badness 4752) has occurred while \output is active []

[25] [26] [27]
Underfull \vbox (badness 10000) has occurred while \output is active []

[28]
Underfull \vbox (badness 10000) has occurred while \output is active []

[29]
Underfull \vbox (badness 10000) has occurred while \output is active []

[30]
Underfull \vbox (badness 10000) has occurred while \output is active []

[31]
Underfull \vbox (badness 10000) has occurred while \output is active []

[32]
Underfull \vbox (badness 10000) has occurred while \output is active []

[33] [34] AED endfloat: Processing end Figures and Tables
(./PhonNetworksProj-r
evised.ttt [35



] [36

] [37]) [38

] (./PhonNetworksProj-revised.fff

LaTeX Warning: File `Images/INT-EXT.png' not found on input line 5.


! Package pdftex.def Error: File `Images/INT-EXT.png' not found: using
draft se
tting.

See the pdftex.def package documentation for explanation.
Type  H <return>  for immediate help.
 ...
```

```
l.5 \includegraphics{Images/INT-EXT.png}

Try typing  <return>  to proceed.
If that doesn't work, type  X <return>  to quit.

LaTeX Font Info:    Trying to load font information for T1+lmtt on input
line 5
.
(c:/TeXLive/2022/texmf-dist/tex/latex/lm/t1lmtt.fd
File: t1lmtt.fd 2015/05/01 v1.6.1 Font defs for Latin Modern
)

LaTeX Warning: File `PhonNetworksProj-revised_files/figure-latex/figure-
GAMM-IN
T-1.pdf' not found on input line 12.


! Package pdftex.def Error: File `PhonNetworksProj-revised_files/figure-
latex/f
igure-GAMM-INT-1.pdf' not found: using draft setting.

See the pdftex.def package documentation for explanation.
Type  H <return>  for immediate help.
 ...

l.12 ..._files/figure-latex/figure-GAMM-INT-1.pdf}

Try typing  <return>  to proceed.
If that doesn't work, type  X <return>  to quit.


LaTeX Warning: File `PhonNetworksProj-revised_files/figure-latex/figure-
GAMM-EX
T-1.pdf' not found on input line 19.


! Package pdftex.def Error: File `PhonNetworksProj-revised_files/figure-
latex/f
igure-GAMM-EXT-1.pdf' not found: using draft setting.

See the pdftex.def package documentation for explanation.
Type  H <return>  for immediate help.
 ...

l.19 ..._files/figure-latex/figure-GAMM-EXT-1.pdf}

Try typing  <return>  to proceed.
If that doesn't work, type  X <return>  to quit.


LaTeX Warning: File `PhonNetworksProj-revised_files/figure-
latex/difference-smo
oth-data-type-1.pdf' not found on input line 26.
```

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! Package pdftex.def Error: File `PhonNetworksProj-revised_files/figure-latex/d
ifference-smooth-data-type-1.pdf' not found: using draft setting.

See the pdftex.def package documentation for explanation.
Type  H <return>  for immediate help.
 ...

l.26 ...e-latex/difference-smooth-data-type-1.pdf}

Try typing  <return>  to proceed.
If that doesn't work, type  X <return>  to quit.


LaTeX Warning: File `PhonNetworksProj-revised_files/figure-latex/plotted-smooth
-data-type-1.pdf' not found on input line 34.


! Package pdftex.def Error: File `PhonNetworksProj-revised_files/figure-latex/p
lotted-smooth-data-type-1.pdf' not found: using draft setting.

See the pdftex.def package documentation for explanation.
Type  H <return>  for immediate help.
 ...

l.34 ...gure-latex/plotted-smooth-data-type-1.pdf}

Try typing  <return>  to proceed.
If that doesn't work, type  X <return>  to quit.

) [39

] [40] (./PhonNetworksProj-revised.aux) )
Here is how much of TeX's memory you used:
 19803 strings out of 476024
 328056 string characters out of 5794017
 1871382 words of memory out of 5000000
 39558 multiletter control sequences out of 15000+600000
 596255 words of font info for 179 fonts, out of 8000000 for 9000
 1141 hyphenation exceptions out of 8191
 77i,12n,81p,3322b,584s stack positions out of
10000i,1000n,20000p,200000b,200000s
{c:/TeXLive/2022/texmf-dist/fonts/enc/
dvips/lm/lm-ec.enc}<c:/TeXLive/2022/texmf-
dist/fonts/type1/public/lm/lmbx12.pfb
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```

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b><c:/TeXLive/2022/texmf-
dist/fonts/type1/public/lm/lmri12.pfb><c:/TeXLive/2022
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Output written on PhonNetworksProj-revised.pdf (40 pages, 284072 bytes).
PDF statistics:
 459 PDF objects out of 1000 (max. 8388607)
 399 compressed objects within 4 object streams
 144 named destinations out of 1000 (max. 500000)
 39033 words of extra memory for PDF output out of 42996 (max. 10000000)
```

Figure 1

Click here to access/download;Figure;INT-EXT.png

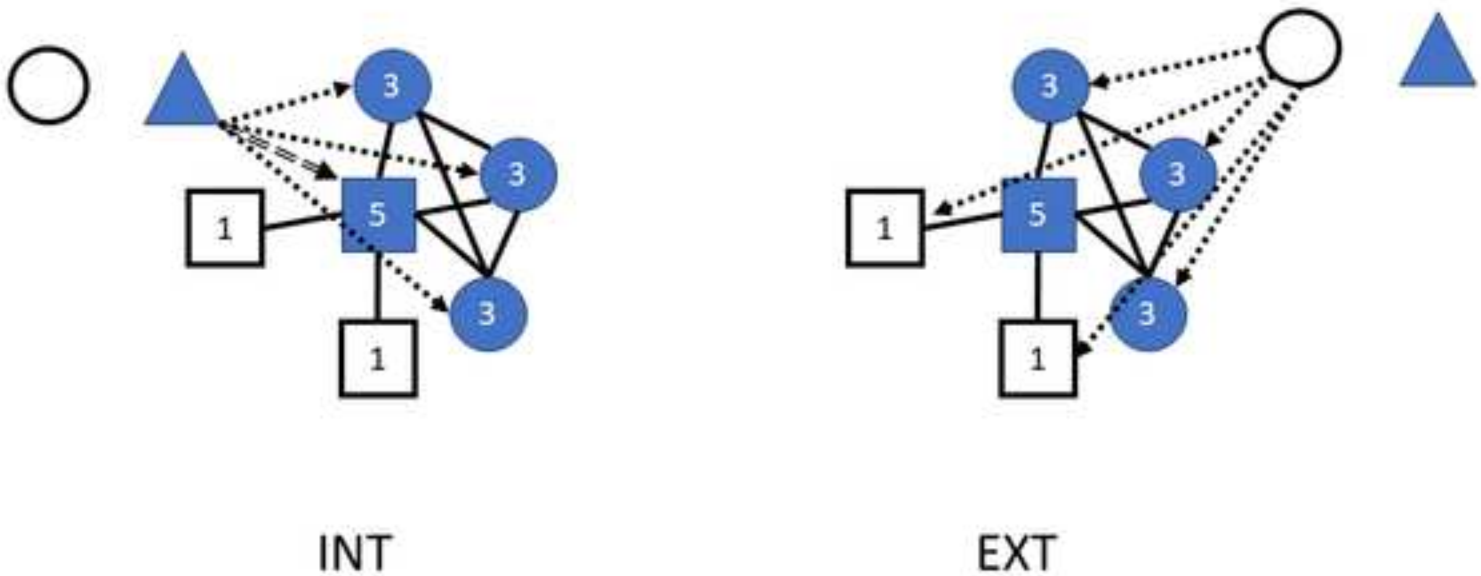

Figure 2

Click here to access/download;Figure;figure-GAMM-INT-1.png

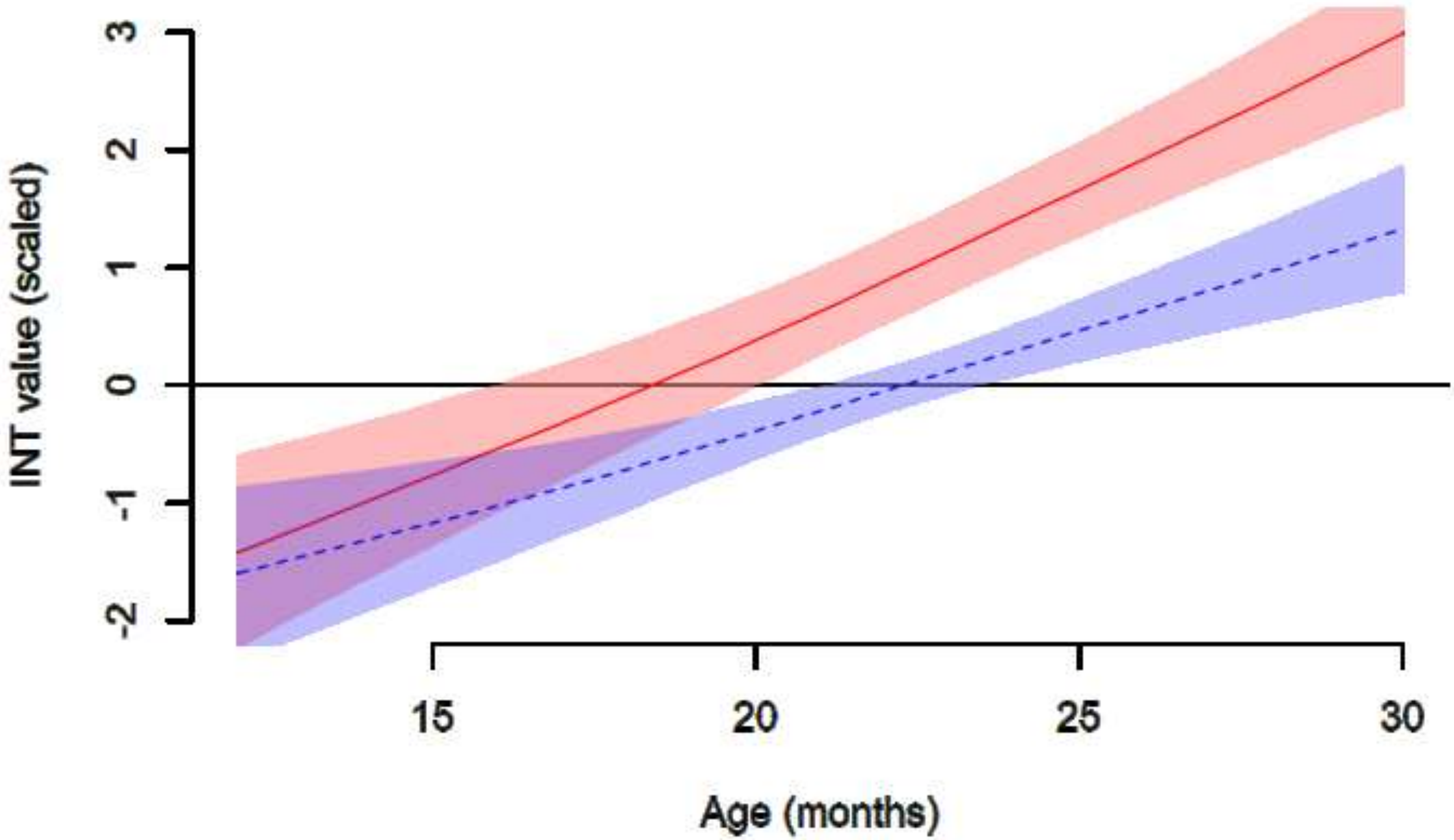

Figure 3

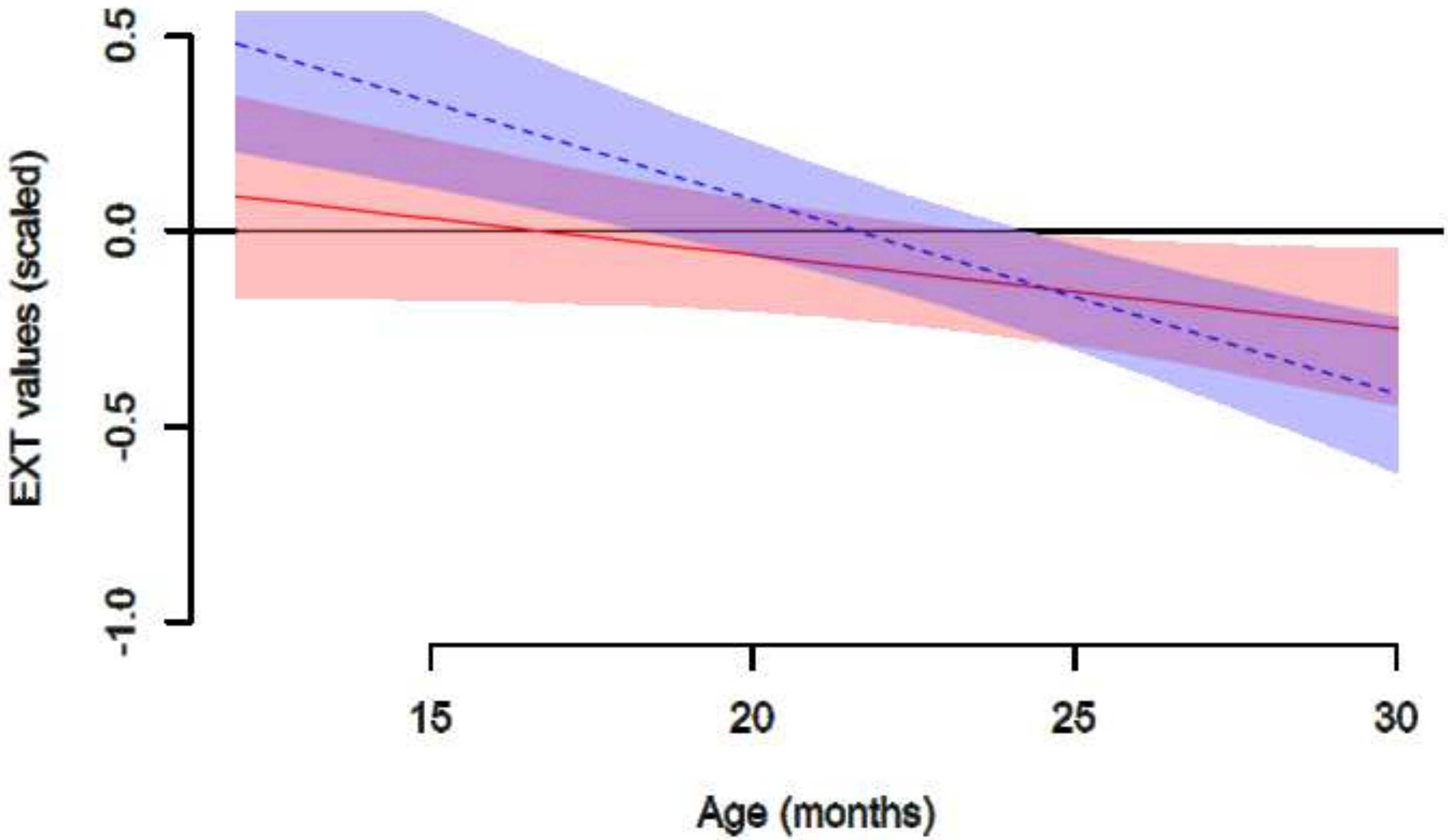

Figure 4

Click here to access/download;Figure;difference-smooth-data-type-1.png

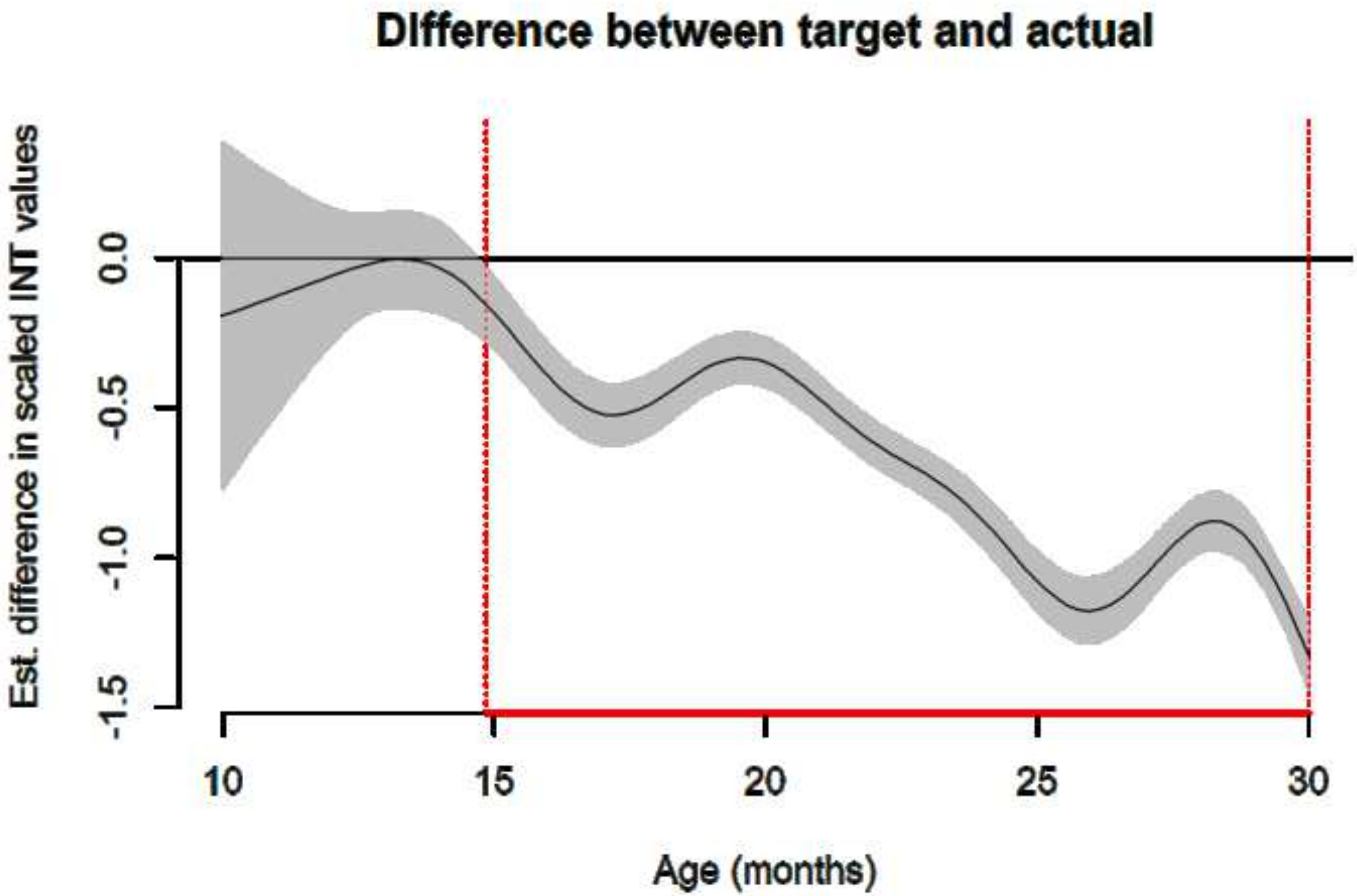

Figure 5

Click here to access/download;Figure;plotted-smooth-data-type-1.png