A new way to identify if variation in children's input could be developmentally meaningful: Using computational cognitive modeling to assess input across socio-economic status for syntactic islands

Lisa Pearl & Alandi Bates
lpearl, ajbates@uci.edu
University of California, Irvine

Abstract

While there are always observed differences in children's input, it is unclear how often these input differences are developmentally meaningful – that is, impacting language development – and why they do (or do not) do so. We describe a new approach using computational cognitive modeling that links children's input to predicted language development outcomes, and can identify if measurable input differences are potentially developmentally meaningful. We apply this approach to investigate if there is developmentally-meaningful input variation across socio-economic status (SES) with respect to the complex syntactic knowledge called syntactic islands, focusing on four island types with available empirical data about the target linguistic behavior. Despite several measurable input differences for syntactic island input across SES, our model predicts this variation not to be developmentally meaningful, as the model predicts no differences in the syntactic island knowledge that can be learned from that input. We discuss implications for linguistic development variability across SES.

Key Words: input variation, child-directed speech, socioeconomic status, computational cognitive modeling, syntactic islands, *wh*-dependencies, quantitative approaches

1 Introduction

1.1 Identifying if input differences are developmentally meaningful

There is a lot of naturally-occurring variation in children's input, including how long children are talked to every day, which people talk to them (e.g., adults, other children), what environments they experience language interaction in (e.g., home, daycare, school), and what people talk to them about, among many other types of variation. Importantly, not all this input variation is *developmentally meaningful* – that is, not all input variation impacts language development in a way that causes different trajectories (e.g., measurable delays in knowledge development) or different knowledge to develop (e.g., dialectal variation). That is, while input differences may appear, the quality of the input is not different when it comes to supporting language development. However, some input variation does indeed impact language development – this variation is then developmentally meaningful. For instance, developmentally-meaningful input deficits would lead to language development delays, and so indicate meaningful input quality differences.

As an example of developmentally-meaningful input differences, we have evidence that language development delays appear across socio-economic status (**SES**), with lower-SES children behind their higher-SES peers for different components of language development (e.g., vocabulary development: Hart and Risley 1995; Hoff 2003, language processing: Fernald et al. 2013). Importantly, variation in children's input can often predict later language development (Hart and Risley, 1995; Huttenlocher et al., 2002, 2010; Rowe, 2012; Weisleder and Fernald, 2013; Hirsh-Pasek et al., 2015; Schwab and Lew-Williams, 2016), suggesting a causal link between observed input variation and language development variation, including the observed language development delays across SES.

Still, when we identify developmental delays that may be linked to variation in children's input, it is often unclear which of the known delays may be caused (at least in part) by which specific input differences across SES, and why. Certainly, there are observed input quantity and input quality differences across SES (though input differences also exist within SES: Blum 2015; Sperry et al. 2018). For instance, when it comes to input quantity at the word-level, some studies have found that lower-SES children may encounter significantly fewer words of caregiver speech than their higher-SES peers (Hart and Risley, 1995; Schwab and Lew-Williams, 2016). For input quality, differences across SES have been observed at the lexical and foundational syntactic levels (Huttenlocher et al., 2010; Rowe, 2012; Rowe et al., 2017). These differences include the relative frequency of word types, word tokens, and rare words, the diversity of syntactic constructions, and the relative frequency of decontexualized utterances like explanations (*Oh, we can't put them in the bus because the bus is full of blocks*), pretend (*I'll save you from the wicked sister*), and narrations (*He is going to look in your nose and your throat and your ears*).

Again, what is often unclear is whether a specific measurable input difference matters for developing a specific component of language. For instance, there are components of language development that do not appear to be delayed across SES, despite the input differences (e.g., some types of complex syntactic knowledge: de Villiers et al. 2008; Vasilyeva et al. 2008). That is, some aspects of language development remain constant despite contextual variability that surfaces as measurable input differences (Hoff, 2006). Moreover, there are many components where we simply do not know if there are developmental delays across SES, despite known input variation.

From an intervention perspective, if we believe an input-based language delay is occurring, it is important to understand what aspect of the input has the disparity, so that interventions can target that aspect of the input and be impactful. That is, not only is it useful to know that a developmentally-meaningful input difference exists, but it is important to know exactly what part of the input is in fact impacting the development of specific language knowledge and why. So, being able to causally link children's input to their developing linguistic knowledge is valuable, because this link allows us to predict if a measurable input difference will potentially cause a difference in language development.

One way to make this causal link between children's input and their developing knowledge, often measured via some observable behavior, is to use computational cognitive modeling (e.g., Pearl, 2007, 2009; Pearl and Lidz, 2009; Pearl, 2010; Perfors et al., 2010; Pearl, 2011; Perfors et al., 2011; Pearl and Sprouse, 2013, 2015; Phillips and Pearl, 2015; Pearl and Goldwater, 2016; Bar-Sever and Pearl, 2016; Pearl and Mis, 2016; Savinelli et al., 2017; Bar-Sever et al., 2018; Bates et al., 2018; Forsythe and Pearl, 2019; Nguyen and Pearl, 2019; Pearl and Sprouse, 2019, 2021; Scontras and Pearl, 2021; Pearl, 2021). A computational cognitive model aimed at explaining some component of language development can implement a specific, concrete learning theory that describes how the input is used by children to update their hypotheses about language over time, and so develop specific language knowledge that is then reflected in their observable language behavior. In this way, computational cognitive modeling connects theories of language development, empirical data on children's input, and child behavioral experiments. Thus, a computational cognitive model allows us to test explicit hypotheses about the language knowledge that could be derived from the information available in children's experience (Hoff, 2006); that is, a computational cognitive model can test hypotheses about what particular aspects of the input may matter and why. More specifically, we can use a computational cognitive model to predict if a measurable input difference will matter for the development of a specific component of linguistic knowledge – that is, when a difference is predicted to be developmentally meaningful, and why that difference is predicted to be developmental meaningful.

This computational cognitive modeling approach complements a standard way that relies on correlation to determine if a measurable input difference is developmentally meaningful: observe some input difference, observe language development outcomes, and then see if the observed input difference is correlated with any observed outcome difference. If so, the language input difference *might* cause the language development outcome difference. In this case, targeting the input difference for intervention may lead to improved language development outcomes (e.g., input-based interventions allowing lower-SES students to improve their language comprehension: Huttenlocher et al. 2002). If input-based intervention is indeed effective, this is support that the language input difference caused the observed language outcome difference, and was therefore developmentally meaningful. However, *why* that input disparity caused the language development outcome difference is still unknown. Moreover, carefully designing, implementing, and evaluating such interventions can often be costly in terms of both time and resources. Computational cognitive modeling can offer a way to predict beforehand if an input difference is likely to cause a language development difference, and so help inform the design of intervention-based approaches that assess if an input difference is developmentally meaningful.

Importantly, because a computational cognitive model describes exactly how the input can cause the predicted knowledge to develop (i.e., the developmental outcome), the model can also determine if an observed input difference is predicted *not* to be developmentally meaningful (because the predicted outcome is not qualitatively different). That is, the model can identify contextual variation surfacing in children's input that is predicted not to impact language development (Hoff, 2006). In this case, we would expect an input-based intervention targeting the aspect of the input identified by the model's learning theory to be ineffective at improving children's development of the language knowledge that depends on that input.

1.2 Input differences for syntactic island knowledge

Here, we harness this computational cognitive modeling approach to identify if input differences across SES for certain aspects of complex syntax are predicted to impact development of that knowledge and so be developmentally meaningful. We focus on a certain type of complex syntactic knowledge known as *syntactic islands* that concerns *wh*-dependencies, such as *wh*-questions (e.g., the acceptable *Who did Lily think the pretty kitty was for?* vs. the far less acceptable *Who did Lily think the kitty for was pretty?*). In syntactic theory (Chomsky, 1965; Ross, 1967; Chomsky, 1973), syntactic islands are structures that interfere with *wh*-dependencies, so that *wh*-dependencies that cross them are far less acceptable (sometimes called simply "ungrammatical"). Knowledge of syntactic islands thus allows speakers to judge which *wh*-dependencies in their language are more vs. (far) less acceptable; that is, even if speakers have never heard a particular *wh*-dependency before, they can use their knowledge of syntactic islands to judge how acceptable it is. This ability to judge dependency acceptability means that speakers with knowledge of syntactic islands have internalized something quite sophisticated about the syntax of *wh*-dependencies: not simply how to understand the *wh*-dependencies that occur in their language, but also (i) how acceptable different *wh*-dependencies are, and (ii) which ones are far less acceptable (and therefore unlikely to occur) because those *wh*-dependencies cross syntactic islands. From a developmental perspective, we can then investigate how children come to have this knowledge about syntactic islands, and more specifically, how children's input influences that linguistic development.

We first briefly review what is currently known about the development of knowledge about *wh*-dependencies, particularly with respect to syntactic islands. We then discuss syntactic island knowledge in more detail, and describe the particular syntactic islands we focus on; we selected these islands due to the available empirical data on the behavior that signals successful acquisition of this knowledge (i.e., judgment data from adults and children). We then review a computational cognitive model for learning syntactic islands that specifies how the input causes the relevant knowledge to develop (Pearl and Sprouse, 2013). That is, this model implements a specific learning theory for how children use their input to acquire knowledge of syntactic islands. The learning theory implemented in the model specifies that the relevant aspect of children's input for learning syntactic islands involves *wh*-dependencies, which rely on "*wh*-words" like *what* and *who* in English (among others). We additionally summarize prior modeling results by Pearl and Sprouse (2013) where the model learned from higher-SES child input and successfully demonstrated knowledge of four syntactic islands, as evidenced by the acceptability judgment patterns it predicted. These prior results provide an initial validation of the learning theory implemented in the model, demonstrating its success at predicting higher-SES acceptability judgment behavior when given higher-SES child input to learn from. We hypothesize that children across SES would use the same learning process to learn about syntactic islands from their input (i.e., as specified by the learning theory implemented in the computational cognitive model). With this hypothesis in hand, we can then use the same computational cognitive model to investigate the impact of input variation across SES for learning about syntactic islands.

We begin by looking at the distributions of *wh*-dependencies in American English child-directed speech (**CDS**) between higher-SES populations and lower-SES populations. We first provide a descriptive corpus analysis comparing higher-SES to lower-SES input. We then assess input quantity differences by deriving realistic estimates of the quantity of *wh*-dependencies that higher-SES vs. lower-SES children would hear by age four, when children across SES seem to demonstrate some knowledge about one of the syntactic island types we investigate (de Villiers et al., 2008). This input quantity assessment highlights what can potentially be a significant difference in overall quantity of *wh*-dependencies that children hear across SES by age four.

With realistic estimates of the input data to higher-SES and lower-SES children, we then provide a computational cognitive modeling analysis of the input quality, using the previously validated model of Pearl and Sprouse (2013). The model predicts the syntactic island knowledge that higher-SES and lower-SES children would be able to acquire on the basis of their *wh*-dependency input by age four, as evidenced by the acceptability judgment patterns they would generate for a variety of *wh*-dependencies.

Our computational cognitive modeling analysis predicts that the lower-SES input supports the development of knowledge about the four syntactic islands we investigate by age four just as well as the higher-SES input does, despite the difference in overall quantity of *wh*-dependencies. In this way, our results predict that input quality for these four syntactic islands is the same across SES – that is, the input variation that exists across SES is not developmentally meaningful by age four. This result accords with known developmental evidence for one type of syntactic island, and predicts additional developmental similarities for the other three types we investigate here.

Interestingly, our modeling analysis predicts that a syntactic building block involving complementizer *that* (e.g., *that* in *Who do you think that Lily likes?*) is crucial for successfully developing knowledge of two syntactic islands types. This building block comes from a different *wh*-dependency type in lower-SES CDS, compared with higher-SES CDS; this difference highlights that surface input quality differences may mask deeper input quality similarities. More generally, our results suggest that the quality of the input for learning about these four syntactic islands does not fundamentally differ across SES, even if the quantity may. We discuss limitations of our current findings, model predictions that are testable with future work, and implications for variability in linguistic development across SES.

2 The development of *wh*-dependency knowledge across SES

Currently, less is known about the development of complex syntactic knowledge across SES (especially with respect to *wh*-dependencies) than about the development of lexical and foundational syntactic knowledge. Still, we do know about the development of some *wh*-dependency knowledge across SES and a little about the *wh*-dependency input.

In terms of *wh*-dependency knowledge, higher-SES English-learning children at 20 months seem to represent the full structure of *wh*-dependencies in *wh*-questions (e.g., *Which cat did the dog bump?*) and relative clauses (e.g., *Show me the dog [who the cat bumped]*), rather than relying on vocabulary-based heuristics to understand these *wh*-dependencies (Seidl et al., 2003; Gagliardi et al., 2016; Perkins and Lidz, 2020). Higher-SES children are also able to correctly repeat back well-formed *wh*-questions like *Who can Falkor save?* and generate new well-formed *wh*-questions by two and a half to three years old (Valian and Casey, 2003).

By age four, we see similar knowledge across SES about several aspects of *wh*-dependencies (see de Villiers et al. (2008) for empirical data across SES, as well as a review of prior empirical data from higher-SES children). This knowledge includes sensitivity to preferred interpretations of certain *wh*-dependencies – that is, which interpretations are more or less preferred because those interpretations depend on which *wh*-dependencies are more or less preferred.

For instance, four-year-olds (like adults) can interpret *wh*-dependencies like "*How did the boy say he hurt himself?*" with *how* modifying the embedded clause verb *hurt*; so, the *wh*-question can be interpreted as asking about how the boy hurt himself. Children as young as four are also sensitive to the difference between the possible interpretations of "*How did the mom learn what to* *bake?*" The preferred interpretation has *how* modifying the main clause verb *learn* (e.g., a possible answer is "from a recipe book"); the strongly dispreferred interpretation has *how* modifying the embedded clause verb *bake* (e.g., a possible answer would be "in a glass dish").

As another example, four-year-olds across SES are sensitive to the difference between the possible interpretations of "*What is Jane drawing a monkey that is drinking milk with?*". The preferred interpretation has *what* linked to a position outside the relative clause ("*What is Jane drawing [a monkey that is drinking milk] with* $\_\_{what}$*?*"), with a possible answer of what Jane is drawing with (e.g., "a pencil"); the strongly dispreferred interpretation has *what* linked to a position inside the relative clause ("*What is Jane drawing [a monkey that is drinking milk with* $\_\_{what}$*]?*"), with a possible answer of what the monkey is drinking with (e.g., "a straw").

So, there appear to significant similarities in the developmental outcomes by age four across SES with respect to preferred and dispreferred interpretations for certain *wh*-dependencies; these interpretations rest on children being sensitive to how preferred (or dispreferred) the different *wh*-dependencies themselves are. These developmental outcome similarities suggest that input differences across SES for these types of *wh*-dependency knowledge should not be developmentally meaningful.

Still, we know much less about any input differences there might be for *wh*-dependencies, let alone how children's input leads to the development of these types of *wh*-dependency knowledge despite any input variation that might be present. For instance, we know that the use of *wh*-questions in input to lower-SES two-year-olds helps build their vocabulary and reasoning skills more generally (Rowe et al., 2017). However, it is unclear how the *wh*-questions (and other *wh*-dependencies) in the input lead to the development of complex *wh*-dependency knowledge, such as preferences for *wh*-dependencies more generally, which include not only the *wh*-dependencies previously assessed but also other types of *wh*-dependencies that adults have stable preferences for. More generally, much remains unknown about the input variation present across SES for learning about *wh*-dependencies, how the input scaffolds the development of this complex syntactic knowledge, why any input variation present does not lead to different developmental outcomes for certain *wh*-dependency knowledge across SES by certain ages, and whether any input variation present is developmentally meaningful for other types of *wh*-dependency preferences that have yet to be assessed in children across SES.

3 Syntactic islands

A key component of syntactic knowledge is the ability to have long-distance dependencies, where there is a relationship between two words that are not adjacent to each other. Long-distance dependencies, such as the *wh*-dependencies between the *wh*-word *what* and *eat* in (1), can be arbitrarily long (Chomsky, 1965; Ross, 1967; Chomsky, 1973). In (1), we can see that this *wh*-dependency can stretch across one, two, three, or four clauses. In each case, *what* is understood as the thing Falkor ate, despite *what* not being adjacent to *eat*.

(1)
  a. What did Falkor eat $\_\_{what}$?
  b. What did Atreyu see Falkor eat $\_\_{what}$?
  c. What did the Childlike Empress say Atreyu saw Falkor eat $\_\_{what}$?
  d. What did Bastian hear the Childlike Empress say Atreyu saw Falkor eat $\_\_{what}$?

However, adult speakers find different *wh*-dependencies to be more or less acceptable (sometimes referred to as "allowed" or "grammatical" vs. "disallowed" or "ungrammatical"), with some *wh*-dependencies being far less acceptable than others. As mentioned previously, this marked decrease in acceptability has been attributed to specific syntactic structures that interfere with long-distance dependencies, called syntactic islands (Chomsky, 1965; Ross, 1967; Chomsky, 1973). Four examples of syntactic islands are in (2), with * indicating very low acceptability and [...] highlighting the proposed island structure that interferes with a *wh*-dependency in English.

(2) a. **Complex NP island**
*What did Falkor make [the claim [that Atreyu fought $\_\_{what}$]]?
b. **Subject island**
*What did Falkor think [[the joke about $\_\_{what}$] was hilarious]?
c. **Whether island**
*What did Falkor wonder [whether Atreyu bought $\_\_{what}$]?
d. **Adjunct island**
*What did Falkor worry [if Atreyu buys $\_\_{what}$]?

During language development, children must infer and internalize the the knowledge that allows the appropriate preferences for long-distance *wh*-dependencies. This knowledge allows them to recognize that the questions in (2) are far less acceptable, while the questions in (1) are much moreso. We note that this recognition is a measurable behavior of children's internalized knowledge – that is, distinguishing more acceptable questions like (1) from far less acceptable questions like (2) is one way to indicate knowledge of the relevant syntactic islands (whatever form that knowledge may take).

4 Assessing knowledge of syntactic islands

Previous work assessing children's knowledge of syntactic islands has focused on the interpretations of *wh*-dependencies that are preferred, rather than the relative acceptability of the *wh*-dependencies directly (Otsu, 1981; De Villiers et al., 1990; Roeper and Seymour, 1994; de Villiers and Roeper, 1995; McDaniel et al., 1995; Vainikka and Roeper, 1995; De Villiers and Pyers, 2002; Coles-White et al., 2004; de Villiers et al., 2008). The idea was that it is easier to ask children if they prefer a particular interpretation that relies on a certain *wh*-dependency (something more similar to naturalistic communication) rather than asking children directly how acceptable they find that *wh*-dependency (something more meta-linguistic that requires reasoning about language forms). If children disprefer a certain interpretation (e.g., "*What is Jane drawing a monkey that is drinking milk with?*" with *what* interpreted as "the straw"), this can be interpreted as children finding the *wh*-dependency that the interpretation relies on (e.g., "*What is Jane drawing [a monkey that is drinking milk with* $\_\_{what}$*]?*") less acceptable. So, this behavior can then be interpreted as children knowing about the syntactic island that interferes with that *wh*-dependency (e.g., a Complex NP island, since "a monkey that is..." is an NP with a relative clause, which is a type of complex NP). In this way, children dispreferring a particular interpretation indirectly indicates their knowledge of a particular syntactic island – specifically, the syntactic island that interferes with the *wh*-dependency that the dispreferred interpretation relies on.

A more direct way to assess syntactic island knowledge is with the less-natural task of directly judging how acceptable a *wh*-dependency is (e.g., in the previous work of Sprouse et al. 2012). When the stimuli are carefully designed (as discussed below), relative differences in judged acceptability can be used to compare the acceptability of island-crossing *wh*-dependencies against the acceptability of *wh*-dependencies that do not cross islands, yet are similar in other important ways to the island-crossing ones. The key idea is that knowledge of the relevant syntactic island is signaled when the island-crossing *wh*-dependency is still judged as far more unacceptable (Sprouse et al., 2012). We therefore follow Sprouse et al. (2012), and use acceptability judgment data to indicate knowledge of syntactic islands, and follow Pearl and Sprouse (2013, 2015) in using these acceptability judgment patterns as a measurable target state for development. In particular, following Pearl and Sprouse (2013), the computational cognitive models we implement will attempt to replicate the appropriate acceptability judgment patterns found by Sprouse et al. (2012) that indicate knowledge of different syntactic islands.

Sprouse et al. (2012) investigated the four islands from (2). A sample set for each island type is shown in (3)-(6), where island structures are indicated with [...]. These stimuli were designed using a 2x2 factorial design, involving two factors deemed important for judging acceptability: *wh*-dependency length (matrix vs. embedded) and absence/presence of an island structure in the utterance (non-island vs. island). Each island stimuli set therefore had four *wh*-dependency types: matrix+non-island, embedded+non-island, matrix+island, and embedded+island. The embedded+island stimulus in each case involved an island-crossing *wh*-dependency, and so was supposed to be far less acceptable than the others.

(3) Sample Complex NP island stimuli

a. matrix+non-island
Who $\_\__{who}$ claimed that Atreyu fought the goblin?

b. embedded+non-island
Who did Falkor claim that Atreyu fought $\_\__{who}$?

c. matrix+island:
Who $\_\__{who}$ made [the claim that Atreyu fought the goblin]?

d. embedded+island:
*Who did Falkor make [the claim that Atreyu fought $\_\__{who}$]?

(4) Sample Subject island stimuli

a. matrix+non-island:
Who $\_\__{who}$ thinks the joke is hilarious?

b. embedded+non-island:
What does Falkor think $\_\__{what}$ is hilarious?

c. matrix+island:
Who $\_\__{who}$ thinks the joke about Atreyu is hilarious?

d. embedded+island:
*Who did Falkor think [[the joke about $\_\__{who}$] was hilarious]?

(5) Sample Whether island stimuli

a. matrix+non-island:
Who $\_\__{who}$ thinks Atreyu bought the medallion?

b. embedded+non-island:
What does Falkor think Atreyu bought $\_\__{what}$?

c. matrix+island:
Who $\_\_{who}$ wonders if Atreyu bought the medallion?

d. embedded+island:
*What did Falkor wonder [whether Atreyu bought $\_\_{what}$]?

(6) Sample Adjunct island stimuli

a. matrix+non-island:
Who $\_\_{who}$ thinks Atreyu bought the medallion?

b. embedded+non-island:
What does Falkor think that Atreyu bought $\_\_{what}$?

c. matrix+island:
Who $\_\_{who}$ worries if Atreyu bought the medallion?

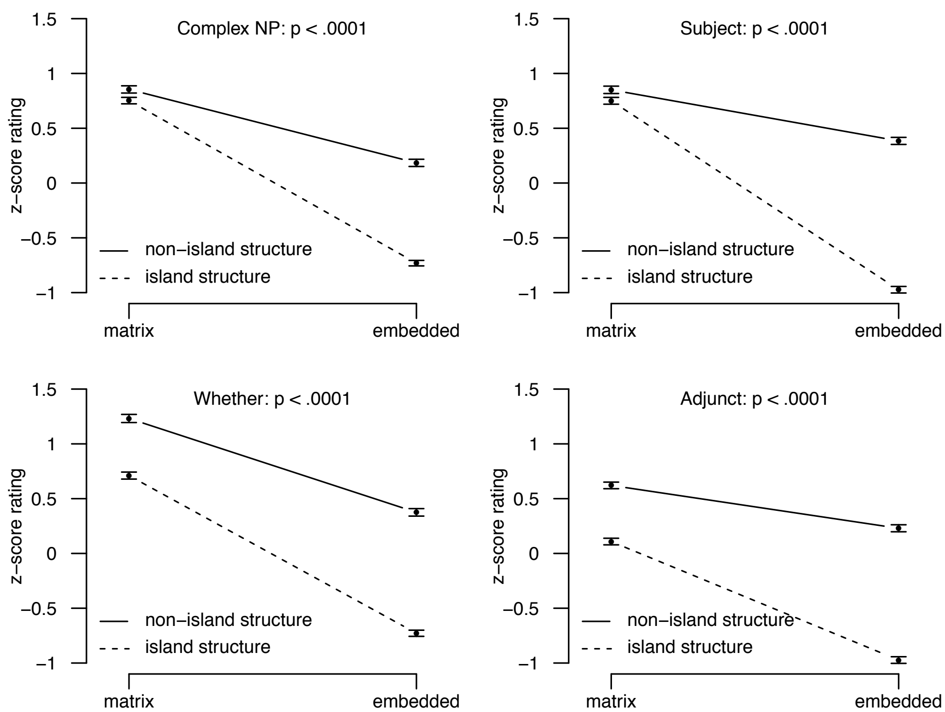
d. embedded+island:
*What did Falkor worry [if Atreyu buys $\_\_{what}$]?

This design allows syntactic island knowledge to surface as a superadditive interaction of acceptability judgments; this superadditivity appears as non-parallel lines in an interaction plot, such as those in Figure 1, which come from the judgments of higher-SES adults tested by Sprouse et al. (2012). We briefly review the logic behind this interpretation, as described in Sprouse et al. (2012). For example, if we consider the Complex NP plot in the top row, there are four acceptability judgments, one for each of the stimuli in (3). The matrix+non-island dependency of (3a) has a certain acceptability score – this is the top-lefthand point. There is a (slight) drop in acceptability when the matrix+island dependency of (3c) is judged in comparison to (3a) – this is the lower-lefthand point. We can interpret this as the unacceptability associated with simply having an island structure in the utterance. There is also a drop in acceptability when the embedded+non-island dependency of (3b) is judged in comparison to (3a) – this is the upper-righthand point. We can interpret this as the unacceptability associated with simply having an embedded *wh*-dependency. If the unacceptability of the embedded+island dependency of (3d) were simply the result of those two unacceptabilities (having an island structure in the utterance and having an embedded *wh*-dependency), the drop in unacceptability would be additive and the lower-righthand point would be just below the upper-righthand point (and so look just like the points on the lefthand side). However, this is not what we see – instead, the acceptability of (3d) is much lower than this. This much-lower acceptability is a superadditive effect for the embedded+island stimuli. So, the additional unacceptability of an island-crossing-dependency like (3d) – interpreted by Sprouse and colleagues (Sprouse et al., 2012; Pearl and Sprouse, 2013, 2015) as implicit knowledge of syntactic islands – appears as a superadditive interaction in these types of acceptability judgement plots. This superadditive acceptability judgment pattern appears for all four island types tested by Sprouse et al. (2012) from (2): Complex NP, Subject, Whether, and Adjunct islands.

5 Linking children's input to syntactic island development

From a computational cognitive modeling standpoint, a modeled learner who can successfully acquire knowledge from its input of any of the four syntactic islands, as measured via acceptability judgments like those of Sprouse et al. (2012), should be able to reproduce the superadditive judgment pattern described above. Successfully generating the superadditive judgment pattern for a

Figure 1: Higher-SES adult acceptability judgments from Sprouse et al. (2012), showing means and standard deviations of adult judgments. These judgments are interpreted as demonstrating implicit knowledge of four syntactic islands via a superadditive interaction of acceptability judgments for the selected *wh*-dependencies that cross dependency length (matrix vs. embeddeded) with the absence/presence of an island structure (non-island structure vs. island structure) in a 2 x 2 factorial design.

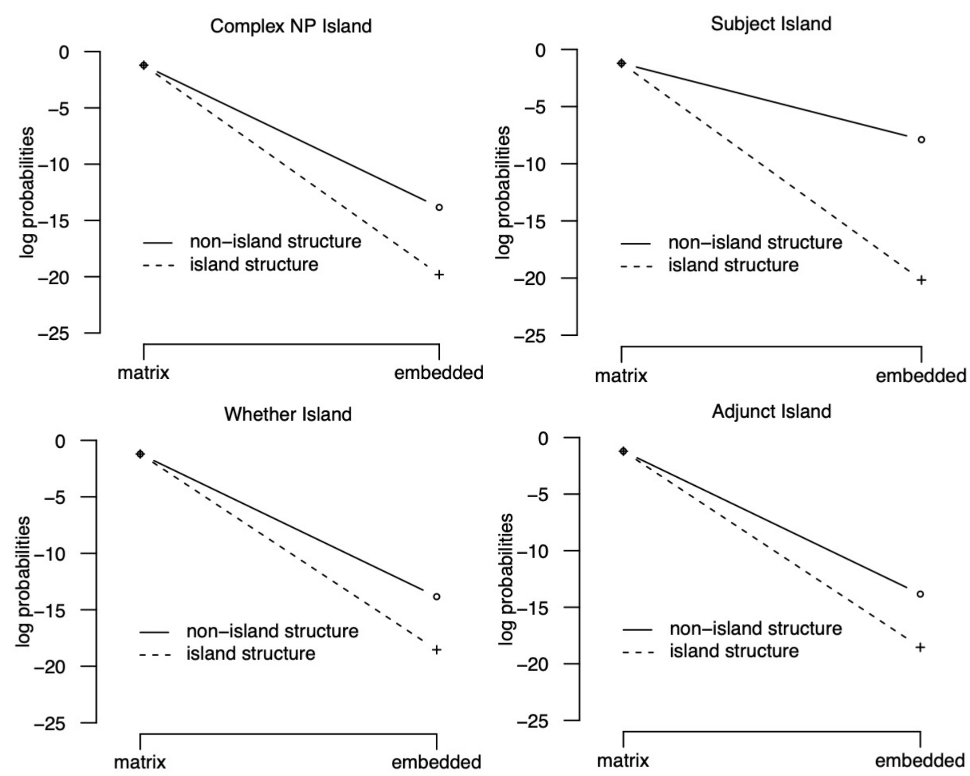


set of *wh*-dependency stimuli associated with a particular syntactic island would thus be the target behavior for successful development. Pearl and Sprouse (2013) proposed a concrete learning theory – the first of its kind and the only published one we are currently aware of – to specify a precise quantitative link between children's input and this measurable output behavior, and then implemented this learning theory in a computational cognitive model.

The proposed learning theory implemented by Pearl & Sprouse's computational cogntiive model is based on the intuition that children will learn what they can from all the *wh*-dependencies available in the input, rather than ones that are identical to the *wh*-dependencies they need to judge the acceptability of. To do this, Pearl & Sprouse's theory proposes that children break *wh*-dependencies they encounter into smaller building blocks that can be used to construct any *wh*-dependency, and not necessarily just the *wh*-dependencies they have encountered before. So, these smaller building blocks are the internalized knowledge that corresponds to syntactic island knowledge. That is, by drawing on these learned building blocks, children can generate acceptability judgements, just as they would presumably draw on their syntactic island knowledge to generate acceptability judgments.

Pearl and Sprouse (2013) evaluated their computational cognitive model by allowing it to learn from a realistic sample of higher-SES child-directed speech, and then seeing if it could generate the superadditive acceptability judgment patterns from Sprouse et al. (2012). They found that the modeled learner could indeed generate the appropriate patterns (see Figure 2). This finding supported the plausibility of the learning theory implemented in the model for explaining the development of syntactic island knowledge in higher-SES children, based on their input. Additionally, the specific finding that *wh*-dependencies spanning Complex NP islands are far less acceptable (Figure 2, upper left) aligns with higher-SES child *wh*-dependency (dis)preferences at age four for *wh*-dependencies crossing Complex NP islands (de Villiers et al., 2008); this alignment also supports the plausibility of the learning theory implemented in the model.

Figure 2: Higher-SES child judgments generated from the computational cognitive model in Pearl and Sprouse (2013). These generated judgements can be interpreted as demonstrating implicit knowledge of four syntactic islands via a superadditive interaction of acceptability judgments for the selected *wh*-dependencies that cross dependency length (matrix vs. embeddeded) with the absence/presence of an island structure (non-island structure vs. island structure) in a 2 x 2 factorial design. Log probabilities correspond to acceptability judgments, with log probabilities closer to 0 indicating higher acceptability.



The model's learning theory assumes children can characterize a *wh*-dependency as a syntactic path from the head of the dependency (e.g., *What* in (7)) through a set of phrase structures that contain the tail (e.g., $\_\_{what}$) of the *wh*-dependency, as shown in (7a)-(7b). These structures correspond to phrase types that make up *wh*-dependencies such as Verb Phrases (VP), Inflectional Phrases (IP), and Complementizer Phrases (CP), among others. Importantly, these are the structures that *wh*-dependencies would cross to create the link between the head of the dependency and the tail of the dependency. Under this view, children simply need to learn how acceptable the syntactic paths, which cross different phrase structures, are for different *wh*-dependencies.

The learning process itself is implemented as a probabilistic learning algorithm that tracks local pieces (i.e., the building blocks) of these syntactic paths. The learning algorithm assumes the learner breaks the syntactic path into a collection of "syntactic trigrams" (groups of three units derived from the syntactic path) that can be combined to reproduce the original syntactic path, as shown in (7c).[1] The modeled learner then tracks the frequencies of these syntactic trigrams in the input, based on the input it encounters, one data point at a time. After the learning period is complete, the modeled learner uses these learned frequencies to calculate probabilities for all syntactic trigrams potentially comprising a *wh*-dependency[2] and so generate the probability of any *wh*-dependency (as shown in (8)- (9)). More specifically, any *wh*-dependency's probability is the product of the individual trigram probabilities that comprise its syntactic path, as shown in (10). Importantly, relying on the frequencies of syntactic trigrams (rather than the frequencies of entire *wh*-dependencies) allows the modeled learner to generate probabilities for any *wh*-dependency, including *wh*-dependencies that it has never seen before in its input. So, an unseen acceptable *wh*-dependency can still have a higher probability than an unseen one that is less acceptable, depending on the syntactic trigrams that comprise each *wh*-dependency.

(7) What did Falkor claim that Atreyu fought $\_\__{what}$?

a. Syntactic structures containing the *wh*-dependency:
What did [$_{IP}$ Falkor [$_{VP}$ claim [$_{CP}$ that [$_{IP}$ Atreyu [$_{VP}$ fought $\_\__{what}$]]]]]?

b. Syntactic path of *wh*-dependency:
start-IP-VP-CP$_{that}$-IP-VP-*end*

c. Syntactic trigrams $T \in$ syntactic path:
= *start*-IP-VP
IP-VP-CP$_{that}$
VP-CP$_{that}$-IP
CP$_{that}$-IP-VP
IP-VP-*end*

(8) Smoothed probabilities of trigrams:
p(*start*-IP-VP) $\approx \frac{count(start{-}IP{-}VP)}{total\ count\ of\ all\ trigrams}$
...
p(IP-VP-*end*) $\approx \frac{count(IP{-}VP{-}end)}{total\ count\ of\ all\ trigrams}$

(9) Probability of new *wh*-dependency: What did Engywook tell Atreyu $\_\__{what}$?
Syntactic structures = What did [$_{IP}$ Engywook [$_{VP}$ tell Atreyu $\_\__{what}$?]]
Syntactic path = *start*-IP-VP-*end*

[1] For discussion of the empirical motivation for the model's implementation choices, including using information only from *wh*-dependencies, using trigrams, the specification of the trigrams, calculating trigram probabilities, and the method of aggregating trigrams into a *wh*-dependency, see Pearl and Sprouse (2013).

[2] The modeled learner smooths these probabilities by adding 0.5 to all trigram counts. This smoothing allows the modeled learner to generate a non-zero probability for *wh*-dependencies composed of trigrams it has never seen before, though it gives these *wh*-dependencies a much lower probability than *wh*-dependencies composed of trigrams it has in fact seen before. See Pearl and Sprouse (2013, 2015) for further discussion of this point.

trigrams = *start*-IP-VP, IP-VP-*end*
Probability = p(*start*-IP-VP-*end*) = p(*start*-IP-VP)*p(IP-VP-*end*)

(10) General formula for generating a *wh*-dependency's probability:
$\prod_{trigrams \in T} p(trigram)$

The probability generated by the modeled learner corresponds to how acceptable the *wh*-dependency is predicted to be. In this way, the modeled learner can generate judgments of *wh*-dependencies. If the learner can generate the same pattern of judgments that adults do, we can interpret this predicted judgment behavior as the learner internalizing some version of the knowledge adults use to make those judgments. In this case, that means the modeled learner has internalized knowledge (via the syntactic trigrams) that allow it to replicate the knowledge contained in syntactic islands. In this way, we can say that it has learned about those syntactic islands.

For the stimuli sets used by Sprouse and colleagues (Sprouse et al., 2012; Pearl and Sprouse, 2013, 2015), each *wh*-dependency stimulus can be transformed into its respective syntactic path (see Table 1). Then, the syntactic trigram probabilities learned from children's input can be used by the modeled learner to generate predicted acceptability judgments. This is the process that allowed Pearl and Sprouse (2013) to generate the judgment patterns in Figure 2, which matched higher-SES adult judgment patterns and so were interpreted as the modeled learner successfully developing knowledge of those four syntactic islands, based on higher-SES children's input.

Table 1: Syntactic paths for experimental stimuli that the modeled learner can generate acceptability judgments for, in a 2x2 factorial design varying dependency length (*matrix* vs. *embedded*) and absence/presence of an island structure (*non*-island vs. *island*). Island-spanning dependencies are indicated with a *.

		Complex NP islands	***Subject islands***
matrix	non	*start*-IP-*end*	*start*-IP-*end*
embedded	non	*start*-IP-VP-CP$_{that}$-IP-VP-*end*	*start*-IP-VP-CP$_{null}$-IP-*end*
matrix	island	*start*-IP-*end*	*start*-IP-*end*
embedded	island	**start*-IP-VP-NP-CP$_{that}$-IP-VP-*end*	**start*-IP-VP-CP$_{null}$-IP-NP-PP-*end*
		Whether islands	***Adjunct islands***
matrix	non	*start*-IP-*end*	*start*-IP-*end*
embedded	non	*start*-IP-VP-CP$_{that}$-IP-VP-*end*	*start*-IP-VP-CP$_{that}$-IP-VP-*end*
matrix	island	*start*-IP-*end*	*start*-IP-*end*
embedded	island	**start*-IP-VP-CP$_{whether}$-IP-VP-*end*	**start*-IP-VP-CP$_{if}$-IP-VP-*end*

We note that the learning theory implemented in this computational cognitive model requires children to have certain (potentially sophisticated) knowledge and abilities in place. More specifically, children are assumed to be able to reliably (i) parse utterances in their input into phrase structure trees, (ii) extract the syntactic paths for the *wh*-dependencies, (iii) track the frequency of the syntactic trigams, and (iv) calculate the probability for the complete syntactic path of a *wh*-dependency, based on its syntactic trigrams. It remains for future work to determine when children are able to accomplish these prerequisite tasks, especially if there is variation with respect to when they can. However, once children can indeed do these things, children would be able to harness the input the way this computational cognitive model does.[3]

[3]Because we intend to use this computational cognitive model as a novel way to identify

6 Input analysis across SES through age four

Here we assess input variation across SES, focusing on the information necessary for the development of syntactic island knowledge for the four islands in (2). The learning theory implemented in the computational cognitive model reviewed above assumes that the relevant aspect of the input is the *wh*-dependencies in it (and the syntactic trigrams that comprise those *wh*-dependencies). So, we consider information available to children across SES in both the *wh*-dependencies and the syntactic trigrams. Because prior child behavioral work indicates that four-year-olds across SES disprefer *wh*-dependencies that cross Complex NP islands (one of the four island types we investigate) (Otsu, 1981; de Villiers and Roeper, 1995; de Villiers et al., 2008)[4], we consider variation present in children's input across SES through age four.

We begin characterizing children's input for learning about syntactic islands by providing a descriptive analysis of the *wh*-dependencies and syntactic trigrams available in samples of higher-SES and lower-SES child-directed speech[5]. We then estimate the quantity of *wh*-dependency input available across SES through age four, finding a potentially large difference in the quantity of *wh*-dependencies between higher-SES and lower-SES children's input.

We then use the computational cognitive model from Pearl and Sprouse (2013) to predict the syntactic island knowledge children would acquire by age four from their input across SES. More specifically, the modeled learner learns from the estimated child-directed speech that higher-SES and lower-SES children encounter by age four, in terms of both the quantity of *wh*-dependencies encountered and the distributions of those *wh*-dependencies, both of which vary across SES. The modeled learner then predicts the acceptability judgments that would be generated by higher-SES and lower-SES children for the four sets of stimuli from Sprouse et al. (2012). We then see if these predicted acceptability judgments suggest any input-based differences across SES by age four, which would signal that differences in the *wh*-dependency input were indeed developmentally meaningful. Conversely, similarity in the predicted acceptability judgment patterns would signal that differences in the *wh*-dependency input are predicted not to be developmentally meaningful for these four syntactic island types.

6.1 Input samples

Higher-SES. Our higher-SES input samples are the data used by Pearl and Sprouse (2013), and come from the structurally-annotated Brown-Adam (Brown, 1973), Brown-Eve (Brown, 1973), Valian (Valian, 1991), and Suppes (Suppes, 1974) corpora from the CHILDES Treebank (Pearl and Sprouse, 2013). These data are child interactions involving 24 children between the ages of one and a half and four, containing 101,838 utterances with 20,923 *wh*-dependencies.

developmentally-meaningful input variation, on the basis of prior work (Pearl and Sprouse, 2013) that applies the model to higher-SES children's input, we will not discuss the theoretical implications of this model's assumptions with respect to questions of innateness. We instead refer interested readers to the discussion in Pearl and Sprouse (2013).

[4]We note that the *wh*-dependencies we refer to as crossing Complex NP islands are referred to in those prior studies as dependencies crossing argument barriers with a relative clause.

[5]Appendix B additionally provides an information-theoretic analysis quantifying how similar the *wh*-dependency and syntactic trigram distributions are in child-directed speech across SES, compared to these distributions within SES but across child-directed vs. adult-directed speech.

Lower-SES. Our lower-SES CDS input samples come from a subpart of the HSLLD corpus (Dickinson and Tabors, 2001) in CHILDES (MacWhinney, 2000), where SES was defined according to maternal education and annual income. Maternal education ranged from 6 years of schooling to some post-high school education. Annual income did not have hard lower and upper bounds; instead, 70% of the families reported an annual income of $20,000 or less, while 21% of the families reported an income of over $25,000. The annual income of the remaining 9% was unreported. In this dataset, we focused on the Elicited Report, Mealtime, and Toy Play sections, which represent more naturalistic interactions. We also drew our samples from Home Visit 1, which recorded child language interactions involving children between the ages of three and five. Our sample contained 31,875 utterances and 3,904 *wh*-dependencies directed at 78 children. We extracted and manually annotated all *wh*-dependencies with syntactic structure, following the format of the CHILDES Treebank, as described in the accompanying documentation for the CHILDES Treebank[6] (Pearl and Sprouse, 2013).

Limitations of corpus samples. Because we draw our samples from already existing corpora freely available through CHILDES, they do differ on other factors besides SES, including age range of the children sampled, number of children sampled, gender ratios of the children sampled, size of the samples, and myriad factors related to the child language interactions themselves, including specific topics of conversation and contexts in which the interactions occurred. Though there are overlaps for some of these factors, such as age range (i.e., three and four-year-olds) as well as some topics and contexts of interactions (meal times and toy-playing sessions), it is certainly possible that the non-SES-based differences between these samples impact the *wh*-dependency distributions.

With respect to the age range differences in these samples, analyses from Pearl and Sprouse (2013) suggest that there is little difference in *wh*-dependency distribution when comparing higher-SES child-directed speech between one and four years old with adult-directed speech. Because the differences between child-directed speech and adult-directed speech are generally more pronounced than child-directed speech at different ages, this prior analysis suggests that the age range differences in the samples here may not impact the *wh*-dependency distributions so much. However, a valuable avenue for future work is to collect data across SES that more explicitly controls for many other factors in order to know more clearly which factors do and do not impact the *wh*-distribution in the input.

***Wh*-dependency coding.** The structural annotations of the *wh*-dependencies in each sample indicate the syntactic structure necessary to characterize the syntactic paths of *wh*-dependencies. We coded the syntactic paths of the dependencies as in (7b) and shown below with a different example in (11)). Following Pearl and Sprouse (2013), the *CP* phrase structure nodes were further subcategorized by the lexical item serving as complementizer, such as CP_{that}, $CP_{whether}$, CP_{if}, and CP_{null}. This subcategorization allows the modeled learner of Pearl and Sprouse (2013) to distinguish dependencies judged by higher-SES adults to be more acceptable, like (11a), from those

[6] This documentation is available with the downloaded corpus at https://www.socsci.uci.edu/~lpearl/CoLaLab/CHILDESTreebank/childestreebank.html and at https://childes.talkbank.org/derived/ (called the Pearl_Sprouse_Corpus at that URL).

judged to be far less acceptable, like (11b) (Cowart, 1997). With these syntactic paths characterizing *wh*-dependencies, we can then assess the distribution of the *wh*-dependencies in each input sample.

(11) a. Who do you think $\_\_{who}$ read the book?
syntactic path: *start-IP-VP-CP*$_{null}$*-IP-end*
b. *Who do you think that $\_\_{who}$ read the book?
syntactic path: **start-IP-VP-CP*$_{that}$*-IP-end*

6.2 Descriptive corpus analyses

***Wh*-dependencies.** Our corpus analyses found 12 *wh*-dependency types in common between the higher-SES and lower-SES child input samples (out of 26 total in the higher-SES and 16 total in the lower-SES).[7] So, the higher-SES input sample contained 14 *wh*-dependency types not in the lower-SES input sample, and the lower-SES input sample contained 4 *wh*-dependency types not in the higher-SES input sample, as shown in the lefthand column of Table 2.[8]

In terms of the distribution of *wh*-dependency types in children's input, there is a striking similarity in the two most frequent *wh*-dependency types across SES: the same two *wh*-dependency types account for the vast majority of *wh*-dependency types in children's input across SES (higher-SES: 89.5%, lower-SES: 85.8%), and these two types seem occur in similar proportions (shown in (12)).[9] This suggests a high-level qualitative similarity in the *wh*-dependency input across SES, despite the individual *wh*-dependency differences.

(12) Proportions of the two most frequent *wh*-dependency types across SES
a. 1^{st} most frequent: *start-IP-VP-end* (e.g., *What did Lily read* $\_\_{what}$*?*)
76.7% higher-SES, 75.5% lower-SES
b. 2^{nd} most frequent: *start-IP-end* (e.g., *What* $\_\_{what}$ *happened?*)
12.8% higher-SES, 10.3% lower-SES

When we compare the rate of *wh*-dependencies across SES (i.e., how often an utterance has a *wh*-

[7] A more detailed description of the *wh*-dependency distribution across SES is available in Appendix A.1.

[8] Interestingly, the last dependency type in Table 2 found only in the lower-SES child input (e.g., *What do you think that happens?*) is an example of a "*that*-trace" violation judged as as far less acceptable by higher-SES adults (Cowart, 1997). Because adults are producing these child-directed speech samples, the presence of this dependency in lower-SES child input represents a potential difference across SES with respect to adult knowledge of specific *wh*-dependency types; in particular, lower-SES adults potentially believe this *wh*-dependency is far more acceptable than higher-SES adults do, unless each instance was a speech error. This prediction can be evaluated by future adult behavioral work, and, if true, would represent a dialectal difference across SES indicating (slightly) different target states for acquisition across SES with respect to *wh*-dependency knowledge.

[9] In fact, despite the sample size differences (20,923 vs. 3,904), the most frequent *wh*-dependency proportion (76.7% higher-SES vs. 75.5% lower-SES) is indeed not statistically significantly different across these samples (two-proportion z-test: p=.10). However, the second most frequent *wh*-dependency proportion (12.8% higher-SES vs. 10.3% lower-SES) does seem to be different, despite the surface similarity in proportions (two proportion z-test: $p<.01$).

Table 2: *Wh*-dependencies and syntactic trigrams unique to speech samples directed at higher-SES and lower-SES children, respectively. Unique syntactic trigrams are on the same row as the unique *wh*-dependencies they come from.

***wh*-dependencies**	**syntactic trigrams**
only higher-SES	
start-IP-VP-CP_{for}*-IP-VP-PP-end* (e.g., *What did she put on for you to dance to* $\_\_{what}$*?*)	*IP-VP-*CP_{for}, *VP-*CP_{for}*-IP*, CP_{for}*-IP-VP*
start-IP-VP-CP_{null}*-IP-VP-IP-VP-IP-VP-end* (e.g., *What did he think she wanted to pretend to steal* $\_\_{what}$*?*)	
start-IP-VP-CP_{null}*-IP-VP-IP-VP-PP-end* (e.g., *Who did he think she wanted to steal from* $\_\_{who}$*?*)	
start-IP-VP-CP_{null}*-IP-VP-NP-end* (e.g., *What did he think she said* $\_\_{what}$ *about it?*)	
start-IP-VP-CP_{null}*-IP-VP-PP-PP-end* (e.g., *What did he think she wanted out of* $\_\_{what}$*?*)	
start-IP-VP-CP_{that}*-IP-VP-end* (e.g., *What did he think that she stole* $\_\_{what}$*?*)	CP_{that}*-IP-VP*
start-IP-VP-IP-end (e.g., *What did he want* $\_\_{who}$ *to steal the necklace?*)	*VP-IP-end*
start-IP-VP-IP-VP-IP-VP-PP-end (e.g., *Who did he want her to pretend to steal from* $\_\_{who}$*?*)	
start-IP-VP-IP-VP-NP-end (e.g., *What did he want to say* $\_\_{what}$ *about it?*)	
start-IP-VP-IP-VP-NP-PP-end (e.g., *What did she want to steal more of* $\_\_{what}$*?*)	
start-IP-VP-NP-end (e.g., *What did she say* $\_\_{what}$ *about the necklace?*)	*VP-NP-end*
start-IP-VP-PP-CP_{null}*-IP-VP-end* (e.g., *What did she feel like he saw* $\_\_{what}$*?*)	*VP-PP-*CP_{null}, *PP-*CP_{null}*-IP*
start-IP-VP-PP-NP-PP-end (e.g., *What do you put it on top of* $\_\_{what}$*?*)	*VP-PP-NP*, *PP-NP-PP*
start-IP-VP-PP-IP-VP-end (e.g., *What did he think about stealing* $\_\_{what}$*?*)	
only lower-SES	
start-IP-VP-CP_{null}*-IP-VP-NP-PP-end* (e.g., *What did he think it was a movie of* $\_\_{what}$*?*)	
start-IP-VP-IP-VP-IP-VP-PP-IP-VP-end (e.g., *What did you want to try to plan on doing* $\_\_{what}$*?*)	
start-IP-VP-PP-IP-VP-end (e.g., *What did she think about buying* $\_\_{what}$?)	
start-IP-VP-CP_{that}*-IP-end* (e.g., *What do you think that* $\_\_{what}$ *happens*?)	CP_{that}*-IP-end*

dependency), we do find a difference, with *wh*-dependencies occurring more frequently in higher-

SES child-directed speech (higher-SES: 20,932/101,383 = 20.5%, lower-SES: 3,904/31,875 = 12.2%; two-proportion z-test: p<.01). Over time (as detailed in section 6.3), this rate difference can lead to a considerable difference in the quantity of *wh*-dependencies encountered.

Syntactic trigrams. For syntactic trigrams, which serve as the building blocks of *wh*-dependencies under the Pearl & Sprouse learning theory, our corpus analysis found 19 syntactic trigrams in common between the higher-SES and lower-SES child input samples (out of 29 total for the higher-SES and 20 total in the lower-SES). So, the higher-SES input sample contained 10 syntactic trigrams not in the lower-SES input sample, and the lower-SES input sample contained 1 syntactic trigram not in the higher-SES input sample, shown in the righthand column of Table 2.[10]

As might be expected from the *wh*-dependency descriptive analysis, the most frequent syntactic trigrams are also very similar across SES; this is because these trigrams come from the most frequent *wh*-dependency types. More specifically, the three trigram types that collectively account for the majority of the trigrams in the *wh*-dependency input are the same across SES and account for about the same proportion of the input (87.9% of syntactic trigrams in higher-SES input, and 85.0% in lower-SES input). In addition, these three most frequent syntactic trigrams occur individually in about the same proportions across SES (shown in (13)). So, as with the *wh*-dependency types, this descriptive analysis suggests a high-level qualitative similarity in the syntactic trigram input across SES, despite the individual syntactic trigram differences.

(13) Proportions of the three most frequent trigram types across SES

a. 1^{st} most frequent: *start-IP-VP*
41.8% higher-SES 41.4% lower-SES

b. 2^{nd} most frequent: *IP-VP-end*
40.0% higher-SES, 38.9% lower-SES

c. 3^{rd} most frequent: *start-IP-end*
6.1% higher-SES, 4.7% lower-SES

6.3 Realistic estimates of input quantity across SES through age four

To estimate the quantity of *wh*-dependency data that children from different SES backgrounds encounter through age four, we can draw on available empirical data sources to estimate both how long children have to learn (i.e., the learning period) and how much data they encounter during that learning period. More specifically, we can estimate when children would begin harnessing the *wh*-dependency information in their input (i.e., when the learning period for syntactic islands could plausibly start), how much time passes between that starting point and age four (i.e., the length of the learning period), and how many *wh*-dependencies children across SES would encounter during that learning period.

When children's learning period plausibly starts. To begin learning about the relative acceptability of different *wh*-dependencies, children must be able to process the structure of *wh*-dependencies. Current research suggests that children begin to represent the full structure of *wh*-

[10] A more detailed description of the syntactic trigram distribution across SES is available in Appendix A.2.

dependencies (e.g., *wh*-questions and relative clauses) at 20 months (Seidl et al., 2003; Gagliardi et al., 2016; Perkins and Lidz, 2020). So, we estimate 20 months as the starting point of the learning period for syntactic islands, which depend on *wh*-dependencies.

How much time awake during the learning period. Taking four years old as the end point of the learning period for syntactic islands, the estimated learning period is then from 20 months through the end of age four (59 months). We estimate the number of hours awake by drawing on Davis et al. (2004), who summarize the hours asleep for young children at different ages, as shown in Table 3. In particular, one-year-olds sleep about 14 hours a day (awake for 10), two-year-olds sleep about 13 hours a day (awake for 11), three-year-olds sleep about 12 hours a day (awake for 12), and four-year-olds sleep about 11.5 hours a day (awake for 12.5). Based on these estimates, we can then estimate the hours awake between age 20 months and age 59 months, and sum those hours to estimate the total hours awake during this learning period. Our calculations in Table 3 yield about 14,174 hours awake. Multiplying by 60 minutes/hour yields about 850,450 minutes awake.

Table 3: Calculating the total hours (cumulative waking hrs) and minutes (cumulative waking min) awake for children between the ages of 20 and 59 months, the estimated learning period for syntactic islands. These calculations are based on waking hours per day (waking) and total waking hours. Cumulative hours awake are shown at age one (20-23 months), two (24-35 months), three (36-47 months), and four (48-59 months).

age	age range	waking	total waking hours	cumulative waking hrs
one	20-23 months	10	11 hrs/day * 365 days/yr * 4/12 = 1216.67	1216.67
two	24-35 months	11	11 hrs/day * 365 days/yr = 4015	5231.67
three	36-47 months	12	12 hrs/day * 365 days/yr = 4380	9611.67
four	48-59 months	12.5	12.5 hrs/day * 365 days/yr = 4562.5	14174.17
				cumulative waking min
				14174.17 * 60 min/hour
				850450.2

How many *wh*-dependencies during the learning period. Based on the estimated minutes awake during the learning period, we can then estimate the quantity of *wh*-dependencies children encounter. More specifically, we estimate this quantity by drawing on estimates of the number of utterances children from different SES backgrounds hear per minute and our own corpus samples of the rate of *wh*-dependencies in children's input.

To estimate utterances per minute across SES during the learning period between 20 and 59 months, we draw on work by Rowe (2012) and Hoff-Ginsberg (1998). Rowe (2012) examined word tokens per minute at ages 18 months, 30 months, and 42 months across SES, finding that quantity of word tokens per minute appears to remain steady (rather than increasing). So, we assume here that the rate of utterances per minute across SES also remains the same during the learning period from 20 months to 59 months. Hoff-Ginsberg (1998) identified average rates of utterances per minute for children age 21 to 24 months from families with different SES backgrounds: (i) parents who were college-educated and worked in professional professional positions (which we will associate with higher-SES), and (ii) parents who were high-school educated and worked in semi-skilled, unskilled, or service positions (which we will associate with lower-SES). The higher-SES children heard 15.8 utterances per minute (standard deviation 4.2), while the lower-SES children heard 13.0 utterances per minute (standard deviation 4.2). To capture 95% of each population, we consider the range of utterance rates within two standard deviations from the average, as shown in Table 4 (higher-SES: 7.4-24.2 utterances/minute; lower-SES: 4.6-21.4 utterances/minute).

Our corpus estimates of *wh*-dependency rate suggest that higher-SES children's input consists of about 20.5% *wh*-dependencies (20,923 *wh*-dependencies of 101,838 utterances), while lower-SES children's input consists of about 12.2% *wh*-dependencies (3,904 *wh*-dependencies of 31,857 utterances). Table 4 shows the resulting range of *wh*-dependency quantity heard during the learning period across SES: 1,293,545-4,230,241 for higher-SES children, and 479,144-2,229,063 for lower-SES children. While there are some points where there appear to be similar quantities of *wh*-dependencies in children's input across SES (e.g., 2 standard deviations below the higher-SES average = 1,293,545 while the lower-SES average = 1,354,103), there can be a marked quantity disparity. On average, higher-SES children will hear about twice as many *wh*-dependencies as lower-SES children ($\frac{2{,}761{,}893}{1{,}354{,}103} = 2.04$). In the most extreme case, higher-SES children at the top of the higher-SES range (2 standard deviations above the average: 4,230,241) hear nearly 9 times as many *wh*-dependencies as lower-SES children at the bottom of the lower-SES range (2 standard deviations below the average: 479,144): $\frac{4{,}230{,}241}{479{,}144} = 8.8$.

Table 4: Calculating the range of total *wh*-dependencies (total *wh*-dep) that higher-SES and lower-SES children encounter between the ages of 20 and 59 months, the estimated learning period for syntactic islands. These calculations are based on 850,450.2 waking minutes between these ages, estimated ranges of utterance rates per min (utt/min), based on average rates (average) and standard deviations (s.d.) across SES, and *wh*-dependencies in the input (*wh*-dep/utt) across SES.

	utt/min	*	**min**	*	***wh*-dep/utt**	=	**total *wh*-dep**
higher-SES		*	850,450.2	*	20,932/101,838		
- 2 s.d.	7.4					=	1,293,545
- 1 s.d.	11.6					=	2,027,719
average	15.8					=	2,761,893
+ 1 s.d.	20.0					=	3,496,067
+ 2 s.d.	24.2					=	4,230,241
lower-SES		*	850,450.2	*	3,904/31,875		
- 2 s.d.	4.6					=	479,144
- 1 s.d.	8.8					=	916,624
average	13.0					=	1,354,103
+ 1 s.d.	17.2					=	1,791,583
+ 2 s.d.	21.4					=	2,229,063

6.4 Summary and implications of corpus analyses

Our descriptive corpus analyses highlight both (i) high-level similarities in the distributions of *wh*-dependency information in children's input across SES (e.g., the most frequent *wh*-dependency types and syntactic trigrams, as well as how frequent they are), and (ii) notable differences (e.g., specific *wh*-dependency types and syntactic trigrams unique to each sample, as well as the rate of *wh*-dependencies in the input). Our estimation of the amount of *wh*-dependencies heard during the estimated learning period for syntactic islands (through age four) highlights how the quantity can be quite different across SES, with higher-SES children potentially hearing nearly nine times the quantity of *wh*-dependencies as lower-SES children.

However, recall that for at least one syntactic island type we investigate (Complex NP islands), children across SES seem to have developed a similar (dis)preference for *wh*-dependencies that cross that island by age four (Otsu, 1981; de Villiers and Roeper, 1995; de Villiers et al., 2008). So, we might expect that the input differences across SES that we have found so far are not developmentally meaningful by age four for learning about Complex NP islands, with respect to finding *wh*-dependencies that cross Complex NP islands far less acceptable than other *wh*-dependencies. This is a prediction we can evaluate using the computational cognitive model from Pearl and Sprouse (2013). More specifically, if the learning theory implemented in that model, connecting children's input to their predicted acceptability judgments, is plausible, we would expect that both higher-SES and lower-SES children's input should allow the target judgment patterns for the Complex NP island stimuli to be generated after the learning period is complete. In this way, the Complex NP island stimuli serve as a sort of checkpoint on the learning theory implemented in the model. If the learning theory implemented in the model is indeed able to generate the appropriate Complex NP judgment patterns from children's input across SES, then we can feel more confident in using that same model to evaluate whether children's input across SES could also support the development of knowledge for the other three island types we investigate: Subject, Whether, and Adjunct islands. Note that each island type involves different syntactic structures – therefore, even if knowledge of one syntactic island type can develop from children's input (e.g., Complex NP islands), there is no guarantee that knowledge of all these island types can develop from that same input.

Of course, as noted previously, there is suggestive evidence from prior modeling work by Pearl and Sprouse (2013) that higher-SES input can support development of all four syntactic island types. However, the input sample used in those prior analyses is not as realistic as the range we explore in our own modeling analyses here, summarized in Table 4. Thus, our analysis with a more realistic range of higher-SES input will serve as a more comprehensive comparison to our analysis with lower-SES input, and thus of input variability across SES for learning about syntactic islands.

6.5 Computational cognitive modeling analysis

We conducted the computational cognitive modeling analysis by implementing a modeled learner that uses the learning theory of Pearl and Sprouse (2013), and then allowing that modeled learner to learn from the estimated input samples described above. In particular, the modeled learner learned from the range of quantities of *wh*-dependencies estimated for higher-SES children by age four, with the *wh*-dependencies distributed as in our higher-SES corpus sample; similarly, the modeled learner learned from the range of quantities of *wh*-dependencies estimated for lower-SES children by age four, distributed as in our lower-SES corpus sample. For each input set, the modeled learner estimated syntactic trigram probabilities and could then generate probabilities for any desired *wh*-dependency, whether seen or unseen in its input.

We then demonstrate what this modeled learner would learn from its input by age four about the syntactic island types we investigate, as measured by its predicted judgments on the *wh*-dependency stimuli from Sprouse et al. (2012), reviewed in (3)-(6) and characterized by the syntactic paths in Table 1. Adult-like acceptability judgment patterns for these different *wh*-dependency stimuli sets, the target state for development, are superadditive (i.e., non-parallel lines in interaction plots, as in Figure 1). As mentioned above, previous computational cognitive modeling results from Pearl and Sprouse (2013) using higher-SES input were able to generate this superadditive judgment pattern for all four syntactic island types, as shown in Figure 2. Our current analysis will see if the higher-SES predicted judgment patterns replicate when using more realistic estimates of higher-SES input encountered by age four. We will additionally be able to predict the lower-SES judgment patterns resulting by age four, and see how those compare to the predicted higher-SES judgment patterns. In this way, we will be able to compare the input quality across SES by age four for learning about these four syntactic island types.

6.5.1 Analysis implementation and visualization

For each SES type (higher vs. lower), a modeled learner was run 1000 times on an input set sampled to match the estimated input quantity (2 standard deviations below average, 1 standard deviation below average, average, 1 standard deviation above average, 2 standard deviations above average), with *wh*-dependencies distributed according to our corpus samples. Averages of these 1000 runs for each SES type and estimated input quantity are plotted in Figures 3 and 4, with the log probability averages and standard deviations for each *wh*-dependency stimuli type available in Appendix C. Standard deviations were not plotted as they were too small to appear on the graphs.

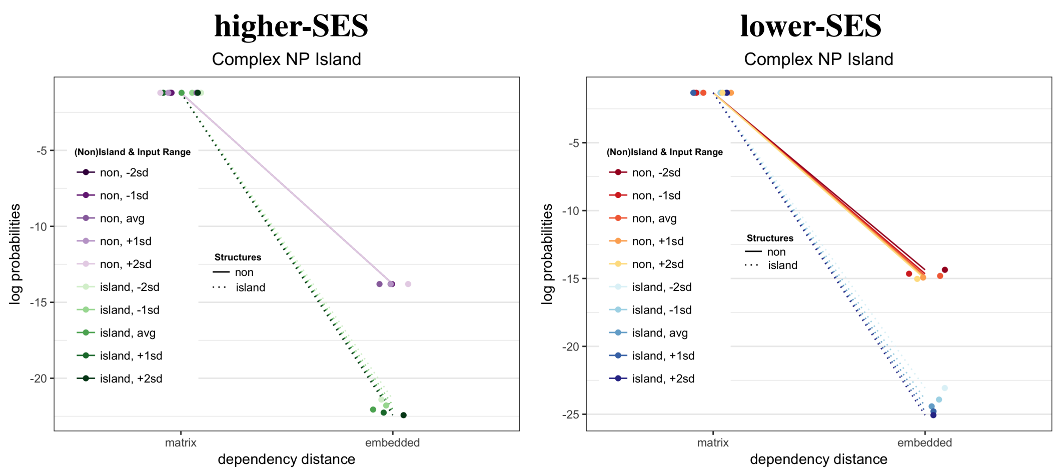
6.5.2 Complex NP islands

Figure 3 shows the results of the computational cognitive modeling analysis for Complex NP islands, assessed by predicted acceptability judgment patterns for the *wh*-dependency stimuli from Sprouse et al. (2012).

For higher-SES child-directed input (left side of Figure 3), we see the same superadditive judgment pattern that higher-SES adults had in Sprouse et al. (2012), and which the prior computational cognitive modeling analysis of Pearl and Sprouse (2013) found. This judgment pattern can be interpreted as demonstrating implicit knowledge of the Complex NP island, as the island-spanning dependency (an embedded dependency with an island structure in it) is far less acceptable than expected if its acceptability were solely based on it being an embedded dependency with an island structure present in the utterance. Thus, these results support prior computational cognitive modeling work suggesting that higher-SES input can lead to implicit knowledge of the Complex NP island, as assessed by the superadditive judgment pattern.

We see this same judgment pattern in the predicted judgments derived from lower-SES child input (right side of Figure 3). So, these results additionally suggest that there is no predicted difference in Complex NP island knowledge by age four across SES. In particular, both higher-SES and lower-SES children should find *wh*-dependencies that cross Complex NP islands to be far

Figure 3: Predicted four-year-old child judgments for Complex NP stimuli by a modeled learner learning from higher-SES (left) and lower-SES (right) input data ranges (2 standard deviations below average (-2sd), 1 standard deviation below average (-1sd), average (avg), 1 standard deviation above average (+1sd), 2 standard deviations above average (+2sd)). Averages are shown from 1000 modeled learner runs per input range. Both interaction plots show the superadditive pattern that appears in adult judgments of these *wh*-dependencies given the factorial design crossing dependency distance (matrix vs. embedded) with the absence/presence of an island structure in the utterance (non vs. island).



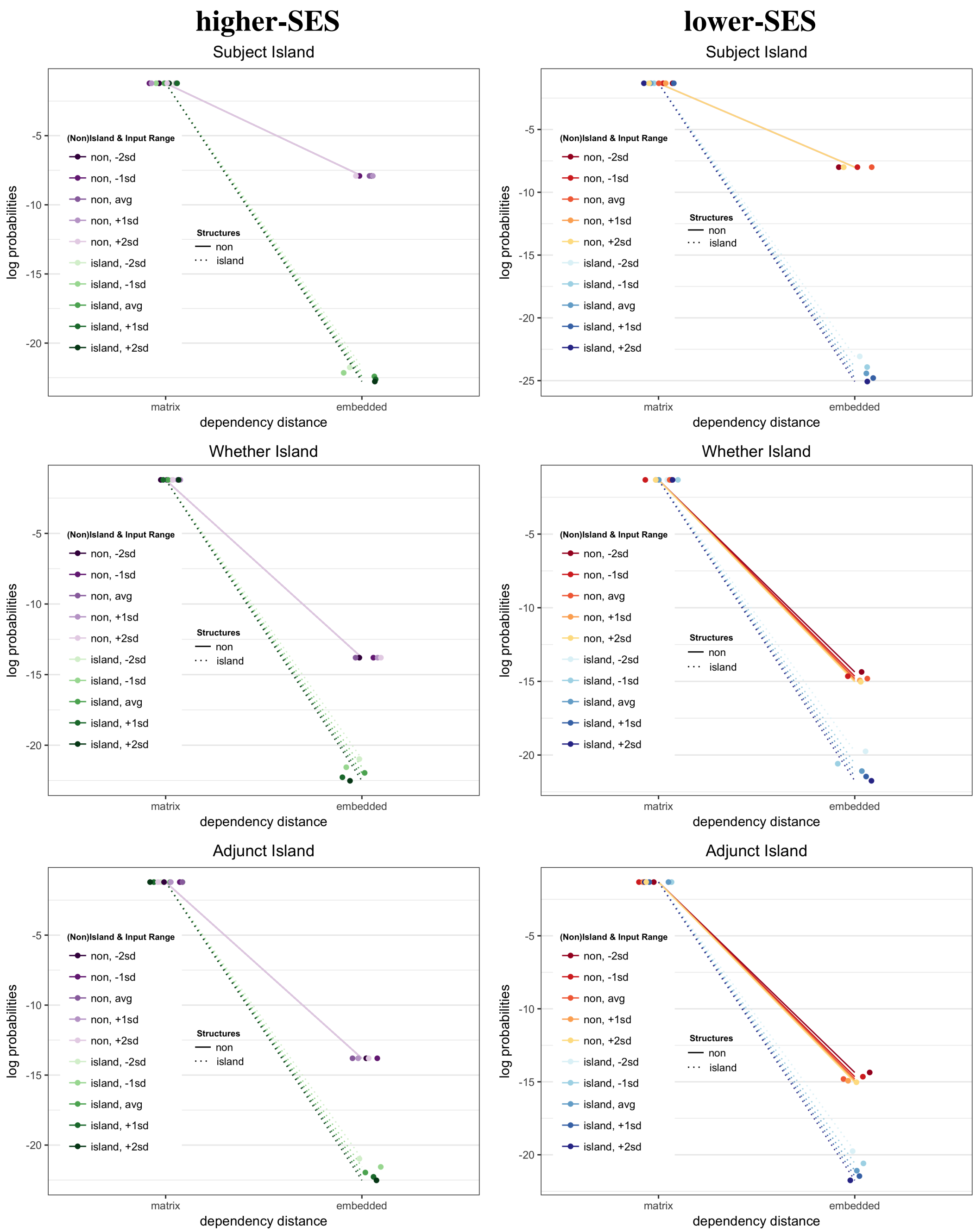
less acceptable. These results align with prior child behavioral data from de Villiers et al. (2008) suggesting that children across SES disprefer *wh*-dependencies crossing Complex NP islands. That is, our computational cognitive modeling results predict that four-year-olds across SES should judge such *wh*-dependencies as much less acceptable, which seems to be true.

So, the computational cognitive model implementing the learning theory of Pearl and Sprouse (2013) correctly predicts that (i) higher-SES children should disprefer *wh*-dependencies that cross Complex NP islands, and that (ii) lower-SES children should also disprefer these *wh*-dependencies. Moreover, a more precise prediction is that both higher-SES and lower-SES children should show the same, adult-like superadditive acceptability judgment pattern on this *wh*-dependency stimuli set by age four. Taken together, these results suggest there is no predicted developmentally-meaningful difference by age four in children's input across SES for learning about the Complex NP island, and this prediction aligns with currently available empirical evidence. We interpret these results to therefore support the plausibility of the learning theory implemented by the modeled learner, which assumes children pay attention to a certain aspect of the input (all *wh*-dependencies), and use this information in a particular way that involves specific prior knowledge and abilities being in place (recall the discussion from section 5). With this in mind, we now turn to the predictions for the other three island types.

6.5.3 Subject, Whether, and Adjunct islands

Figure 4 shows the results of the computational cognitive modeling analysis for the Subject, Whether, and Adjunct islands, assessed by predicted acceptability judgment patterns for the *wh*-dependency stimuli from Sprouse et al. (2012).

Figure 4: Predicted four-year-old child judgments for Subject, Whether, and Adjunct stimuli by a modeled learner learning from higher-SES (left column) and lower-SES (right column) input data ranges (2 standard deviations below average (-2sd), 1 standard deviation below average (-1sd), average (avg), 1 standard deviation above average (+1sd), 2 standard deviations above average (+2sd)). Averages are shown from 1000 modeled learner runs per input range. All interaction plots show the superadditive pattern that appears in adult judgments of these *wh*-dependencies given the factorial design crossing dependency distance (matrix vs. embedded) with the absence/presence of an island structure in the utterance (non vs. island).



For higher-SES child-directed input (left side of Figure 4), we see the same superadditive judgment pattern that higher-SES adults had in Sprouse et al. (2012), and which the prior computational cognitive modeling analysis of Pearl and Sprouse (2013) found. This judgment pattern can be interpreted as demonstrating implicit knowledge of the Subject, Whether, and Adjunct islands, as the island-spanning dependencies (embedded dependencies with an island structure in them) are far less acceptable than expected if their acceptability were solely based on them being embedded dependencies with an island structure present in the utterance. Thus, these results support prior computational cognitive modeling work suggesting that higher-SES input can lead to implicit knowledge of the Subject, Whether, and Adjunct islands, as assessed by the superadditive judgment pattern.

We see this same judgment pattern in the predicted judgments derived from lower-SES child input (right side of Figure 4). So, these results additionally suggest that there is no predicted difference in the Subject, Whether, or Adjunct island knowledge by age four across SES. In particular, both higher-SES and lower-SES children by age four should find *wh*-dependencies that cross the Subject, Whether, and Adjunct islands to be far less acceptable.

So, as with the Complex NP island, the computational cognitive model implementing the learning theory of Pearl and Sprouse (2013) predicts that (i) higher-SES children should disprefer *wh*-dependencies that cross the Subject, Adjunct, and Whether islands, and (ii) lower-SES children should also disprefer these *wh*-dependencies. As with the Complex NP island type, a more precise prediction is that both higher-SES and lower-SES children should show the same, adult-like superadditive acceptability judgment pattern on these *wh*-dependency stimuli sets by age four. Taken together, these results suggest there is no predicted developmentally-meaningful difference in children's input by age four across SES for learning about the Subject, Whether, or Adjunct islands either.

6.5.4 Summary of modeling results

As mentioned above, our computational cognitive modeling analysis predicts no difference in children's knowledge across SES by age four about these four island types, as assessed by acceptability judgment patterns for specific sets of *wh*-dependencies. These predictions can be tested experimentally in future child behavioral work that assesses acceptability judgment patterns.

If these predictions are indeed true, and there is no difference in acceptability judgments for all four of these island types by age four across SES, then those future behavioral results would additionally support our basic finding: lower-SES input is qualitatively similar to higher-SES input, when it comes to the development of this syntactic island knowledge. That is, the measurable input differences across SES are not developmentally meaningful. Importantly, because of the learning theory implemented concretely by the modeled learner, we understand why this result occurs, both in general and more specifically. In general, the observable differences in the *wh*-dependency distributions in children's input across SES do not affect input quality for the part of that input that scaffolds knowledge of these syntactic islands. More specifically, the building blocks (i.e., the specific syntactic trigrams associated with each *wh*-dependency) that are necessary to yield the appropriate acceptability judgment patterns appear in the appropriate relative frequencies in children's input across SES.

7 Discussion

Our computational cognitive modeling analysis suggests that the *wh*-dependency input, and in turn the syntactic trigram input, that higher-SES children receive is similar to the input of lower-SES children with respect to how that aspect of the input can support the development of certain syntactic island knowledge (Complex NP, Subject, Whether, and Adjunct islands) by age four. This is true despite the small differences in *wh*-dependency distribution and the potentially large differences in quantity of *wh*-dependency input encountered by age four. So, any input differences across SES are not predicted to be developmentally meaningful with respect to learning this syntactic island knowledge. In this way, any measurable quantitative differences across SES in this aspect of the input do not appear to be qualitative differences, with respect to the development of this syntactic island knowledge. That is, surface input differences mask deeper input similarities across SES.

One benefit of our computational cognitive modeling approach is that it makes predictions about children's observable behavior (here: acceptability judgments for *wh*-dependencies at age four) that can be evaluated against existing and future child behavioral data. Current data from de Villiers et al. (2008) align with the predictions for Complex NP islands, supporting the plausibility of the learning theory implemented in the computational cognitive model that specifies a causal link between children's input and their observable language behavior. We note again that, to our knowledge, this is the only learning theory of this kind that we are aware of for syntactic islands that is specified enough to generate precise, testable predictions from children's input. Thus, we believe it is valuable to continue to validate the learning theory's predictions against empirical data, though of course future work may explore other learning theories for syntactic islands and evaluate their predictions against available empirical data.

In particular, future child behavioral work can evaluate the specific predicted behavior for acceptability judgements of Complex NP islands, to provide further validation both of the learning theory and the prediction that there should be no difference in this Complex NP island knowledge across SES by age four. Future child behavioral studies can also evaluate the predictions for the other three island types (Subject, Whether, and Adjunct), where the computational cognitive modeling analysis also predicts no differences across SES by age four.

Below, we first discuss some interesting input differences across SES involving the complementizer *that*, which the learning theory implemented by the computational cognitive model identifies as important for the development of certain syntactic island knowledge. We then turn to other testable model predictions for related syntactic knowledge concerning *wh*-dependencies. We then consider the plausibility of the prior knowledge and abilities assumed by the learning theory implemented in the model, as these prerequisites are also potential points of variation across SES that could therefore impact when children across SES could harness the information in their input in the way the learning theory proposes.

7.1 Interesting input differences involving complementizer *that*

There is a striking difference in the exact *wh*-dependency distribution across SES that is predicted by the learning theory implemented in the computational cognitive model to be crucial for learning about two of the syntactic island types, Whether and Adjunct islands. This input difference involves a particular structural building block, which comes from *wh*-dependencies that have the complementizer *that* and so are characterized with CP$_{that}$.

As noted before in (11), the only distinction between certain *wh*-dependencies judged more acceptable and other *wh*-dependencies judged less acceptable by higher-SES adults is the complementizer. With respect to the *wh*-dependencies we have investigated related to different syntactic island types, *wh*-dependencies like (14a) with complementizer *that*, are judged as more acceptable, while equivalent *wh*-dependencies like (14b) with complementizers like *whether* (Whether islands) or *if* (Adjunct islands) are judged as far less acceptable. Again, the only difference in the syntactic path of these *wh*-dependencies is the CP building block, which is CP$_{that}$ for the *wh*-dependency in (14a) and CP$_{whether}$ or CP$_{if}$ for the *wh*-dependencies in (14b).

(14) a. What do you think that Jack read $\_\__{what}$?
syntactic path: *start-IP-VP-CP$_{that}$-IP-VP-end*
b. *What do you wonder whether/if Jack read $\_\__{what}$?
syntactic path: **start-IP-VP-CP$_{whether/if}$-IP-VP-end*

This instance highlights that it is important for children to encounter *wh*-dependencies in their input that involve complementizer *that* (and not ones that involve complementizers *whether* or *if*), if they are to learn about Whether and Adjunct islands the way the learning theory here proposes. When children do in fact encounter *wh*-dependencies with complementizer *that* (CP$_{that}$), the learning theory implemented by the computational cognitive model here can leverage the CP$_{that}$ piece to predict that (14a) should be judged as more acceptable than (14b).

However, *wh*-dependencies involving CP$_{that}$ are actually fairly rare in naturalistic usage. Pearl and Sprouse (2013) only found 2 of 20,923 (0.0096%) in high-SES CDS.[11] Based on our estimated input ranges by age four for higher-SES children, this would correspond to between about three and ten *wh*-dependencies with CP$_{that}$ every month.[12] In our lower-SES CDS sample, there are 2 of 3,094 (0.051%) *wh*-dependencies involving CP$_{that}$. Based on our estimated input ranges by age four for lower-SES children, this would correspond to between about six and 29 *wh*-dependencies with CP$_{that}$ every month.[13] If these corpus samples are accurate, this calculation highlights that lower-SES children could actually hear a crucial building block for certain syntactic islands far more often in their input than higher-SES children do (e.g., 29 times vs. ten times per month even at the highest input estimates), despite higher-SES children likely hearing more *wh*-dependencies overall before age four. That is, input quantity for this particular building block (i.e., *wh*-dependencies involving CP$_{that}$) is estimated to be more for lower-SES children, rather than for higher-SES children, in contrast to overall *wh*-dependency quantity.

Interestingly, the type of *wh*-dependency in children's input that contains the crucial CP$_{that}$

[11] They additionally found that CP$_{that}$ *wh*-dependencies are rare in both high-SES adult-directed speech (7 of 8,508 = 0.082%) and adult-directed text (2 of 4,230 = 0.048%).

[12] Two standard deviations below the average: CP$_{that}$ rate $\frac{2}{20932}$ * 1,293,545 *wh*-dependencies in the learning period = 124; 124 / 40 months in the learning period = 3.1 CP$_{that}$ *wh*-dependencies per month. Two standard deviations above the average: CP$_{that}$ rate $\frac{2}{20932}$ * 4,230,241 *wh*-dependencies in the learning period = 404; 404/40 months in the learning period = 10.1 CP$_{that}$ *wh*-dependencies per month.

[13] Two standard deviations below the average: CP$_{that}$ rate $\frac{2}{3094}$ * 479,144 *wh*-dependencies in the learning period = 245; 245 / 40 months in the learning period = 6.1 CP$_{that}$ *wh*-dependencies per month. Two standard deviations above the average: CP$_{that}$ rate $\frac{2}{3094}$ * 2,229,063 *wh*-dependencies in the learning period = 1142; 1142/40 months in the learning period = 28.6 CP$_{that}$ *wh*-dependencies per month.

building block also appears to differ across SES, based on our corpus samples. In the higher-SES sample, both dependencies involving CP_{that} are of the same type: *start-IP-VP-*CP_{that}*-IP-VP-end* instances like (14a). However, in our lower-SES CDS sample, the CP_{that} building block comes from a different *wh*-dependency type, which happens to be a "*that*-trace violation" that is judged as much less acceptable by higher-SES adults (Cowart, 1997): *start-IP-VP-*CP_{that}*-IP-end* instances like (15).

(15) What do you think that $\_\__{what}$ happens?
What do $[_{IP}$ you $[_{VP}$ think $[_{CP_{that}}$ that $[_{IP}$ $\_\__{what}$ $[_{VP}$ happens]]]]]?
syntactic path: *start-IP-VP-*CP_{that}*-IP*

So, the presence of this *wh*-dependency type, which is judged less acceptable in the higher-SES dialect, is predicted to provide the crucial CP_{that} building block necessary for the acquisition of Whether and Adjunct islands for lower-SES children. That is, the key linguistic experience that would allow a child learning from lower-SES CDS to acquire the same syntactic knowledge about Whether and Adjunct islands as a higher-SES child actually comes from data that would be unlikely to occur in a higher-SES child's input because it is judged less acceptable by higher-SES adults who produce the child-directed speech. This finding underscores the power of learning theories that generate the linguistic knowledge of larger structures (such as *wh*-dependencies) from smaller building blocks (such as syntactic trigrams), like the learning theory implemented in the computational cognitive model here. In particular, children with different input experiences who rely on smaller building blocks may be able to find evidence for the same building blocks (e.g., syntactic trigrams involving CP_{that}) in different places (e.g., different *wh*-dependencies involving CP_{that}).

However, we note again that these findings and implications rest on the accuracy of our corpus samples. In particular, for the lower-SES *wh*-dependencies containing CP_{that}, it is possible that these *wh*-dependency instances were speech errors from the adult speakers. We feel this possibility is less likely, as the two *wh*-dependency instances came from two different speakers, and so are more likely to reflect naturalistic lower-SES usage. Still, this prediction that these *wh*-dependencies would in fact be judged as acceptable by lower-SES adults remains to be validated.

However, suppose these *wh*-dependency instances in the lower-SES corpus samples were in fact speech errors and so are unlikely to occur in lower-SES children's input in general, because lower-SES adults would find them as unacceptable as higher-SES adults do. In that case, we would not expect lower-SES children in general to encounter these *wh*-dependencies with CP_{that}. Because these were the only *wh*-dependencies in our lower-SES sample containing CP_{that}, we might then expect that lower-SES children do *not* in fact encounter any *wh*-dependencies with the crucial CP_{that} building block. Without the CP_{that} building block in lower-SES children's input, the learning theory implemented by the computational cognitive model would predict that lower-SES children would not in fact judge *wh*-dependencies crossing Whether and Adjunct islands as any less acceptable than *wh*-dependencies crossing embedded clauses with complementizer *that* (e.g., no difference in judged acceptability of the *wh*-dependencies in (14a) and (14b)). That is, they would not learn the same syntactic knowledge as higher-SES children with respect to Whether and Adjunct islands, as reflected in judged acceptability of the relevant *wh*-dependencies.

In this situation, the computational cognitive modeling analysis would predict a developmentally-meaningful input difference across SES for these syntactic island types (i.e., Whether and Adjunct islands). In particular, higher-SES children's input would be predicted to support the development of this knowledge, while lower-SES children's input would not. More specifically, lower-SES children would be predicted to *not* have the adult-like superadditive judgment pattern by age four for the Whether and Adjunct *wh*-dependency stimuli, in contrast with higher-SES children.

To explore whether this input situation is in fact occurring, there are at least two specific things we can investigate in future work, using both corpus and behavioral techniques. First, we can analyze larger samples of lower-SES input to see if and how *wh*-dependencies with CP_{that} occur. The CHILDES database (MacWhinney, 2000) has additional data from the HSLLD corpus (Dickinson and Tabors, 2001) that we drew from for our lower-SES corpus sample here, as well as other lower-SES CDS samples in the Hall (Hall and Tirre, 1979) and the Brown-Sarah (Brown, 1973) corpora.

Second, we can use behavioral techniques to evaluate whether lower-SES adults judge the specific *wh*-dependency with CP_{that} that we found in our lower-SES sample (i.e., the "*that*-trace violation") more acceptable than higher-SES adults do. If so, this would support the plausibility of lower-SES adults using this *wh*-dependency type in lower-SES children's input, rather than it being a speech error. Lower-SES children would then be likely to encounter this *wh*-dependency type, and importantly, the CP_{that} building block it contains. If instead lower-SES adults find that *wh*-dependency type less acceptable (as higher-SES adults do), this would suggest the instances in our lower-SES corpus sample were speech errors; then, lower-SES children would not be likely to encounter this *wh*-dependency type in their input in general. Information about the CP_{that} building block needed for learning about Whether and Adjunct islands would need to come from some other type(s) of *wh*-dependency involving CP_{that}, if lower-SES children are to learn about these islands the way higher-SES children are proposed to do.

7.2 Other model predictions

While our investigation here focused on four island types and the specific *wh*-dependency stimuli related to them where empirical data was already available about their judged acceptability, the learning theory implemented by the computational cognitive model is capable of generating predictions for any *wh*-dependency. Recall that this is because the learning theory proposed that all *wh*-dependencies are comprised of the same building blocks (i.e., the syntactic trigrams). So, the learning theory proposes that children are learning about those building blocks from their input, and then can use those building blocks to judge the acceptability of any *wh*-dependency they encounter.

Because there are additional data available about children's preferences and dispreferences for certain *wh*-dependencies across SES (e.g., from de Villiers et al. 2008), the model itself can be evaluated by seeing how well it can capture those known preferences. For instance, de Villiers et al. (2008) found that four-year-old children across SES prefer a *wh*-dependency like *What did he fix the table with* $\_\__{what}$*?* (with syntactic path *start*-IP-VP-PP-*end*) over a *wh*-dependency crossing a Complex NP syntactic island. This preference is easily captured by the comparing the probabilities generated by the model learning from either higher-SES or lower-SES input data: the probability for the preferred *wh*-dependency is much higher[14], yielding a prediction that children across SES

[14]Higher-SES: the preferred dependency has a predicted log probability about 10^{18} times more probable than the dispreferred one. Lower-SES: the preferred dependency has a predicted log probability about 10^{21}

prefer that *wh*-dependency, just as children across SES actually do.

Of course, there are many *wh*-dependencies for which we do not know children's preferences (e.g., the *that*-trace violations discussed above). In these cases, the model's predictions can be used to design future child behavioral studies that can evaluate those predictions. In addition, because the model generates more precise predictions about judged acceptability patterns (for which we do not currently have child behavioral data) rather than simple preference, future child behavioral studies can be designed to test predicted acceptability judgment patterns in children across SES.

7.3 Learning prerequisites and possible variation

It is not trivial to leverage the information that the learning theory implemented in the computational cognitive model relies on from *wh*-dependencies and syntactic trigrams. More concretely, several foundational knowledge components and processing abilities must be "good enough" to scaffold acquisition of the specific syntactic island knowledge investigated here the way the learning theory assumes. First, the child must know about syntactic phrase structure; she must be able to use that phrase structure knowledge to extract the syntactic path of a *wh*-dependency in real time (including accurately identifying where the *wh*-word is understood). As noted in section 6.3, current research suggests children begin to represent the full structure of *wh*-dependencies at 20 months (Seidl et al., 2003; Gagliardi et al., 2016; Perkins and Lidz, 2020), which is why we took that age as the starting point for our modeled learner. Yet, it is possible that that there is variation across SES on when this ability is good enough for the learning theory implemented in the computational cognitive model, as there are known delays in language processing in lower-SES children compared to their higher-SES counterparts (Fernald et al., 2013).

The child must also know to break syntactic paths into smaller syntactic trigram building blocks that can be used to generate a probability for any *wh*-dependency; she must be able to identify these syntactic trigrams in real time. As with extracting the syntactic path, it is possible that a "good enough" version of this ability could be delayed in lower-SES children relative to their higher-SES counterparts because it involves language processing.

In addition, the child must know to track the relative frequency of the syntactic trigrams and know to combine these syntactic trigrams to generate the probability for a new *wh*-dependency; she must be able to do both of these in real time. These components rely on statistical learning abilities, as they involve sensitivity to input frequencies and the ability to aggregate probabilistic information. Recent work on statistical learning abilities across SES (Eghbalzad et al., 2016, 2021) found no differences by age 8. It is therefore possible that younger children across SES also would not differ in statistical learning abilities, though of course they might.

More generally, it is possible that the components reviewed above that are related to language processing are delayed in lower-SES children, while the domain-general components related to statistical learning are not. Any delays could lead to lower-SES children being less able to harness the complex syntactic information available in their input as early as higher-SES children do, even if the necessary information is in fact there (as our modeling analysis predicts it to be). However, prior child behavioral work by de Villiers et al. (2008) suggests that any delays present are surmounted by the time children are four years old when it comes to learning certain preferences about Complex NP islands, as there are no delays across SES. So, those prior behavioral results

times more probable than the dispreferred one.

suggest that it is possible more generally that the necessary prerequisites for learning about syntactic islands are good enough across SES for some amount of time before age four such that the computational cognitive model predictions here are plausible by age four.

8 Conclusion

We have aimed to provide a new approach harnessing computational cognitive modeling, complementing existing behavioral approaches, for identifying if and when variation in children's input could be developmentally meaningful. In particular, computational cognitive modeling can be used to assess if a particular measurable difference is likely to be developmentally meaningful by predicting what children should be able to learn from their input, given a specified theory of learning from that input that is implemented concretely in the model. If input variation is potentially developmentally meaningful, then the model predicts different learning outcomes; in contrast, if the input variation is not developmentally meaningful, the model predicts similar learning outcomes.

One practical benefit of this approach is that it is typically less costly in terms of time and resources to implement, compared to behavioral approaches that assess developmental outcomes and then look for correlations with children's input. However, this approach does require that reasonable samples of children's input data are available, as well as a learning theory that specifies how the input causes linguistic knowledge to develop over time. Still, with the input samples and learning theory in hand, the computational cognitive modeling approach can provide a "first pass" input variation assessment, which can predict if input differences are likely to matter. These predictions can be followed up by targeted behavioral work evaluating those predictions, and thus offer a way to guide future research relying on behavioral approaches.

To demonstrate the computational cognitive modeling approach, we applied it to input variation across SES related to the development of syntactic island knowledge. Our model predicted that there were no developmentally-meaningful input differences by age four, as similar outcomes were predicted to occur for all the island types we investigated, despite measurable input differences. One predicted developmental similarity about a specific island type aligns with prior child behavioral work, though more targeted behavioral work can confirm the precise outcome predictions for that island type as well as the predictions for the other island types. Still, the alignment of model predictions with existing empirical data both supports the plausibility of the learning theory implemented in the computational cognitive model and the plausibility of the model predictions. More generally, because the learning theory implemented in the computational cognitive model provides an explicit link between the input and linguistic knowledge development, this approach can help us better understand (i) when and why observable input differences are not predicted to be developmentally meaningful, (ii) what parts of the input are predicted to be especially important, and (iii) where those important parts appear in different input samples that reflect different linguistic input experiences.

This result broadens the body of research on linguistic input variation across SES to include the nature of the input for more complex syntactic knowledge, such as syntactic islands. To our knowledge, this is the first comparison across SES using a computational cognitive modeling approach to investigate the impact of input variation with respect to learning about the syntactic island knowledge investigated here. Our results suggest that if we do see developmental differences in syntactic island knowledge across SES, it is not because of the information available in the input. Instead, children's ability to harness that information may differ. In short, the information for learning about these syntactic islands is predicted to be there for children to use, no matter their SES – a key developmental step may instead be for them to figure out how to use it.

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A Appendices

A.1 *Wh*-dependency distribution across SES

Table A1 shows the distribution of *wh*-dependencies across the different corpora, including the lower-SES and higher-SES child-directed speech corpora, as well as higher-SES adult-directed speech and adult-directed text corpora. The *wh*-dependencies in common across all four corpora are used when calculating the Jensen-Shannon divergence analyses in Appendix B.

Table A1: Distribution of *wh*-dependencies in lower-SES child-directed speech (L-CDS) and higher-SES child-directed speech (H-CDS), as well as higher-SES adult-directed speech (H-ADS) and text (H-ADT). Percentages are shown for syntactic paths, based on the total *wh*-dependencies in each corpus, with the quantity observed in the corpus on the line below. An example of each syntactic path is given below the path. Dependencies in common across all four corpora are in **bold**. The dependency in the lower-SES CDS sample that is judged to be far less acceptable by higher-SES adults is in ***pink bold italics***.

Distribution of *wh*-dependencies in the input				
Syntactic path and example utterance	L-CDS	H-CDS	H-ADS	H-ADT
IP	10.3%	12.8%	17.2%	33.0%
Who saw it?	402	2680	1464	1396
IP-VP	75.5%	76.7%	73.0%	63.3%
What did she see?	2949	16039	6215	2677
IP-VP-AdjP-IP-VP	0.0%	0.0%	<0.1%	0.1%
What are you willing to see?	0	0	1	5
IP-VP-AdjP-IP-VP-PP	0.0%	0.0%	<0.1%	0.0%
What are you willing to go to?	0	0	1	0
IP-VP-AdjP-PP	0.0%	0.0%	<0.1%	<0.1%
What are they good for?	0	0	1	1
IP-VP-CP$_{for}$-IP-VP-PP	0.0%	<0.1%	0.0%	0.0%
What did she put on for you to dance to?	0	1	0	0
IP-VP-CP$_{null}$-IP	0.1%	0.1%	0.6%	0.3%
Who did he think stole it?	5	24	52	12
IP-VP-CP$_{null}$-IP-VP	0.9%	1.1%	0.4%	0.2%
What did he think she stole?	39	236	30	8
IP-VP-CP$_{null}$-IP-VP-IP-VP	<0.1%	0.1%	<0.1%	0.0%
What did he think she wanted to steal?	3	28	3	0
IP-VP-CP$_{null}$-IP-VP-IP-VP-IP-VP	0.0%	<0.1%	0.0%	0.0%
What did he think she wanted to pretend to steal?	0	2	0	0
IP-VP-CP$_{null}$-IP-VP-IP-VP-IP-VP-PP	0.0%	0.0%	<0.1%	0.0%
Who did he think she wanted to pretend to steal from?	0	0	1	0
IP-VP-CP$_{null}$-IP-VP-IP-VP-PP	0.0%	<0.1%	0.0%	0.0%
Who did he think she wanted to steal from?	0	1	0	0
IP-VP-CP$_{null}$-IP-VP-NP	0.0%	<0.1%	<0.1%	<0.1%
What did he think she said about it?	0	1	5	1
IP-VP-CP$_{null}$-IP-VP-NP-PP	<0.1%	0.0%	0.0%	0.0%
What did he think it was a movie of?	3	0	0	0
IP-VP-CP$_{null}$-IP-VP-PP	0.1%	0.1%	<0.1%	<0.1%
What did he think she wanted it for?	4	28	5	1

Distribution of *wh*-dependencies in the input				
Syntactic path and example utterance	L-CDS	H-CDS	H-ADS	H-ADT
IP-VP-CP$_{null}$-IP-VP-PP-PP What did he think she wanted out of?	0.0% 0	<0.1% 1	0.0% 0	0.0% 0
IP-VP-CP$_{that}$-IP What do you think that happens?	<0.1% 2	0.0% 0	0.0% 0	0.0% 0
IP-VP-CP$_{that}$-IP-VP What did he think that she stole?	0.0% 0	<0.1% 2	<0.1% 5	<0.1% 2
IP-VP-CP$_{that}$-IP-VP-IP-VP What did he think that she wanted to steal?	0.0% 0	0.0% 0	<0.1% 1	0.0% 0
IP-VP-CP$_{that}$-IP-VP-PP Who did he think that she wanted to steal from?	0.0% 0	0.0% 0	<0.1% 1	0.0% 0
IP-VP-IP Who did he want to steal the necklace?	0.0% 0	<0.1% 9	<0.1% 2	0.0% 0
IP-VP-IP-VP What did he want her to steal?	7.5% 296	5.6% 1167	3.4% 287	1.3% 57
IP-VP-IP-VP-IP-VP What did he want her to pretend to steal?	<0.1% 2	<0.1% 11	<0.1% 6	<0.1% 1
IP-VP-IP-VP-IP-VP-PP Who did he want her to pretend to steal from?	0.0% 0	0.2% 43	<0.1% 6	0.0% 0
IP-VP-IP-VP-IP-VP-PP-IP-VP What did you want to try to plan on doing?	<0.1% 1	0.0% 0	0.0% 0	0.0% 0
IP-VP-IP-VP-NP What did he want to say about it?	0.0% 0	<0.1% 6	0.0% 0	0.0% 0
IP-VP-IP-VP-NP-IP-VP What did he have to give her the opportunity to steal?	0.0% 0	0.0% 0	0.0% 0	<0.1% 1
IP-VP-IP-VP-NP-PP What did she want to steal more of?	0.0% 0	<0.1% 1	<0.1% 1	0.0% 0
IP-VP-IP-VP-PP What did she want to steal from?	0.8% 35	0.4% 74	0.4% 33	<0.1% 4
IP-VP-IP-VP-PP-PP What did she want to get out from under?	0.0% 0	0.0% 0	0.0% 0	<0.1% 1
IP-VP-NP What did she say about the necklace?	0.0% 0	0.2% 52	0.1% 10	0.1% 5
IP-VP-NP-IP-VP What did he give her the opportunity to steal?	0.0% 0	0.0% 0	<0.1% 1	<0.1% 2
IP-VP-NP-PP What was she a member of?	<0.1% 1	<0.1% 7	<0.1% 6	0.0% 0
IP-VP-PP Who did she steal from?	4.0% 159	2.5% 524	4.3% 369	1.3% 57
IP-VP-PP-CP$_{null}$-IP What did she feel like was a very good place?	0.0% 0	0.0% 0	<0.1% 1	0.0% 0
IP-VP-PP-CP$_{null}$-IP-VP What did she feel like he saw?	0.0% 0	<0.1% 1	0.0% 0	0.0% 0
IP-VP-PP-IP-VP What did she think about buying?	<0.1% 2	0.0% 0	<0.1% 3	0.0% 0
IP-VP-PP-NP	0.0%	0.0%	<0.1%	0.0%

Distribution of *wh*-dependencies in the input				
Syntactic path and example utterance	L-CDS	H-CDS	H-ADS	H-ADT
Where was she at in the building?	0	0	2	0
IP-VP-PP-NP-PP What do you put it on top of?	0.0% 0	<0.1% 2	0.0% 0	0.0% 0
IP-VP-PP-NP-PP-IP-VP What is she in the habit of doing?	0.0% 0	0.0% 0	<0.1% 1	0.0% 0
IP-VP-PP-PP What does he eat out of?	0.5% 1	0.1% 22	0.0% 0	0.0% 0
IP-VP-PP-IP-VP What did he think about stealing?	0.0% 0	<0.1% 1	0.0% 0	0.0% 0

A.2 Syntactic trigram distribution across SES

Table A2 shows the distribution of the syntactic trigrams across the different corpora, including the lower-SES child-directed speech (L-CDS) and higher-SES child-directed speech (H-CDS), as well as higher-SES adult-directed speech (H-ADS) and adult-directed text (H-ADT). The syntactic trigrams in common across all four corpora are used when calculating the Jensen-Shannon divergence analyses in Appendix B.

Table A2: Distribution of the syntactic trigrams across lower-SES child-directed speech (L-CDS) and higher-SES child-directed speech (H-CDS), as well as higher-SES adult-directed speech (H-ADS) and text (H-ADT). The 14 trigrams in common across all four corpora are in **bold**.

Distribution of trigrams in the input				
Trigrams	L-CDS	H-CDS	H-ADS	H-ADT
AdjP-IP-VP	0.0% 0	0.0% 0	<0.1% 2	<0.1% 5
AdjP-PP-end	0.0% 0	0.0% 0	<0.1% 1	<0.1% 1
CP$_{for}$-IP-VP	0.0% 0	<0.1% 1	0.0% 0	0.0% 0
CP$_{null}$-IP-VP	0.6% 49	0.7% 298	0.2% 44	0.1% 10
CP$_{null}$-IP-end	<0.1% 5	<0.1% 24	0.3% 53	0.2% 12
CP$_{that}$-IP-VP	0.0% 0	<0.1% 2	<0.1% 7	<0.1% 2
CP$_{that}$-IP-end	<0.1% 2	0.0% 0	0.0% 0	0.0% 0
IP-VP-AdjP	0.0% 0	0.0% 0	<0.1% 3	<0.1% 6
IP-VP-CP$_{for}$	0.0% 0	<0.1% 1	0.0% 0	0.0% 0
IP-VP-CP$_{null}$	0.6% 54	0.7% 321	0.6% 96	0.3% 22
IP-VP-CP$_{that}$	<0.1% 2	<0.1% 2	<0.1% 7	<0.1% 2

Distribution of trigrams in the input				
Trigrams	L-CDS	H-CDS	H-ADS	H-ADT
IP-VP-IP	4.0% 340	3.2% 1398	2.1% 353	0.9% 65
IP-VP-NP	<0.1% 4	0.1% 67	0.1% 23	0.1% 9
IP-VP-PP	2.4% 202	1.6% 698	2.5% 423	0.8% 63
IP-VP-end	38.9% 3292	39.9% 17487	38.5% 6553	37.4% 2753
NP-IP-VP	0.0% 0	0.0% 0	<0.1% 1	<0.1% 3
NP-PP-IP	0.0% 0	0.0% 0	<0.1% 1	0.0% 0
NP-PP-end	<0.1% 4	<0.1% 10	<0.1% 7	0.0% 0
PP-CP$_{null}$-IP	0.0% 0	<0.1% 1	<0.1% 1	0.0% 0
PP-IP-VP	<0.1% 3	<0.1% 1	<0.1% 4	0.0% 0
PP-NP-PP	0.0% 0	<0.1% 2	<0.1% 1	0.0% 0
PP-NP-end	0.0% 0	0.0% 0	<0.1% 2	0.0% 0
PP-PP-end	<0.1% 1	<0.1% 23	0.0% 0	<0.1% 1
VP-AdjP-IP	0.0% 0	0.0% 0	<0.1% 2	<0.1% 5
VP-AdjP-PP	0.0% 0	0.0% 0	<0.1% 1	<0.1% 1
VP-CP$_{for}$-IP	0.0% 0	<0.1% 1	0.0% 0	0.0% 0
VP-CP$_{null}$-IP	0.6% 54	0.7% 321	0.6% 96	0.3% 22
VP-CP$_{that}$-IP	<0.1% 2	<0.1 2	<0.1% 7	<0.1 2
VP-IP-VP	4.0% 340	3.2% 1389	2.1% 351	0.9% 65
VP-IP-end	0.0% 0	<0.1% 9	<0.1% 2	0.0% 0
VP-NP-IP	0.0% 0	0.0% 0	<0.1% 1	<0.1% 3
VP-NP-PP	<0.1 4	<0.1% 8	<0.1 7	0.0% 0
VP-NP-end	0.0% 0	0.1% 59	<0.1% 15	<0.1% 6

Distribution of trigrams in the input				
Trigrams	L-CDS	H-CDS	H-ADS	H-ADT
VP-PP-CP$_{null}$	0.0%	<0.1%	<0.1%	0.0%
	0	1	1	0
VP-PP-IP	<0.1	<0.1%	<0.1	0.0%
	3	1	3	0
VP-PP-NP	0.0%	<0.1%	<0.1%	0.0%
	0	2	3	0
VP-PP-PP	<0.1	<0.1%	0.0%	<0.1
	1	23	0	1
VP-PP-end	2.3%	1.5%	2.4%	0.8%
	198	671	416	62
start-IP-VP	41.4%	41.7%	41.5%	38.6%
	3502	18283	7049	2835
start-IP-end	4.7%	6.1%	8.6%	19.0%
	402	2680	1464	1396

B Input distribution comparisons

One way to quantify how similar (or not) the input distributions are for both *wh*-dependencies and syntactic trigrams across SES is to use the Jensen-Shannon divergence (**JSDiv**) (Endres and Schindelin, 2003). JSDiv values range from 0 to 1, with 0 indicating identical distributions. That is, higher JSDiv values indicate greater divergence in the distributions, while values closer to 0 indicate distributions that are more similar. In this way, JSDiv analysis provides a way to quantify similarity between distributions; this makes JSDiv analysis useful as a comparative measure, where different distributions are assessed for their relative similarity to each other.

With this in mind, we use JSDiv to assess child-directed speech in comparison to adult-directed speech and text, in order to provide a comparison baseline for the similarity across input samples of both *wh*-dependencies and syntactic trigrams. In particular, we assess how similar the lower-SES and higher-SES CDS *wh*-dependency and trigram distributions are to those in higher-SES adult-directed speech (**ADS**) and adult-directed text (**ADT**) samples from Pearl and Sprouse (2013), based on the *wh*-dependencies and syntactic trigrams in common across these corpus samples. The adult-directed corpora are described in Table A3. This JSDiv analysis can thus suggest which factors impact *wh*-dependency and syntactic trigram distributions more: SES, whether the speech is directed at children or adults, or whether the input is speech-based vs. text-based. Of course, this analysis is limited by the corpus samples available. In particular, including samples of lower-SES adult-directed speech and lower-SES adult-directed text would provide a more complete testbed for the JSDiv analysis with respect to the factors above. However, the analysis based on the currently-available samples seems a useful preliminary assessment.

***Wh*-dependencies.** Figure 5 shows the results of the JSDiv analysis for *wh*-dependencies, calculated over the distribution of the 9 *wh*-dependencies (shown in Table A4) that these four corpora had in common. We see that lower-SES CDS and higher-SES CDS are the most similar in *wh*-dependency distribution (JS: 0.00445), and appear to be twice as similar as the next closest comparison, which is higher-SES CDS vs. higher-SES ADS (JS: 0.00948). This affirms a quantitative similarity across SES in child *wh*-dependency input, in terms of *wh*-dependency distribution. Moreover, these results highlight that CDS *across* SES is more similar than CDS vs. ADS *within* SES. We can tentatively intepret this result as follows: whether the

Table A3: Corpora statistics for lower-SES CDS (L-CDS), higher-SES CDS (H-CDS), higher-SES adult-directed speech (H-ADS), and higher-SES adult-directed text (H-ADT) samples used for JSDiv analysis.

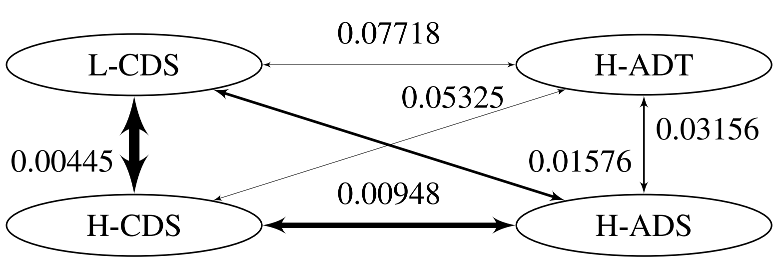
corpora	# utterances	# *wh*-dependencies	# children	ages
L-CDS	31,875	3,904	78	3 - 5
H-CDS	101,838	20,923	25	1 - 5
H-ADS	74,576	8,508	N/A	N/A
H-ADT	24,243	4,230	N/A	N/A

Table A4: The nine *wh*-dependencies shared across all four corpora that are used in the JSDiv analysis.

Shared dependencies	Example utterance	Corpora percentage
start-IP-*end*	*Who saw it?*	10.3% - 33.0%
start-IP-VP-*end*	*Who did she see?*	63.3% - 76.7%
start-IP-VP-CP_{null}-IP-*end*	*Who did he think stole it?*	0.1% - 0.6%
start-IP-VP-CP_{null}-IP-VP-*end*	*What did he think she stole?*	0.2% - 1.1%
start-IP-VP-CP_{null}-IP-VP-PP-*end*	*What did he think she wanted it for?*	<0.1% - 0.1%
start-IP-VP-IP-VP-*end*	*What did he want her to steal?*	1.3% - 7.5%
start-IP-VP-IP-VP-IP-VP-*end*	*What did he want her to pretend to steal?*	<0.1%
start-IP-VP-IP-VP-PP-*end*	*What did she want to get out from under?*	<0.1% - 0.8%
start-IP-VP-PP-*end*	*Who did she steal from?*	1.3% - 4.3%

speech is directed at children or adults matters more than whether speech is coming from a higher-SES or lower-SES population. However, as mentioned above, this interpretation would be strengthened by having samples of lower-SES adult-directed speech and lower-SES adult-directed text for a fuller comparison. Still, we note that these JSDiv results accord with intuitions that speech of any kind is more similar to other speech than it is to text: higher-SES ADS diverges more from higher-SES ADT (JS: 0.03156) than it does from either higher-SES CDS (JS: 0.00948) or lower-SES CDS (JS: 0.01576).

Figure 5: JSDiv analyses for lower-SES child-directed speech (L-CDS), higher-SES child-directed speech (H-CDS), higher-SES adult-directed speech (H-ADS), and higher-SES adult-directed text (H-ADT). Line thickness corresponds to similarity, with thicker lines indicating more similar distributions.

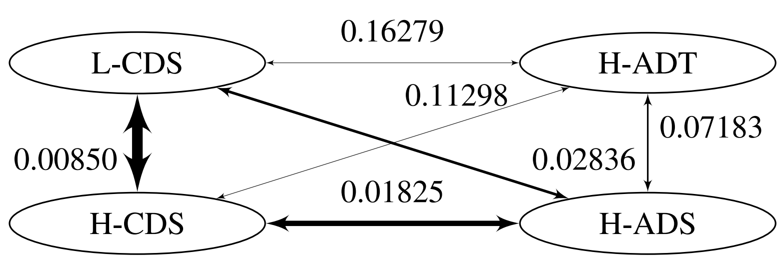


Syntactic trigrams. Figure 6 shows the results of the JSDiv analysis for syntactic trigrams, calculated over the distribution of the 14 trigrams shown in Table A5 (see Table A2 in Appendix A.2 for the full list of trigrams) that these four corpora had in common across all *wh*-dependencies. These trigrams accounted for 99.5-99.8% of the total trigrams in these corpora. As with the analysis of the *wh*-dependencies, we see the same pattern emerge: (i) lower-SES CDS is more similar to higher-SES CDS (JSDiv: 0.00850) than any other input type, and (ii) all speech is more similar to other types of speech than to text (speech vs. speech: JSDiv=0.00850-0.02836; speech vs. text: JSDiv=0.07183-0.16279).

Table A5: Distribution of the 14 syntactic trigrams across lower-SES child-directed speech (L-CDS) and higher-SES child-directed speech (H-CDS), as well as higher-SES adult-directed speech (H-ADS) and text (H-ADT).

Syntactic trigrams	Syntactic trigram percentage
CP_{null}-*IP-VP*	0.1% - 0.7%
CP_{null}-*IP-end*	<0.1% - 0.3%
IP-VP-CP_{null}	0.3% - 0.7%
IP-VP-CP_{that}	<0.1%
IP-VP-IP	0.9% - 4.0%
IP-VP-NP	<0.1% - 0.1%
IP-VP-PP	0.8% - 2.5%
IP-VP-end	38.5% - 39.9%
VP-CP_{null}-*IP*	0.3 - 0.7%
VP-CP_{that}-*IP*	<0.1%
VP-IP-VP	0.9% - 4.0%
VP-PP-end	0.8% - 2.3%
start-IP-VP	38.6% - 41.7%
start-IP-end	4.7% - 19.0%

Figure 6: JSDiv analyses for low-SES CDS (L-CDS) trigrams, high-SES CDS (H-CDS) trigrams, high-SES adult-directed speech (H-ADS) trigrams, and high-SES adult-directed text (H-ADT) trigrams. Line thickness corresponds to similarity, with thicker lines indicating more similar distributions.



Distributional analysis summary. Our JSDiv analyses suggest that the input children encounter for learning about syntactic islands is very similar across SES. In particular, both the *wh*-distributions and the syntactic trigram distributions appear quite similar, despite some individual *wh*-dependency and trigram differences.

C Predicted acceptability judgments

To aid comparison of predicted acceptability judgments across SES, the resulting log probability averages and standard deviations from 1000 model runs for each *wh*-dependency type from the stimuli are shown in Table A6. Log probability averages and standard deviations (rather than plain probability averages and standard deviations) are reported for each wh-dependency type because the probabilities are very small numbers, due to the multiplication of syntactic trigram probabilities.[15]

Table A6: Log probability averages (with standard deviations in parentheses) from 1000 model runs, representing predicted judgments, for different syntactic paths characterizing *wh*-dependencies in the stimuli from Sprouse et al. (2012). Log probabilities are generated by modeled learners learning from estimates of higher-SES child-directed speech (Higher-SES) and lower-SES child-directed speech (Lower-SES) heard through age four. Results are shown for quantity ranges of estimated input: 2 standard deviations below the average (-2 sd), 1 standard deviation below the average (-1 sd), the average (avg), 1 standard deviation above the average (+1 sd), and 2 standard deviations above the average (+2 sd). *Wh*-dependencies that are judged as more acceptable by higher-SES adults are on the top, while island-spanning dependencies (indicated with *) that are judged as far less acceptable are on the bottom.

Higher-SES log probability avg (sd)					Lower-SES log probability avg (sd)				
-2 sd	-1 sd	avg	+1 sd	+2 sd	-2 sd	-1 sd	avg	+1 sd	+2 sd
start-IP-_end_									
-1.21	-1.21	-1.21	-1.21	-1.21	-1.32	-1.32	-1.32	-1.32	-1.32
(.0011)	(.00083)	(.00072)	(.00066)	(.00060)	(.0020)	(.0014)	(.0012)	(.0010)	(.00090)
start-IP-VP-CP$_{null}$-IP-_end_									
-7.91	-7.91	-7.91	-7.91	-7.91	-8.00	-8.00	-8.00	-8.00	-8.00
(.014)	(.011)	(.0095)	(.0087)	(.0079)	(.023)	(.016)	(.014)	(.012)	(.011)
start-IP-VP-CP$_{that}$-IP-VP-_end_									
-13.80	-13.80	-13.80	-13.80	-13.80	-14.36	-14.65	-14.81	-14.93	-15.03
(.12)	(.096)	(.084)	(.070)	(.064)	(.057)	(.039)	(.033)	(.029)	(.026)
Complex NP: *_start_-IP-VP-NP-CP$_{that}$-IP-VP-_end_									
-21.40	-21.79	-22.06	-22.26	-22.43	-23.07	-23.92	-24.42	-24.79	-25.07
(.040)	(.033)	(.028)	(.024)	(.022)	(.020)	(.014)	(.012)	(.010)	(.0089)
Subject: *_start_-IP-VP-CP$_{null}$-IP-NP-PP-_end_									
-21.76	-22.15	-22.41	-22.62	-22.78	-20.73	-21.30	-21.63	-21.88	-22.07
(.018)	(.015)	(.012)	(.011)	(.0096)	(.023)	(.017)	(.014)	(.013)	(.011)
Whether: *_start_-IP-VP-CP$_{whether}$-IP-VP-_end_									
-20.98	-21.56	-21.96	-22.27	-22.52	-19.75	-20.59	-21.09	-21.46	-21.75
(.00067)	(.00054)	(.00046)	(.00042)	(.00037)	(.0011)	(.00082)	(.00071)	(.00057)	(.00054)
Adjunct: *_start_-IP-VP-CP$_{if}$-IP-VP-_end_									
-20.98	-21.56	-21.96	-22.27	-22.52	-19.75	-20.59	-21.09	-21.46	-21.75
(.00067)	(.00054)	(.00046)	(.00042)	(.00037)	(.0011)	(.00082)	(.00071)	(.00057)	(.00054)

We first observe that the standard deviations are always quite low, which reflects the consistency with which the modeled learners converge on these predicted probabilities, given the different input

[15]For log probabilities, less negative numbers are equivalent to higher probabilities. For example, log(.001) = log(10^{-3}) = -3, while log(.000001) = log(10^{-6}) = -6.

sets that were learned from. We can also see that the input quantity differences within SES seem to matter less than the input *wh*-dependency distribution across SES. For instance, higher-SES results for the more acceptable *wh*-dependencies (top of Table A6) are identical across the entire range of input quantities (from 2 standard deviations below the average to 2 standard deviations above). Notably, these final log probabilities differ from the lower-SES results for the same *wh*-dependencies, though the lower-SES results differ little from themselves across the range of input quantities.

We note also that the results for Whether and Adjunct island-spanning *wh*-dependencies are identical for a given input quantity and SES class (e.g., the log probability for 2 standard deviations below the input average for higher-SES = -20.98). This is because the syntactic paths for these *wh*-dependency types are identical except for the complementizer used (CP$_{whether}$ vs. CP $_{if}$). Because both these complementizers never appear in *wh*-dependencies in children's input (either higher-SES or lower-SES), the syntactic trigrams using those complementizer building blocks have the same very low probability that is assigned to trigrams that are never observed in the input.

More generally, we can also observe that a core pattern emerges when learning from either higher-SES or lower-SES child-directed speech: all dependencies judged as more acceptable by higher-SES adults have higher probabilities (equivalent to less negative log probabilities) than the island-spanning dependencies. In particular, dependencies judged as more acceptable have log probabilities ranging from -1.21 to -15.03, while island-spanning dependencies range from -19.75 to -25.07. So, even the least acceptable dependency that does not span an island (with log probability -15.03: Lower-SES, +2 sd, *start*-IP-VP-CP$_{that}$-IP-VP-*end*) is predicted to be much more acceptable than the most acceptable dependency spanning an island (with log probability -19.75: Lower-SES, -2 sd, *start*-IP-VP-CP$_{whether/if}$-IP-VP-*end*). (For this particular comparison, the more acceptable dependency has a probability $\frac{10^{-15.03}}{10^{-19.75}} \approx 52,481$ times higher.) We note that because human acceptability judgments likely rely on additional factors beyond *wh*-dependency probability, the exact "amount" of relative acceptability may not map directly to human acceptability judgments. However, following Pearl and Sprouse (2013), we assume that the probability of a *wh*-dependency is a significant component of its judged acceptability, and so we expect the relative patterns of acceptability to hold (i.e., which *wh*-dependencies are judged more vs. less acceptable), as indicated by these predicted probabilities.