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# Do We Need Natural Language? Exploring Restricted Language Interfaces for Complex Domains

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## ABSTRACT

Natural language interfaces (NLIs) that aim to understand arbitrary language are not only difficult to engineer; they can also create unrealistic expectations of the capabilities of the system, resulting in user confusion and disappointment. We use an *interactive language learning game* in a 3D blocks world to examine whether limiting a user's communication to a small set of artificial utterances is an acceptable alternative to the much harder task of accepting unrestricted language. We find that such a restricted language interface provides same or better performance on this task while improving user experience indices. This suggests that some NLIs can restrict user languages without sacrificing user experience and highlights the importance of conveying NLI limitations to users.

## INTRODUCTION

Due to recent advances in natural language processing, machine learning, and speech recognition [8], *natural language interfaces* (NLIs) have become a major medium of human-computer interaction (HCI). As voice assistants such as Siri and Alexa master simple one-shot commands (e.g. *what's the weather?*),

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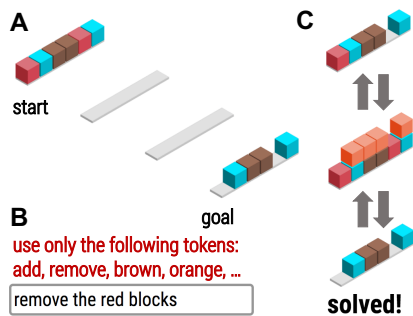
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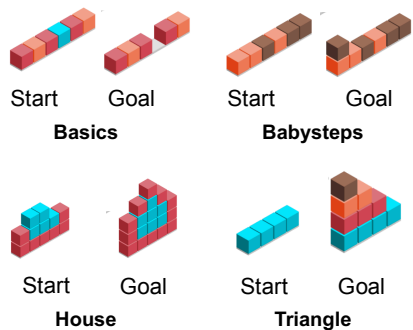
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## KEYWORDS

natural language interfaces; user experience;  
speech technology; chatbots



**Figure 1: SHRD LURN.** A: Game with *start* and *goal* states and 2 intermediate states. B: The player issues a language command. "use only..." message appears only for players in restricted condition. C: The player scrolls through candidate configurations until she finds the one matching the meaning of the utterance. The correct interpretation (bottom) solves the puzzle.



**Figure 2: Example SHRD LURN levels.** Earlier levels (top row) are substantially easier than later levels (bottom row), which rely on abstractions learned earlier.

the next frontier of NLI is more complex, multi-step domains such as analyzing and visualizing data [4], text [10], and images [11], querying databases [2], and controlling robots [14]. These NLI must learn to map ambiguous human language to precise computer actions in a collaborative dialog where the user's goal is continuously updated and expanded.

Arguably, not a single NLI today has achieved human-level abilities in these settings, as natural language understanding is a notoriously difficult problem [8]. However, little existing work in HCI examines whether such broad-coverage language interfaces for these domains are actually desirable from a user experience perspective. While NLI are thought to have several benefits *prima facie*, such as familiarity and flexibility [7, 16], several studies have demonstrated worrying user experience issues with current-generation personal assistants due to mismatches between user expectations and system capabilities [3, 12]. These problems could be compounded in the aforementioned domains where quickly understanding the underlying logic of the system is crucial for productivity.

For complex, multi-step domains, is it possible to preserve the advantages of language interaction while better guiding user behavior (and freeing researchers from the burden of handling unrestricted language)? In this work, we explore whether users prefer true NLI compared to a simpler, "restricted" language interface. We study an *interactive language learning game* [15] (Figure 1) where a user and a state-of-the-art natural language processing system jointly develop a language from scratch to build structures in a toy blocks world, and either (1) freely develop their own language or (2) are restricted to a small quasi-language of well-defined utterances which mirror the computer action space.

We find that restricting user languages to be artificially simple results in same or even better task performance, and even unrestricted users tend to organically prefer simpler languages and perform better as a result. Crucially, restricted languages also significantly improve user experiences in the task, reducing cognitive load and perceived effort while increasing perceived performance. These results suggest that for some well-specified domains, guiding users towards consistent, artificial languages can improve user experience while simultaneously making NLI design and engineering far easier.

## RELATED WORK

Research into user experiences of voice- and natural language-based interfaces has been historically scarce [1]. Studies have assessed experiences and expectations with commercial products such as Alexa and Siri [3, 12, 13] and so are limited by the relatively simple services they currently provide.

NLI for more complex, domain-specific tasks have often assumed various advantages of natural language interaction: they eliminate the need to learn a specialized programming language [4, 10] or advanced GUI [11] and can more succinctly convey abstract behavior [14]. Some user studies have demonstrated increased satisfaction with NLI compared to a non-linguistic baseline [11].

**Table 1: SHRD LURN logical primitives. Primitives are recursively composed into candidate actions  $Z_i$  (e.g. `add(red, cyan)`, `remove(except(brown))`).**

Primitive	Description
<code>all</code>	all blocks
<code>cyan, red, brown, orange</code>	colors
<code>except(B)</code>	all blocks except $B$
<code>leftmost(B)</code>	leftmost block of $B$
<code>rightmost(B)</code>	rightmost block of $B$
<code>add(B; C)</code>	add color $C$ to $B$
<code>remove(B)</code>	remove $B$

<sup>1</sup>Amazon Echo launch trailer; youtube.com/watch?v=FQn6aFQwBQU

**Effort:** How hard did you have to work (mentally and physically) to accomplish your level of performance?

**Frustration:** How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?

**Mental Demand:** How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex?

**Performance:** How successful were you in performing the task? How satisfied were you with your performance?

**Figure 3: NASA-TLX Scale Descriptions**

The evidence for the benefits of NLI in these domains compared to specialized programming languages or GUIs is strong. However, we aim to formally examine whether truly “natural” language is desirable. In doing so, we build on previous work designing effective dialogue systems [5, 9].

## SHRD LURN: INTERACTIVE LANGUAGE LEARNING GAME

Our testbed is SHRD LURN [15], an interactive language learning game where a human and computer develop a language to manipulate blocks from start to goal configurations in an artificial world (Figure 1). The game is inspired by classic work on language interfaces and interaction (SHRD LU; [16]). Following Wang et al. [15], we study this game as it shares the complex and compositional nature of many real-world tasks. Additionally, the underlying logical language of the computer is hidden from the user, which mimics current NLI where users are encouraged to *give [any] command*.<sup>1</sup>

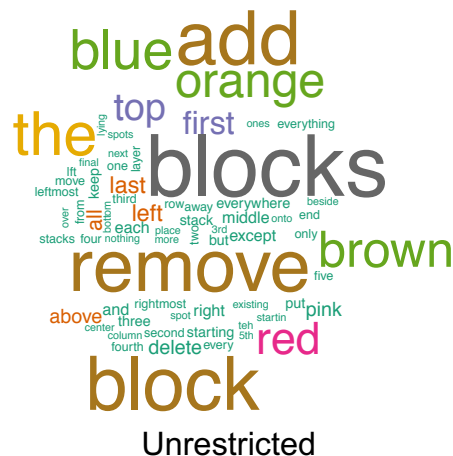
### Formalization

Formally, let  $\mathcal{Y}$  be the set of possible configurations of blocks. In each SHRD LURN level, human and computer are presented with a *start* state  $s \in \mathcal{Y}$ , while only the human observes a *goal* state  $t \in \mathcal{Y}$ . The task of the human is to transform the *start* configuration into the *goal* configuration with a sequence of language commands  $\langle x_1; \dots; x_n \rangle$ .

For each utterance  $x_i$ , the computer constructs a set of possible *actions* corresponding to the meaning of the utterance,  $Z = \langle z_1; \dots; z_k \rangle \subseteq \mathcal{Z}$ , ranked by their plausibility, where  $\mathcal{Z}$  is the set of actions in the game. It then computes the set of successor states  $Y = \langle y_1; \dots; y_k \rangle \subseteq \mathcal{Y}$ , where  $y_i = z_i \circ s$  is the result of applying action  $z_i$  to the current state  $s$ . The human chooses the successor state  $y_i$  corresponding to the meaning of the utterance  $x_i$ . The state then updates  $s = y_i$  and the computer updates its parameters with the known utterance-state pair  $\langle x_i; y_i \rangle$ . The level ends when  $s = t$ . Note that the human never observes the actions  $Z$  and instead must build a mental model of the system’s capabilities, similar to existing natural language interfaces whose underlying mechanisms are hidden to the user. Figure 1 depicts the user interface for this process.

The action space  $\mathcal{Z}$  is defined by a simple grammar corresponding to adding and removing blocks of color  $C \in \{\text{red}; \text{orange}; \text{cyan}; \text{brown}\}$  to the top of a set of stacks of blocks  $B$ , where  $B$  is recursively specified with operators such as `all`, `leftmost(B)`, and `except(B)` (Table 1).

The semantic parser in SHRD LURN is a simple log-linear model over logical forms given lexical features of an utterance (e.g. bigrams, trigrams). It initially knows nothing, but is designed to learn quickly via efficient gradient descent updates. Generally, the system only needs one or two uses of an utterance such as *remove the red blocks* to learn the mapping to `remove(red)`. Thus, users are generally much quicker at completing later levels of a stage than earlier levels, and consistent and efficient use of language can greatly increase task performance. There are 27 levels in the game, with



**Figure 4: Unique tokens used by participants in restricted and unrestricted conditions. Size indicates frequency.**

<sup>2</sup>Defined as the negative log likelihood of the logical forms given utterances under the model.

later levels depending on abstractions learned in the earlier levels (examples in Figure 2). For full details, see Wang et al. [15].

## METHOD

We recruited 16 participants (14 male; 2 female), all graduate students and recent college graduates from the US and UK. We evenly divided these participants into two conditions:

In the *unrestricted* setting, users were instructed to communicate to the system using any language of their choice;

In the *restricted* setting, user utterances were restricted to contain only combinations of the 11 tokens corresponding to the logical SHRDLURN primitives: all, cyan, red, brown, orange, except, leftmost, rightmost, add, remove, plus the connective to. Utterances with other tokens were rejected and users were asked to try again via the prompt in Figure 1.

## Measures

For each utterance, the computer produces a list of possible interpretations ordered by likelihood, and the user must *scroll* through interpretations to find the correct state (the computer is *correct* if the user does not have to scroll at all). We thus used the *number of positions scrolled* as a performance metric: the fewer positions scrolled, the smaller the gap between the user’s intended meanings and the computers’ inferred interpretations. This serves as a proxy for the *surprisal* of the system [15].<sup>2</sup>

To measure subjective experiences in the task, we use the Raw NASA-TLX survey post-experiment [6], using the **Effort**, **Frustration**, **Mental Demand**, and **Performance** scales (Figure 3), dropping the Temporal and Physical scales as they were unrelated to the task.

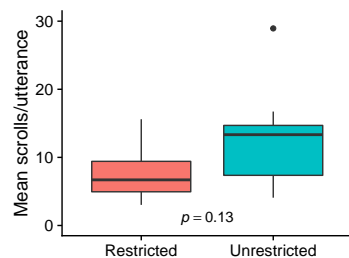
## RESULTS

Participants played all 27 levels of SHRDLURN, taking 15 minutes on average. Across all participants, we collected 585 utterances, averaging 36:6 4:18 utterances per participant.

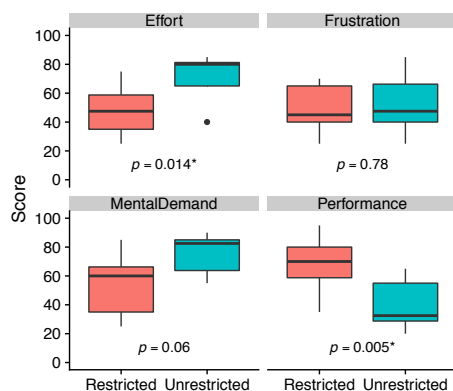
Unsurprisingly, the languages developed in the restricted setting were simpler, with a mean length of 3:36 1:10 tokens versus 5:12 1:80 ( $t^{1497:6^{\circ}} = 14:3; p < 0:0001$ ). Each restricted participant used all 11 tokens available, compared to the average 28:8 7:17 distinct tokens used by unrestricted participants (Figure 4). These simpler languages seemed to translate to same or better task performance (Figure 5): restricted participants needed an average of 7:63 4:11 scrolls per utterance, compared to unrestricted users’ 12:9 7:98 scrolls, but the difference was not significant ( $t^{110:5^{\circ}} = 1:66; p = 0:13$ ).

Figure 6 depicts the distribution of NASA-TLX question responses for users in the restricted and unrestricted conditions. For many questions, significant differences were seen in user responses: restricted users reported less required effort (48:8 17:5 vs. 72:5 15:4; Mann-Whitney  $U = 9; n_1 =$

<sup>3</sup>Ties broken with the *mid-rank* method.



**Figure 5: Mean scrolls/utterance for users in restricted and unrestricted conditions. Lower scores indicates less model surprisal and thus higher task performance.**



**Figure 6: NASA-TLX scores for users in restricted and unrestricted conditions.**

$n_2 = 8; p = 0:014$ )<sup>3</sup> and *perceived* their task performance to be higher (66:9 20:3 vs. 39:4 16:6;  $U = 57; p = 0:005$ ). Mental demand also appeared to be lower, though the difference was not quite significant (54:4 20:8 vs. 75:6 13:5;  $U = 14; p = 0:06$ ). There was no significant difference between reported task frustration (49:4 15:7 vs. 52:5 19:5;  $U = 29; p = 0:78$ ).

Finally, we qualitatively analyze the communication strategies (in the unrestricted setting) that lead to good task performance. Table 2 displays utterances made by the most and least successful players in the unrestricted condition, with a restricted player for reference. The best player uses consistent language and logical specifiers remarkably similar to the restricted language setting. Although the player does not use the exact tokens corresponding to the logical language, the system still comfortably learns, for instance, to map *first* to *leftmost* and *last* to *rightmost*. The low-performance player uses nonsensical utterances (*move nothing*) and multiple specification systems (e.g. *all except blue* vs. *fifth*).

## DISCUSSION

We investigated users playing an interactive language learning game in a toy blocks world. By imposing restrictions on how users communicate, we found that artificial languages tend to result in same or better task performance (Figure 5) without detriment to user experience: in fact, participants reported *less* effort and higher performance in the restricted condition (Figure 6). Qualitatively, we also showed that users that organically developed simpler languages tended to perform better (Table 2).

These results are partially unsurprising, since players in the restricted condition are forced to be perfectly consistent, which improves model learning. However, we also hypothesize that a guided, consistent language helps users understand the limitations of the system and, within these constraints, infer the abstractions needed to succeed in the task.

These preliminary results come with some limitations. First, these experiments are more relevant for text-based NLI, since text input is more amenable to restriction and shorthand than voice communication. Second, they are limited to well-specified domains with finite action spaces, unlike open-ended tasks such as unrestricted question answering.

Indeed, our intent is not to suggest that full human-level language capabilities will never be desired in future NLI. We instead argue that given the capabilities of current NLI, we will see diminishing returns in user experience and performance by attempting to accommodate arbitrary natural language input, especially for repetitive, compositional tasks like SHRDLURN. More generally, rather than considering only two extremes—a specialized programming language or GUI versus a human-level language understanding system—designers should consider “restricted” language interfaces which trade off full expressivity for simplicity, learnability, and consistency. We have not fully explored the range of options in this work, but as our initial results show, such systems may not only be easier to build: they may even preserve the benefits of natural language interaction while helping users better understand the system, improving user experience as result.

**Table 2: Sample utterances for the best and worse unrestricted players, with a restricted player for comparison.**

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**Player 1/8** (Mean scrolls/utterance: 4.08)

add blue blocks to blue blocks  
 add red block on the last orange stack  
 remove last red block  
 remove top orange blocks  
 remove first red block

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**Player 8/8** (Mean scrolls/utterance: 28.9)

move nothing  
 move all but blue  
 move all but red  
 remove 5th  
 remove first

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**Restricted Player** (Reference)

remove brown  
 add brown to cyan  
 remove all except leftmost brown  
 add rightmost red  
 add leftmost red

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