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Extracting Information for Creating SAPPhIRE Model of Causality from Natural Language Descriptions

Kausik Bhattacharya[1*], Apoorv Naresh Bhatt[1], Ranjan B.S.C.[2], Sonal Keshwani[2], Srinivasan V.[3], Amaresh Chakrabarti[1]
[1]*Indian Institute of Science, Bangalore*
[2]*Dayananda Sagar University, Bangalore*
[3]*Indian Institute of Technology Delhi, New Delhi*
[*] *kausikb@iisc.ac.in*

Abstract

Structured representations from natural language descriptions of biological and engineered systems are a good source of inspiration in analogical design. Researchers proposed methods for developing knowledge representations from such documents, to make them conducive for use as a source of analogy. Ontology-based representations, such as FBS, SBF, SAPPhIRE, etc. are effective in analogical design, but manually creating accurate descriptions using these models is both time- and resource-intensive. Hence, methods to automatically create ontology-based representations are useful for developing a repository of biological and engineered systems. However, such methods are partially automated, with major human decision-making touchpoints. Before standardizing and automating the process, it is important to understand it end-to-end for accuracy and variability. This paper reports results from a detailed study on manual information extraction from systems description texts, using the SAPPhIRE model. A new process is proposed that aims to reduce variability in the extracted information across subjects, with preliminary results that show significant promise.

Design Computing and Cognition DCC'22. J.S. Gero (ed), pp. xx-yy. © Springer Nature

Introduction

This paper presents a study on the process for extracting information that is relevant for creating causality descriptions using the SAPPhIRE model from natural language descriptions of biological and engineered systems. Understanding such a process is essential to choose right automation strategy for creating an ontology-based representation from descriptions in natural language for analogical design. The goals of this research are: (1) to understand the process of creating causality descriptions using the SAPPhIRE model from descriptions in natural language and (2) to develop a new, generalized process of extracting information of entities of the SAPPhIRE model from descriptions in natural language. The paper starts with a brief introduction that explains the design-by-analogy as an essential method for design creativity and gives a quick overview of its various support. It explains the importance of converting a natural language description of a system into a ontology-based data representation, reports research on method for this conversion and presents new research opportunities. The paper then presents the research questions, work done and the results. The paper ends with a conclusion which includes an outline of the next step in this research.

Design Creativity and Design by Analogy

A design is a means for changing existing situations into preferred ones [1]. Creativity in design is often characterized as a process by which an agent uses its ability to generate something that is novel and useful [2]. Researchers also studied the influence of different design methods on creative design outcomes [6] and developed methods for enhancing creative ideation in design. Literature provides evidence that the presence of a stimulus can lead to the generation of more ideas [4]. Systematic use of knowledge from both artificial and natural domains helps designers generate a variety of solutions and develop them into realizable and practical prototypes [7]. "Design-by-Analogy is the process of developing solutions through mapping of attributes, relations, and purposes that a source problem or situation may share (or at least partially share) with an existing target solution or situation" [8]. Many empirical studies were conducted to understand the process and factors influencing the effectiveness of Design-by-Analogy [3, 4, 9, 10, 11, 12]. Representation of stimulus plays an important role in Design-by-Analogy [15, 16] and it can reduce fixation and enhance designers' creativity during idea generation [13, 14, 17, 18].

Support for Design by Analogy

Search for Analogue(s) is a key step in the Design-by-Analogy process [19], and finding relevant and good analogues directly influences the design outcome. Many pieces of support are developed to facilitate Design-by-Analogy, including with the recently developed powerful techniques of AI and Data Sciences [20, 21]. In this paper, an outline of the commonly cited Design-by-Analogy support from literature is provided.

Support like Functional Model database [22] and AskNature [23] use a function-based approach to identify analogues from a database. The Functional Model database has an engineering-to-biology thesaurus that maps biological terms to the functional basis of technical systems. AskNature categorizes the information of the biological functions according to the four layers of Biomimicry Taxonomy (Group, Sub-group, Function, Strategy). Biological models are mapped into different engineering fields using "strategy". Analogy Retriever [24] uses 16 ontological relationships to describe the connections between various system entities. This supports analogical reasoning for creative idea generation by solving proportional analogy problems.

On the other hand, support like Functional Vector [25] and SEABIRD [26] use vector space method to find analogue based on semantic similarity of words. In the Functional Vector model, a query vector of functions is generated. A relevancy score of the query with a functional vocabulary is calculated using a patent database. SEABIRD method generates the Product Aspects (PA) and Organism Aspects (OA) matrices from a database of technical system documents and biological functions. Mapping between two domains is then quantified based on the values from the mathematical product of the PA and OA matrices.

There is a third category of support, like DANE [27] and IDEA-INSPIRE [28], which use ontology-based data models. DANE uses data query at multiple levels of abstractions in a controlled database comprising structured data models of SBF (i.e., Structure-Behavior-Function) [29]. In SBF, 'Structures' are the constituent components and substances and relations among them; 'Behavior' is the series of state changes from an input to an output state, and the transition from one state to another happens through functions. 'Function', therefore, is used as a behavioral abstraction. In IDEA-INSPIRE, the search strategy uses single or multiple levels of abstraction of the SAPPhIRE model [28]. The SAPPhIRE model has seven layers of abstraction, namely, State Changes, Actions, Parts, Phenomena, Inputs, oRgans, and Effects. They cover the physical components of the system and interface and their interactions, along with the structural context and the scientific law that governs them. The SAPPhIRE model with an example (heat transfer from a hot body to cool surrounding air) is shown in Figure 1.

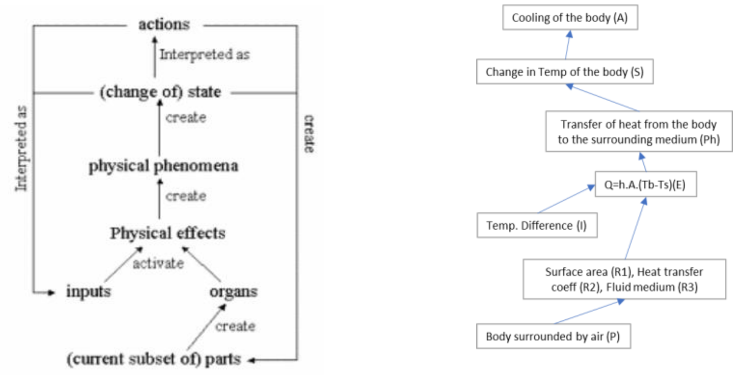

Figure 1 – SAPPhIRE model of causality with an example of heat transfer from a hot body to cool surrounding air [28]

Structured Representation from a Natural Language description

Generating large number of stimuli and maintaining diversity and variety of content, are important requirements along with ‘Abstraction’, ‘Mode of representation’, and ‘Open-endedness’ of the cases in any Design-by-Analogy database [35, 37]. Though ontology-based models are very effective, they are hand crafted and limited in number. On the other hand, there is an abundant source of knowledge of biological and technical systems, available in the form of technical documents and many websites. However, such information or data are unstructured because they are not associated with any specific format or data model. Structured data has a schema or model that defines how the data is organized [43]. Since structured data are preferred in Design-by-Analogy because of computational advantages, researchers proposed methods using the numerical techniques of AI and Data Sciences that can generate structured data or knowledge representation from information given in natural language descriptions [20]. Semantic networks are considered as effective for knowledge representation from vast data sources and hence many such networks were developed [38]. While working with Engineering examples, TechNet could be better than other common sense semantic networks such as WordNet or ConceptNet [39]. However, all the literature pointed out that more study is needed with TechNet or any similar networks. Despite huge potential of knowledge graph as knowledge representation from vast NLP data, they are limited by construction effort, evolvement, and portability [41]. Another knowledge graph-based representation was developed using a rule-based approach for engineering examples which was found to be large and scalable compared to publicly available Knowledge graphs [40].

However, these knowledge graph or Semantic networks do not provide any abstraction levels as such and can't explain the system causality. Ontology models have many advantages in analogical reasoning. They can provide multiple level of abstractions of a system and can be used to explain the system functions [44]. Results show that ontology-based models, such as SAPPhIRE or SBF, are very effective in design ideation [7, 36]. So, numerous techniques were developed to automatically create ontology-based representation of texts. One such Natural Language Programming (NLP) based technique was developed to find causal relations between biological functions using a linguistic pattern of biologically meaningful keywords [31]. It progressively refines search keywords until a suitable match is found. A simple template is used to capture causal relations of biological functions from a sentence in natural language [45]. Another support called IBID (Intelligent Bio-Inspired Design), was developed for the conversion of natural language description into SBF [32]. IBID uses a combination of a knowledge-based and machine learning-based approach to extract and represent the knowledge using the SBF model. This work on IBID reported a detailed comparative study of multiple machine learning algorithms used to classify knowledge using Structure, Behavior and Function tags. In another research, a four-step process for converting natural language description into descriptions using SAPPhIRE model was reported [12, 33]. In this work, all the sentences with potential SAPPhIRE constructs are extracted and then split into words or collections of words. A Support Vector Machine based classifier is used to classify the SAPPhIRE label of each word or collection of words.

Research Questions and Research Methodology

Opportunities for research

All these different kinds of support proposed in literature for creating an ontology-based data model from natural language text, uses supervised learning with hand-annotated data for training and validation. However, none of these explain how the hand-annotated data were created. These support are semi-automated with many major decision-making touchpoints. The end-to-end process for creating such structured data model from a natural language description and its overall accuracy have not been reported.

Therefore, the main factors that influence creation of ontology-based models and how to validate them, are not adequately researched. An empirical study, comparing three approaches, namely keyword search using Ask Nature (handcrafted database), NLP- based approach (unstructured corpus) and one where Biologists manually perform the search in literature, reports that though NLP- based technique is very promising, it is currently error prone [34].

Research Questions

Therefore, the main question posed in this research is 'How can we create an accurate and repeatable ontology-based data model from a natural language description?' The assumption is that without the conversion process being accurate and repeatable, the process cannot be automated. We divided this research question into two sub-questions for the first part of this research:

1. What is the current process of developing a structured data model from a given natural language document, and what are the issues?
2. What should be a process for creating a structured data model based on the information given in a natural language document that overcomes these issues?

In this research, we used the SAPPhIRE model to represent the causality of the final outcome. The SAPPhIRE model captures the details of a system through its seven levels of abstraction, namely, State Changes, Actions, Parts, Phenomena, Inputs, oRgans, and Effects, and the causal relations between these entities. The SAPPhIRE model can describe the working of both natural and engineered systems, scalable for complex systems through multi-instance modelling and can help produce rich, comprehensive descriptions [30]. It can be used in both Analysis and Synthesis of Design, including for novel ideation [30, 35] and for transfer in Biomimetics [19].

Research Methodology

To answer the first sub-question, an Intercoder Reliability (also known as Inter-Encoder Reliability) study was carried out to create descriptions of systems using the SAPPhIRE model from their descriptions in natural language. To build a description of a system using the SAPPhIRE model from its natural language description, the main step is to extract the SAPPhIRE construct-specific information from the description in natural language. Hence in the second sub-question, a major focus has been on the process for this information extraction. Based on the lessons from the Intercoder Reliability study, we proposed a generalized process for extracting SAPPhIRE information from a description in natural language, with an aim to at least reduce, if not eliminate, the variability in the interpretation of the information given in a natural language description. Before continuing further, user trials were conducted for validation of the process. The results of these user trials should help understand whether the new process is in the right direction of addressing current issues and which areas need to be worked on further.

Intercoder Reliability Study

Goals of the Study

The goals of this Intercoder Reliability study were the following:

- What was the degree of agreement between two or more researchers creating descriptions of systems with the SAPPhIRE model from the given descriptions in natural language?
- What were the issues that researchers faced while creating descriptions of systems with the SAPPhIRE model from the given descriptions in natural language?

Study Procedure

For the first research question, a study was conducted with four researchers, each having a minimum of 4 years of experience in using the SAPPhIRE model for their own research. Each researcher was given the description in natural language for 4 systems (we call each description 'a sample') and was asked to create a description using the SAPPhIRE model for each system. Intercoder Reliability score was then calculated based on the word/group of words identified for each SAPPhIRE construct in each sample. We calculated the Intercoder Reliability Score for a given sentence and aggregated score for all the sentences in each sample. The '*% Intercoder Reliability*' score of a sentence is calculated as:

$$\frac{Total\ number\ of\ SAPPhIRE\ clauses\ agreed\ at\ (a)\ 75\%\ and\ (b)\ 50\%\ levels}{Total\ number\ of\ ALL\ SAPPhIRE\ clauses\ identified\ by\ all\ researchers} X\ 100$$

We calculated the score at the following two levels:

a) 75% level: here, we consider those words for which three or more out of 4 researchers agreed with the words and their labels
b) 50% level: here, we consider those words for which two or more out of 4 researchers agreed with the words and their labels

The above calculation is illustrated here with this sentence – "Respiration can be a significant cause of water loss". This sentence was part of one of the four samples. The four researchers together identified the SAPPhIRE words as given in Table 1:

Table 1 – SAPPhIRE constructs identified by researchers in a sentence, "Respiration can be a significant cause of water loss"

Word(s)	**SAPPhIRE constructs** (identified by four researchers)			
	Action	Phenomenon	State Change	Explanation
Respiration	1	3		3 out of 4 agreed that 'Respiration' is a Phenomenon and 1 felt it is an Action
Water loss	1		2	2 out of 4 agreed that 'Water loss' is a State Change and 1 felt it is an Action and 1 didn't assign any label

From Table 1, we can observe that:

- Three or more researchers agreed with only one word (i.e., 'Respiration as a Phenomenon)
- Two or more researchers agreed with both words (i.e., 'Respiration' & 'water loss' as Phenomenon and State Change respectively)

Hence, we can compute the score as follows in Table 2:

Table 2 – Intercoder-Reliability score of a sentence, "Respiration can be a significant cause of water loss"

Total # of Words	3 or more of 4 researchers agreed		2 or more of 4 researchers agreed	
	Count	%	Count	%
2 (Respiration, Water loss)	1 (Respiration)	50%	2 (Respiration, Water loss)	100%

Samples used in the Intercoder Reliability study and Results

Designers typically look at large number of short descriptions of biological or engineered systems and hand pick the relevant ones for which later they seek more details. Such short descriptions are usually about 'how a system works' and therefore has causal information. Four samples (natural language descriptions of four systems) used in the study are 'Elephant Turbinate', 'Bombardier Beetle', 'Thermal Wheel' and 'Electric Horn' and represented by the sample ID 'EG1', 'EG2', 'EG3' and 'EG4' respectively. The contents of these samples were hand curated with information taken from the commonly available websites such as howstuffworks.com, asknature.org or Wikipedia etc. The details of these samples are available at https://github.com/kausikbh/DCC22_SAPPhIRE_Data . The final summary of the Intercoder Reliability score of all four samples is given in Table 3.

Table 3 – Intercoder Reliability score of all 4 samples

Sample ID	**Total # of Words**	**3 or more out of 4 researchers agreed**		**2 or more out of 4 researchers agreed**	
		Count	**%**	Count	**%**
EG1	71	6	8%	21	30%
EG2	69	2	3%	8	12%
EG3	68	1	1%	6	9%
EG4	221	2	1%	22	10%
Overall	429	11	3%	57	13%

The results above indicated disagreement among the researchers on deciding about the SAPPhIRE information in each sample. Hence workshops were conducted with the 4 researchers to collect feedback and identify the root causes for the differences. Based on the workshop, the following key root causes were identified:

- Differences in natural language interpretation among the researchers, leading to multiple representations of the same information given in a natural language text.
- Often natural language text does not have enough information to complete the model, but there is no standard way of assessing the information gaps and how to fill the gaps.
- The definition of the SAPPhIRE constructs is not applied consistently due to perceptual differences among humans. This leads to interpretational differences of the same definition.
- The text in natural language often describes the technical process at a high level and does not mention the underlying physical principles. As a result, different technical or scientific terminologies were used to represent the same physical behavior by the researchers.

For the final root cause, an observational study was conducted to share the benefits of using a catalogue of physical laws and effects [5]. It was found that the use of standard terminologies reduced the total number of SAPPhIRE words to describe a model by 28% by increasing the use of common words to represent the same physical behavior. Please note that while low Intercoder Reliability does not necessarily indicate lack of accuracy but lack of consistency. For instance, ‘how a pendulum works’ can be written in different physics books in different details; while all may be accurate descriptions, not all may be consistent with one another.

Proposed Process

We developed a new process for extracting the SAPPhIRE construct-specific information from a natural language description. In this new process, we propose the following:

1. Knowledge graphs are found to be very powerful for knowledge representation from large natural language documents [38]. Hence Knowledge graphs is used in this process as a standard way of representing the information extracted from a natural language text to reduce any interpretational differences of natural language document.
2. Rule-based reasoning applied to a knowledge graph simulates human reasoning ability and allows incorporating prior knowledge to assist in reasoning [42]. Hence a set of SAPPhIRE construct-specific standard rules is developed to identify candidate words for each SAPPhIRE construct. This will help in applying the definition of the SAPPhIRE constructs consistently.
3. Use of a standard vocabulary of physical laws is proposed in the new process, to avoid use of different words or terminologies that represent the same physical behavior. However, more work is needed to implement this.

Process descriptions

The process flow diagram of the new generalized process is shown in Figure 2. Though the process flow diagram has the provision for all the features mentioned above, the first version of the process implemented only the first two features (i.e., Knowledge Graph and rules). Here, we first convert all compound sentences into simple ones by splitting them into independent sentences. Then we identify the Parts-of-Speech (POS) tag of every word. Once pre-processing is completed, a knowledge graph is generated using the POS tags of the words and their syntactic relationships. The objective of the knowledge graph is to represent the information given in the natural language description in a common format so that extracting information later, relevant for a particular SAPPhIRE construct, becomes easy. POS tags that are used in building the knowledge graph are (a) Nouns, (b) Verbs (we distinguish transitive and intransitive verbs), (c) Adjectives, (d) Adverbs, (e) Prepositions, and (f) Conjunctions. POS tagging is done in the following sequence. For each sentence, first the verb(s), subject(s) and object(s) are identified. Then other relations between the words (e.g., Nouns connected through prepositions, Adjectives with Nouns and Adverbs with Verbs) are identified. Then any Conjunction, Adverb or Preposition that connect two independent clauses (a sentence or a group of words that has its own meaning) are identified, and finally, the sequence of actions (transitive verbs) as given in the natural language description are identified.

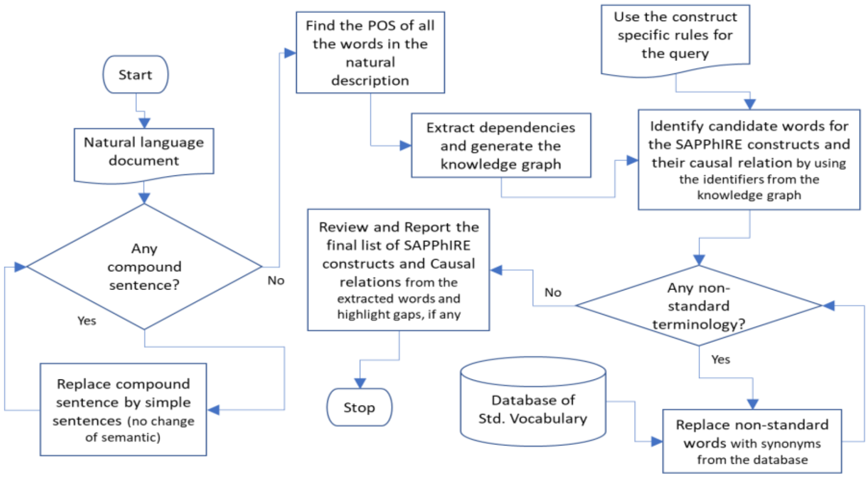

Figure 2 - Process for extracting information from a natural language description

Through the steps explained above, we capture the following three types of information in the knowledge graph,

a) Relation between two entities: This is done by identifying: (i) two nouns which are connected by a verb, (ii) a noun and an adjective or adverb connected by a verb and (iii) two nouns connected by a preposition.
b) Conditions between two events: Here, events are represented by transitive verbs, and we capture whether two transitive verbs are connected using a conjunction or an adverb.
c) The sequence of events: This is essentially a sequence of transitive verbs, representing a description of a technical process.

While building the Knowledge Graph and identifying candidate words, the meaning of the words should not be considered standalone or isolated. It is to be understood as to what information is conveyed and a single word or a group of words that convey a specific meaning in the context of the paragraph or document is to be picked up.

After this step, the construct-specific rules will be used to identify, from the knowledge graph, the candidate words for each SAPPhIRE construct and the causal relationships among them. For extracting the candidate words, the following sequence should be followed,

- First, work on all the nouns and identify those which could be the 'Parts'. Then rest of the nouns should be considered for the 'Inputs' and the 'State Change'. 'State Change' nouns will be associated with verbs that imply a meaning of a change in the noun.
- Then look for all the transitive verbs. Most of the natural language text describes a technical process comprising a sequence of action verbs. Once we identify the action verbs representing a technical process, we identify 'Actions' and 'Phenomena'.
- Then work on the rest of the POS tags, like, Adjectives, Adverbs, Prepositions, Conjunctions etc., to identify Organs.

It should be noted that a particular word should be used in only one construct[1]. The candidate words identified using the construct-specific rules are the potential SAPPhIRE constructs given in the natural language text to build the model. However, these words might not be the true SAPPhIRE constructs conforming to the definition given for the construct. Hence at this stage a review would be necessary to determine the appropriateness of the candidate words for each SAPPhIRE construct. A set of interpretation guidelines are created to assist this review process. This review will also determine any missing SAPPhIRE construct. A reviewer will require (some/ necessary) domain knowledge to perform the review task effectively.

Process Validation

A thorough developer testing was done first, before taking up user validation of the newly developed process.

Developer Testing

Developer testing was done using eight different sample cases where each sample has the natural language description of a system and its physical process. Samples used in the developer testing included all the four samples used during the Intercoder Reliability study before the new process was developed, as well as fresh samples. Old samples were used to compare the results obtained using with and without the new process. New samples were used as additional tests to verify whether the process is consistently working outside of the known examples. In all these samples (old and new ones), it was observed that the process was consistently able to extract candidate words for the SAPPhIRE constructs and their causal relations. Following

[1] In the multi-instance cases, this may not be true. For example, change in parts can become the input.

this process, it was also possible to identify any missing information related to any SAPPhIRE construct. It was also observed that (some) domain knowledge was necessary to review the information extracted using the process and make a final choice of words for the SAPPhIRE constructs.

Figures 3 shows a comparison of the total number of words for each SAPPhIRE construct, generated without and with the process, in the two sample cases (a) Thermal Wheel and (b) Elephant Turbinate. The words generated without the process are the ones identified by the researchers during the Intercoder Reliability study at the beginning. In both these samples, the distribution of total number of words for the SAPPhIRE constructs were similar for without and with the process. We also observed that many common words used by the researchers for different SAPPhIRE constructs matched with the candidate words generated by the process. We therefore see that the new process can capture the common thinking of the test participants.

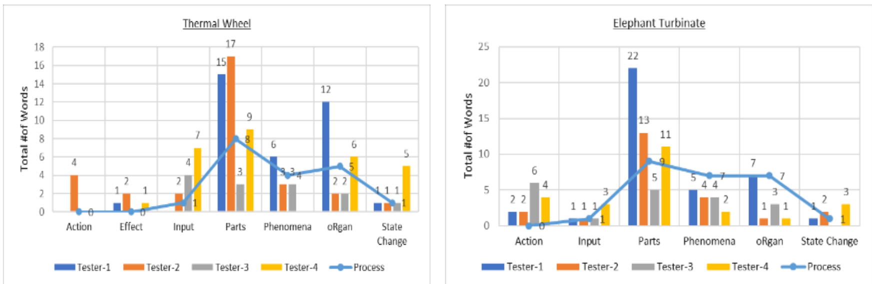

Figure 3 - comparison of the total number of SAPPhIRE words generated without and with process for the (a) 'Thermal Wheel', (b) 'Elephant Turbinate'

User validation of the new process

User validation was conducted after verification of the new process through developer testing. User validation was done with the same four researchers who participated in the previous study before process development. There were four new sample cases namely, electric battery, a solar water heater, a mechanical lock and visualizing infrared rays by fish. We took new samples to ensure, testers are not producing the outputs out of their memory of the previous study. Like in the previous study, these samples are brief description of how a system, biological or engineered, works and are hand curated with information taken from the commonly available websites such as howstuffworks.com, asknature.org or Wikipedia. Each researcher first created the knowledge graph-based representation of the natural language description. Then they used the construct specific rules to select a list of candidate words for each SAPPhIRE construct. Since all the candidate words may not be a valid SAPPhIRE construct, interpretation guidelines were applied to arrive at the final list of words. The details of these four samples as well as some example of the deliverables created by the testers during the study (knowledge graph and the SAPPhIRE labels that coders used to encode words from the sample texts), are available at https://github.com/kausikbh/DCC22_SAPPhIRE_Data.

With the final list of SAPPhIRE words, we computed the Intercoder Reliability score to find out the level of agreement. Table 4 shows the Intercoder Reliability score for the final choice of words list. Table 5 summarizes the Intercoder Reliability score without and with the new process in one place, for comparison.

Table 4 – Intercoder Reliability score in user validation

	Total # of Words	**3 or more out of 4 researchers agreed**		**2 or more out of 4 researchers agreed**	
		Count	**%**	Count	**%**
EG5 (Electric Battery)	21	12	57%	16	81%
EG6 (Solar Heater)	15	13	87%	13	87%
EG7 (Mechanical Lock)	35	23	66%	28	80%
EG8 (Visualizing Infrared Rays by Fish)	51	26	51%	38	75%

Table 5 – Intercoder Reliability scores WITHOUT and WITH new process

		Total # of Words	**3 or more out of 4 researchers agreed**		**2 or more out of 4 researchers agreed**	
			Count	**%**	Count	**%**
WITHOUT New process	EG1	71	6	8%	21	30%
	EG2	69	2	3%	8	12%
	EG3	68	1	1%	6	9%
	EG4	221	2	1%	22	10%
	Overall	429	11	3%	57	13%
WITH New process	EG5	21	12	57%	16	81%
	EG6	15	13	87%	13	87%
	EG7	35	23	66%	28	80%
	EG8	51	26	51%	38	75%
	Overall	122	74	61%	95	78%

From Table 5, we can see that in both scenarios, namely, (a) A: 3 or more out of 4 researchers agreed, and (b) B: 2 or more out of 4 researchers agreed, there is an improvement in the overall level of agreement when the new process is used. This was confirmed by a one-way within-subjects ANOVA given in Table 6 for the above two scenarios ('A' and 'B'). In both these scenarios at $p < .05$ level, we reject the null hypothesis that both groups ('without' and 'with' new process) are the same. In other words, when the process is used result is significantly different from those which did not use it.

Table 6 – One-way within-subjects ANOVA Test Results

Scenarios	Groups **with Intercoder Reliability Score**	**Test Statistics**
A: 3 or more out of 4 researchers agreed	Without process [M = 0.032, SD = 0.029] and with process [M = 0.653, SD = 0.136]	$F(1, 6) = 59.32$, $p<.05$, $\eta^2 = 0.91$
B: 2 or more out of 4 researchers agreed	Without process [M = 0.153, SD = 0.086] and with process [$M = 0.808$, $SD = 0.043$]	$F(1, 6) = 140.1$, $p<.05$, $\eta^2 = 0.95$

Discussion

The new process, based on rules involving the parts of speech of English grammar and their syntactic dependencies, acts as a guard rail, making everyone look at a common list of possible words or clauses for a given construct (we call them candidate words in the process). Results obtained from user validation confirm that the new process can help reduce the variability in the extracted SAPPhIRE information by different users. Though the results are encouraging, it has room for further improvements. A detailed analysis of the results indicated that the Parts and the Actions-Phenomena have the maximum agreement. It is so because Parts are mainly those Nouns that represent a material entity, and Action/Phenomenon are mainly the Transitive Verbs denoting an action. We however see need for a better interpretation guideline to differentiate a Phenomenon (which represents an interaction of a system entity with its surrounding) from Action (which is the interpretation of the state change resulting from the same interaction). Often natural language text will have either of this two information (Phenomena and Action), hence in our study we tried to ensure we are able to capture the system interaction from the text, irrespective of its label (Phenomena or Action). Other constructs, Input, Organ, Effect and

State Change, do not have the same degree of straightforwardness. do not have the same degree of straightforwardness. Most of the time, a natural language description would not explicitly call out what are the inputs for an interaction, the conditions or structural context for a physical law (or effect) to trigger interactions and the resulting state changes. These must be derived from the given information using the interpretation guidelines. In the absence of a known physical law, this decision becomes subjective. Hence, we see opportunities for extending the rules beyond grammar to make appropriate choices and a guideline around dealing with any missing information. We continue to see people using different words to express the same physical interactions in absence of a common catalogue. Although the new process calls for a common catalogue, it was not used in this study.

Our main research question was to know how to create accurate and repeatable ontology-based data models from natural language descriptions. Answer to this question will help to design suitable automation strategy for extracting SBF or SAPPhIRE information from natural language documents, as researchers did in the past. The process will also help in producing necessary accurate data to validate such automation scheme without the constraints of specialists' availability. An actual quantitative cost-benefit of any automation and what are any limitations, will be known once an accurate and repeatable end to end process with automation is created.

Conclusions

Design thinking needs exploration of design space repeatedly. A large Design-by-Analogy database with systems models, like SAPPhIRE, will help having more (count) inspirations or stimuli in the conceptual phase of design and therefore can have a strong positive influence on creativity. Hence a process that can generate the descriptions of the SAPPhIRE model from the information in natural language documents, which are available in plenty, will be very useful in design. To understand the current process of creating descriptions of the SAPPhIRE model from a natural language text, an Intercoder Reliability study was conducted. This study revealed the challenges with the current process which we attempted to address through a new, generalized process of extracting SAPPhIRE information from natural language descriptions. From the validation of the new process, we see that the new process helps identifying candidate words for the various SAPPhIRE constructs and revealing gaps in the SAPPhIRE information in the same natural language description. Through the user validation of the new process, we also identified areas in which the rules need to improve. So far, our research has been limited to natural language understanding and extracting information relevant for a given abstraction level. We saw evidence that documents in natural language often do not have information related to all the seven abstraction levels of the SAPPhIRE model. Hence, we need to expand the approach so that will also help accurately fill in any missing information. It might be noted that the designers may choose to represent the same information in many ways. Hence, we need a method that can compare different SAPPhIRE representations of the same system and assess their similarities and dissimilarities. Our future research intends to investigate these opportunities. Due to the diverse nature of technical documents in natural language, there are complexities with natural language understanding of these. We therefore approached in an iterative way, where we first learn and then improve. Our results showed us a path to proceed with further refining the process by addressing the observations from user validation as well as by incorporating more complex scenarios and variability of natural language descriptions. A detailed process validation via lab experiments, and further process optimization and automation after the validation are also planned.

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