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WATERFALLS AS A FORM OF AI-BASED FEEDBACK FOR CREATIVITY SUPPORT

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Introduction

In our daily lives, we face an extensive range of practical problems that can be solved by employing novel and creative solutions. The ability to construct such solutions can empower us, enable us to transform our environment and even extend our human attributes to the unknown. However, the creativity and success (or lack thereof) of our solutions is often attributed to simple chance, hard work or innate talent.

This chapter explores whether an AI-based system aimed at creativity support can provide real-time, implicit feedback for conversations involving design thinking. The cornerstone of the developed approach is that the system itself is able to determine the success of a design solution as it is generated. Furthermore, the two main issues explored in this research are the complexity and comprehension of the feedback offered and a conversation around intrusiveness of the system in the creative process. To address these issues, a prototype system that analyses creative design thinking conversations in real time and provides implicit feedback in the form of an 'anti-gravity' illusory mini waterfall system has been developed and explored. The guiding principle behind this approach is that the system will be able to determine the success of the solutions as they are generated, even before we subconsciously feel, know or consciously determine their fate (Georgiev & Georgiev 2018). According to the approach, such solutions can be considered as successful if they are novel, useful and adopted in practice.

We might imagine that a consultative AI-based creativity support system could be deployed as part of a distributed home assistant technology, such as

Google Assistant or Amazon Alexa, to aid in our everyday problem solving. Such a system could help with addressing complex problems, and sensemaking (Weick 1995), with the goal being to help people select ideas that are novel, creative and ultimately, successful. In creative problem solving, sometimes we must make a mistake to learn from it. A consultative AI-based creativity support system can help us identify mistakes while we are in the process of making them. This might prevent us from investing effort in ideas that are less creative and unsuccessful in addition to facilitating reflection, learning and skill acquisition. Failing fast is pre-planned and instrumental for innovation (Leifer & Steinert 2011).

In a data-saturated world, it can be difficult to make decisions or imagine solutions that are novel or creative (Weinstein et al. 2014). Furthermore, complex feedback that requires much cognitive resources or time can hamper creativity or creative problem solving (Norman & Stappers 2015). A consultative AI-based creativity support system could perhaps help navigate this complexity by providing feedback in a simple manner.

To address the aforementioned issues, a prototype system was developed that can analyse design problem-solving conversations in real time and provide implicit feedback though a dynamic data physicalization – which in this case takes the form of an ‘anti-gravity’ mini waterfall. The metaphor of the waterfall was used as it resonates with both the nature of problem-solving conversations and the concept of flow in creativity. The playful anti-gravity concept relates to human emotions, such as surprise (Becattini et al. 2017) and inspiration. AI-generated recommendations were presented in a physical form to make them feel more tangible and related to the physical/natural world we live in, the water-based media was well-suited to this purpose.

AI-based creativity support

An explicit list of rules is required for the construction of an AI-based creativity support system to allow machines to compute the creativity or future success of a design solution. Current AI-based support systems do not provide unattended feedback or require the interaction of the user with the system. For example, Han and colleagues (2018) developed a computational tool for assisting designers in generating creative ideas during the early stages of design. The tool is based on analogical reasoning and can improve the fluency and flexibility of idea generation and the usefulness of ideas (Han et al. 2018).

In the project explored in this chapter, semantic networks were employed to provide a structural representation of knowledge in the form of graphs (mathematical structures used to model relations between pairs of words) (Miller & Fellbaum 1991). After exteriorizing and representing knowledge in the form of a semantic network, a number of graph-theory measures were employed for quantitative analysis (Steyvers & Tenenbaum 2005).

A recent study by Georgiev and Georgiev (2018) analysed a dataset of design problem-solving conversations in real-world settings by using a sizable number of semantic measures. The study utilized four different semantic variables to quantify design thinking conversations: polysemy, abstraction level, information content and semantic similarity.

More information on these variables is as follows:

- **Polysemy** is the number of direct links between a word node X and its meaning nodes, accounting for the number of meanings of the word node. For example, the 'car' node has five meaning nodes: 'auto', 'railcar', 'gondola', 'elevator car' and 'cable car'. While these nodes are not generated in a specific conversation or context, they represent a model of human thinking. Certainly, in actual problem-solving conversations, there can be numerous other nodes. For example, polysemy appears during designers' verbalizations, and it shows the multiplicity of significations that an object can have (Dabbeeru & Mukerjee 2011). Polysemy has been identified as an essential manifestation of the richness, flexibility and adaptability in meaning potential in thinking (Fauconnier & Turner 2011).
- **Abstraction** in this context is the normalized fraction of the length of the shortest path from the root word node to a word node X and the length of the maximal shortest path from the root to any node in the network. Abstraction indicates the extent to which the word node is generalized, compared to the most specific instance. For example, the word 'vehicle' is more abstract than the word 'boat'. It is known that the abstraction of specific ways of thinking can lead to novel ideas (Ward, Patterson & Sifonis 2004). Moreover, abstraction is a key requirement for the successful use of external sources in design creativity (Goldschmidt 2011).
- **Information content** (IC) is the bits (amount) of information carried by a word node inside the graph. This is measured inside the graph structure of all words represented in WordNet, which is a tree-like hierarchical and interconnected database. IC is measured as the normalized fraction of the number of 'leaves' (terminal nodes) of the word node in the tree and the maximal number of leaves in the network (whole tree). IC is a measure of the informativeness of a unit. For example, IC was found to be an effective method of quantifying design fixation (when consciously or unconsciously adhere to prior ideas, unable to generate new ones) (Gero 2011).
- **Semantic similarity** of two word nodes (Fellbaum 2012; Miller & Fellbaum 1991), X and Y, is measured by the IC of the least common subsumer of the two words (the most specific concept that is an ancestor of both words in a semantic network), essentially quantifying the similarity of the two word nodes. The least common subsumer (LCS) of X and Y is the most specific word node ancestor of both X and Y in the 'is-a' hierarchy (e.g. the LCS of 'car' and 'boat' is 'vehicle'). As an example, semantic similarity has been used to assess the novelty potential of the resulting combination of two concepts (Nomaguchi et al. 2019).

Georgiev and Georgiev (2018) found that three semantic factors can predict the success of generated ideas that have implications for creativity: divergence of semantic similarity, increased information content and decreased polysemy. The following examples illustrate this premise:

- Divergence of semantic similarity: This occurs when, during the design thinking process, a pair of concepts A and B is substituted by another pair of concepts C and D, which are more dissimilar compared to the A and B pair.
- Increased information content: This refers to when concept E is substituted by concept F, which carries more information than E.
- Decreased polysemy: This occurs when a concept G is substituted by another concept H that is less polysemous.

The temporal dynamics of these semantic factors identifies real-world processes in human problem solving that are relevant to the success of produced solutions. However, more importantly, these factors are easily computable, and hence straightforwardly implementable in AI-based creativity support systems. Thus, there is potential for the real-time monitoring of design thinking using AI, which may improve our training, learning and skill acquisition.

Two main issues can be envisioned regarding such feedback:

1. the complexity and comprehension of the feedback might influence the flow of the design thinking process, and
2. the intrusiveness of the system 'telling' the users engaged in design thinking conversations could influence the trend towards success.

The types of data we used are the four semantic variables outlined above. Each of these has a single direction; hence, the overall data have four dimensions. The density of the data depends on the intensity of the conversation analysed. A typical problem-solving conversation has high density.

Analysis of design-thinking conversations

A real-time analysis system that calculates and visualizes the semantic variables of a design thinking conversation was developed. Analysing a natural real-time conversation, although data intensive and not entirely clean (owing to the possible use of jargon and unfinished sentences), can provide rich information regarding the fundamental processes that underlie design thinking (Becattini et al. 2020; Casakin & Georgiev 2021; Georgiev & Georgiev 2018).

In this experiment, the system recognizes the speech of two participants and measures and visualizes four semantic parameters (e.g. convergence and divergence) of the participants' speech in real time. In the initial testing, the time from recording speech and calculating semantic variables to a visual response (plot of the consequent calculation of variables as shown in Figure 14.1b) on screen took approximately 3 to 5 seconds.

The developed conversation analysis system performed three main tasks:

1. Transcribing the conversation into text with a Speech-to-Text (StT) subsystem.
2. Part-of-Speech (PoS) tagging, where nouns in texts are tagged, and the measurement of semantic variables.
3. Calculation and output of the semantic variables through screen-based visualization or other means.

In this research design, the thinking was quantified by using four different semantic variables: polysemy, abstraction level, information content and semantic similarity.

The first experiments with the system were performed to explore the functionality of the system and the possibility of feedback mechanisms. We tested the system with two conversations, each with a different pair of people. The test participants were university students, and all of them spoke English proficiently as a second language. The participants were tasked with 'Designing a solution for the dark and cold winters in Oulu', a town in Northern Finland where

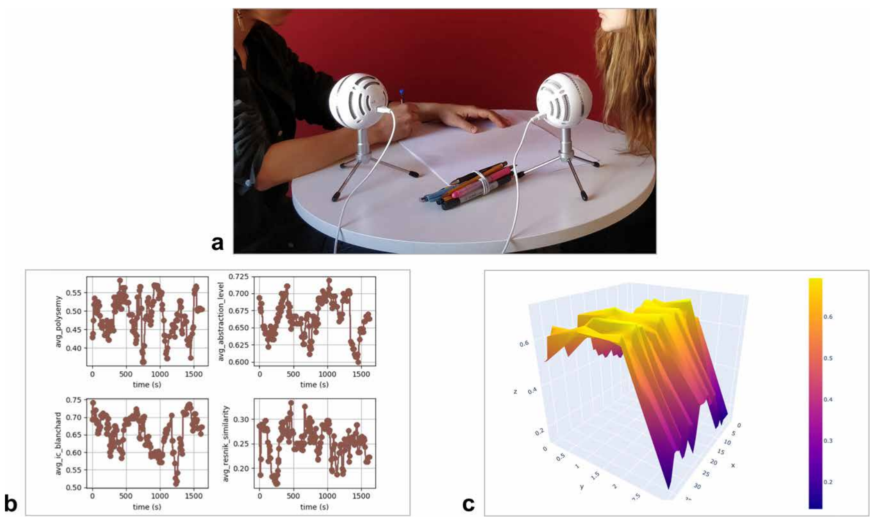

Figure 14.1 Design thinking conversation during the initial testing of the real-time analysis and evaluation system (a) Design thinking conversation feedback with separate; (b) and compound; (c) plots of real-time conversation data. In example (c), four semantic measures are plotted on the y axis, taking values on the axis z over time on the axis x. Images: Yazan Barhoush.

the experiments took place. They were asked to do this using pen and paper, as shown in Figure 14.1a. The participants were asked to work and converse about this task for at least 20 minutes until they felt that they were done. After providing solution(s) for the task, the prototype screen-based visualization output of the system was shared with the pairs of participants. The AI-interpreted data generated during the conversation was shown in the format of Figure 14.1b immediately after the conversation. The meanings of the four semantic variables visualized were also explained to the participants in simple terms. The participants were then interviewed and asked to answer a set of questions related to the data visualization. The explorative example visualization of the same data, as shown in Figure 14.1c, was developed later.

These initial experiments demonstrated that the AI data interpretation system performed in a satisfactory manner. However, the participants identified problems with understanding and interpreting the different variables.

Feedback

As demonstrated by the results of the preliminary study, the explicit feedback in the form of plots (Figure 14.1b and c) was not adequately clear when presented to the participants after the end of their conversations. The participants experienced problems with both understanding and interpreting the feedback owing to the complexity of the graphs. The visualized data was presented at the end of each conversation as it was thought that the feedback, if presented in this form during the conversation, would be distracting, especially because of the complexity of the visualized data and the comprehension required to make sense of it. Feedback in this form during the conversation could negatively influence the flow of the design thinking process.

All participants had some difficulty in making sense of the visualizations or relating them to what was discussed in the conversation. Initially, the participants had some problems with understanding the different variables. One participant suspected that the abstraction level fluctuated because when coming up with ideas, they tended to start with a general idea, which was then focused into a more concrete idea. The participants noted that the system seemed interesting and helpful. When asked about what they thought about the usage of the system, one participant noted that it could help them with critically thinking about the way they speak and cause them to use a more information-rich vocabulary. The system also made the participants ponder on the nature of language and the relationship between language and thinking.

Based on these qualitative observations a more simplified and implicit feedback form that would fit better in the overall design thinking process was proposed as previous research had suggested that conveying implicit feedback is potentially useful in the context of creativity (Georgiev & Nagai 2011).

A Prototype of an ‘anti-gravity’ illusory feedback system

Based on the results of the conversation analysis experiment, a prototype system that focused on more implicit feedback was developed. The premise for this experimental prototype was to have a binary representation in the form of yes/no (successful/unsuccessful or creative/less creative) trajectory in the trend of the conversation, based on a single semantic variable. We used the divergence/convergence of semantic similarity as the variable with highest potential in terms of the prediction of successfulness or creativity (Georgiev & Georgiev 2018). A waterfall metaphor was used to physicalize this data in real time.

Water and falling water curtains have been used to visualize data and information for several decades. For example, Moere (2008) proposed ambient displays using water, turning everyday spaces into interfaces by changing the states of liquids and those of other media contained in such liquids with data-driven values and representing information using water as a communication medium.

In this experiment, the visual effect of the waterfall as it visualized the data was either the normal effect of water flowing downwards, or that of ‘anti-gravity’ (creating what is known as the levitating-water effect), where the water freezes in the air or flows upwards (Barhoush et al. 2018). We connected the unsuccessful or less creative trend to the normal effect and the successful or creative trend to the anti-gravity effect (Figure 14.2). Although water flow is a continuous series of close, flowing water droplets, the ‘binary representation’ is not based on a series of water droplets but on changes in the frequency of the light of the waterfall. At particular frequencies, light creates the perception of water going upwards or freezing in mid-air, but at other frequencies it the water appears to fall as normal. Thus, in this setup a binary visualization of up (anti-gravity) and down (normal) was viewable.

The visualized data can be observed in real time during the conversation instead of during playback after the conversation as in the earlier experiments. The use of water and the waterfall metaphor played with the way in which we think and make creative decisions – creative moments are disruptive and may be surprising, like the idea of water following upwards.

The AI-based system consisted of microphones, a laptop computer with an AI-based conversation analysis system and a mini waterfall system in a closed-box container. The implemented system used two microphones, one for each of the participants. A natural language processing (NLP) pipeline software module was responsible for the calculation of the four semantic variables. In the implemented system, the NLP pipeline module transformed the input text data through a series of steps to a calculation value for each of the four semantic variables.

The NLP module starts with a StT subsystem using Google speech recognition and performs PoS tagging, where nouns in texts are tagged. Then, the module loads corresponding graphs and takes the text from StT processing and the created list of nouns. In the following step, values of each of the four semantic measures are calculated (see Becattini et al. (2020) for example implementations of four variables). In the last step, the output of the semantic variables is created through visualization with the waterfall. In the case of this prototype, only the semantic similarity variable was utilized as it is proven to be the most influential in terms of the successfulness of ideas generated in creative problem-solving conversations (Georgiev & Georgiev 2018). Selection of this variable also allowed for more straightforward feedback – the identified trend of semantic similarity based on a moving window of five nouns either downwards or upwards. In previous research, the downward trendline of semantic similarity has been

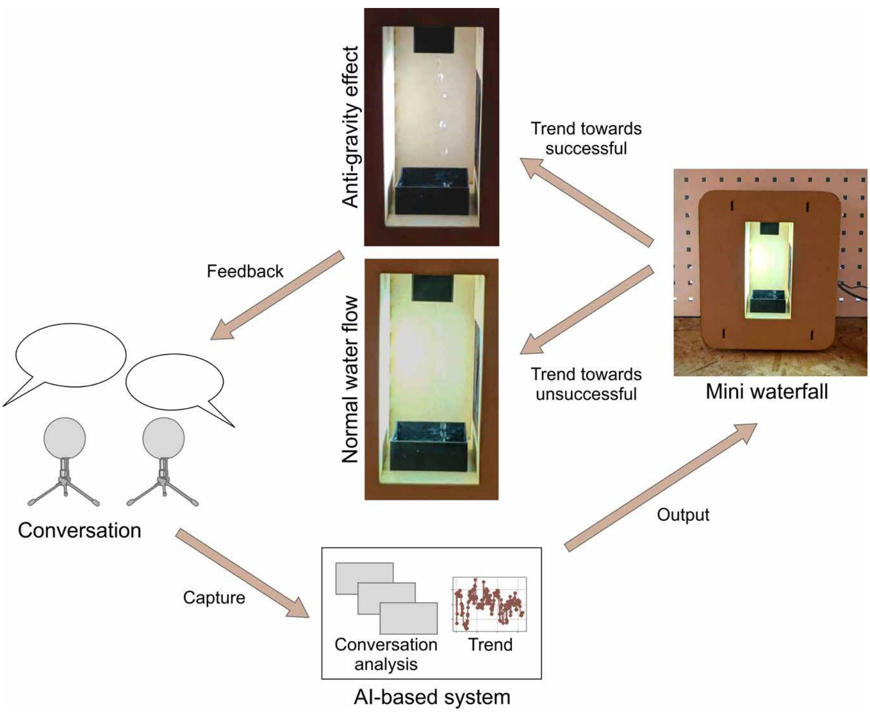

Figure 14.2 Feedback with an anti-gravity illusion waterfall. Image: Yazan Barhoush and Georgi Georgiev.

identified as a feature of successful and possibly creative ideas, whereas the upward one (more similar) is a feature of unsuccessful ideas that are possibly less creative (Georgiev & Georgiev 2018).

The physically prototyped container includes water tanks, a pump and a large strobe light (LED light that was switched on/off at certain frequencies to create the anti-gravity effect) controlled by an Arduino microcontroller and powered by an external power supply (Barhoush et al. 2018). All of the parts of the waterfall system were designed and fabricated in a Fab Lab, including the 3D printing, laser cutting and electronic board production processes.

Discussion and conclusion

Implicit feedback from the anti-gravity illusion waterfall was observed to have the potential to address some of the earlier perceived issues with regard to AI-based feedback on design thinking conversations. Preliminary testing of the system with existing pre-recorded conversations demonstrated that the system can provide simple feedback via the normal and anti-gravity effect. Further work will include larger-scale testing of the proposed system.

In particular, the waterfall can help unravel the complexity of the data and facilitate better comprehension of the trends of the participants' conversations. In addition, the intrusiveness of the AI system and visualized data was mitigated by the implementation of the mini waterfall, which could become a part of an interior space where the participants are engaged in design thinking conversations.

The implementation of this type of data in a physical, interactive object opens further possible directions for interaction, tangibility and experimentation. The tangibility of data has been identified as a powerful way to create memorable user engagement (Petrelli et al. 2017). The customization of solutions via data visualization in different forms is deemed to be critical from a human-centredness perspective (Prendiville, Gwilt & Mitchell 2017). A possible further exploration of the feedback could be focused on other interactions. An example of such interactions is the comprehension and emotions that a participant would experience if they could put their hand in the water and feel the changes of the stream of 'AI data' in real-time.

In this study, we explored a prototype AI-based system aimed at implicitly supporting creativity by providing real-time feedback for design thinking conversations via an illusory waterfall. The developed prototype AI system addressed two main issues with regard to such feedback: the complexity and comprehension of the feedback and the intrusiveness of the system. By analysis of data generated during creative problem-solving conversations with an AI programme, content feedback in the form of an anti-gravity mini waterfall was shared in an implicit, human centred manner. To create a hybrid 'data-object', an AI-based system is proposed that capitalizes on the potential of digital AI technologies to be combined with real-world affordability in a novel and informative way. This project provides only a glimpse of the manner in which these types of systems can be created, and further research regarding successfully developing and deploying such hybrid systems is certainly needed.

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