IJDCI Editorial

Nascent Directions for Design Creativity Research

Design is recognized as one of the creative professions but that does not mean that design equals creativity. Much of design is not creative, rather it is routine in the sense that the designs produced are those that are similar to existing designs and are only unique in terms of the situation they are in. However, there is value in producing designs that are considered creative in that they add significant value and change people's perceptions and, in doing so, have the potential to change society by changing its value system. A search for the terms "design" and "creativity" in books over the last 200 years (using Google's Ngram) shows that the term "design' was well established by 1800 and its use dropped between 1800 and 1900, after which its use increased to 2000. The term "creativity" only came into noticeable use from 1940 on. It is, therefore, not surprising that creativity research is a young field. Much of early design creativity research has focused on distinguishing design creativity from designing; typically, by attempting to determine when and how a designer was being creative while they were designing. This still remains an important area of design creativity research that deserves considerable attention. Much of the design creativity research over the last 30-40 years has focused on either cognitive studies of designers or on building computational models of creative processes, generally using artificial intelligence or cognitive models. As in other areas of design research, there has been interest in developing cognitive creativity support tools. These two paradigmatic approaches have yielded interesting and important results. Tools can be categorized along a spectrum from passive through responsive to active. Passive tools need to be directly invoked by the designer and remain unchanged by their use. A spreadsheet is an exemplary example of a general passive tool. Passive tools that support design creativity include, for example, morphological analysis and TRIZ. Responsive tools need to be directly invoked by the designer but are changed by their use and do so by learning (Gero, 1996). They aim to tailor their response to the user over time. They tend to be developed for a specific purpose and are often proprietary. Active tools interact with the designer, i.e., they respond to what the designer is doing and make proposals.

More recently, there has been interest in studying creativity when the designer is using responsive and active creativity aids. These aids cover a wide spectrum. Here two new categories will be considered: artificial intelligence that supports co-creation and neuro-based creativity enhancement. These two approaches form the basis of two nascent directions that are fundamentally different to the current directions of cognitive studies and passive cognitive support tools. In addition, there have been studies with drugs that affect the brain and that anecdotally enhance creativity. Alcohol has been shown to have a mild positive effect on the remote association creativity test but impairs divergent thinking, which is involved in design creativity (Norlander, 1999). However, controlled studies with Ritalin (methylphenidate) (Baas, et. al., 2020), cannabis (tetrahydrocannabinol) (Kowal, et. al., 2015) and LSD (lysergic acid diethylamide) (McGlothlin, et. al., 1967) showed that either these had no significant effect on creativity or in many cases reduced divergent thinking. Thus, the evidence that brain changing drugs improve creativity remains primarily anecdotal.

Artificial intelligence for co-creation: Recent developments in machine learning centered around deep learning using convolutional neural networks have made large data sources much more accessible. Deep learning over large data sources turns the minimally structured data into a form that is a multidimensional space that is much larger than the space of the input data. In doing this, deep learning, when used in designing, has the potential to open up the design space beyond the space of the input designs. This can be used as the basis of a computational creativity support agent, an AI, that can use its pattern matching capability to take what the designer is doing and find places in this multidimensional space that match or partially match it. It then uses that match to access point in that space that are not in the original input space. The AI works alongside the designer and responds to what the designer is doing by making suggestions based on where it finds itself in the multidimensional space. An early example of a co-creative AI takes Google's Quick Draw data set (https://quickdraw.withgoogle.com/data), represented through deep learning, and the AI looks at the designer's sketch and proposes a sketch near the designer's based on either appearance or semantics The designer can take some or all of the elements of the proposed sketch and incorporate them in their own sketch and continue to develop the sketch with iterative interaction with the AI (Karimi, et. al., 2020). Another direction is to develop an analogy based on the Generate Paragraphs of Text (GPT) approach from OpenAI (Radford, et. al., 2019). GPT generates coherent words, sentences and paragraphs as predictions from starting text. GPT is based on learning from a very large data set of natural language text. By analogy, an AI could take a very large set of designs developed incrementally as systems, subsystems, and components, produced by parameter cycling through a parametric modeler, and use them as input to a deep learning system where the structure of the system–subsystem–component relations are represented in the multidimensional space. Then, the system can operate as a co-creative AI with a designer, where the AI makes proposals that move across, up or down the system hierarchy in ways not immediately obvious to the designer, based on the larger space of possibilities. AIs as co-creative active tools iteratively interact with the designer.

Neuro-based Creativity Enhancement: As we learn more about brain activity during designing and in particular where idea generation occurs, we can make use of this knowledge to produce creativity enhancement tools. Here we will discuss two approaches within this direction. The first uses neuro-cognitive feedback and the second uses direct brain stimulation. Feedback has been shown to be a driver of cognitive change through self-regulation. It is one of the pedagogical foundations of education. Feedback of physiological measurements is used by athletes to improve their performance. The same concept can be applied to design creativity. It is known that, in general, higher activations of the right prefrontal cortex are involved with idea generation along with lower activations of the left prefrontal cortex. In a recent pilot study, designers wore a neuroimaging cap (in this case using functional near infra-red spectroscopy – fNIRS). Showing designers the activation level of the right prefrontal cortex of their brains derived from the fNIRS measurement, and asking them to keep that activation level up, resulted in an increase in the number of concepts generated compared to the number generated in same time period without neuro-cognitive feedback (Shealy, et. al., 2020). Although this was a preliminary study, it demonstrated the potential of this neuro-cognitive feedback approach for design creativity research and practice

Whilst neuro-cognitive feedback involves only indirect involvement by the tool, transcranial direct current stimulation (tDCS) involves the passing of an electrical current from the device to the brain. In studying creativity, tDCS uses electrical currents to activate the right prefrontal cortex and deactivate the left prefrontal cortex. A recent experiment using tDCS in these locations showed that there was a consequential increase in performance in psychometric creativity measurements (Hertenstein, et. al., 2019). These results demonstrate the potential of the tDCS approach for design creativity research and practice.

Artificial intelligence for co-creation and neuro-based creativity enhancement represent two nascent directions that have the potential to expand the ambit of both design creativity research and design creativity itself.

References

Baas, M., Boot, N.C., Gaal, S.V., Dreu, C.K., & Cools, R. (2020). Methylphenidate does not affect convergent and divergent creative processes in healthy adults. *NeuroImage*, 205. https://doi.org/10.1016/j.neuroimage.2019.116279.

Gero, J. S. (1996). Design tools that learn: A possible CAD future. In B. Kumar (ed.), *Information Processing in Civil and Structural Design,* Civil-Comp Press, Edinburgh, pp. 17-22

Hertenstein, E., Waibel, E., Frase, L., Riemann, D., Feige, B., Nitsche, M.A., Kaller, C.P., Nissen, C. (2019). Modulation of creativity by transcranial direct current stimulation. *Brain Stimul.* 2(5):1213-1221. doi: 10.1016/j.brs.2019.06.004.

Karimi, K., Rezwana, J., Siddiqui, S., Maher, M. L., & Dehbozorgi, N. (2020). Creative sketching partner: An analysis of human-AI co-creativity. In *Proceedings of the 25th International Conference on Intelligent User Interfaces (IUI '20)*. Association for Computing Machinery, New York, pp. 221–230. https://doi.org/10.1145/3377325.3377522.

Kowal, M. A., Hazekamp, A., Colzato, L. S., van Steenbergen, H., van der Wee, N. J., Durieux, J., Manai, M., & Hommel, B. (2015). Cannabis and creativity: highly potent cannabis impairs divergent thinking in regular cannabis users. *Psychopharmacology*, 232(6): 1123–1134. https://doi.org/10.1007/s00213-014-3749-1.

McGlothlin, W., Cohen, S. & McGlothlin M.S. (1967). Long lasting effects of LSD on normals. *Arch Gen Psychiatry*, 17: 521-532.

Norlander, T. (1999) Inebriation and inspiration? A review of the research on alcohol and creativity, *Journal of Creative Behavior*, 33: 22-44.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). *Language Models are Unsupervised Multitask Learners*, OpenAI Inc., San Francisco. (https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask _learners.pdf)

Shealy, T., Gero, J.S., Milovanovic, J. & Hu, M. (2020). Sustaining creativity with neuro-cognitive feedback: A preliminary study, *International Conference on Design Creativity – ICDC2020*. (to appear) (available from: http://johngero.com/publications/Progress/20ShealyGeroMilovanovicHu-ICDC.pdf)

John S Gero
Computer Science and Architecture
University of North Carolina at Charlotte, USA
http://johngero.com/
john@johngero.com