Impact of cognitive load associated with learning and using parametric tools in architectural design

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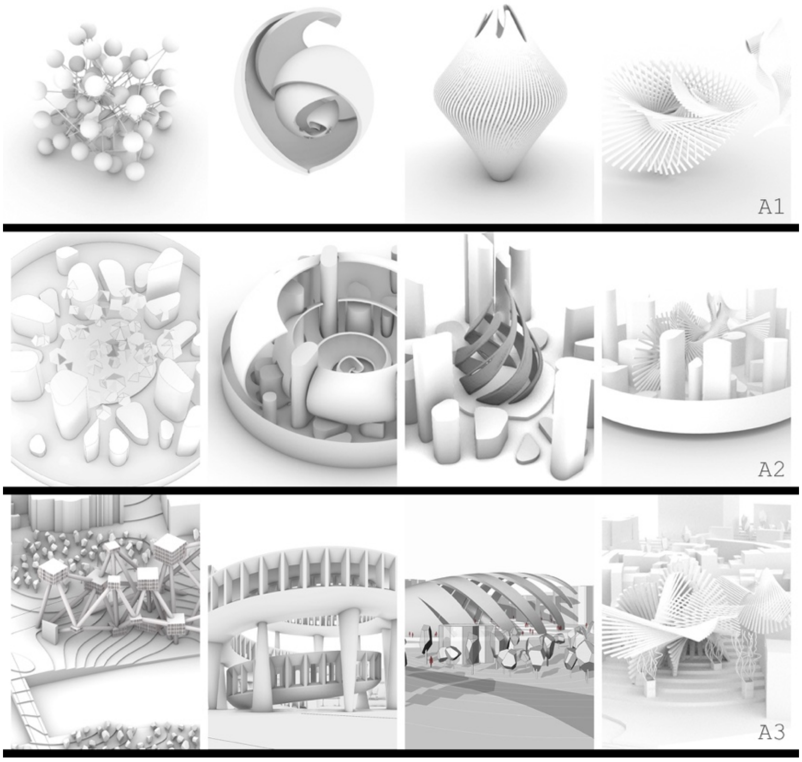

Figure 1. Results of the three assignments (A1, A2, A3) showing process similarities despite the different sets of constraints.

Abstract
This research aims to explore the impact of cognitive load associated with parametric tools on design ideation. Cognitive Load Theory refers to leveraged resources in limited working memory. In design, benefits have been found in higher load situations. However, semantic processing, associated with learning processes, has shown negative impact on the design outcome. Because of the rapid evolution of software, computational expertise tends to be increasingly transient, and architects find themselves in a situation where they constantly must partially re-learn their tools. Only few research takes the mental activity associated with digital environments into account, especially more complex ones such as parametric. Furthermore, there is no trace of research regarding how mental load associated with learning can affect design production. This paper focuses on an elective master course on computational design for architects. Both retrospective and concurrent protocol analysis are used in combination with the function behaviour structure ontology and linkography We observe that most of the cognitive effort is geared towards resolving issues related to using parametric tools, which is contradictory to previous studies. We find that their use of over-constrained experimental environments does not enable them to capture the learning related cognitive activity. Thus, it raises the question of experimental settings and research methodology regarding cognition in the digital age.

Keywords
Parametric design; Cognitive load; Procedural design; Education; Visual Programming

1. Introduction

The cognitive load theory is based on the principle of a limited working memory (Baddeley, 1992). Any task imposes a cognitive load that can go beyond mental capacity and thus lead to errors, stress or even its abandonment (Safin et al., 2008). To alleviate this overload, tools are used as cognitive supports. Due to their intrinsic complexity and expertise requirements, they can carry a load of their own. Therefore, tool expertise becomes essential for load reduction. However, because of the rapid evolution of software, computational skills become increasingly transient. Architects are put into a situation where they constantly must partially re-learn to master their tools and potentially during the design process. Enters information. Its rise in quantity, freedom of access and production has transformed human's relationship with tools. Yet coarse data can be overwhelming, obsolete, and even sometimes wrong. Furthermore, low-quality information production and sharing can lead to considerable cognitive load (Sweller et al., 2019).

Parametric Design Environments (PDEs) are a prime example. The shift to process-based thinking where architects need to model functions and define relationships through parameters and functions brings a new kind of complexity (Lee and Ostwald, 2019). Consequently, new tools such as visual programming interfaces become unfamiliar and relying on external information becomes a necessity. On the other hand, PDEs bring a new kind of cognitive support. Indeed, the construction of process schemata needed in PDEs resembles long term memory storing strategy of learning introduced by Chi and colleagues (1982). It can then be argued PDEs ultimately help in automating tasks without demand on working memory.

Our goal is to analyse the impact cognitive load related to PDEs has on architectural design considering how learning through external information is now embedded in the process. Previous research on design and cognitive load associated with computational tools is scarce and often neglect the mental activity associated with digital environments, especially more complex ones such as parametric tools. Furthermore, there is no trace of research regarding how mental load associated with learning, and so how supportive information, can affect design production.

The paper focuses on method to apprehend the relevant cognitive load. It extends on earlier experiments through a mixed approach using both retrospective and concurrent protocol analysis, a common method used to study behaviours through sketches, video and audio recordings. Given the short format of this paper, quantitative data will only be looked at qualitatively.

Most studies involving protocol analysis (Ericsson and Simon, 1993) use concurrent think aloud techniques to get cognitive insight for a specific design task (Hay, et al., 2017; Jiang & Yen, 2009). Because of the lack of granularity, retrospective protocols are often omitted (Gero and Tang, 2001) but there is a case to be made for longer experiments as they might be better suited to report on design activity happening outside of supervised environments. It allows for information searching, peer communication and longer cognitive processes such as incubation without physical or digital supervision. Past examples have shown ways to reduce issues related to retrospective reports (Suwa & Tversky, 1997).

For this research, the Function Behaviour Structure an established framework in design cognition was chosen. It defines ideation states and their relationships which translate into 8 cognitive processes. To each cognitive process relates a cognitive load, it seldom becomes a medium of choice for investigation. The FBS is associated to Linkography, an analysis tool introduced by Goldschmidt (2014), used in the study of design. It has been proven to function well with the FBS model as it allows the definition of every state. After analysis, states are linked together, and resulting cognitive processes are defined according to FBS. Those cognitive processes illustrate the cognitive load and are visible on the linkograph as connections (fig 2). Working this way allows for linking states beyond adjacency (Jiang & Gero, 2017). It also reveals which ideas contribute the most to the overall result. However, Linkography requires granularity and thus, in our case, can only be applied with concurrent data. FBS, combined with Linkography, provides a common ground for comparison with similar research (Kan and Gero, 2017; Yu et al., 2013; 2014; 2015; Lee & Oswald, 2019).

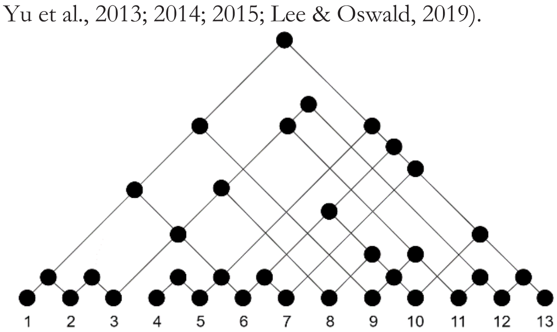

Figure 2. Example of a linkograph. The bottom row represents the different states of an idea which all have an id. All the rows above represent a cognitive process connecting one state to another.

2. Discussion

The pilot experiment presented in this paper was conducted on an elective master course on computational design for architects. Students were given 3 assignments with increasing complexity by the addition of constraints and were given 2 weeks for each of them. They had in class sessions but were also able to continue their work at home. The first week was introduced to them as an exploratory phase from which they had feedback. This was made to emphasize their access to supportive information. The second week was presented as the production phase.

Concurrent verbal data as well as screen recordings are collected through group conversation during live exercises. Retrospective data is gathered by weekly verbal reports of their activity regarding the assignments outside of class. All the data is then transcribed and coded according to the FBS framework. After a first qualitative assessment, Linkography is applied to selected design episodes which allows for further qualitative as well as quantitative analysis (see fig. 3).

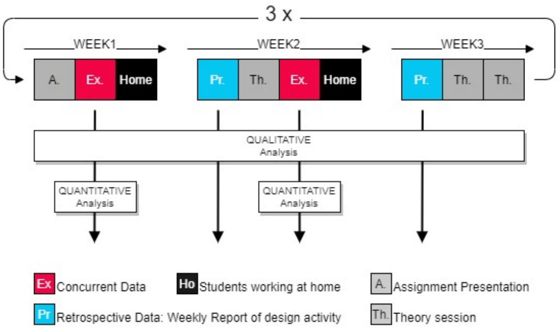

Figure 3. Global view of the experimental process for capturing the cognitive load

The results show how cognitive resources are invested in the design process over the course of the 3 design tasks. We observe an extensive investment into supportive information searching but only during the first assignment, which was unexpected. During the second and third assignments, investment is focused on debugging and testing alternative parameters to fit the previous geometry into the new constraints. There is little to no consideration for alternative design spaces.

From a cognitive load perspective this strategy could translate into long term mental savings meaning there's an important mental investment for the first design task that will save cognitive load memory for later. However, working memory is then invested into vertical adaptation in task 2 and 3 rather than lateral exploration. So, it might be perceived as cost-effective, but the users get trapped in the process. Ultimately, they end up having to deal with an overwhelming number of possibilities through epistemic actions they are not familiar with (Erhan et al., 2017).

That behaviour is specific to the nature of PDEs, and it shows how vulnerable users are to supportive information for design decision-making. Eventually, a limited investment in information retrieval could dictate the design space of multiple future designs regardless of constraints. That influence is emphasized here as students have no earlier experience with PDEs and it might be argued that architects unconsciously temper that effect.

Further retrospective interviews were conducted after the conclusion of the course. When students were asked why they hadn't relied more on supportive information, the lack of time was consistently mentioned which is a reality students and professionals must deal with. They also felt they didn't need to explore other design spaces to fit the constraints. Only one student said that he tried to expend on design alternatives but the lack of time and frustration due to incomprehension led to abandonment.

3. Conclusion

This pilot study reveals the management of cognitive load of architecture students learning while designing in PDEs. However, results cannot be generalized due to the size of the sample and the narrow range of experience. Moreover, this study assumes cognitive students' profiles to be the same although variations in motivation levels for example, could result in higher working memory capacity (Grogan et al., 2021).

The strategy observed in students is to focus all cognitive resources on the parametric design tool and its vertical adaptation capability with a minimum investment into learning even though they had no prior experience.

Because of the poor use of supportive information, we were able to highlight a weakness: the lack of resources when facing massive pools of unfiltered information. As mentioned in cognitive load theory by vanMerriënboer and Sluijsmans (2009), it is important to supply the necessary skills to get control over their own learning process through information-rich and ever evolving computational tools (Sithole et al., 2017; deBruin & vanMerriënboer, 2017). Having no experience, by decreasing the amount of supportive information, criticism over the process declines and external information gains more influence over the design decisions. And because of its complexity the PDE requires that new relationship with supportive information. Those findings are inconsistent with previous studies on computational design tools and cognition that used more constrained experimental environments. Our results thus raise the question of experimental settings and analysis methods in computational design and cognition studies.

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