INVESTIGATING THE PROCESS, DESIGN OUTPUTS AND NEUROCOGNITIVE DIFFERENCES BETWEEN PROTOTYPING ACTIVITIES WITH PHYSICAL AND DIGITAL LEGO

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ABSTRACT

Design neurocognition is an emerging research area that can provide insights into the black box of designers' cognitive processes. However, work to date has focused on neurocognition on its own, without integrating this with other design measures.

This paper presents the results of a pilot study which brings together designer neurocognition with design output and assessment of the design process followed in a constrained prototyping activity comparing use of physical and digital Lego. This was achieved via EEG data capture, a TLX survey and measures of design output variance.

Differences between physical and digital prototyping methods were found with respect to Task Related Powers of EEG signals and the design process followed with digital prototyping methods found to take longer, require more effort and cause more frustration. No differences were found with regard to design output.

Whilst the sample size used (n=12) was small, future studies will use large sample sizes to increase their statistical power and will consider alternative EEG or fNIRS to capture brain activity due to challenges with the headset used in this study.

Keywords: Design cognition, Design methods, Neurocognition, Prototyping, Human behaviour in design

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1 INTRODUCTION & BACKGROUND

Prototyping is an integral part of the product development process (Houde and Hill, 1997). Methods for prototyping span a wide variety of techniques and tools, and can take place in both the physical and digital domains (Goudswaard et al., 2021b). Different prototyping methods will have different affordances and as such can influence the quality of outputs. As a result, typical product development workflows will use a range of methods from both the digital and physical domains, (Goudswaard et al., 2021a), however there is no best prototyping method for a given activity, (Lim et al., 2008) and the choice of tool and domain to use is not a simple one. Since the design tool does not often translate from the physical to the digital domain and vice versa, it can be difficult to compare the domain independently of the design tool. Physical prototyping methods have been shown to increase creativity and communication and encourage collaboration and design exploration, (Mathias et al., 2018; Donati and Vignoli, 2014; Garde and van der Voort, 2016), whereas digital tools often lend themselves to detailed design work, with the added risk of design fixation.

There have been various comparison studies of prototyping techniques, such as the comparison of sketching, card modelling and digital tools (Isa et al., 2015), which found card modelling to illicit more creativity and variation in designs. Physical methods have also been shown to increase the speed of idea generation through a comparison of CAD sketching and foam modelling (Häggman et al., 2015).

While characterisation and comparison of prototyping methods have been widely performed, relatively few studies have investigated the cognitive effects of prototyping domain on the designer. Multiple non-invasive methods exist for capturing the neurocognitive activity in a designer's brain, such as functional Magnetic Resonance Imaging (fMRI), functional Near Infrared Spectroscopy (fNIRS), and Electroencephalography (EEG). EEG records the electrical activity of the brain via electrodes placed on the scalp, it is non-invasive and has a high temporal resolution. These attributes, coupled with its relative affordability when compared to fNIRS or fMRI, mean that it is the most commonly used method for recording brain activity (Schomer and Lopes da Silva, 2017).

EEG studies have been undertaken to compare the brain activity of mechanical engineers, industrial designers and architects when completing both open and constrained design tasks. The results of these studies provided evidence that there are differences between open and closed design tasks, as well as differences between disciplines (Vieira et al., 2020, 2019b,a).

While the neurocognitive effects of the level of design constraint have been investigated, there exists a gap in the knowledge in terms of how the use of media, and in this case physical or digital prototyping methods, impacts design neurocognition. In addition to addressing this gap, this paper also looks to examine the design process as well as its outputs in order to facilitate comparison of design outputs, process and design cognition. As such, the research questions for this paper are as follows:

1. Can process differences between physical and digital prototyping methods be observed?
2. Can neurocognitive differences between physical and digital prototyping methods be observed?
3. Are there differences in outputs between prototypes made via digital and physical methods?

The remainder of the paper is structured as follows. Section 2 explains the paper's methodology, Section 3 presents the results which are then discussed in Section 4. The paper closes with conclusions in Section 5.

2 METHODOLOGY

To investigate the research questions, participants were instructed to complete constrained design tasks using both physical and digital prototyping methods. The experiment was approved by the University of Bristol ethics committee (ref 2021-0298-265). Twelve participants took part in the experiment, 11 male and 1 female, 9 were right handed. Participants had a mean age of 29, with a standard deviation of 6.3 years. All participants had at least 2 years of design experience and varied in education from masters students to a professor of 20 years. Figure 1 shows an overview of the experimental methodology.
The following sections explore the corresponding elements of Section 2 and detail the study set up (Section 2.1), design measures (Section 2.2), and analysis (Section 2.3).

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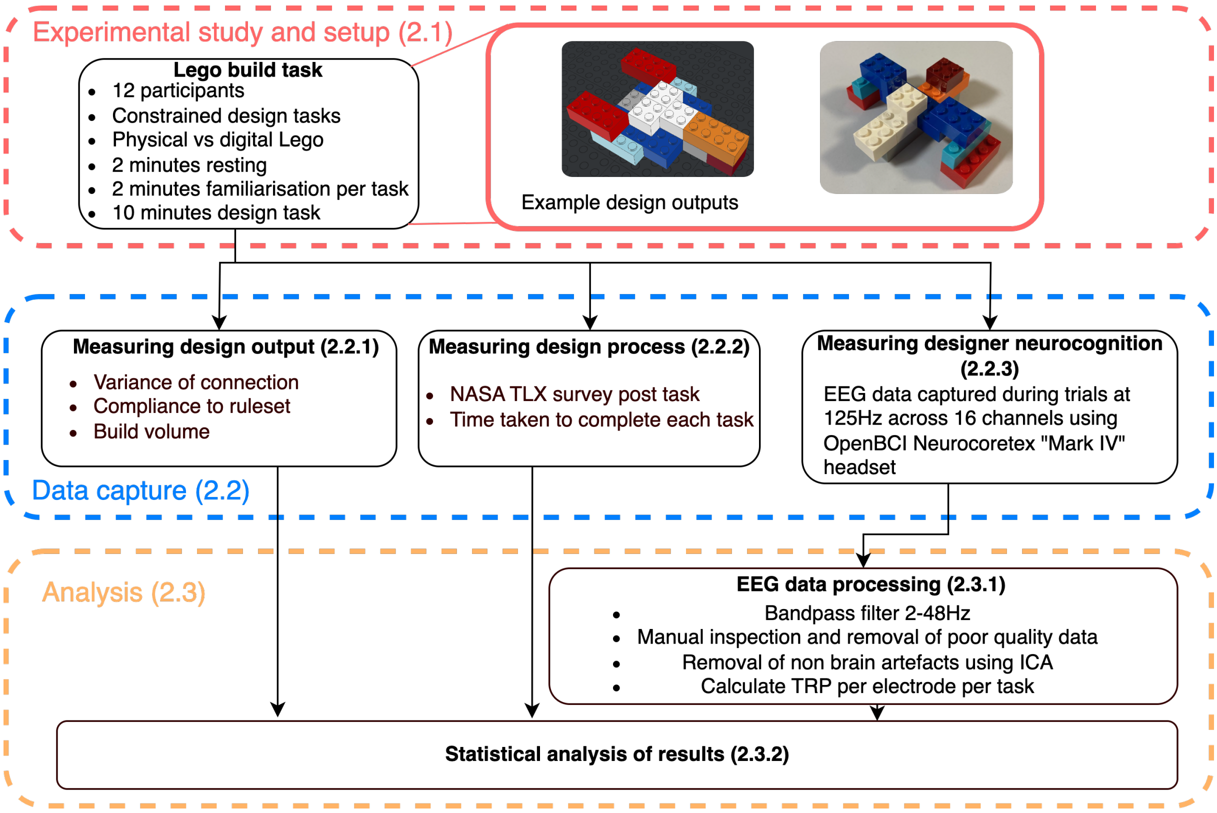

Figure 1. Overview diagram of the methodology used. Reference numbers correspond to section headings.

2.1 Experimental and study setup

The experiment consisted of participants completing two consecutive design tasks, each completed using a different prototyping tool. The task was to construct a Lego spaceship that complied with a pre-determined set of design rules. Each brick colour represented a different component and had a constraint associated with it. Three rule sets were generated, with different rule sets given to participants for each design task to prevent learning bias. The rule sets were based on those proposed by (Mathias et al., 2018). Each contained 14 bricks and an equal number of constraints that the design had to comply with. The three different sets of rules were equally constrained to provide the same level of freedom to the designers. Rule sets were distributed equally across participants, prototyping domains and order of undertaking and were provided to participants on paper. The physical design tool was a collection of Lego bricks corresponding to the colours in the ruleset. The digital design task mirrored the physical but used LeoCAD, a Lego CAD software (LeoCAD, 2022), in place of the physical Lego bricks. Lego was used as it translates well from a physical object to a digital representation, allowing the same prototyping tool to be evaluated physically and digitally. Figure 2 shows the order that tasks were performed by participants.

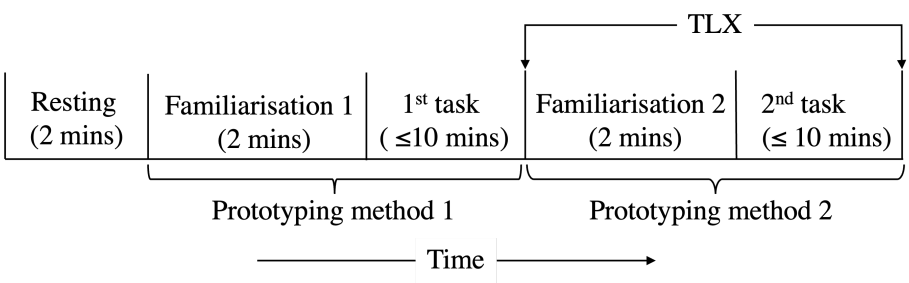

Figure 2. Data capture phases of experiment

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Half of the participants completed the physical design task first, while the other half completed the digital design task first.Participants were given two minutes to familiarise themselves with the design tool before beginning the design task. The design tasks had a time limit of ten minutes and rested for two minutes before beginning the experiment. Table 2 shows a breakdown of the rulesets given to each participant, which order they were completed in and the time taken for each task.

2.2 Design measures

The data capture stage is depicted in Fig. 1 and involves the collection of data used to quantify the differences between the prototyping domains. Three data streams were captured to characterise this: i) the design outputs (Section 2.2.1); ii) the design process (Section 2.2.2); and, iii) designer neurocognition Section 2.2.3.

2.2.1 Measuring design output

To establish whether the design tool used had an impact on the quality and variation of the design outputs, several metrics were determined to assess the outputs from each task. First, each output was inspected for compliance with the ruleset presented to the participant. This inspection was completed *post-hoc*, and the participant was not informed whether their design was compliant.
Variation in designs was determined by two measures: build volume and entropy.
The build volume for each design was calculated, using the studs on the Lego bricks to calculate the build area multiplied by the number of brick layers as a measure of the height.
Entropy was calculated by following the method used by Mathias et al. (2018) and calculated by first creating a Design Structure Matrix (DSM) (Eppinger and Browning (2012) for each spaceship. The DSM contains the number of connections each brick type has with each other brick types (example presented in Fig. 4).
For each DSM its entropy is calculated using the Shannon Entropy formula (Eq. (1)) providing a measure of the level of inter-connectivity of each design with a low entropy value indicating few connections.

$$H(X) = -\Sigma_{i=1}^{n} P(x_i) \log_2 P(x_i) \tag{1}$$

where $H(X)$ is the entropy, $P(x_i)$ is the probability of the i^{th} and and n is the number of elements in the DSM. Calculating the entropy required normalisation of each DSM so that the sum of values was equal to one. These values could then be input into Eq. (1) returning the entropy for each matrix.

2.2.2 Measuring design process

Design process was measured by asking each participant to complete a NASA Task Load index (TLX) assessment (NASA, 2020) at the end of each trial. The TLX is a subjective workload assessment to assess the perceived workload of a task. The results of the TLX questionnaires was combined with the time taken to complete each task to gain an understanding of how the prototyping tool impacted the designer's performance and subjective workload. It consists of self-assessment on a 21-point scale of mental demand, physical demand, temporal demand, performance, effort and frustration.

2.2.3 Measuring designer neurocognition

Before beginning the design tasks, an EEG headset was fitted to a participant's head and electrodes adjusted to ensure satisfactory signal acquisition. EEG data was collected using an Ultracortex "Mark IV" headset from OpenBCI transferring data via Bluetooth at a sampling rate of 125Hz. 16 dry electrodes were used, equally spaced across the scalp according to the international 10-20 system (Homan, 1988), to facilitate broad capture of brain activity. The locations of these electrodes can be seen in Figure 3. An ear clip on the left earlobe was used as the ground and the Cz electrode, as defined in the international 10-20 system, was used as the bias.
To capture the neurocognitive activity of designers during each task, EEG data was captured throughout the experiment. The data captured was classified into three categories;

- Resting (2 mins): the participant is in a resting state with minimal movement and cognitive activity.
- Familiarisation (2 mins): the participant is using the design tool without a specific aim
- Design (10 mins max): the participant is using the tool to complete the assigned design task

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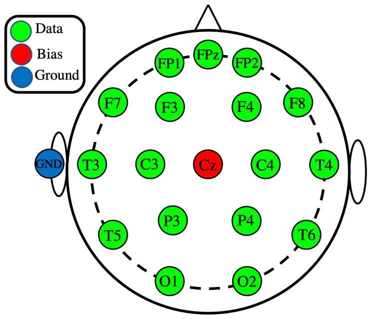

Figure 3. Electrode locations used to capture EEG data, locations based on the 10-20 system of measurement

2.3 Analysis

This section will detail the EEG data processing and the statistical tests used to compare datasets.

2.3.1 EEG data processing

Analysis of the EEG data was performed using EEGLab in Matlab (Delorme and Makeig, 2004). The captured data was band pass filtered from 2-48Hz to remove low amplitude artifacts and line noise. The filtered data was subsequently manually inspected to remove periods of high amplitude. This resulted in a mean percentage of data kept of 53.5%, SD=21.5%, with a maximum of 95.1% kept and a minimum of 7.6%. This, in some cases large, proportion of data removal will be discussed further in Section 4. Independent component analysis (ICA) was used to remove components of the signal associated with undesired brain activity, such as muscle movements and blinks. ICA components were classified using the ICLabel plugin for EEGLab, which returned a classification for each signal component (Pion-Tonachini et al., 2019). Components were then manually inspected and removed if they contained large components due to activity unrelated to brain activity. Of the 16 components returned by the ICA, the mean number rejected was 5.1 across all participants, with a standard deviation of 2.2.

The cleaned data was used to compute the Task Related Power (TRP) across each electrode per participant per task. TRP measures the difference in total transformed power, denoted *Pow*, between the task and the resting state. This metric has been used in previous studies to calculate differences in brain activation between two groups with different backgrounds completing the same design task (Vieira et al., 2020).

Pow is defined as the mean of the squared values of microvolts per second recorded from the headset. TRP for each participant is calculated using Eq. (2),

$$TRP_i = \log(Pow_{i,task}) - \log(Pow_{i,ref}), \quad i = 1,2...n \qquad (2)$$

where n is the number of the electrodes in use. Positive values of TRP indicate an increase in power during the task compared with the reference. For the results presented in section 3, TRPs were calculated for the physical and digital design tasks, with the resting state used as a reference.

2.3.2 Statistical analysis

Statistical analysis was undertaken in Graphpad Prism 9 software. A variety of statistical techniques were used to analyse data from the study:

- To compare build times and design entropies, paired T-tests were used.
- To compare ordinal TLX data a Wilcoxon matched pairs signed rank test was used.
- To compare TRPs, an ordinary 2-way ANOVA with Šidák's multiple comparison were used for which hypothesis testing was used to correct for multiple comparisons.

3 RESULTS

In this section, the results of the analysis performed on the various data collected during the experiment is presented.

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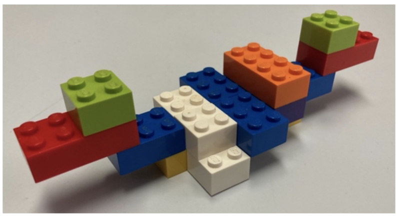
3.1 Design outputs

Table 1 presents the quantity of designs that were compliant with the required rulesets. No differences are observed between prototyping domains and compliance.

Table 1. Table showing compliant and non-compliant builds per domain and ruleset

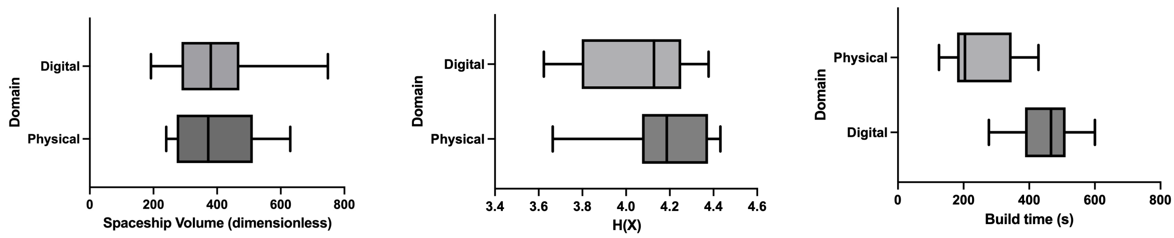
	Physical		Digital	
Ruleset	**Compliant**	**Non-compliant**	**Compliant**	**Non-compliant**
1	4	0	3	1
2	3	1	3	1
3	2	2	3	1
Total	9	3	9	3



	Red	Yellow	Green	Blue	White	Purple	Orange
Red	0	0	2	2	0	0	0
Yellow	0	0	0	4	4	1	0
Green	2	0	0	0	0	0	0
Blue	2	4	0	2	3	2	0
White	0	4	0	3	3	0	0
Purple	0	1	0	2	0	0	1
Orange	0	0	0	0	0	1	0

Figure 4. Sample spaceship and its corresponding DSM

Figure 4 demonstrates a sample spaceship with its corresponding design structure matrix which is used to calculate entropy as defined in Section 2.
Figure 5a presents the impact of prototping domain on use of space during the design task and Fig. 5b presents the impact of domain on build volume. In both cases, data were found to be normally distributed via means of a D'Agostino and Pearson test and were compared via means of paired T-tests. No statistically significant differences were found (ie p>0.05) in either case suggesting that prototyping domain does not impact design output in this case.



(a) (b) (c)

Figure 5. The effect of domain on design output in terms of build volume,entropy and build time. (a) denotes build volume, expressed as length (studs) × width (studs) × height (#bricks). (b) presents the Entropy for physical vs digital prototypes. (c) presents build time for digital vs physical prototypes.

3.2 Design process

Summary TLX data for digital vs. physical are shown in Fig. 6. In all categories, from a user experience perspective, physical prototyping methods were shown to perform better than digital. The data was compared via means of a Wilcoxon matched pairs signed rank test. Statistically significant results were found for Temporal Demand (p=0.001), Effort (p=0.0048) and Frustration (p=0.001).

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*Table 2. Table showing the ruleset completed by each participant and the time taken to complete each. Ruleset numbers marked with a * indicate the first task completed.*

Participant number	1	2	3	4	5	6	7	8	9	10	11	12	Mean
Physical ruleset	1*	2	1*	1	2*	1	2*	2	3*	3	3*	3	-
Digital ruleset	3	1*	2	2*	1	3*	3	3*	1	1*	2	2*	-
Digital duration (s)	510	600	375	460	510	368	277	511	600	440	473	425	462.4
Physical duration (s)	389	672	213	195	428	125	166	270	180	180	233	185	244.6

Figure 5c demonstrates the impact that domain has on build time. Data was found to be normally distributed via means of a D'Agostino and Pearson test and were compared via means of paired T-test. Differences in build time were found to be statistically significant with $p<0.0001$, corroborating the differences in temporal demand reported by participants in the TLX data.

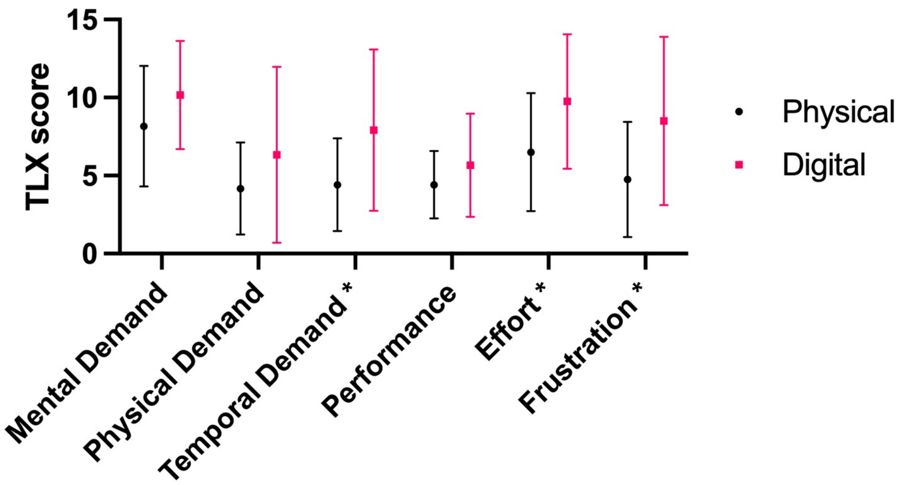

*Figure 6. TLX data summary. Factors marked with * were found to have statistical significance. For all factors a low score is better as it corresponds to low demand, effort or frustration and high performance.*

3.3 Designer neurocognition

Task Related Powers (TRPs) were calculated for each electrode for digital and physical design tasks with the resting activity used as a baseline for each. Figure 7 shows the mean calculated values of TRP across all participants for each electrode. Table 3 shows an overview of the results of the two way ANOVA tests conducted on the TRP data.

Table 3. ANOVA table for TRP comparisons between physical and digital design tasks

	SS	DF	MS	F (DFn, DFd)	P value
Interaction	15.81	15	1.054	F(15, 352) = 0.4535	p=0.9614
Electrode	103.1	15	6.875	F(15, 352) = 2.958	p=0.0002
Design domain	22.18	1	22.18	F(15, 352) = 9.541	p=0.0002
Residual	818.2	352	2.324		

A two-way ANOVA was performed to analyse the impact of electrode and design domain on TRP (results in Table 3). The tests revealed that there was not a statistically significant interaction between the effects of electrode and design domain $F(15, 352) = 0.4535$, $p=0.9614$. Main effects analysis showed that electrode ($F(15, 352) = 2.958$ $p=0.0002$) and design domain ($F(15, 352) = 9.541$ $p=0.0002$) both had statistically significant impacts on TRP. These however only accounted for 10.75 and 2.3 % of the observed variance respectively. Šidák's multiple comparison tests were carried out to identify differences between physical and digital design tasks but did not show statistical significance.

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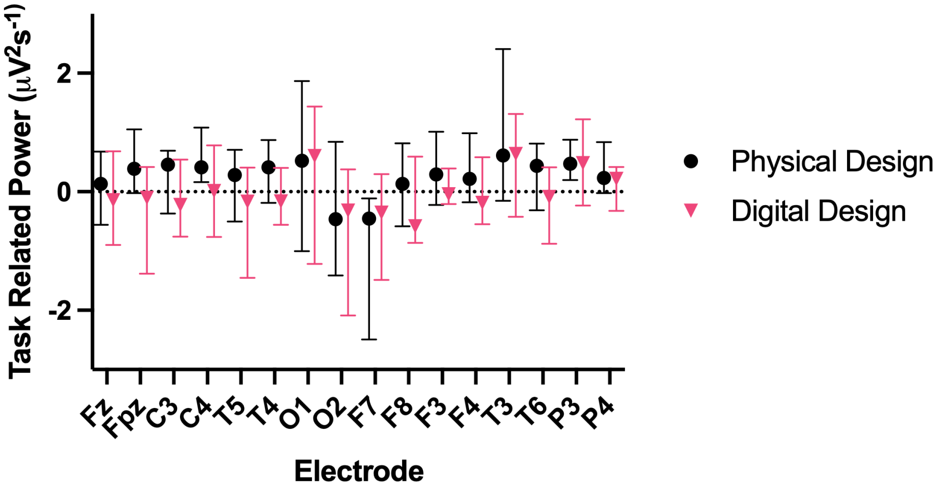

Figure 7. Summary TRP data. Plots present median and interquartile range

4 DISCUSSION

The discussion section will consider the response to the research questions proposed, as well provide comments on the experimental setup and consider further work.

4.1 Answers to research questions

Design processes, as reported by TLX and the time taken to complete the task, were shown to vary substantially. The time taken to complete the digital design task was significantly longer than the physical task, with the mean digital task time being 47% greater than the mean physical task time. This difference in task completion time correlates with the reported differences in the TLX responses among participants. Temporal demand, effort and frustration were all significantly higher in the digital task then the physical and these factors are likely to cause the time to increase. These differences could be attributed to the ease of use of Lego or participants' lack of familiarity with the LeoCad software, as each was only given two minutes to become familiar with it with no participant having previous experience with the specific software. To answer research question 1), process differences can be observed between physical and digital prototyping methods, with physical methods shown to be less frustrating, and time consuming, than digital methods.

The results of the statistical analysis on the calculated TRP values suggests that small differences in neurocognitive function can be observed overall. ANOVA shows that condition does have a significant effect on TRP however no individual statistical differences between electrodes means it is difficult to link this difference to specific cognitive functions. Between participant differences were far greater than electrode or condition suggest that there may be problems with data capture. To answer research question 2), the results show that differences may occur, however the methods of data capture utilised in this study may have been insufficient to identify these differences.

Design outputs were found to be similar, with no statistical differences in terms of build volume and entropy. Compliance to the rulesets also showed no differences across prototyping domains, with the same number of compliant designs in each domain. Therefore in response to research question 3), the results do not suggest evidence that there are quality differences between the outputs of physical and digital prototyping methods.

4.2 General comments

Whilst no specific differences were found in activity at individual electrodes, if designers are frustrated and report differences in their design experience it seems counter-intuitive that more specific neurocognitive differences are not occurring during design. This could suggest issues around neurological data capture with regard to the suitability of the equipment used for the study. Small amounts of movement

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was required from participants during the task as participants operate either the computer or manipulate Lego bricks indicating that movement artefacts beyond those removed by the ICA could remain in the analysed signals. The headset used dry electrodes that had difference in signal strength dependent on contact quality with participants' scalps, often due to amount and thickness of head hair. Whilst these differences should be accounted for in the TRP calculation, with each design activity using resting activity as a baseline, it is possible that this effect is not fully accounted for. Alternative EEG headsets or an fNIRS are considered as alternative options that may be more appropriate for this kind of longitudinal design study.

4.3 Limitations and further work

This study has several limitations that should be highlighted. First, while all participants were involved in the field of mechanical engineering, the level of experience in design, and familiarity with digital design tools varied significantly. Future iterations of the work would seek to use a more homogeneous groups of participants

Second, the results found from the design tasks using Lego may not translate to other prototyping analogues. Digital and physical design tools take a large number of forms, so the use of Lego is not necessarily representative of all physical and digital design tools. Lego is considered a good starting design medium due to there being direct digital and physical analogues. Future work will look to compare additional digital and physical design media.

As mentioned in the previous section, data capture could be improved by exploring alternate methods of capturing the neurocognitive activity of designers. Alternative approaches, such as a wet electrode EEG device, fNIRS headset or multi-modal (EEG + fNIRS) device could provide better capture of designers' neurocognition during tasks such as that undertaken in this study.

In addition to changes in data capture, greater samples sizes would be required for statistically significant results. Neuroscience focused studies in the field of design research have mean sample sizes of 20.97 (SD=14.55) and in the field of neuroscience 27.44 (SD=12) (Balters et al., 2022). These indicate the typical sizes of study required for a full run of the study presented in this paper.

5 CONCLUSIONS

This paper presented the results of a pilot study with the aim of determining if there are observable differences in process, output and neurocognition when comparing the same prototyping method executed physically and digitally. The study involved 12 participants completing a constrained design task using physical and digital Lego. Within the study, participant brain activity was monitored via a 16 electrode EEG headset, and the quality and variety of the design outputs was quantified by calculating the build volume and entropy of the designs as well as compliance to the rules of the design task. Design process was evaluated using the time taken to complete each task, and the results of a NASA TLX questionnaire. TRP values were calculated per participant for each electrode between the physical and digital design tasks and the resting state. The effect of the prototyping domain was shown to be significant, but no observable differences were found between individual electrodes. No significant differences were found between the outputs of the physical and digital methods, however the results of the TLX showed that digital methods were more frustrating and mentally demanding. Digital methods also took significantly longer (47%) than the physical equivalent to complete the design activity. These findings indicate that there are benefits to prototyping physically. Limitations in the capture of EEG data were identified, which could explain the lack of significant differences observed for individual electrodes. Addressing these issues via use of alternative EEG or fNIRS headsets is a focus of future work and could potentially allow for improved deduction of neurocognitive differences between physical and digital prototyping methods.

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REFERENCES

Balters, S., Weinstein, T., Mayseless, N. and Auernhammer, J. (2022), "Design science and neuroscience: A systematic review of the emergent field of design neurocognition", *Design Studies*. http://doi.org/10.1016/j.destud.2022.101148.

Delorme, A. and Makeig, S. (2004), "Eeglab: an open-source toolbox for analysis of eeg dynamics", *Journal of neuroscience methods*, Vol. 134, pp. 9–21. http://doi.org/10.1016/j.jneumeth.2003.10.009.

Donati, C. and Vignoli, M. (2014), "How tangible is your prototype? designing the user and expert interaction", *International Journal on Interactive Design and Manufacturing (IJIDeM)*, Vol. 9. http://doi.org/10.1007/s12008-014-0232-5.

Eppinger, S. and Browning, T. (2012), *Design Structure Matrix Methods and Applications*. http://doi.org/10.7551/mitpress/8896.001.0001.

Garde, J. and van der Voort, M. (2016), "Could lego® serious play® be a useful technique for product co - design?", http://doi.org/10.21606/drs.2016.24.

Goudswaard, M., Gopsill, J., Harvey, M., Snider, C., Bell, A. and Hicks, B. (2021a), "Revisiting prototyping in 2020: A snapshot of practice in uk design companies", *Proceedings of the Design Society*, Vol. 1, pp. 2581–2590. http://doi.org/10.1017/pds.2021.519.

Goudswaard, M., Snider, C., Gopsill, J., Jones, D., Harvey, M. and Hicks, B. (2021b), "The prototyping fungibility framework", *Procedia CIRP*, Vol. 100, pp. 271–276. 31st CIRP Design Conference 2021 (CIRP Design 2021).

Häggman, A., Tsai, G., Elsen, C., Honda, T. and Yang, M. (2015), "Connections between the design tool, design attributes, and user preferences in early stage design", *Journal of Mechanical Design*, Vol. 137. http://doi.org/10.1115/1.4030181.

Homan, R.W. (1988), "The 10-20 electrode system and cerebral location", *American Journal of EEG Technology*, Vol. 28 No. 4, pp. 269–279. http://doi.org/10.1080/00029238.1988.11080272.

Houde, S. and Hill, C. (1997), "Chapter 16 - what do prototypes prototype?", in: M.G. Helander, T.K. Landauer and P.V. Prabhu (Editors), *Handbook of Human-Computer Interaction (Second Edition)*, North-Holland, Amsterdam, second edition edition, pp. 367–381. http://doi.org/10.1016/B978-044481862-1.50082-0.

Isa, S., Steinert, M. and Liem, A. (2015), "The value of prototypes in the early design and development process".

LeoCAD (2022), "LeoCAD - a CAD application for creating virtual lego models". https://www.leocad.org/

Lim, Y.k., Stolterman, E. and Tenenberg, J. (2008), "The anatomy of prototypes", *ACM Transactions on Computer-Human Interaction*, Vol. 15, pp. 1–27. http://doi.org/10.1145/1375761.1375762.

Mathias, D., Hicks, B., Snider, C. and Ranscombe, C. (2018), "Characterising the affordances and limitations of common prototyping techniques to support the early stages of product development", *Proceedings of International Design Conference, DESIGN*, Vol. 3, pp. 1257–1268. http://doi.org/10.21278/idc.2018.0445.

NASA (2020), "NASA task load index". https://humansystems.arc.nasa.gov/groups/tlx/

Pion-Tonachini, L., Kreutz-Delgado, K. and Makeig, S. (2019), "Iclabel: An automated electroencephalographic independent component classifier, dataset, and website", *NeuroImage*, Vol. 198. http://doi.org/10.1016/j.neuroimage.2019.05.026.

Schomer, D.L. and Lopes da Silva, F.H. (2017), *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, Oxford University Press.

Vieira, S., Gero, J., Delmoral, J., Gattol, V., Fernandes, C. and Fernandes, A. (2019a), "Comparing the design neurocognition of mechanical engineers and architects: A study of the effect of designer's domain", *Proceedings of the Design Society: International Conference on Engineering Design*, Vol. 1, pp. 1853–1862. http://doi.org/10.1017/dsi.2019.191.

Vieira, S., Gero, J., Delmoral, J., Gattol, V., Fernandes, C., Parente, M. and Fernandes, A. (2019b), "Understanding the design neurocognition of mechanical engineers when designing and problem-solving", http://doi.org/10.1115/DETC2019-97838.

Vieira, S., Gero, J., Delmoral, J., Gattol, V., Fernandes, C., Parente, M. and Fernandes, A. (2020), "The neurophysiological activations of mechanical engineers and industrial designers while designing and problem-solving", *Design Science*, Vol. 6, pp. 1–35. http://doi.org/10.1017/dsj.2020.26.

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