1 INTRODUCTION

Design rules govern the design process by imposing constraints on the development of a product. Examples of design rules include engineering standards, regulations, standard operating procedures and existing designs as protected by patents. These design rules are important for ensuring product safety, environmentally sustainability and ability to interface with other products. However, the number of design rules have increased dramatically, potentially over-constraining the design space and reducing innovation (Blind, 2012, 2013). To highlight this, between 1994 and 2015, the ISO 9001 Quality Management Standards grew nearly four-fold in length (British Standards Institution, 1994, 2015). Similarly, the number of patent applications filed to the European Patent Office grew by 32% between 2006 and 2015 (European Patent Office, 2015) meaning that it is becoming more difficult to avoid patent infringement, which in turn is a type of design rule. In addition, these rules often come in the form of a written document and the form in which this information is presented has a significant effect on a variety of engineering tasks, such as comprehension (Boa & Hicks, 2016).

The issue with design rules is two-fold: quantity of design rules and the expression of them. The quantity of rules makes checking for violations challenging and slowing the development process and innovation. The expression of design rules may potentially create a form of design fixation, further reducing innovation. To deal with the issue of quantity and complexity of design rules, methods are required for managing design rules. If done correctly this could lead improvements in product innovation (Blind, 2012, 2013). A system for managing this could simultaneously distribute and filter design rules to deal with the complexity and quantity of them. This would allow design rules for the aspect of the product being developed to only be displayed when they are relevant.

This has been explored by Bennett et al. (2017) in which it was demonstrated that distributed rules in individual bricks of LEGO models facilitated playful interpretation of the design rules. By distributing the design rules, a level of ambiguity was introduced that promoted innovation in the construction of simple LEGO models. The study reported in this paper builds on Bennett et al.'s work by exploring how the expression of the embedded design rules affects innovation in the construction of LEGO models.

An important aspect of design rule expression is the richness of the design rule. For the purposes of this paper, the design rule richness is defined as the quantity and explicitness of information described in the rule. For example, a low richness design rule would include information only about a single component and would lack quantified information regarding its relation to the whole model. The richness of this rule could be increased by adding in this quantified information such as relative position, frequency of occurrence or adjacency limitations.

In this paper, an exploratory study investigates how the richness of embedded design rules affects the innovativeness of LEGO models. To achieve this, this paper first defines design rule richness and the system used to investigate rules richness - InstructiBlocks. The paper continues by describing the experimental setup where twenty participants were tasked with constructing four spaceships, each with a different set of design rules with varied levels of richness. Individual LEGO bricks were assigned design rules relating to the construction of a simple spaceship (see Section 4.1). The results are then presented where the focus has been on variation in designs.

2 DESIGN RULE RICHNESS

The richness of design rules is highly contextual and dependent on the product being designed. Design rules can be considered to increase in richness as quantity and explicitness of information about the rules also increases.

Design rule richness is increased in this experiment by increasing the number and type of design rules associated with each LEGO brick. Table 1 shows the rule types and their descriptions in the context of constructing a simple LEGO spaceship. These rule types are based loosely on Gero's Function-Behaviour-Structure model of designing (1990) in lieu of another over-arching design rule schema.

To increase the richness of the rules, the three categories (after the 'Physical Properties' category) were added consecutively and cumulatively to the LEGO bricks in each subsequent exercise. This increased the constraint of the design rules, making the design requirements more explicit.

Table 1. A table showing the rule types and their descriptions

Rule	Rule type	Rule description
1	Physical Properties	Geometric size of brick and quantity in system. No information relative the model being constructed.
2	Function	A short description of the component relative to the model being constructed.
3	Behaviour	An explanation of the component (brick's) behaviour relative to the model being constructed.
4	Structure	A description of the component's location relative to other components in the model being constructed

Taking one of the bricks (the red brick) in the LEGO spaceship model for example, the first level of rule describes the stud geometry and quantity in the model (e.g. "size: 2x4, quantity: two"). The second level for the red brick describes its function (e.g. "Rocket Engine"). The third level adds the behaviour of the component to its function (e.g. "Rocket Engine, Generates thrust to propel the ship"). The fourth and final level includes a description of the components location relative to other components (e.g. " Rocket Engine, Generates thrust to propel the ship, Must be attached to the wings"). See Table 2 for a complete list.

3 INSTRUCTIBLOCKS SYSTEM

The InstructiBlock system has been developed to deal with design rule management and consists of RFID tags embedded in individual components and a corresponding digital system to query and display design rules associated with the RFID tag. Complexity of design rules can therefore be managed by distributing the design rules and integrating automatic violation checking of the design rules. The benefit of using LEGO bricks with embedded design rules and physical modelling is that it has been shown these help reduce design fixation, a potential impact from increasing quantity and complexity of design rules (Youmans, 2011).
The InstructiBlocks system can be seen in Figure 1. Users can scan LEGO bricks on an RFID reader and, on a separate computer screen, design rules, or any other information about the brick is shown. An advantage of the InstructiBlocks system is the quick and playful exploration of design rules, constraints or information. We utilise the InstructiBlocks to display information on what the brick represents and the constraints that need to be met.

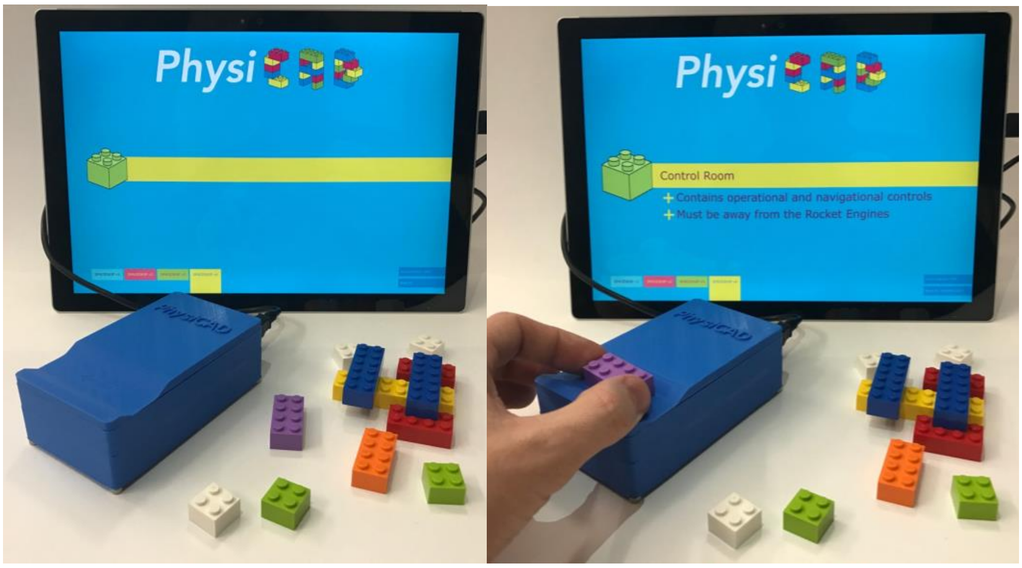


Figure 1: Two images showing the InstructiBlocks system and a user scanning a brick

4 EXPERIMENTAL SETUP

The InstructiBlocks system used in the study to explore the effect of the richness of design rules is described in this section.

4.1 LEGO Model to be constructed

A spaceship was chosen as the simple LEGO model to be built by the participants as it was deemed that there are no strong conventions in the layout of space ships, ensuring the possibility of a large variation of models by reducing fixation effects (Ward, 1994). Spaceships are present enough in popular culture for users to appreciate fundamental items, but the lack of established convention leaves the combination and meaning of these rules open to interpretation. Furthermore, a simple model was needed so that the participants only needed a few minutes to construct it, a spaceship can be approximated with a limited number of bricks ensuring a fast build time. Finally, the spaceship has been successfully used in previous work (Bennett et al., 2017) and so was considered a suitable option.

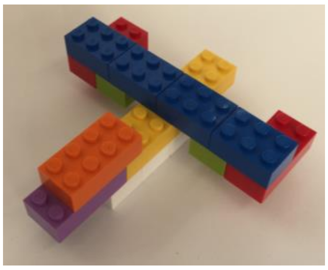


Figure 2. An example of the simple spaceship model

4.2 InstuctiBlocks System Hardware

The InstructiBlock system hardware consists of a 125kHz RFID reader (ID-12LA) connected to an Arduino Mega that handled passing of serial data to the host PC. The RFID tags provide a unique identifier for each LEGO brick. Figure 3a shows the hardware setup including the 3D printed enclosure for the Arduino Mega and the RFID reader. 14 LEGO bricks were embedded with rules, the sizes and quantities can be seen in the first column of Table 2. Seven classes of bricks were used, where bricks of the same colour were considered to be in the same class.

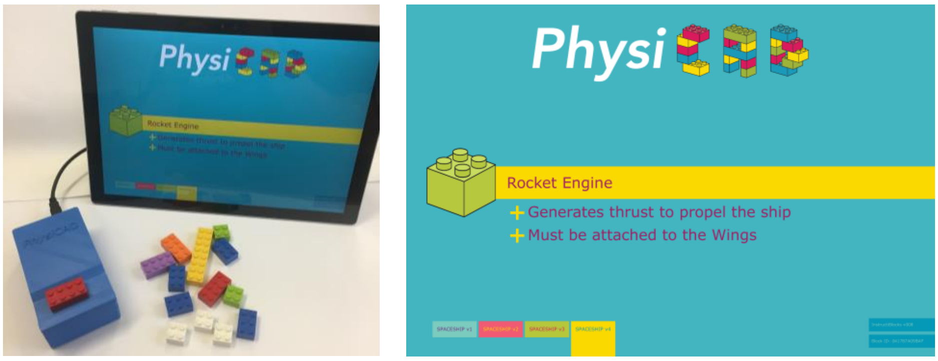


Figure 3a & b. A picture showing the enclosed RFID reader and Arduino Mega and the LEGO bricks. A screenshot of the user interface showing the rules of the bricks.

There were two elements to the software side of the rig: the Arduino code and the user interface. The Arduino code consisted of a serial pass through function that reported the tag information to the PC. Processing (Processing Foundation, 2016) was used to produce a graphical user interface to show the rules for each brick when it was scanned. This script parsed the tag information and compared it to a list of known tags, and the rules were then displayed. Figure 3b shows a screenshot of the user interface. The rules are shown in the middle, and the rule richness can be selected at the bottom.

5 STUDY

The experimental approach involved asking participants to build a LEGO model in four exercises where the embedded rules increased in richness. The design task was to build a spaceship using all 14 LEGO bricks whilst adhering to the design rules embedded in the parts. The task was repeated four times with differing levels of rule richness.

5.1 Rules and Exercises

In each exercise, the richness of the rules was increased so that exercises were going from least rich to richest. The presentation order was fixed for all participants. The number of bricks, 14, the number of classes, seven, and the numbers of brick in each class were kept constant. Table 2 shows the rules for the four exercises. In the first exercise, there were no rules however the size and quantity of each class of brick was shown to keep the scanning element consistent between the exercises. This also allowed the participants to familiarise themselves with the system. Exercise 3 showed the bricks' behaviours as well as their functions, and 4 showed structure, function and behaviour. This increasing level of rule richness aims to reduce design freedom of consecutive designs, with high richness mimicking design scenarios constrained by large numbers of standards and rules.

Table 2. The four exercises showing the rules for each of the brick classes

Brick Colour	**Exercise 1: System**	**2: Function**	**3: Behaviour + Function**	**4: Structure + Behaviour + Function**
Red	Size: 2x4, Quantity: 2	Rocket Engine	Generates thrust to propel the ship	Must be attached to the Wings
Yellow	Size: 2x8, Quantity: 1	Fuselage	Core of the ship providing access between modules	Must connect Living Quarters and Control Room
Green	Size: 2x2, Quantity: 2	Fuel Tank	Contains fuel for the rocket engines	Must have an adjacent face with a Rocket Engine
Blue	Size: 2x3, Quantity: 4	Wing	Generates lift in atmosphere	Must be directly attached to the Fuselage
White	Size: 2x2, Quantity: 3	Living Quarters	Houses the crew and passengers	Must be adjacent to another Living Quarter
Purple	Size: 2x4, Quantity: 1	Control Room	Contains operational and navigational controls	Must be away from the Rocket Engines
Orange	Size: 2x4, Quantity: 1	Comms Module	Allows communication with home planet	Must be attached to the top of the Control Room

5.2 Participants

20 participants took part in the experiment. They had a mean age of 27.6 with a standard deviation of 5.96. Of the 20, 19 were male and the majority had a background in mechanical engineering at degree level or higher.

5.3 Data Capture

Three methods of data capture were performed during the experiment: photos of the models, interrogation sequence captured through data logging and a questionnaire. Photos were taken of each of the four models the participants built, which were then clustered by a panel of experts into similar groups. The panel of judges were asked questions about their grouping rationale. The goal of clustering is to identify the level of similarity within the outputs and hence potential restriction from the rule set. In addition, to this an algorithmic approach was used to measure to the design variation.

There was also a short questionnaire with overall questions about the InstructiBlock system.

6 RESULTS

In this section, the results from the experiment are presented regarding the observed design variation across the participants' models.

6.1 Grouping

Structural topology, in the context of this paper, is the overall shape and structure of the models that the participants built. Grouping based on structural topology was performed by a panel of experts comprising of senior engineers, and occurred for each of the four exercises. The primary considerations that the panel cited for their grouping rationale was the locations of bricks based on their colour and characteristics of the overall form including aspect ratio and relative proportions.
Table 3 shows the number of groups as well as the maximum, minimum and average populations. The significance of the number of groups is that more groups show more variation between the models. As the level of rule richness increased the number of groups decreased, indicating that design variation reduced. However, only Level 4 showed reasonable grouping - with the other levels mostly grouped as individuals or pairs as shown by the average size in Table 3.

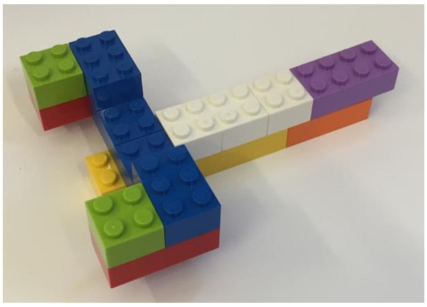
Table 3. Showing the number of clusters and their sizes for the four rule richness levels.

	Exercise 1	Exercise 2	Exercise 3	Exercise 4
Groups	14	11	11	5
Max Group Size	3	4	3	7
Min Group Size	1	1	1	2
Av. Group Size	1.43	1.82	1.82	4.00

The large number of groups in exercises 1-3 suggest that using the structural topology does not reveal much and it is hard to test without a robust grouping rationale. An alternative approach of analysing the data was performed using Design Structure Matrices

6.2 Entropy of Design Structure Matrices

From each of the participants' models, Design Structure Matrices (Eppinger & Browning, 2012) were constructed. A DSM shows the interconnectedness of different elements or subsystem of a product or system. In this study, the DSM consisted of the number of joins each brick had with another brick by class type. Bricks were considered adjacent if any of its six faces were coterminous with another brick. From these matrices it was possible to calculate the relative entropy for that model. Entropy here is a measure of a class of brick's connectedness to other brick classes in the model. Low entropy indicates that the brick class is isolated and has few connections to other classes. Entropy values are contextual, but the variance in them can be considered as an indicator for design variation. That is the greater the variation the greater the distribution of entropy values for a given rule level.



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

Figure 4. An example of a spaceship with its Design Structure Matrix

Figure 4 shows a built spaceship model with its corresponding design structure matrix. The matrices were calculated for each of the participants over all the exercises.

6.2.1 Calculating Entropy

The Shannon Entropy Formula (Shannon, 1948) was used to calculate the entropy for each of the DSMs.

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

Where $H(X)$ is the entropy, $P(x_i)$ is the probability of the ith and n is the number of elements in the DSM. In order to calculate the entropies, the matrices had to be normalised so that the sum of all their elements equalled one. They then could be entered into Equation 1, returning the entropy for that matrix. Entropy calculations were performed using MATLAB.

6.2.2 Analysing Spaceship Model Entropy

From the entropy values for the four exercises, a kernel density estimation was applied to estimate the probability density functions. The PDF shows the spread of the solutions in the design space: a narrower distribution shows that fewer different spaceships were built and so the design space is more constrained. These were plotted to graphically inspect the effect of the rules on entropy.

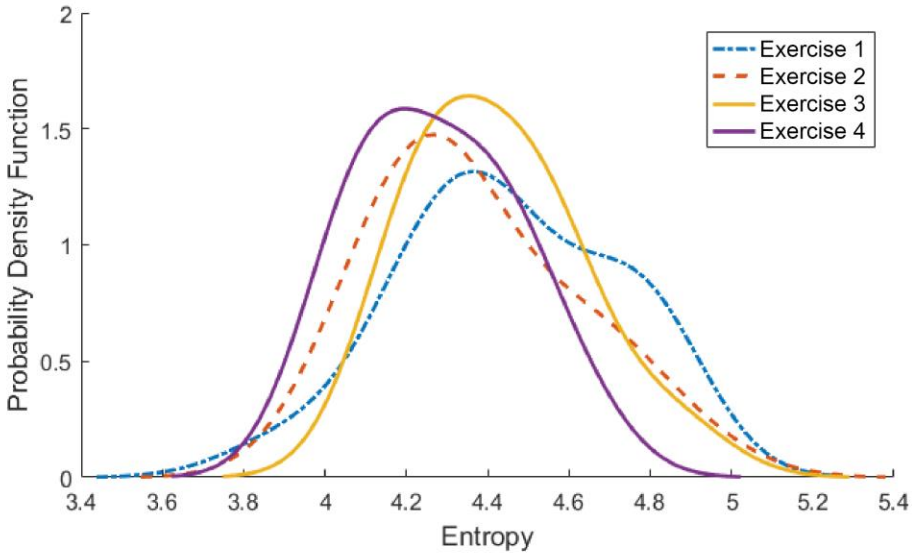


Figure 5. Probability density function of entropy for the four exercises

Figure 5 reveals that exercise 1 has the largest spread showing that it had the greatest variation between designs. Conversely, exercise 4 has the lowest spread giving the least variation in the design space. exercises 2 and 3 sit in the middle.

To investigate this further, two way analysis of variance (ANOVA) was performed to understand the potential correlations between the entropy data. This allowed the effect of the participants and rule levels to be tested against a null hypothesis of having no effect. Table 4 shows that while the individual participants have the greatest effect on the outcome of the design variation, the rule level also has a significant effect.

Table 4. Source of data variability, their P-Value and significance

Variability Source	P-Value	Significance P<0.05	Significance P<0.01
Rule Level	0.0339	Yes	No
Participant	0.0069	Yes	Yes

Further statistical analysis was performed using the ANOVA results. This consisted of testing the difference of means between exercises. This found that only exercises 1 and 4 were significantly different at a 95% confidence interval. Figure 6 shows the means plotted, along with their error bars.

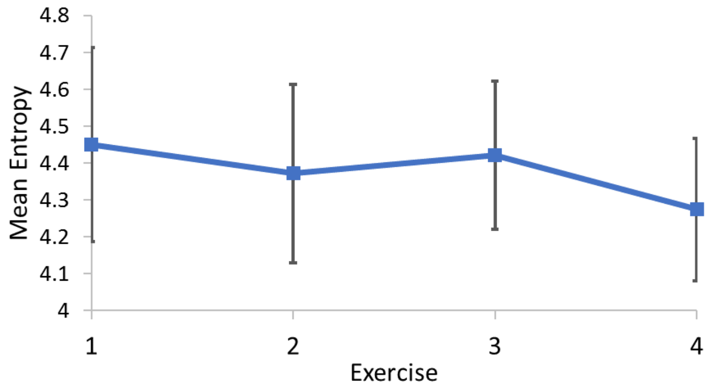


Figure 6. A plot of the means and the standard deviation error bars of the four exercises.

7 DISCUSSION & FURTHER WORK

This section discusses the results and comments on the chosen method and its suitability for studying design rules and their impact on design variation. By analysing DSMs of the models, it was found that there is a point at which the richness of design rules impacts the design freedom and over constrains the design space. This should be investigated further by increasing the complexity of the design task through using more bricks with a greater number of rules. This would increase the granularity of the exercises so that this point could be found with greater confidence.

7.1 Results

The study results are discussed with considerations on how they can be improved and their impact.

7.1.1 Grouping

Grouping should have provided a clear and intuitive insight into how the design rules affected the variation of the built models. However, there were a couple of issues that meant it was not the ideal way to represent the results in this study: the grouping method and the number of participants.

The grouping rationale was chosen before the models were viewed. The choice of structural topology initially seemed reasonable as it would be time efficient looking at the overall shape of the models, however it was difficult to quantify 'shape' in practice. This resulted in a grouping approach that is hard to replicate with another group of experts performing the grouping.

Due to the small number of participants, 20, grouping the models in each of the four exercises was difficult due to the lack of common features between models. The results show that, excluding exercise 4, the three exercises had an average group size less than 2. This meant that the groups only contain one or two models resulting in a number of groups in the same order as the number of participants. If the study was performed with a much larger group, over 150 participants, then it is expected that the grouping would be more robust and produce more significant results.

The advantage of grouping is that similar models can be grouped together showing the different structures while measuring design variation, an affordance the entropy data does not allow. It is also a more intuitive way to view and understand the data and is easier to use when the number of models increases or they have more components.

7.1.2 Entropy

The entropy of DSMs was used as an alternate approach for measuring design variation. The DSMs were generated by hand, which was slow in this study and would be prohibitive with a larger number of participants and model bricks. Despite this, the entropy of these matrices allowed the authors to analyse the data more reliably.

The absolute entropy value provides a measure of the inter-connectedness of the brick classes in each model, but by itself it does not shed any light on design variation in each of the exercises. The variance of the distribution of entropies provided greater insight. The distribution was estimated using the kernel density function, with a sample of 20 data points. A smaller spread (lower variance) shows that the spaceship models have similar entropies, therefore similar assemblies, resulting in a less varied range of

models. By using the variance of the entropies distributions, a more repeatable approach is achieved. The results show that the design variation is reduced as the richness of the rules is increased. Further analysis using ANOVA, found that while the participants have the largest effect on the outcome of the designs, the rule also had a significant effect. This was statistically proven between exercises 1 and 4, but was inconclusive between exercises 2 and 3 and the other levels. This showed that while the rules increased in richness, the levels of richness (see Table 1) were too close together - with the two furthest apart showing a statistically significant difference. This is logical as richness is a continuous measure, however the point at which a noticeable difference occurs was found.
Using the entropy, in this manner allows for different models to be robustly compared and the design variation to be calculated, however, as the matrices are generated from brick adjacencies, the overall form of the spaceships is lost. This can result in models with similar entropies having different structural topology.

7.2 Chosen Method

A simple model allowed the participants to build all four models in around 10 minutes. The short nature of the experiment lent itself to participant engagement and enthusiasm.
The component classes were kept consistent throughout, with the richness increasing in subsequent models. This increase in richness was undertaken to ensure that the participants were not learning 'richer' rules and applying them to the less rich models later. Keeping the component classes the same allowed models to be compared across rule sets. However, this meant that there was some learning bias as the participants used their experience of brick classes from previous models to inform their later ones. It would be worth considering modifying the approach to change the brick classes so that, while the participants were still building a spaceship, they had different classes associated with the physical bricks from the previous build task. This would remove some of the learning bias observed between rule levels. Overall, the method is an effective approach to studying design rule impact on output variation

7.3 Participant Bias

As was shown in the results, there was no significant difference between exercises 2 and 3. The authors believe that this stems from the fact that the majority of the participants were engineers. Meaning that adding the behavioural rule ("Rocket Engines produce thrust to propel the ship") to the functional rule ("Rocket Engines") did not provide additional richness for the participants as all it was doing was making their implicit knowledge explicit. This increase in richness would have been more important to non-experts as it might have added useful contextual information to the components. This problem also highlights the challenges of qualifying richness for different groups of people.
Furthermore, as the participants came from a predominantly engineering background this would likely affected how they viewed the problem of designing a spaceship. It would be useful to repeat the experiment with participants from a wider range of backgrounds, both technical and non-technical.

7.4 Further Work

The richness levels and the corresponding written design rules used should be refined in future work, this scoping study found that the proposed levels of richness were too similar (Exercises 2 and 3) to incite significant changes in design output.
The results show that there is a point at which the richness of design rules limit design variation. However, as richness is a continuous measure, the four exercises did not offer high enough levels of granularity to determine the point at which the design variation is affected. The next step is to investigate this point and explore the trade-off between design rules and innovation. This could be achieved by increasing the complexity of the design task by using more bricks with a greater number of rules per brick. The authors are working on a follow up study that includes a greater number of participants with a more complex design task and a finer granularity of design rule richness.
InstructiBlocks also affords a potential solution for dealing with the complexity and number of design rules by distributing them amongst individual elements. However, this aspect of the system is not considered in this paper and should be considered for further work by testing a central list of rules (akin to standards) against distributed rules in individual elements.

8 CONCLUSION

The increasing number of standards and constraints has made it increasingly challenging for designers to explore the design space. This paper posits that embedding design rules within components is one way to overcome this barrier.

This study explored a link between richness of embedded design rules and the resulting design variation in a simple LEGO spaceship. The method of placing RFID tags in LEGO bricks and assigning design rules, allowed the participants to playfully explore the design space with varying levels of design rules richness. Four rule richness levels were tested: 1. physical, 2. functional, 3. behavioural and functional, and 4. structural, behavioural and functional with each participant building a spaceship in each of the exercises. Subjective grouping of the models by experts led to a large variation in groupings with little similarities between experts. However, measuring design variation through Design Structure Matrices revealed that the richness of the design rules had a significant effect on the design variation but this was only significant between the least and most rich design rules. Further work on how to take the work from this scoping study forward was posited.

From this study, the results show that there is a point at which the richness of design rules limit design variation. The next step is to investigate this point and explore the trade-off between design rules and innovation; where the rules cover safety, quality and environmental as constraints but their expression and delivery can improve innovation.

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