INTERNATIONAL DESIGN CONFERENCE – DESIGN 2024
https://doi.org/10.1017/pds.2024.41

Design delusions and prototyping: eliciting the link between prototypes and product performance

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Abstract

This study investigates the relationship between the number and type of prototypes developed in rapid prototyping contexts, a team's performance self-estimations, and final actual performance. Findings suggest a strong correlation between each of these elements, with the converse also found to be true, motivating the introduction of the concept of Design Delusion - a type of cognitive dissonance due to differences between perceived and actual states. The paper suggests that early prototyping helps identify and mitigate design delusion, improving design decisions and preventing technical debt.

Keywords: prototyping, design activities, case study, self-assesment

1. Introduction and background

Prototyping plays a pivotal role in Engineering Design (Wall et al., 1992). It facilitates learning by creating tangible testable objects (Jensen et al., 2016) that support decision making (Lauff et al., 2018) and allows designers to evaluate specific aspects of a design (Houde and Hill, 1997). Most design projects inevitably involve iteration. Iteration enables the progressive generation of knowledge, concurrency, and integration of design changes (Wynn and Eckert, 2017), and has been shown to improve design performance (Dow et al., 2009). Yassine and Braha (2003) describe 3 reasons for why iterations are necessary:

1. Designer cannot make all design decisions at once.
2. A design cannot be computed directly from a set of requirements.
3. Ambiguity and uncertainty often occur, demanding adjustments of initial plans.

Despite these benefits, during compressed design scenarios such as those often experienced in industrial settings, with tight time constraints and limited resources, iteration can be discouraged because of increased duration and cost (Dow et al., 2009; Wynn and Eckert, 2017). Excessive iterations can also escalate sunk costs by consuming additional resources without guaranteeing proportional improvements in outcome (Viswanathan and Linsey, 2010).

Prototypes can be broadly categorized into digital or physical. Physical prototypes are tangible representations of a product or system's features and have been emphasized for their role in enhancing design outcomes (Dow et al., 2009; Neeley et al., 2013). They facilitate early insights in the design process at a lower cost than digital simulations (Kriesi et al., 2016) and address the ambiguity of early-phase design (Leifer and Steinert, 2011). Digital prototypes are typically observed in the embodiment and detailed design stages (Hsu and Liu, 2000; Otto and Wood, 2001) where the level of definition enables the generation of parametric geometry and simulations that can evaluate specific tasks and optimisation can occur (Hamon et al., 2014). Digital prototyping also often require deep domain

knowledge and skills, with a steep learning curve (Kent et al., 2021). Whilst there exist a range of strategies (Camburn et al., 2017; Christie et al., 2012; Menold et al., 2017) and recommendations for best prototyping practice (Lim et al., 2008) there remains a lack of clarity over when to use physical or digital prototyping (Ege et al., 2024a), or how and when to iterate.
To address the above research gap, this paper investigates the impact of the number of prototypes generated in time-constrained design scenarios on performance and self-assessment of performance. It begins by introducing the IDEA Challenge hackathon, the source of the study's data, and explains how correlation analysis was employed to synthesize the findings. The results of the study lead to a discussion and development of theory, culminating in the proposition of the concept 'design delusion'.

2. Methodology

The following section reports how data for the study was captured and a description of it. It summarizes the hackathon where data was generated and provides a description of the analysis used.

2.1. Data capture and benchmarking

Data for this study was captured during and after the 2022 IDEA Challenge- a virtually hosted hackathon for design researchers, summarized in Figure 1. The different data points include a database of prototypes, answers to a self-estimate performance questionnaire, validation test results and a correlation analysis. Each data point is further described in the following paragraphs.

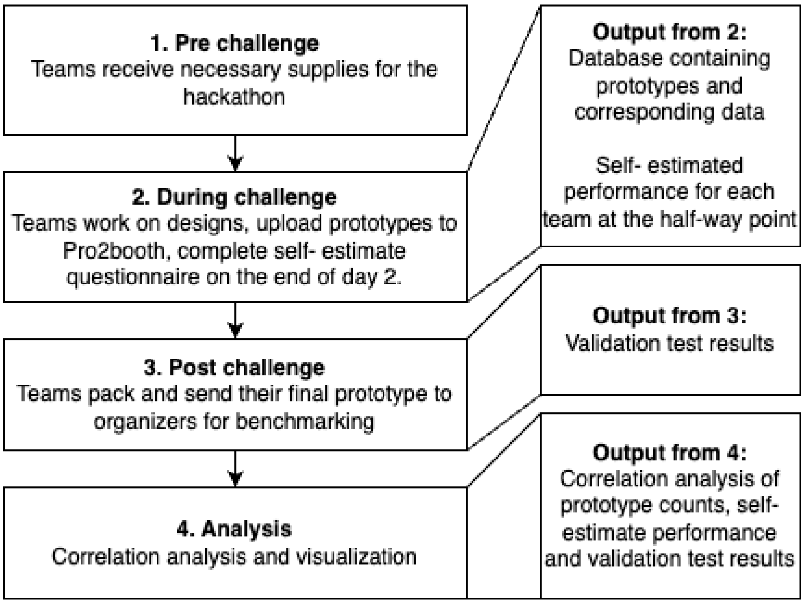

Figure 1. Methodology diagram

5 teams from universities across Europe competed in a prototyping challenge, while continuously uploading entries on all prototypes they produced to an online database. Prototypes were loosely defined as any representation used by a designer to explore or demonstrate some aspect of a future artifact (Houde and Hill, 1997), implying that this study does not differentiate between partial and full-system prototypes. Instead, it posits that each new artifact iteration inherently constitutes a prototype.
More information on the IDEA Challenge (Ege et al., 2023b; Goudswaard et al., 2022) and the captured dataset (Ege et al., 2024b) can found elsewhere in literature, but short summary is provided here.
The design challenge was given to participants on the first day of the challenge and mandatory supplies for testing designs were shipped to participants prior to the challenge, including stepper motors, material for rectifying circuits and a Adafruit INA260 power meter. Teams were challenged to prototype and build a small-scale hydro-power generator that could be powered by rainwater, with the aim of making a design that generates the most amount of power. The supplied stepper motor had to be used as a power generator, and the amount of power available to run the generator was limited. Teams had to deliver a

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physical prototype for testing, supported by digital prototypes such as CAD, renders etc. Teams chose their own methods and strategies for developing prototypes.
Table 1 presents the demographics for each team, including average age, gender ratio, professional or academic status, years of design experience, and fields of expertise. Experience was defined to include relevant degrees, academia, and industry work. Every team had at least one member with both academic and industry experience. Participants, selected for their roles as researchers in the engineering design community across Europe, were invited for their expertise and engagement in the field. Participants attended the hackathon from their home institutions, utilizing tools and technologies they were already familiar with. Each team had access to well-equipped prototyping facilities with 3D printers, hand tools, CAD software, mechatronics, card modelling, sketching, junking, and construction kits. Each team except for Team 5 also had access to a laser cutter and CNC machines for the duration of the IDEA Challenge.

Table 1. Participant demographics

Team	Average age	Gender	Current Position	Field of study	Experience
1	24	4♂, 0♀	4 PhD students	3 Mech.Eng, 1 Aero.Eng	5
2	29	4♂, 0♀	4 PhD students	4 Mech.Eng	6,75
3	31	3♂, 0♀	3 PhD students	3 Mech.Eng.	6
4	30	1♂, 2♀	3 PhD students	2 Mech.Eng., 1 Ind.Design	8
5	29	3♂, 1♀	3 PhD students, 1 post-doc	3 Mech.Eng., 1 Comp. Sci	6

At the midpoint of the challenge, by the end of the second day, participants were required to complete an online form to estimate the performance of their final designs, to measure the gap between teams estimated and actual performance. The performance was a measure of efficiency, indicating how well the design converts potential energy into output power, and was predicted as a percentage range from 0% to 100%, with both a minimum and maximum value provided.
Following the conclusion of the IDEA Challenge, the final physical prototypes from each team were shipped to the organizers to undergo an objective benchmarking and testing process. To ensure accurate and comparable test results, the test setup was consistent for all prototypes. We used an Adafruit 12V servo motor connected via a shaft coupler to each prototype, and energy output was measured using a rectifying circuit and an Adafruit INA260 power meter interfaced with an Arduino Uno. For all tests, a standard garden hose with an internal diameter (ID) of 13 mm and the same nozzle were employed to maintain uniformity.
The potential energy (E_p) available for conversion by each prototype was calculated using the formula $E_p = mgh$. The source of the energy was a water reservoir containing 5 L of water suspended 10 meters above the ground, amounting to approximately 500 joules ($E_P \approx 5 * 10 * 10 \approx 500J$. With the water reservoir emptied in 58 seconds, the potential power ($P_{potential}$) was determined as 8.57 watts ($P_{Potential} = \frac{500J}{58s} \approx 8.57W$). During testing, the power output of each prototype was measured and compared to $P_{potential}$ to ascertain the efficiency percentage.

2.2. Correlation analysis

Correlation analysis was used to evaluate the strength and direction of linear relationships between quantitative variables. Specifically, we were interested in exploring the linear relationships among four key variables: 1) number of prototypes, 2) number of physical prototypes, 3) self-estimated performance, and 4) tested performance.

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The pairwise Pearson correlation coefficients for each combination of the aforementioned variables were calculated and presented in a correlation matrix. The Pearson correlation coefficient quantifies the degree of linear relationship between each of the two variables. Its value ranges from -1 to 1, with values closer to the extremes indicating stronger linear relationships. A positive value suggests a direct linear relationship, while a negative value indicates an inverse linear relationship. This correlation analysis was performed using the Pandas Python package(McKinney, 2010).

3. Results

The following section details how far teams had come in their design processes at the half-way point, each team's self-estimated performance measure and actual performance, and a correlation analysis between prototype counts, self-estimates, and performance.

3.1. State of development at half-way point

At the time of the performance self-estimations, teams found themselves at vastly different development stages. At the time, Team 1 had developed 20 physical prototypes, and were currently testing various 3D printed bucket designs using a LEGO arm on a scale, suggesting a thorough iterative design process for component optimization. Team 2 had made 28 physical prototypes and were testing a fully integrated prototype made up of laser cut acrylic sheets (Figure 2a) and receiving actual insights on power output from their prototype. Team 3 had conversely made 3 physical prototypes, and where at the time of the performance self-estimation testing water flow from a suspended tank and hose. Team 4, also having made 3 physical prototypes, were making card-board mock- ups (Figure2b) at the time, reflecting being in a conceptualization phase. Team 5 has finished an energy measuring system, enabling them to test forthcoming designs. The had made a total of 3 physical prototypes at the time, and were, as several teams, without experience of how designs would perform in real life when answering the self-estimation questionnaire. Interestingly, both Team 2 and 5 shared insights at the time of the self-estimations that the motor-friction the prototype had to overcome would be a challenge. Figure 2 visually illustrate some of the discrepancies among teams' development stages at the time of the performance self-estimation.

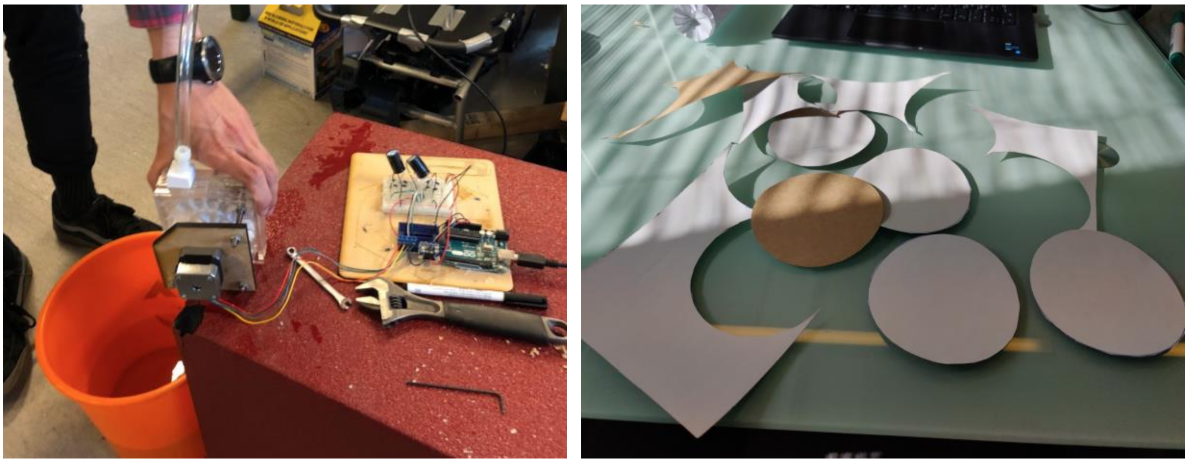

Figure 2. Side-by-side comparison of a) a fully integrated prototype made by Team 2 and b) a card-board mock-up made by Team 4 at the time of the performance self-estimation

3.2. Performance and self-estimations

Table 2 show how the different teams' final designs performed in the objective tests. Team 2 had the best results, followed by 1 and 5. Team 4 did not send back a prototype for testing as they were unsuccessful in creating a working design. Team 3's design did not produce any power under the conditions of testing, with a water reservoir suspended at 10 meters and the limited water flow of a 13mm ID garden hose.

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Table 2. Validation test results post IDEA challenge

	Team 1	Team 2	Team 3	Team 4	Team 5
Watts	0,15	0,57	0,00	0,00	0,10
Actual eff	1,79	6,66	0,00	0,00	1,17
Predicted eff	25	15	40	35	18
Delta	24,21	8,34	40,00	35,00	16,83
Mid-point Prototypes	38	46	7	7	7
Mid-point Phys. Prototypes	20	28	3	3	3
Total Prototypes	66	95	14	18	47
Total Phys. Prototypes	45	54	10	14	18
Final design					

Figure 3 shows team halfway self-estimates and final results (left axis) and the number of prototypes and physical prototypes created at the halfway point of the challenge (right axis). Self-estimates were given as a range bound by an upper and lower limit.

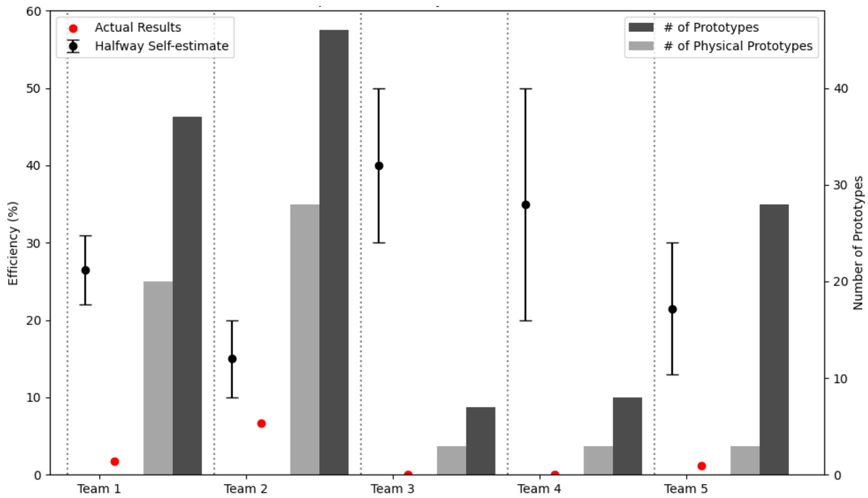

Figure 3. Expected efficiency vs results and number of prototypes at halfway point

Teams 1, 2 and 5 reported the most conservative self-estimations, at an average of 26%, 15% and 18 % respectively, with teams 1 and 2 having narrower ranges between top and bottom estimates compared to their counterparts. Notably, these two teams exhibited a higher prototyping rate, having made a significant number of both physical prototypes and other prototypes relative to other teams. Teams 1 and 2 made a total of 38 and 46 prototypes respectively, with 20 and 28 of those being physical, contrasting the 3 physical prototypes made by each of the other teams. Team 5 differs from Team 3 and 4 by having a higher prototype count, at 28 prototypes and a smaller range between top and bottom efficiency estimates.

Team 2 achieved the best final result in the challenge, while Team 1 secured the second-best, underscoring the correlation between their prototype production and performance. Furthermore, the self-estimations from both Teams 1 and 2 demonstrated a closer alignment with the actual results, suggesting

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a more accurate self-assessment. Among them, Team 2's estimate was particularly noteworthy for its proximity to the actual result, a performance complemented by their leading count of physical prototypes.
In contrast, Teams 3, 4, and 5 displayed comparable quantities of physical prototypes, with teams producing three each. Despite this similarity in prototype production, their performance outcomes varied: Team 5 secured the third position, Team 3 and 4 tied for last place, despite their high self-estimations. Specifically, Teams 3 and 4 projected the highest upper-bound estimates at 50%. Team 4's range was the largest across teams with a lower-bound estimate standing at 20%.

3.3. Correlation analysis

The correlation matrix in Figure 4 shows the linear relationships between the variables denoted in Table 3, where 1 indicates perfect correlation, 0 indicates no correlation, and -1 indicating perfect invers correlation.

Table 3. Correlation matrix variables

Prot	Number of prototypes created throughout the challenge
Phy prot	Number of physical prototypes created throughout the challenge
2 day prot	Number of prototypes created after 2 days
2 day phy prot	Number of physical prototypes created after 2 days
Performance	Measured efficiency post- challenge (final results)
Self est. performance	Midpoint of the self-estimated efficiency range
Range	Size of the range between low and high self-estimate
Delta	Size of the range between performance and self.est performance

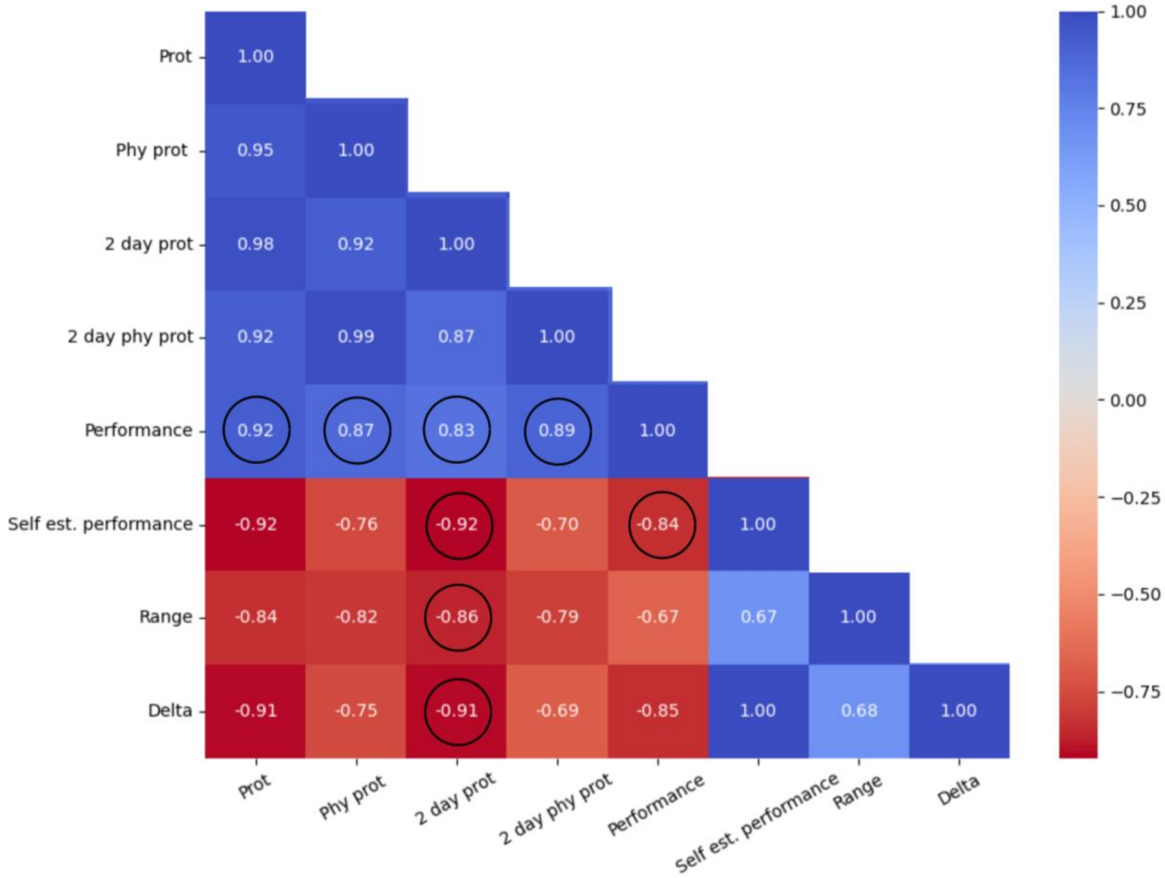

Figure 4. Correlation matrix showing pairwise Pearson coefficients with key values circled

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Within the computed correlation matrix, several noteworthy associations emerged. A strong positive correlation was observed between the count of physical prototypes fabricated within the initial 2 day and the resultant outcomes ($r = 0.89$). Similarly, the total count of physical prototypes exhibited a strong correlation with outcomes ($r = 0.87$). These associations surpassed the correlations observed between actual results and the total number prototypes made on the first two days ($r = 0.83$).

Conversely, a significant inverse relationship was discerned between the number of prototypes produced in the first two days and the average anticipated efficiency ($r = -0.92$). This negative trend persisted when comparing self-estimated efficiency with physical prototypes post the 48-hour mark ($r = -0.76$). Analogously, both the prototypes and physical prototypes made within the initial two days exhibited strong negative correlations with the Range, delineated by the highest and lowest anticipated efficiencies, with coefficients of $r = -0.86$ and $r = -0.79$, respectively. Interestingly, the performance and self-estimated performance exhibit an inverse correlation ($r = -0.84$). The strong inverse relation between Delta and prototypes made in the first 2 days ($r =-0.91$) indicate that teams prototyping the most had estimates closest to the true performance and vice versa with teams prototyping the least.

4. Discussion

The findings from this study provide a nuanced understanding of the relationship between prototyping frequency and the accuracy of performance self-estimates in compressed design scenarios. The data underscores the importance of iterative prototyping in enhancing predictive accuracy. Teams 1 and 2, which had higher prototyping rates, were more accurate in their performance predictions. Table 1 also indicates that, compared to their competitors, they had an advantage in learning from actual design tests rather than relying solely on assumptions. This suggests that the act of prototyping not only refines the design but also calibrates designers' expectations and experiences of reality, aligning well with previous studies on how prototypes aid learning (Lande and Leifer, 2009; Lauff et al., 2018).

The strong positive correlation between the number of physical prototypes created within the initial two days and the final design outcomes is intriguing. It suggests that early engagement in physical prototyping might be a critical factor in achieving better design outcomes in compressed design scenarios. This study suggests that when the complexity (and difficulty) of design tasks increases, self-estimates become more conservative, indicating that early prototyping made designers more aware of potential challenges- and providing more realistic estimates. In fact, teams testing designs early realized sooner the implications of using stepper motors for capturing energy, even without previous knowledge on the potential output the system could make. Simply connecting the stepper motor to the rectifying circuit and power sensor would let participants feel the amount of resistance the motor would have to overcome in order to turn (which was significantly higher than when the motor was not connected to the power sensor). Teams testing early realized sooner the large amount of resistance from the motor designs had to overcome with time left to account for it, as opposed to Team 3s' design that failed because it lacked the torque necessary to spin the motor. The inverse correlations between early prototyping and the range of self-estimates suggest that early prototyping might lead to more certainty in designers' predictions. This could be because early prototyping provides tangible feedback, reducing the ambiguity and uncertainty in designers' minds.

Building on the finding that the performance and self-estimated performance exhibit an inverse correlation, we propose the term "Design Delusion". It refers to a type of cognitive dissonance experienced by a designer or design team due to differences between their perceived and actual states relating to design capabilities, progress in the design process, and/or product performance. Understanding and recognizing this delusion is crucial for several reasons. It emphasizes the importance of iterative prototyping as a tool not just for refining design outputs, but also for calibrating self-perception. Secondly, by reducing this delusion, designers can make progress in their designs based on their actual position rather than their perceived and/or imagined position.

Due to omnipresent ambiguity in design, design delusions will always exist to some extent. The challenge lies in keeping design delusions manageable, such that design decisions taken are sensible given the reality of a situation, not only its imagined state. Design delusions that are too high can result in technical debt due to leaving key design challenges unresolved, with design decisions potentially worsening the situation rather than improving it, and increasing the accumulation of technical debt in

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the future. This delusion can hinder growth and lead to stagnation, as it prevents an honest evaluation of work against industry standards or client expectations. Design delusion not only affects personal development but can also influence team dynamics, client relationships, and the end product's success. Recognizing and overcoming this delusion is critical for achieving true excellence in design.

Team 4's inability to produce a working design and Team 3's design not producing power under the given conditions highlight the challenges inherent in compressed design scenarios. Rapid prototyping might not always lead to successful outcomes, especially when faced with tight constraints or complex challenges.

The findings have specific implications for design hackathons or similar compressed design scenarios. Emphasizing early and frequent prototyping might be a strategy to enhance both design outcomes and predictive accuracy. Though the findings are from a specific scenario, it can be argued that a hackathon setting shares several analogous characteristics with ordinary design processes, making findings from one domain relevant to the other. Both environments prioritize rapid ideation, prototyping, and problem-solving within a constrained timeframe. In a hackathon, participants often iterate on their solutions, refining their ideas based on feedback, much like designers do in iterative design processes. Additionally, both settings emphasize collaboration, cross-disciplinary thinking, and adaptability in the face of unforeseen challenges. Given these parallels, insights derived from this paper can offer valuable perspectives on improving design processes and strategies.

For educators and mentors in design and engineering, emphasizing the importance of early and frequent prototyping might be a key takeaway. Encouraging students to engage in hands-on prototyping early in the design process could enhance both their design skills and their ability to predict design outcomes.

For design teams, especially those working in rapid innovation contexts, the findings suggest that investing in early and frequent prototyping could be beneficial. This might involve allocating resources, time, and effort towards prototyping early in the design process.

4.1. Further work

In this paper, the team with the most physical prototypes (and prototypes in total) emerged as the top performer. This observation prompts further exploration into the nuances of prototyping and its relationship with design success. Firstly, it's essential to discern whether the observed association between the number of prototypes and performance indicates a causal relationship. Does the act of creating more prototypes inherently lead to superior outcomes, or might highly experienced and/or capable teams naturally gravitate towards more frequent prototyping due to other intrinsic qualities or strategies? Secondly, the emphasis shouldn't solely be on the quantity of prototypes but also their quality, i.e. that they contribute to the right knowledge for the least amount of time or cost possible. It's crucial to investigate whether the more successful teams are producing higher fidelity prototypes or if their iterative process is inherently more focused and efficient. Lastly, beyond sheer numbers, understanding the specific strategies or methodologies employed during the prototyping phase can be enlightening. These considerations highlight the multifaceted nature of prototyping in design and underscore the need for a deeper, more nuanced understanding of its role in driving successful outcomes.

4.2. Limitations

The study's findings are constrained by several factors: the limited number of teams participating reduces the statistical robustness and broader applicability of the results, while the homogeneity of the designers involved may not adequately represent the diversity of design approaches that exist in the field. While the observed correlations were strong, the limited data points make the results more susceptible to the influence of outliers and may not accurately represent the broader population. It's essential to interpret the results with caution, and further research with a larger sample is recommended to validate and expand upon these findings. Furthermore, the investigation's focus on a single design task limits the ability to extrapolate the findings to different types of design challenges, which can vary widely in nature and complexity. Additionally, the lack of detailed information on the designers' levels of expertise means that the study only provides a surface-level understanding of the participants' design processes and how their experience might have influenced their process and answers- although it has been shown that even novice designers actions coincide with design experts (Cash et al., 2013).

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5. Conclusion

The present study explores the relationship between the frequency of prototyping, the predictive accuracy of designers, and performance in compressed design scenarios. The data reveals that teams that made the most physical prototypes early on not only achieved better design outcomes but also demonstrated a heightened accuracy in their performance predictions, with the converse also found to be true (8.34% difference between predicted and actual vs. 40.0%), The concept of "Design Delusion"—the cognitive dissonance arising from a discrepancy between perceived and actual design capabilities and progress—emerges as a critical phenomenon to be understood and managed because of these findings. By engaging in early prototyping, designers become aware of potential design challenges and adjust their performance estimates accordingly, leading to more informed and effective design decisions. Recognizing and addressing the risks of "Design Delusion" early on can prevent the accumulation of technical debt, leading to more robust and reliable design solutions. While the findings offer valuable insights, they should be interpreted with care because of a small sample size and specific scenario, prompting further exploration and validation in broader contexts. Future research might further investigate the optimal balance between prototyping frequency, quality, and strategy, and how these factors interplay to influence design success.

Acknowledgement

This research was funded by the Research Counsil of Norway (ref. 321386), UKRI funded projects 21st Century Prototyping (EP/W024152/1), and The Development of the Physical-Digital Affordance Index (Researcher In Residence grant reference 142212012-2).

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