Design Strategies that Work: How Engineers Use Sequential Decision Making to Improve Design Performance in Concept Selection

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Despite increased efforts to improve the quality of early-stage concepts, research has found that engineers often do not select the best designs available. Unnecessary time and money are spent when lower-performing concepts are selected and pursued within engineering design. This research studies the design strategies engineers utilize in completing a multi-objective concept selection task and their influence on design performance over task duration. Fifty-seven participants explored a design space containing 21 alternatives and gathered additional information about a subset of these alternatives through limited testing before submitting a final decision. Performance was measured via a quantified success rate, an experimental value developed in this work. Strategies such as isolating design parameters and prioritizing parameters improved design performance. In conclusion, there are clear strategies that engineers and designers benefit from using to guide their decision process. Future work will consider how these strategies are utilized within traditional concept selection methods.

Introduction

Concept selection is a critical phase in the engineering design process that significantly impacts later stages such as testing, development, and final deliverables [1]. After a problem is defined, engineers brainstorm possible solutions, usually via words and sketches. Then engineers must compare concepts and decide which concept(s) to select to advance to later stages in the

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design process. While the selected concept may not become the final design, features or functions of the concept may appear in the final solution [2].

The design research community seeks to increase innovation and creativity in the design process through early-stage design by assisting engineers and designers in improving their innovative and creative potential in concept generation [3,4]. Despite these increased initiatives resulting in more innovative or creative ideas, research has identified that engineers do not always select the best designs available instead of opting for more feasible solutions [5–8]. This tension serves as the motivation behind this research, which investigates the concept selection dynamics behind the sequential decisions made in this phase to understand how designers select less optimal concepts.

How designers select a concept can be formal using decision matrices or mechanical design principles [9–11] or informal without using such tools relying on intuition or a gut feeling [12]. A designer's final concept assessment could be captured in Pugh matrices as scores or weighting, but this tool/method does not capture the order of assessment attributes or the influence of exploration of prior designs on future design considerations. The order of assessment provides rich design data used to extract design strategies. Concept selection is a dynamic process composed of a series of sequential decisions influencing one another [13–15]. This research investigates the strategies designers use in the concept selection process and how they influence design outcomes (i.e., quantifiable design performance). The primary research question is, what concept selection strategies positively influence design outcomes?

Background

The motivation behind this research and relevant literature are discussed further in the following three sections. Selecting design concepts highlights why this research focuses on this stage in the engineering design process. Concept selection as a series of sequential decisions introduces a process approach in which nuances in design behavior can emerge for this study. Design strategies that influence design performance feature both positive and negative impacts known decision-making strategies have on design outcomes.

Selecting design concepts

Evaluating a concept is a crucial stage that converges on fewer concepts than initially generated [1]. Uncertainties associated with each design add to the difficulty of this stage. Designers usually must consider multiple design criteria, often criteria that contradict one another. Due to this stage's importance in engineering design, many methods and tools are available to assist decision-makers. Tools include but are not limited to decision matrices, analytic hierarchy processes, uncertainty models, economic models, optimization concepts, and heuristics [16]. Decision matrices vary in their effectiveness [10,17]. A Pugh decision matrix lists the concepts to be evaluated, then the design team (individually or as a whole) rates the concepts on a series of qualities the team deems most important [9,12]. Although the tool focuses on objectivity, literature has identified cases where team members have selected criteria to rate that would help confirm and support their preferred concepts [18]. Multi-attribute decision-making methods result in different outcomes [19]. Therefore, this research is not concerned with why designers select the method or approach but instead focuses on designers' observable actions throughout the concept selection process.

Concept selection is a series of sequential decisions

Engineering design is an interactive and cyclic process composed of divergent and convergent stages [16,20]. Concept selection should not be viewed as a single final decision but rather a process in which design alternatives are considered before the ultimate decision is made. Concept selection can be decomposed into multiple subsections of information gathering, evaluating the designs, weighing the evidence, and deciding between alternatives. Selecting a concept is generally convergent behavior; however, exploration and consideration of design alternatives align with divergent behaviors [20]. Taking a process approach in concept selection enables nuances in a design strategy to emerge that prior design research has not yet considered.

A design strategy consists of a string of design actions. This paper defines design actions as observable and quantifiable steps such as viewing a design, testing a design, or submitting a design. Participants can learn sequences based on the information provided or design actions possible, and this learning may or may not be conscious [21]. Due to the parameter tradeoffs and ability to test designs in this research study, optimization techniques [22–24] and interdependencies (coupled decisions) [25] on viewing and testing prior designs are explored. The use of design strategies in parameter tradeoff problems seeks to minimize or maximize a function. In this study, maximizing design performance means selecting a design with a high success rate.

Moreover, the design research community seeks to capture sequential decision behavior from human designers to transfer to computational agents. Research from McComb et al. identified decision sequences as beneficial to designers via Markov chains [14] which aligns with prior sequence learning work [21]. Another paper from McComb et al. mined process heuristics via Hidden Markov models that differed by design performance [15]. The first paper identifies that participants used operation sequences but did not go into the types of operational sequences and how they relate to engineering principles [14]. The second paper further identifies differences among designers based on performance; however, hidden states in this model lack an understanding of what those states are and why they result in specific design actions [15]. Similar work from Raina et al. focused on extracting design heuristics and transferring them to computational agents [26–28]. While successful in creating designs of similar performance or better, the agent takes design actions that will likely improve the design, but the rationale or motivation behind those actions remains unclear.

The purpose behind the three strategies of interest, listed in Table 1, is to generalize the findings beyond this specific design task. The complex nature of engineering design decisions often means the results and discussions in design research are unique to the type of design challenge. By taking a process approach focusing on systematic strategies, we highlight the design behavior that comes naturally to designers and its impact on design performance over task duration. These intuitive strategies, if present in this task without the explicit instruction to use a design method, should also appear in design processes where concept selection methods and tools are used. The strategies defined in this study are inspired by the literature on optimization as a concept selection method [23,16,22] and early observations from [29]. In previous observations, participants mentioned identifying the parameters that can be tuned (*isolating variables*) and focusing on one parameter at a time (*prioritizing variables*). The term *shifting between variables* refers to the shift in focus from one parameter to another. Such transitions within a process are similar to Atman et al. [30], but instead of engineers switching through engineering design phases, micro phases in concept selection focus on how engineers engage with the tunable variables.

Design strategies that influence design performance

Not only does this research identify and describe design strategies within concept selection, but it aims to determine the impact such strategies have on design performance. Prior work showed that designers' navigation through the design space and testing procedures impacted design performance [29]. Confirmation bias, ownership bias, or anchoring/design fixation are known biases influencing engineering design [18,31,32]. By moving beyond a single action, insight regarding how designers approach design problems and engage in the concept selection process could help uncover how biases unfold into design actions. The key to comparing design strategies relies on comparing design performance for a design task. Evaluation methods might use human raters to evaluate designs [3,4] or use strength-to-weight ratio calculations. Objective measures based on experimental data are used in this study, not just for the final design submitted, but this measure assessed a participant's real-time performance over task duration.

Once the impact of design strategies on design outcomes is known, there are two common approaches to incorporating them into design practice. One might identify beneficial strategies, then teach those strategies to other designers—learn from what others do well. Alternatively, the research could identify pitfalls to avoid and bring these common issues to the attention of others—learn from others' mistakes. With the development of computational tools to assist in the design process, agents also need to learn how to design. Agents may learn human preferences or design approaches from traditional engineering principles; however, there is merit in understanding how designers design without structured methods or tools [26,27]. Often such approaches use datasets from human designers to extract design strategies and biases that naturally occur. By understanding the influence design strategies have on the solution space and consequentially design performance, nudges can be used, for example, to help a designer pursue a particular strategy that causes them to increase their search space when a high degree of design fixation is detected.

Table 1 Concept selection strategies of interest and descriptions of the design behavior rooted in preliminary work [29].

Strategy	**Explanation**
Isolating variables	Adjusting one variable at a time while holding all other parameters constant such as single parameter tuning. Multiparameter tuning does not fall into isolating variables [22,29].
Prioritizing variables	Focusing on a given variable throughout a portion of the decision-making process is measured by the number of sequential steps per one variable [22,29].
Shifting between variables	Transitioning focus from one parameter to another is measured by the number of transitions [22,29].

Methods

This study identifies strategies used in the concept-selection process and their influence on design performance. Data from a human subject study carried out by the authors of this paper was analyzed to explore these patterns for insights into decision-making behavior [29]. The study asked participants to submit a design for a gripper surface for a dishwashing robot.

Concept selection task

Participants were instructed to submit one design to move forward to production, the next step in the fictional robotics team's design process. They were tasked with designing a gripper surface for a robotic arm, as shown in Fig. 1. The dishwashing robot uses a grasper in a wet and slippery environment due to dish soap. A design's success was determined by the robot's success rate in grasping a range of dishware. The designer has 21 alternatives to select among which are combinations of seven surface geometries and three material hardness options. After clicking on a design, as noted in Fig. 2, a screen displayed its datasheet where participants could test that design which revealed the testing result. The success rate is based on empirical friction data scaled proportionally between zero and 100%. Each participant had ten minutes to complete the task with the option to test up to five designs to see corresponding success rates (design performance). No specific concept selection method or tool was provided.

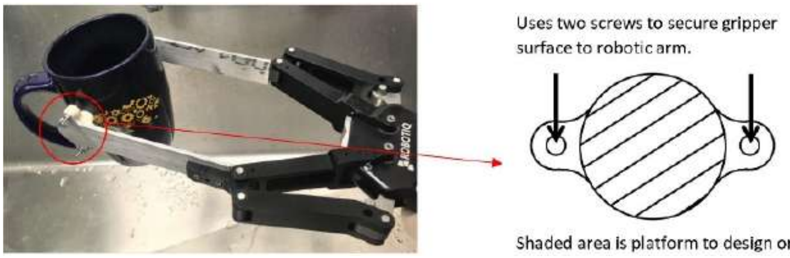

Fig. 1 Diagram of the design challenge to show participants the gripper surface and its interaction mechanism with the grasper on the dishwashing robot.

Participants

A total of 68 participants were recruited for the design study using a call for participation at the University of California, Berkeley. Participants were compensated $10 for their participation for 30 minutes. A bonus of up to $20 was offered contingent on task performance. Participants were screened and required to be 18 years or older with engineering or design experience to participate in the research study. Experience ranged from completing a single design class upwards to over ten years as an engineer in industry (0-4 years, 34, 5-9 years, 21, and 10+ years, 2). Participant demographics included undergraduate, graduate, and working professionals with engineering and science backgrounds. Data from 57 participants (30 men, 26 women, and one non-binary person) was used for data analysis. Data from 11 participants were removed due to a lack of following instructions and equipment errors.

Research Design

The experiment took approximately 30-minutes and consisted of two parts: the design task and a post-task survey. For the scope of this research, only the design task is of interest, and thus information regarding the post-task survey is not mentioned but can be found in [29]. Colleagues provided the 21 gripper surface designs (seven geometries and three material hardness options) and experimental data based on a slippery environment [33]. Those friction values, not shown to participants, were then translated into success rates between 0 and 100%. A five-test limit was set to mimic real-life constraints in the design process, where a limited number of designs can be tested due to time or financial constraints. Preliminary experiments found that few participants converged on a "good" design with less than five tests.

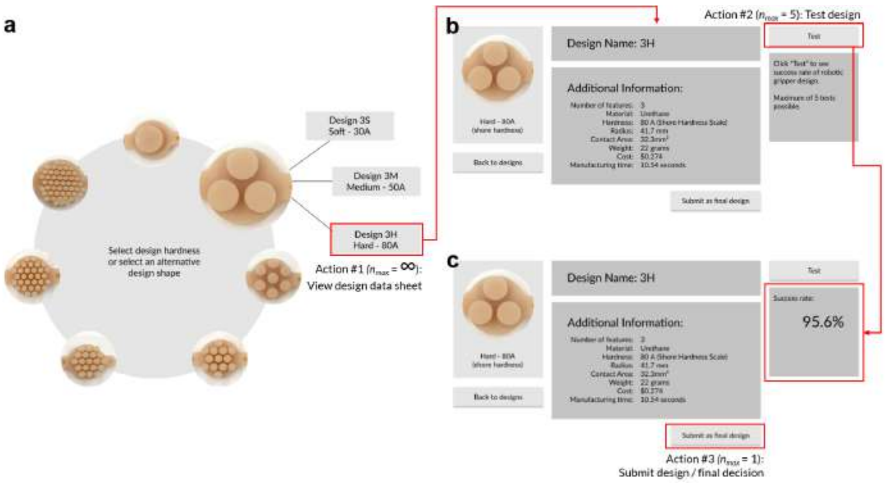

Fig. 2 The design actions of interest are represented as actions 1-3, and n_{max} indicates the number of times said action could occur. (a) Each of the seven geometries (shown as images) branched out to include a soft, medium, and hard version. Clicking one of the branched-out designs opened a datasheet (b) for that design. A test displayed a design's success rate (c).

As shown in Fig. 2, participants interacted with an interface for the design task portion, which displayed the consent form, task instructions, and possible design options. The interface collected the time and number of tests but left it to the participant to monitor due to interface constraints. However, this decision to self-monitor was aligned with what engineers and designers experience outside of controlled studies, where they are expected to meet deadlines and stay within budget. Although the robotic gripper design could have been optimized using a computer program, this predefined solution space removed researcher subjectivity in classifying a participant's design actions and performance that alternative experimental setups may have introduced (e.g., having participants sketch their designs followed by researchers rating designs using rubrics).

Data Analysis

Design actions defined in this study were steps traveled within the solution space, and objective methods such as the success rate were used to evaluate a design's performance [18]. Data was collected from the Figma website using Maze.co, a clickstream collection platform. Each screen a participant visited was recorded, and each participant's duration, screenId, and sequential path were exported. Participant groupings were determined using design performance measured by the design's success rate.

Decision strategies of isolating, prioritizing, and shifting parameters were coded using the sequential path per participant. Isolating parameters means using single parameter design actions. An increase, decrease, or hold was determined for each parameter, hardness, and geometry. A single parameter move means one parameter was held constant while the other moved. The percentage of single parameter moves quantifies the isolating variables strategy, as measured using the number of single parameter moves over the sum of single and multiparameter moves. Prioritizing parameters highlights a participant's focus on a given variable throughout the task duration. Percent prioritization was computed as the number of sequential steps where one variable is the focus over the number of single parameter design actions. Shifting between parameters identifies the number of transitions where a participant's focus shifts from one parameter to another. Each transition count was coded when a multiparameter move occurred or when the parameter held constant changed within single parameter moves. The percentage of transitions was computed using the total number of transitions over the total number of design actions per participant.

Results

The strategies of interest utilized by participants in the design task include 1) isolating variables, 2) prioritizing variables, and 3) shifting between variables. These strategies were extracted from 2451 total design actions where participants took as few as 20 and upwards of 162 design actions (M = 44) and viewed between four and 18 unique concepts (M = 7). First, the relationship between these strategies and design performance is presented, followed by the differences between strategy usage among high and low-performing designers.

Isolating parameters and prioritizing parameters improved design performance

Isolating variables or single parameter tuning are the most identifiable and likely to improve design outcomes. Single parameter tuning means adjusting one variable at a time while holding the other parameter constant (e.g., changing geometry while holding material hardness constant). Spearman's rank correlation tests were carried out between the percent of single parameter moves and the success rate achieved. The percentage of single parameter moves was coded as the number of single parameter classifications over the sum of single and multiparameter classifications. The results show a moderate correlation, as shown in Fig. 3, which is statistically significant ($r_s = 0.32, p <.05$). Therefore, participants who engaged in a higher number of single parameter moves were more likely to have improved performance. When participants did not use single parameter moves, they made multiparameter design actions which means they adjusted both parameters simultaneously. By completing multiparameter moves, participants jumped around the design space and could not understand the influence each variable had on design performance when conducting tests.

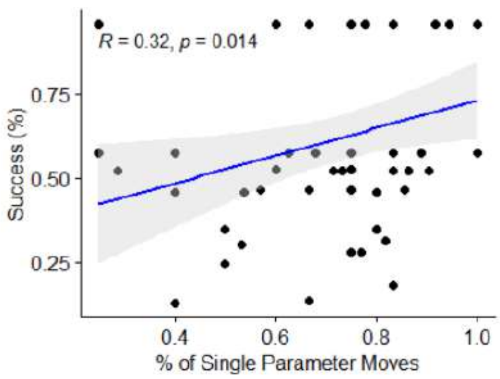

Fig. 3 The percentage of single parameter moves and corresponding success rate percentage. Each participant is represented by one data point. The shaded region represents a 95% confidence interval for the regression line.

Prioritizing variables was a second design strategy shown to result in improved outcomes. Prioritizing variables means focusing on a given variable throughout a portion of the decision-making process as measured by the number of sequential steps per one variable. Moreover, single parameter design actions or isolating variables need to occur for one variable to be held constant. Spearman's rank correlation tests were carried out between the percent of variable prioritization and the success rate achieved. Percent prioritization is the sum of moves that were single parameter and held constant between a series of sequential steps over the total number of design actions. A participant with high prioritization carried out primarily single parameter moves and, of those moves, held hardness constant while adjusting geometry. The results show a moderate correlation, as shown in Fig. 4, which is statistically significant (*r_s = 0.44, p <.01*).

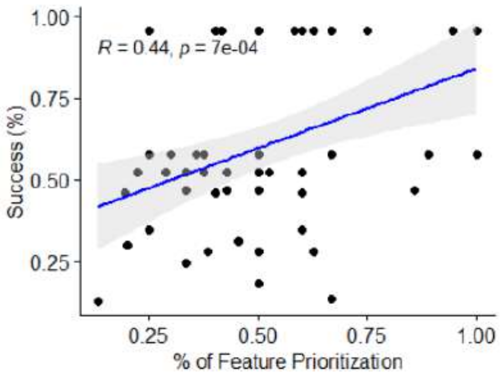

Fig. 4 The percentage of max feature prioritization and corresponding success rate percentage. Each participant is represented by one data point. The shaded region represents a 95% confidence interval for the regression line.

Shifting between variables means a participant's focus shifted from one parameter to another as measured by the number of transitions. Thus, a transition was coded as any time a multiparameter move occurred or when the parameter held constant changed within single parameter moves. The percentage of transitions is the number of transitions over the total number of design actions. Spearman's rank correlation tests were carried out between the percent of transitions and the success rate achieved. Fewer transitions indicate increased focus on a given parameter. A lower percentage is expected for participants engaged in single parameter moves and prioritized one variable for a longer duration. A higher percentage of transitions is expected for participants who only engaged in multiparameter moves or who changed the parameter of focus multiple times throughout the task duration (i.e., a participant who engaged in single parameter moves but only held a parameter constant for a brief number of steps and instead kept changing the tuning parameter). The results show a very weak negative correlation, as shown in Fig. 5, which is not statistically significant (*r_s = -0.17, p =.20*).

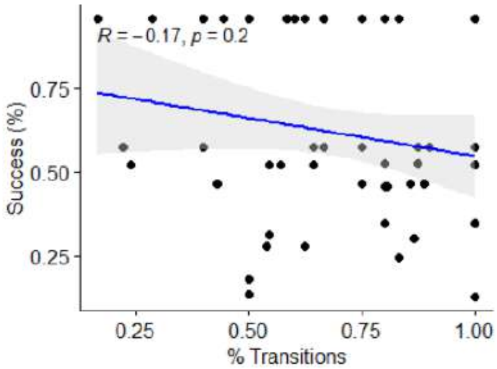

Fig. 5 The percentage of transitions and corresponding success rate percentage. Each participant is represented by one data point. The shaded region represents a 95% confidence interval for the regression line.

High and low performing designers differed in their design strategies

Participant groupings were determined using design outcomes measured by the design's success rate. Participants in the high-performing category (*n=19*) achieved the best possible design (96% success rate). The average-performing category achieved success rates above 50%, excluding the optimal design (*n=20*), while those in the low-performing category achieved success rates under 50% (*n=18*).

Figure 6 shows the mean usage for the three strategies (isolating, prioritizing, and shifting) for high and low-performing designers, as indicated in light and dark blue, respectively. The y-axis represents the number of design actions categorized as a given design strategy over total design actions as a percentage. Design actions were categorized as isolating variables when only one variable was adjusted while holding the other parameter constant as measured by the number of single parameter moves. Design actions were characterized as prioritizing variables when a participant focused on a given variable throughout a portion of the decision-making process as measured by the maximum number of sequential steps per variable. Design actions were labeled as shifting between variables when the focus transitioned from one parameter to another as measured by the number of transitions.

For isolating variables, there was a 15% statistical difference across usage for high and low performers (M_{high} = 81% and M_{low} = 66%; Mann–Whitney U = 92.5, n_1 = 19, n_2 = 18, $p < .05$ two-tailed). Expanding beyond the ability to isolate variables, to feature prioritization there was a 23% statistical difference across usage between the groups (M_{high} = 68% and M_{low} = 44%; Mann–Whitney U = 72.5, n_1 = 19, n_2 = 18, $p < .05$ two-tailed). Lastly, regarding the frequency of transitioning between variables, high performers had -11% difference in usage than low performers (M_{high} = 62% and M_{low} = 73%) which was not statistically significant (Mann–Whitney U = 118, n_1 = 19, n_2 = 18, p = .11 two-tailed). High performing participants had an increased usage in isolating and prioritizing parameters. No conclusion can be drawn regarding the shifting between variables strategy.

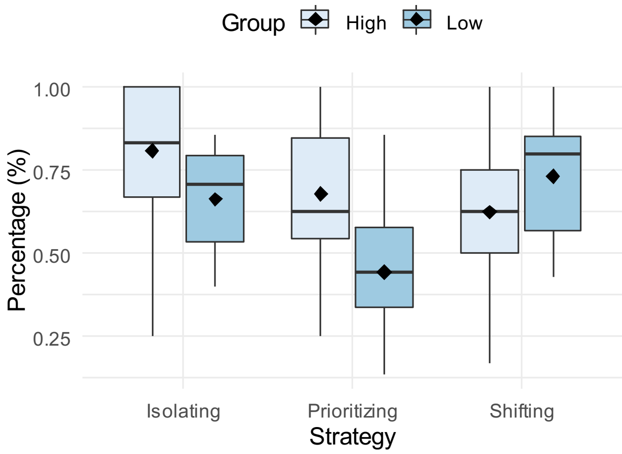

Fig. 6 Three strategies of interest and their corresponding mean percentage as indicated by the diamond shape (% of parameter isolation, % of parameter prioritization, and % of parameter transitions) split by high and low-performing designers.

Since high and low performers differed in their ability to isolate design parameters over task duration, an additional analysis was carried out using Markov models to predict the probability of strategy used when considering the most recent design action. A first-order Markov model from the behavioral data was utilized to identify transition probabilities of moving from one state to another. The transition probabilities help explain the behavior observed and the likelihood of a specific sequence of decisions would occur. The three-state Markov approach is a simplified version of the initial 21 states explored (e.g., one for each design). With a 21-state model, entire path sequences could be generated for *t* timesteps, and their corresponding success rate could be computed. The three-state Markov model aims to generalize design actions beyond the specific robotic gripper surface design task via single parameter (SP), multiparameter (MP), and testing (TEST) design actions.

Figure 7 demonstrates that high performers focus more heavily on single parameter moves (i.e., isolating design parameters). In the few instances that high performers use multiparameter design actions, they do so primarily before (.90) and after (.21) a test action. Based on the behavioral data, when high performers conduct a multiparameter move, they have a .10 chance of conducting another multiparameter move, a zero chance of conducting a single parameter move, or a .90 chance of running a test. Alternatively, low-performing participants engage more with both single and multiparameter design actions. The transition probabilities to and from a non-test state are within a range of .19 and .27, as noted in Fig. 7. Across both group groups, they each have a higher probability of moving into a single parameter state after conducting a test and a higher probability of conducting a test when in a single or multiparameter state.

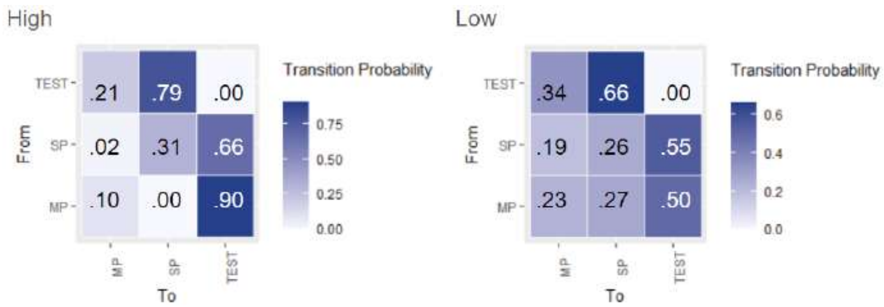

Fig. 7 Transition probabilities of a first-order Markov model split by design performance.

Discussion

Three design strategies (isolating, prioritizing, and shifting between parameters) were investigated within concept selection, and their influence on design performance was determined. Fifty-seven participants were tasked with selecting the best gripper surface design for a dishwashing robot. Design performance for each of the predefined set of 21 concepts was based on experimental data. To answer the main research question, the findings show that the two strategies (isolating and prioritizing parameters) positively influenced design outcomes, while shifting between parameters did not significantly influence outcomes. These distinctions in design behavior reveal the nuances and complexity of an individual designer's approach and are discussed below.

Case Study: Strategy usage for a high-performing participant

Figure 8 displays the three strategies of interest by visualizing the two tunable parameters and corresponding success rates for a high-performing participant over the task duration. In this design challenge, participants needed to recognize that geometry and hardness were the two tunable parameters and adjust them accordingly to find the optimal design. Initially, the participant switched between designs randomly, alternating quickly between parameter one (geometry), both parameters, and parameter two (hardness), indicating the participant had not yet figured out which parameters to isolate. After the first test was conducted, the participant focused on tuning geometry (prioritization) for most of the remaining time and only varied hardness three times (shifting). Once the shift occurred, this was the point in which a participant isolated variables and switched to prioritizing variables. Taken together, in Fig. 8a, the participant starts at the middle range for geometry and incrementally increases geometry while holding hardness constant, as shown in Fig. 8b. Visualizing design behavior over task duration indicates that high-performing participants employed a high percentage of single parameter moves and engaged in a high degree of prioritization of parameters. In a scenario where a participant had a low single parameter usage percentage, their moves for both parameters would vary at every step with fluctuating y-values.

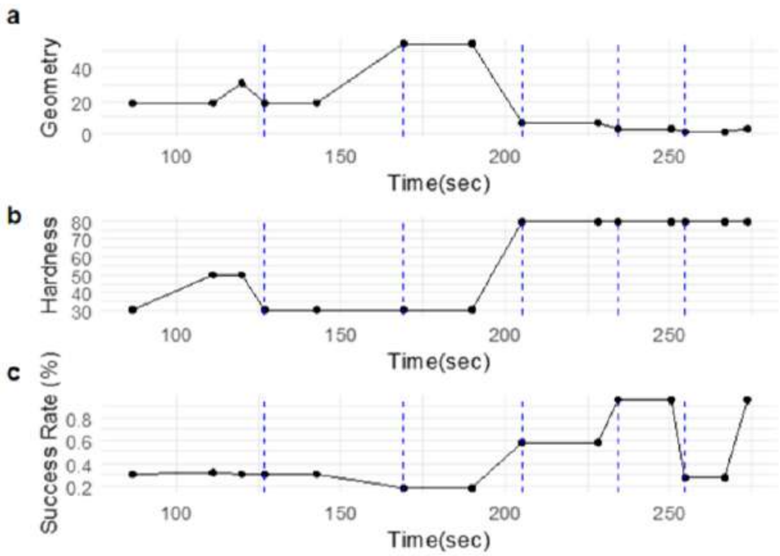

Fig. 8 Design parameter tuning over task duration for a high-performing participant. The five dashed blue vertical lines represent the moment the participant conducted a test, enabling the success rate to become known for that design. (a) Parameter 1 – Geometry over task duration. (b) Parameter 2 – Hardness over task duration. (c) The success rate as a percentage over the task duration. The success rate is known to the researcher for each design explored. A participant can learn the success rate only after conducting a test for a maximum of five designs.

Implications of key results

Performing a high percentage of single parameter moves did not guarantee success. Instead, the findings suggest that using single parameter moves and making incremental adjustments to one parameter for multiple steps did increase the likelihood of success. Across the 57 participants, all utilized single parameter moves. However, the data shows that only seven participants used single parameter moves exclusively, and the lowest percentage of single parameter usage was 25%. Of the participants engaged in high single parameter move usage, their success rates were not all in the highest performing category. The participant who utilized single parameter moves almost entirely yet performed poorly could be explained by the large leaps between designs they took or lack of order in testing. For example, a participant who used single parameter moves but adjusted one parameter in large leaps rather than incremental changes, or a participant who changed which parameter they held constant (e.g., switching from parameter one to the other while holding the opposite parameter constant). The strategies participants used resemble techniques commonly used in algorithms for optimization problems, such as agent search strategies or methods to maximize objectives [16,22,34]. Thus, improving design outcomes relied on a combination of systematic strategies rather than random walk approaches.

Humans are naturally uneasy with uncertainty and desire order [35,36]. These patterns of sequential design actions emerged, regardless of whether such patterns were conscious [21]. Participants' usage for design strategies could be explained by the brain's intrinsic desire to reduce cognitive load whenever possible (i.e., use heuristics or biases). Cognitive load means the mental effort needed to learn new information [37]. Research suggests that improved design performance might be caused by a decreased cognitive load [38,39]. Kahneman's systems one and two could help explain the differences observed in the speed of decision making and the degree of mental effort used by participants [40]. Fast and strategic actions might be associated with system one for a participant who has increased design expertise or a participant who is simply guessing throughout the task [41]. In contrast, participants who took longer between decisions might be utilizing system two, which requires more effort due to their unfamiliarity with the problem type and time limit imposed.

The cognitive load of single parameter moves should be smaller than multiparameter moves since the information for the next design explored shares a parameter with the previous design. Multiparameter moves do not share either geometry or hardness. Participants then integrated the information received and established relationships between design actions and knowledge (e.g., identifying which design parameters were relevant, determining the relationship between each parameter and success rate). Engaging in the design strategies studied, the cognitive effort required was likely decreased, thus making key relationships easier to identify and integrate into the design process.

Contrary to what one might expect, participants did not mention traditional concept selection methods or tools such as weighting or ranking of designs via decision matrices in their open-end responses regarding their decision process [9,16,42,43]. All participants stated they had completed a design course, and most have participated in design project-based teams in a course or industry that likely included standardized decision processes. Research from López-Mesa and Bylund that studied concept selection method usage inside a company identified that five of the 22 interviewees used none or one method in their concept selection process; The lack of use was explained by the roles of the engineers working in late-stage design and an engineer who is known to be 'against' methods [12]. Neither of these explanations appeared in the participants' open-ended responses in this study. Perhaps the results reveal the underlying building blocks (e.g., design strategies) designers use within standard concept selection methods. The varying percentage of design strategies used may help explain why standard concept selection methods have varying outcomes in design performance.

The task duration, problem type, or presentation of concepts for the robotic gripper task may have limited participants' concept selection methods and tools. Ten minutes was used based on research that found designers spend a relatively short time deciding between concepts (between three and eight minutes) [30]. An extended timeframe might have led participants to use commonly taught concept selection methods or develop more complex design strategies. The presentation of designs may have also influenced the strategies designers used, which might have differed from physical prototypes, excel spreadsheets, or an interactive prototype that could have parameters altered via a sliding tool. Note that future work could extract additional strategies using methods (i.e., varying the levels of analysis concerning time and transitions between design activities/stages) from Atman et al. that explored the nuances between novice and expert designers' engagement with different aspects of the design process [30,44].

Incorporating design strategies of interest into practice

There is a need to assist human designers and computational design agents in the concept selection phase [26,27]. Human designers could benefit from understanding what they do well and not so well. Depending on the purpose of a computational agent, one might want to mimic human design behavior for modeling, alternatively outperform human designers, or build a collaborative computational tool that collaborates with human designers. Regardless of the application, understanding human design behavior is necessary to integrate design strategies into practice.

The two strategies of isolating and prioritizing parameters could be integrated into computational models to describe, explain, or predict design behavior. The Markov models generated in the results section could be transferred for computational modeling of design behavior, as previous research has shown possible [14,15,27]. Fictional design data could be generated with a transition matrix of state-state probabilities, enabling comparisons between computational agents and human designers. Future analyses in this application might consider the speed or rate of exploration as another measure in systematic strategies. Alternatively, the two strategies of interest could be integrated into engineering education.

Figure 8 shows the designs a participant explored over time as split by parameter with corresponding success rates. Visualizing design behavior for evaluation or assessment could be one use case; however, visualizing a designer's learnings or providing real-time design feedback might be more beneficial. This visualization could show a student's or employee's decisions in solving a design challenge. Students and practicing engineers could see the sequence of decisions they performed at a high level and pinpoint when they were and were not systematic in the design process. Not systematic, meaning design strategies of interest are not captured. One should note that not using one of the strategies of interest does not mean no strategies were used but more likely that they are using strategies not captured in this research design. Future work might explore the use of design behavior dashboards to highlight efficient and less efficient portions and explore how this tool impacts design outcomes and designer experience.

Conclusion

Engineers routinely select lower-rated concepts despite higher-rated alternatives within the solution space. Prior research has studied the influence of specific concept selection methods and tools that influence final decisions; however, the focus of this research investigated the concept selection phase as a series of sequential decisions in which strategies for exploring and evaluating designs emerge. Not only do the findings identify strategies participants used in the robotic gripper design task but also how strategies in isolating and prioritizing design parameters positively influenced design outcomes. High-performing designers were found to engage more with isolating and prioritizing design parameters than low-performing designers.

While a select number of strategies were highlighted in this study, there are likely additional decisions strategies worth studying, such as degrees of transitions and time spent on design parameters. Isolating and prioritizing design components are likely used within other concept selection methods and tools such as Pugh matrices, where designers need to assess multiple concepts. How an engineer explores and evaluates design alternatives will provide further insight into how engineers select lower-performing designs despite using standardized selection methods. Design researchers should evaluate how these design strategies show up within standard concept selection methods, not just which strategies or methods designers use, but work to understand their influence on design outcomes.

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