Chapter 11
Human and Computational Approaches for Design Problem-Solving

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Abstract Human and computational approaches are both commonly used to solve design problems, and each offers unique advantages. Human designers may draw upon their expertise, intuition, and creativity, while computational approaches are used to algorithmically configure and evaluate design alternatives quickly. It is possible to leverage the advantages of each with a human-in-the-loop design approach, which relies on human designers guiding computational processes; empirical design research for better understanding human designers' strengths and limitations can inform the development human-in-the-loop design approaches. In this chapter, the advantages of human and computational design processes are outlined, in addition to how they are researched. An empirical research example is provided for conducting human participant experiments and simulating human design problem-solving strategies with software agent simulations that are used to develop improved strategies. The chapter concludes by discussing general considerations in human and computational research, and their role in developing new human-in-the-loop design processes for complex engineering applications.

Keywords Problem-solving · Complexity · Human-in-the-loop

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11.1 Human and Computational Design Approaches

Although many design methodologies are presented as a concise series of steps to follow, in practice, design is typically anything but formulaic. Successful human designers draw upon years of experience and use non-sequential approaches to solve problems with deductive, inductive, and abductive reasoning processes (Dorst 2011). Empirical design research approaches have begun forming a foundation of scientific evidence to describe human design reasoning, but there is still much to learn (Dinar et al. 2015). Basic design reasoning, such as logically evaluating quantitative design trade-offs, is often easier to measure and scientifically describe than blurrier processes such as creative thinking. Current research endeavours have begun simulating basic design reasoning with computational approaches, which could lead to automated approaches for solving design problems at a much faster rate than human designers may accomplish. Findings may also provide insights for better understanding human design reasoning processes (Egan et al. 2015a; McComb et al. 2015; Yu et al. 2015).

The vision of computers perfectly mimicking human reasoning processes has long sparked the imagination of researchers, but there have been many roadblocks in creating an artificial intelligence that fully emulates intelligent human behaviours (French 2012). Although major advances have been made in artificial intelligence fields, it is likely that highly complicated reasoning processes, such as design, will not be fully recreated by computational approaches in the immediate future. In the meantime, computational design approaches are useful for efficiently making algorithmic design decision-making processes that support human design process. When deployed effectively, computational automation can improve the pace of a design project by rapidly generating, evaluating, and selecting design concepts. To effectively use computational processes to support human designers, it is important to understand the advantages and differences amongst human and computational design approaches (Fig. 11.1).

Design problems are typically ill-defined initially which makes them difficult to formalize for computational processes. Human designers, however, are capable of redefining a design problem towards a more manageable representation (Björklund 2013). Once better defined, a designer can use creative processes to propose solutions that draw from their experiences beyond the design problem itself. These are generally qualitative processes that are difficult to translate into algorithmic logic

Fig. 11.1 Advantages of human and computational design processes

Humans	Computers
Creative	Fast
Flexible	Algorithmic
Intuitive	High repeatability
Qualitative and abstract	Do not fatigue
Bring outside expertise	Consistent biases
Formulate heuristics	Precise calculations

for computational processes. However, a designer has a limited cognitive capacity for reasoning about the many variables that may be found in a design problem; depending on the situation, a designer may use their intuition (Pretz 2008) or formulate heuristics (Daly et al. 2012) to quickly propose a good solution that works, rather than exhaustively searching a design space to find an absolute best solution.

Computational design processes, in contrast, tend to work best when they extensively search a design space according to a set of rules. These rules remove many biases from the design process that humans are likely to carry from past design experiences. Computers can store a large number of variable relationships simultaneously and are not subject to fatigue like human designers that only work effectively for a limited duration of time. Computational processes also offer a high degree of repeatability when solving problems, whereas humans may be inconsistent. When repeatable deterministic approaches for solving a design problem are found to limit a computational search's ability to find high-performing alternative design solutions, computers may be programmed with stochastic or probabilistic decision-making strategies (Cooper 1990). Stochasticity is often necessary to encourage a computational process to explore a diversity of solutions before converging on its best considered solution. Due to computational approaches being advantageous for algorithmically finding solutions to a design problem, they are commonly used once a design problem has already been framed by a human user, such as optimizing an already parameterized design.

Because there are both advantages and disadvantages to human and computational design approaches, it is important to carefully consider the characteristics of a design problem prior to selecting a process. An approach that considers both human and computational processes can leverage the benefits of each and is particularly helpful for engineering complex systems (Ottino 2004; Simpson and Martins 2011). Complex systems are notoriously difficult for humans to understand (Hmelo-Silver et al. 2007; Chi et al. 2012) due to their large number of variables and emergent behaviours. Computational processes can be used to quickly evaluate variable relationships and provide analytical output describing a complex system for a human designer to interpret. A human designer may then steer computational processes with a "human-in-the-loop" design approach by making high-level decisions that guide the computational processes towards more beneficial solutions (Simpson et al. 2011). In this framework, a human designer could potentially steer computational processes based on knowledge of multilevel parameter interactions that influence qualitatively distinct emergent system behaviours (Egan et al. 2015c) and could potentially be difficult to formalize computationally. Empirical research studies can play a role in scientifically determining the most effective way to interface human and computational decision-making processes for solving such design problems.

The aim of this chapter is to investigate the use of human and computational approaches for solving design problems and how to empirically study them. Research methods and findings concerning human and computational processes are covered next in Sect. 11.2. In Sect. 11.3, an empirical research approach for developing new design strategies with human participant experiments and computational simulations is provided as an example for conducting a controlled scientific investigation for empirically researching design problem-solving. Further considerations for using human and computational processes in empirical design research and for human-in-the-loop applications are discussed in Sect. 11.4 prior to concluding the chapter.

11.2 Human and Computational Design Research

This section covers a few of the many research approaches and findings for empirically studying human design reasoning processes and conducting computational design research. The use of graphical user interface (GUI) experiments is introduced as a basis for bridging human and computational processes in empirical design research.

11.2.1 Human Participant Experiments

There are a large number of approaches used by researchers for empirically studying human designers, which include verbal protocols, case studies, and controlled experiments (Dinar et al. 2015). Controlled experiments are particularly useful because they enable precise study of specific design processes with rigorous statistical comparisons, rather than case studies and verbal protocols that may contain more conflating variables that obscure the validity of conclusions. Experimental comparisons of novices and experts are common in design research (Björklund 2013) and particularly useful because they can reveal key attributes of expert designers that novice designers do not possess, but could learn. However, even expert designers are subject to cognitive limitations (Linsey et al. 2010) and could benefit from computational support, especially when considering the fundamental limits of human cognitive processes.

Numerous experiments have demonstrated that humans have limited working memory and are subject to cognitive load. Three types of cognitive load that may influence a designer's reasoning processes are: intrinsic, extrinsic, and germane (Van Merriënboer and Sweller 2010). Intrinsic load is caused by a design problem itself, extrinsic load is related to other information presented to a designer not directly related to solving the design problem, and germane load is proportional to the effort a designer places into solving a problem. Designers are more successful when all types of load do not surpass a particular threshold that is dependent on the cognitive capabilities of the designer. Germane load can aid in design problem-solving if it is not too large, since the effort placed into solving a design problem can result in learned knowledge that helps enable the designer to make better decisions while solving a problem. There are a number of techniques used to measure cognitive load (Hart and Staveland 1988; Paas et al. 2003; DeLeeuw and Mayer 2008) that are typically conducted by exposing human designers to increasingly difficult problems and measuring their performance and/or considering self-reports from designers.

The amount of information humans may consider at a time is limited to a few pieces of information (Miller 1956), which can impede human design problem-solving performance. Such limitations have been observed as humans solve increasingly difficult parametric design problems (Hirschi and Frey 2002) with experiments showing that as the number of considered variables increases human problem-solving performance declines significantly. These findings are related to design since each parameter could theoretically be tied to a real-world design variable. This decline in human performance occurs because it is difficult for human problem solvers to retain information concerning all parameter relationships while also making decisions for solving a problem. Due to these limitations, problem-solving strategies that enable humans to change only one variable at a time are beneficial (Kuhn et al. 2008; Chen and Klahr 1999), in part because they enable learning how each variable works in isolation rather than reasoning about multiple parameter interactions simultaneously.

11.2.2 Computational Design Research

Unlike human designers, computers are not subject to the same limitations in working memory and cognitive load. Computational design approaches are particularly well-suited for solving optimization design problems, since computational approaches perform quantitative operations at a much faster rate than any human. A difficulty in using computational approaches emerges when selecting the best algorithmic strategy for solving design problems. There is a diversity of strategies for solving design problems (Belegundu and Chandrupatla 2011), and the most effective strategy depends on the nature of a design space. Common computational search strategies range from being deterministic and reaching the same answer every time they solve a design problem to being highly stochastic (Du Pont and Cagan 2012; Yin and Cagan 2000). Stochastic searches are necessary when a design space has many locally optimal designs since a deterministic approach is more likely to converge on a final design that underperforms in comparison with the best possible solution.

The use of software agents is common in computational design research to solve a wide variety of design problems, with the potential for software agents to work together through using a diversity of strategies (Campbell et al. 1999). Software agents are computational objects with varied capabilities in perceiving, manipulating, and learning about a virtual environment. Both stochastic and deterministic search approaches may be used by agents in addition to agents adapting their strategies during a design space search (Hanna 2009; Landry and Cagan 2011). Agents can use processes that mimic human reasoning, learn during problem-solving (Buczak et al. 2006; Junges and Klügl 2012), and may be tuned with varied strategical preferences suited to different design problems. In addition to strategical preferences, agents may possess knowledge that emulates human experts (Schiaffino and Amandi 2009). These qualities of agents make them highly amenable to simulating human design reasoning processes and could provide insights for new ways that humans could solve design problems (Egan et al. 2015a).

11.2.3 Graphical User Interface Experiments

Graphical user interfaces (GUIs) are interfaces that enable human users to interact with electronic devices or software programs using graphical icons or visual indicators. They are commonly used in psychology studies to gain data that enable inferences of human reasoning processes. In design contexts, a GUI can present a user a set of design inputs and then evaluate the performance of a user-configured design. Engineering design experiments have demonstrated that information presented to a user via a GUI can influence their design decision-making choices, with participants having higher design optimization success when information is provided in real-time in comparison with a delayed response (Simpson et al. 2007).

Some GUI studies have investigated human understanding of complex systems (Vattam et al. 2011), which can inform design approaches where humans guide computational routines with a GUI (Parasuraman et al. 2000). A key consideration in constructing a GUI is the tuning of cognitive load a designer experiences (Hollender et al. 2010). Extrinsic cognitive load may be minimized by only presenting information relevant to solving a design problem, which is demonstrated in a screen capture of a design GUI in Fig. 11.2 for optimization problems.

The GUI in Fig. 11.2 presents an optimization problem prompt in the top left of the screen and enables users to manipulate design inputs via sliders on the left

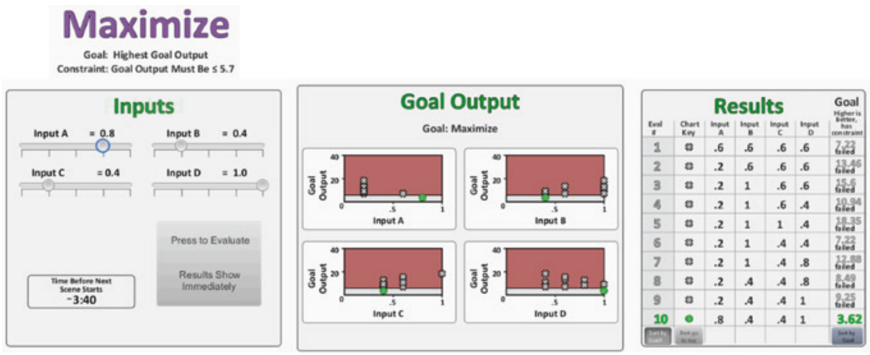

Fig. 11.2 Screen capture of a GUI for tracking human design searches

side of the screen and evaluate designs with a large button. Constraints in the problem statement are represented by red areas in charts in the middle of the screen. In the charts, evaluated design inputs are plotted as independent variables and the goal output is plotted as a dependent variable which provides a visualization of the design space (Kollat and Reed 2007). Due to the difficulties humans have in interpreting multivariable plots (Zhang et al. 2012), a table on the right of the screen presents results in a second format. Buttons along the bottom of the table enable automated design sorting to aid users in quickly comparing design evaluations.

Figure 11.2 GUI is only one possible way of presenting information visually to a designer and is particularly well-suited for conducting experiments concerning designers' decision-making processes. GUIs for other experiments, such as tracking a user's creative thought processes, may look very different and could include input areas for designers to write about their thought processes or sketch designs.

11.3 Example: Empirical Human-Agent Research Approach

Our goal in this section is to communicate core techniques and processes required to conduct empirical design research with humans and computational process, where human participant data are tracked with a design GUI and computational processes are carried out by software agents. An example is illustrated with abridged findings from an empirical human-agent research approach (Egan et al. 2015a), which we refer the reader to for a more thorough explanation of experimental techniques and findings. In brief, the example is motivated by recent advancements in the understanding of cognitive approaches that now make it feasible to understand a human design search strategy, model that strategy computationally, and then computationally optimize refined search strategies that humans can apply to more effectively and efficiently solve future design problems of similar ilk.

11.3.1 Defining an Experiment

The first step in carrying out an empirical design research study requires clearly defining the experimental goal. For our design problem, a complex muscle biosystem was considered across scales, with a particular emphasis placed on the mechanical design of nanoscale motor proteins (Howard 2001; Egan et al. 2013). Due to the complexity of the design problem, human-in-the-loop approaches (Simpson and Martins 2011) were identified as a potential design strategy that motivates the need for human participant experiments for empirical testing and validation (Egan et al. 2015b). A specific research goal was formulated to isolate a highly successful and empirically validated search strategy for human designers.

Table 11.1 Testable cognitive-based design search strategies

Design search strategy	Human reasoning process	Software agent rules
Near	Designs are improved through small changes	One or more design inputs for current best design are perturbed
Univariate	Manipulating one variable at a time enables controlled changes for finding better designs	One design input for current best design is perturbed
Learn and Apply	Learning how each variable influences a design can inform search decisions	One design input for current best is perturbed; findings direct future design perturbations

A sample set of search strategies amongst the diversity of existing optimization strategies (Belegundu and Chandrupatla 2011) were identified as potentially useful for humans to use and inform which search behaviours of human designers should be tracked in the experiment. A restriction is made in this study to only consider designs that are algorithmic, so strategies may be implemented and refined by software agents. Three cognitive-based strategies informed by the literature were proposed and are presented in Table 11.1.

The Near strategy in Table 11.1 is proposed by considering a human designer's limited cognitive capacity, meaning search decisions should require low effort (Hirschi and Frey 2002), which could be facilitated by making small changes to an existing best design. The approach was also used in engineering strategies such as the extended pattern search (Yin and Cagan 2000) that uses information based on the current best designs to inform choices in selecting new designs. The Univariate strategy (Chen 1999; Kuhn 2008) in Table 11.1, where only one design input is changed when modifying a design, is proposed since it requires a low cognitive effort in human decision-making while also reducing the effects of parameter coupling from an engineering perspective. The Learn and Apply strategy in Table 11.1 is proposed since humans may learn parametric relationships that are stored initially in short-term memory (Hirschi and Frey 2002) and apply knowledge of relationships towards improving a design. The application of knowledge during a search could promote fast convergence on a high-quality design from an engineering perspective. These strategies are only a portion of the possible strategies that could be investigated and are chosen as feasible strategies for initially testing and implementing the empirical research approach.

11.3.2 Experimental Method

Once potential strategies are identified for testing, an experimental methodology is developed to measure human design behaviours in an effort to empirically determine which strategies humans may use and are most effective. Our approach

Fig. 11.3 Empirical human-agent research method. *1* Humans search with no provided strategy. *2* Agents refine most successful human-derived search strategies. *3* Humans search with best agent-refined strategy

consists of human participant experiments and software agent simulations with steps for the following: (1) collecting human search data and identifying the most successful search trends related to proposed cognitive-based strategies, (2) refining the best human-derived search strategies through exploration with software agents solving the same design tasks, and (3) validating the usefulness of the agent-refined strategies with a final human subject experiment. Participants using the agent-refined strategy should, on average, find significantly better designs than designers in the initial human subject experiment (Fig. 11.3). The best strategy found is representative of an empirically validated approach for human designers to use to support a human-in-the-loop design approach.

The numbers in Fig. 11.3 reflect the growth of design scores across steps when designs are rated on a scale of 0–1. Design ratings are expected to improve through each phase, but do so according to a statistical distribution since there is typically a stochastic element in human decision-making and all participants in an experiment are likely to search the design space uniquely. Software agents are also programmed to make design decisions stochastically. Due to the stochastic nature of searches, there is a need to collect large samples of data to find meaningful averages for statistical comparisons.

The method uses only two human subject experiments since they are typically resource expensive. The first human subject experiment is necessary for deriving initial cognitive-based search strategies, such that agents only refine strategies that a human designer could conceivably understand and implement, rather than search strategies that are computationally efficient but are potentially impractical for humans to use efficiently. It is possible to use the initial set of human searches as a control for validating the best agent-refined strategy in the second human subject experiment and to determine whether humans have greater search success when provided the agent-refined strategy.

11.3.3 Human Participant Experiment with no Provided Strategy

The first human participant experiment aims to determine whether successful human search behaviours agree with the proposed cognitive-based strategies in Table 11.1. 31 mechanical engineering students participated. Optimization problems with constraints on a goal/objective output and/or other performance outputs were used as design optimization tasks. An easy design task was created by adding a goal output constraint while a difficult task had an additional constraint on a secondary output variable.

Participants used a design GUI (Fig. 11.2) to manipulate 3 design inputs for configuring a single motor protein and 1 design input to determine how many proteins are in a system (Egan et al. 2013). Participants were allowed ten design evaluations and four minutes for each task. Once experiments were completed, data were separated by the 25 % most and 25 % least successful searches for each task, named the "best" and "worst" designer populations, respectively. Trends were assessed for each task separately and analysed to determine how often search rules were used by human participants that reflect each of the strategies explained in Table 11.1; results are plotted in Fig. 11.4 and search success was determined by rating a designer's best found design on a scale of 0–1 relative to the objective function value of the global optimal design for a given problem.

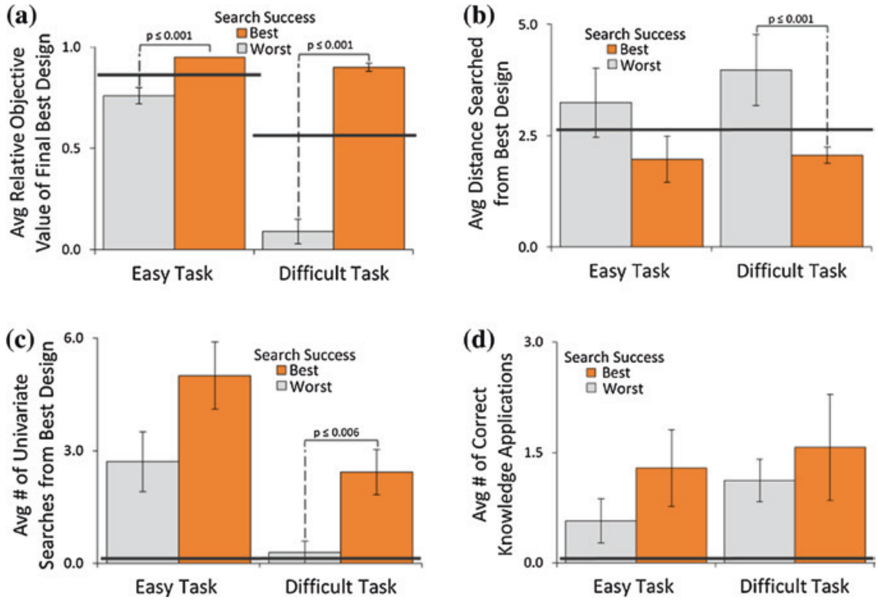

Fig. 11.4 Empirical results of initial human participant experiment

Figure 11.4a demonstrates that the best population found significantly better designs on average than the worst population on each task, so any search trends of the best population that significantly differ from those of the worst population may account for the differences in each group's success. A comparison of results with a random solver (black lines in plots) suggests that participants made deliberate decisions that may represent strategies used. Random solvers are useful as a basis of comparison since they can act as a form of experimental control when no other empirical data are available for comparison.

Figure 11.4b shows that the average distance searched was much lower for the best population on the difficult problem, suggesting that small changes to a good design can lead to higher search success. Figure 11.4c demonstrates that univariate searches were used by the best population much more often than the worst population on the difficult task. There are no significant trends in Fig. 11.4d to show evidence that one population used a Learn and Apply strategy more often; however, there is also no evidence to refute the strategy as beneficial.

11.3.4 Agent Simulations to Refine Human-Derived Search Strategies

Since cognitive-based strategies proposed in Table 11.1 are shown to correspond to how the best population searched in Fig. 11.4, it is promising to propose slight variations in each strategy and rapidly test and refine them with software agent simulations to find highly successful search strategies. Agents can explore strategical variations and test their influence on design search success at a much faster rate than further human studies. Additionally, agents have greater comparative power since simulations may run until there is little error.

Each software agent has access to the same information as human designers, which includes the design inputs and output values provided by the GUI. Agents assess the current state of a design search and input a new design based on a set of rules reflecting an agent's preferred strategy. Agent rules reflect the three cognitive-based strategies presented in Table 11.1. Differences in agent preferences reflect how far they search away from a previous best design or how they select design inputs initially. All agents with a particular strategy repeatedly solved a task and results are aggregated until error is negligible.

The average best relative objective function value found by agents for each cognitive-based strategy is plotted in Fig. 11.5. For all agent strategies, selecting a random set of design inputs was found as the most beneficial initial input.

Results demonstrate that the Near strategy performed worst for each task and the Learn and Apply strategy performed best. The Learn and Apply strategy marginally improved search success on the easy task compared to both other strategies and greatly improved search success on the difficult task. A black line that represents the findings of a random solver in Fig. 11.5 suggests that only the Learn and Apply strategy offers a large improvement over a random search. This finding is

Fig. 11.5 Best performance achieved by each agent-refined strategy

important, since when viewing the human data in isolation from Fig. 11.4, it is not possible to determine which differences in the best and worst populations' search trends may cause higher design search success.

11.3.5 *Human Participant Experiment with Agent-Refined Strategy*

A second human participant experiment was conducted to determine whether the Learn and Apply strategy improves human search success in comparison with the first experiment when no strategy is provided. A participant population of 30 students from a master's level engineering course was selected to closely match the first experimental population.

All aspects of the second human participant experimental protocol were identical to the protocol used for the first human participant experiments, except for a modification to the GUI to guide participants in making choices restricted to the same strategic rules as followed by the best agent-refined strategy. The results for the average best relative objective found by the humans in the first and second experiments and agents using the Learn and Apply strategy are presented in Fig. 11.6, with black horizontal lines reflecting random solver results.

Results demonstrate that on both tasks humans with guidance performed significantly better than humans with no guidance from the first experiment. These findings suggest that the introduction of the agent-refined strategy is beneficial for human searches and demonstrates the merits in implementing an empirical human-agent approach to discover and refine cognitive-based search strategies. These results illustrate how synergistically using human and computational approaches in research can reveal key insights concerning the design process, namely that human designers benefit from using control of variables strategies when solving complex system design problems. These findings are also informative for how to present a design problem for humans to solve when guiding automated processes in a human-in-the-loop design approach.

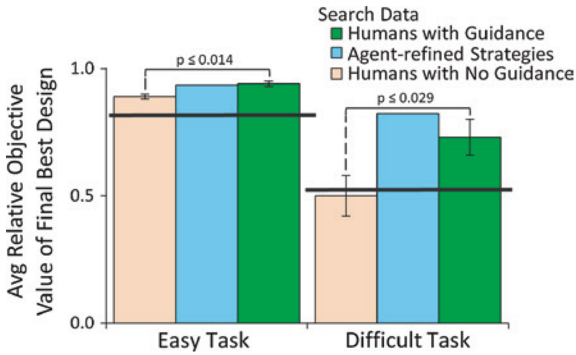

Fig. 11.6 Comparison of human search data with no guidance, agent-refined strategies, and human search data with guidance

11.4 Discussion of Human and Computational Design Processes

The need for further empirical research endeavours opens many new questions for discussion, including possibilities for extending experimental approaches with humans and agents and the potential to study diverse cognitive phenomena relevant to design. Studies of human designers can directly inform the set-up of human-in-the-loop design approaches for varied design applications and there is a great need for continued empirical design research for both understanding designers and establishing effective design approaches.

11.4.1 Human and Agent Experimental Approaches

There are many potential approaches for extending the example approach for simulating human designers with computational processes presented in Sect. 11.3, which may be accomplished by embedding different programming logic or assumptions in design problem-solving simulations. Software agents are particularly amenable for testing how varied assumptions influence design problem-solving outcomes since they provide a modular platform for implementing varied logic circuits. Agents also have autonomous decision-making capabilities that resemble human designers. Some possibilities include providing agents design heuristics used by human designers or with a priori knowledge of a design domain so agents can emulate human experts familiar with a domain. Findings of agents embedded with expert knowledge have demonstrated faster convergence for finding design solutions (Egan et al. 2015a). However, sometimes fast convergence is detrimental if it encourages the selection of a locally optimal design that underperforms in comparison with many other potential solutions. Introducing stochastic search logic (Du Pont and Cagan 2012; Yin and Cagan 2000) can encourage early design exploration for these types of design problems by enabling convergent searches to potentially begin from a more fortuitous starting point.

Recent studies have considered the simulation of entire teams for investigating cognitive phenomena by using similar agent simulation approaches. One approach has sought to recreate non-obvious human design behaviours with agent simulations paired with simulated annealing optimization approaches (McComb et al. 2015). This model investigates how designers work in teams to configure a complex truss structure and was validated with human participant experiments. By using the simulated annealing approach, a number of different cognitive phenomena were modelled, which demonstrates the robustness of using computational processes to recreate and explore human designer behaviour. Another study that used a simulated annealing approach has found that the most successful designers in a human participant experiment used search process that resemble a well-tuned simulated annealing optimization algorithm (Yu et al. 2015). The worst designers in the study tended to use pseudorandom approaches.

11.4.2 Potential Cognitive Phenomenon to Investigate

There are many reasoning processes designers use that could inform new empirical research investigations. Basic cognitive phenomena related to design are typically characterized initially in the psychology literature and require further investigation from a design perspective. There is a need to follow-up on fundamental psychologically studies with more specific design oriented experiments since design research seeks to answer questions that typically are not investigated in basic psychology research. For instance, human understanding of complexity has been studied psychologically (Hmelo-Silver et al. 2007; Chi et al. 2012), but there are fewer efforts to determine how understanding of complexity influences a designer's capabilities for making decisions.

One of our recent human participant experiments demonstrated that human understanding of qualitative behaviours across complex system scales improves human design decision-making performance (Egan et al. 2015c). However, a precise cognitive mechanism for how designers translate such understanding towards better design decision-making was not identified. This lack of explanation may be attributed to the small number of participants in the study and the large number of different strategies a designer may employ to use learned knowledge effectively. Therefore, the study has opened doors for new scientific investigations with alternate experimental designs that could specifically investigate potential cognitive mechanisms. Because experiments must be designed to target specific phenomenon, many empirical research endeavours pursue incremental advances based on unanswered questions from previous studies. Further cognitive phenomenon that may be of interest to design researchers are qualitative reasoning (Kuipers 1986) and spatial intelligence (Bhatt and Freksa 2015), which are both core cognitive processes that human designers use but are difficult to simulate computationally.

11.4.3 Empirical Findings for Human-in-the-Loop Approaches

Empirical research can inform design approaches by providing a scientific basis for how to design effectively. The research example provided in this chapter forms a basis for experimentally determining which human search strategies are potentially effective for aiding human-in-the-loop design approaches for complex systems design (Simpson and Martins 2011). In human-in-the-loop approaches, humans can use intuitive and qualitative reasoning processes that are difficult to automate, but crucial for generating novel concepts and quickly removing bad designs when solving a design problem. Computational processes are necessary to support design space searches when the number of considered variables surpasses human cognitive capabilities, since computational processes can quickly traverse a space and suggest design alternatives.

Empirical research can provide a basis for determining how well a human designer can understand a design space and form effective decisions. In the Sect. 11.3 example, empirical results showed that human designers could effectively reason about complex system design if they learned and applied knowledge using a control of variables approach when design optimization problems consisted of 4 design inputs and up to 2 performance outputs. The inclusion of a second performance output in a difficult problem significantly reduced human search success when compared to easy problem results (Fig. 11.4a), which suggests computational processes are increasingly needed as design tasks become more difficult.

These findings have now been used to form the basis of a human-guided system that includes computationally automated processes for discovery, description, and development of complex biological system designs (Egan et al. 2015b). In this approach, computational optimization is used to search a complex design space and find high-performing biolibraries. A biolibrary is considered a catalogue of biological parts used for forming a set of nanotechnologies similar to a product family. The human-in-the-loop approach is effective for this type of problem because a computational process can use stochastic search processes to find a generally high-performing set of nanotechnologies constructed from the biolibrary, with each individual nanotechnology being represented by 4 design inputs and evaluated with up to 2 design outputs that are suitable for humans to refine. The initial optimization problem solved by computational processes includes the optimization of many nanotechnologies that require simultaneous consideration of a much larger number of design inputs and outputs. Therefore, humans can make high-level decisions to improve the overall design of a biolibrary and developed nanotechnologies by making small changes to initial designs found during a computational search. The use of empirical design research has provided a basis for tuning the complexity of representations for human searches that would otherwise be difficult to determine, and how humans may best make strategic decisions for tuning designs suggested by initial computational searches.

11.4.4 Future Considerations for Empirical Design Research

Controlled scientific investigations are crucial for building a body of knowledge for design research, but there are limitations. Scientific investigations relying on statistical analyses tend to place a higher emphasis on studying successful processes that are favoured significantly by a majority of designers. It is possible that some successful design processes go unnoticed, which could be a problem in studies with low participant numbers. For instance, if the theoretically best possible design process was used by only one human participant, it would be difficult to identify the process used amongst other measured design behaviours more commonly used. Secondly, the process would likely not appear as significantly better than others when statistical tests are employed. Due to the logistics of experiments, it is not possible to empirically explore with human participants all possible influences on design search processes; design researchers must carefully consider the research goals they wish to explore prior to conducting a study. These limitations are an inherent part of the scientific process and also push experiments towards pragmatically investigating phenomena that are measurable since all scientific experiments must be conducted within the confines of time and resources available.

It is particularly important for design researchers to differentiate between the knowledge they hope to gain from scientific studies, and the knowledge that is feasible to gain from scientific studies. Although the introduction of computer simulations to mimic human designers can significantly enhance the rate of discoveries in design research, there are always roadblocks in setting up experimental controls and correctly validating studies with scientific rigour. These considerations can significantly influence the future outlook in empirical design research since rigorous research must constrict each new study to only measuring a small number of design phenomena. These limitations encourage the creation of new methods and empirical approaches that build upon one another to facilitate future research discoveries. These established findings may form a foundation for repeatable and controlled scientific investigations and act as anchors in empirical design research for continued discoveries with increasingly mature findings.

11.5 Concluding Remarks

In this chapter, an overview was provided for human and computational design processes and the need for empirical studies to better characterize human design reasoning, particularly for developing human-in-the-loop design approaches. Human reasoning processes tend to be creative, intuitive, and qualitative while computational approaches are fast, algorithmic, and quantitative. Human-in-the-loop approaches are advantageous since they can benefit from advantages offered by both human and computational design approaches. Empirical design research can play a large role in determining how to best tune a human-in-the-loop approach so human designers can effectively make decisions to guide computational processes.

Processes for empirical design research were demonstrated that include defining an experiment, developing a method for carrying out an experiment, measuring human design behaviour, and analysing data. An example empirical research approach was summarized that used human participant experiments and software agent simulations. Software agents are a particularly helpful approach since they may simulate human designers' reasoning processes and test human design problem-solving strategies at a much faster rate than extensive human participant experiments would allow. Continued research in this area has great potential in reaching new insights in how designers design through simulating their reasoning processes computationally, and using those findings for developing integrated human and computational processes for designing diverse systems.

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