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A Conceptual Framework for Value-Driven Design and Systems Engineering

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Abstract

Value-driven design starts from the premise that a designer has preferences, which can be modeled in terms of value maximization. In this paper, we consider value maximization from three increasingly comprehensive perspectives: artifact-, process-, and organization-focused. Based on this framework, we then identify five characteristics of common design processes, and explain and justify these characteristics in terms of value maximization. Although the framework is based on normative decision theory, an important conclusion of the paper is that heuristics play a crucial role in design. The paper therefore ends with a reflection on the role of heuristics in design and systems engineering research.

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Keywords: value-driven design; normative decision theory; design heuristics; systems engineering.

1. Introduction

When studying engineering design, it is important to keep in mind its primary characteristic, namely, that design is a purposeful activity. "Purpose" is what distinguishes Engineering from the Natural Sciences. This purpose has often been characterized in the systems engineering and design literature as the goal to satisfy a stated need [1], which then leads to the formulation of a set of requirements to be satisfied. However, in the context of this paper, we take a step back and ask: What truly drives designers in their design activities? And what can we learn about designing by focusing on this driving factor?

By shifting the focus from "design" to the "designer," a second important characteristic of design comes to the forefront, namely, that design is a human activity. This is important from two perspectives: economic and psychological.

From an economic perspective, we recognize that designers, as all humans, have preferences and strive to achieve more preferred outcomes over less preferred ones. In economics and decision theory, such preferences are expressed as "value," so that striving for the most preferred outcome can be modeled as maximizing value. Based on simple axioms of rationality, decision theory prescribes how one should go about choosing the most preferred, most valuable alternative (under uncertainty) [2]. Clearly, from this perspective, value maximization is at the core of design—value maximization is what drives designers.

However, there is more to design then just applying decision theory. Before being able to select a design alternative that maximizes value, designers must first identify value opportunities and then generate creative concepts for taking advantage of these opportunities. These are activities that rely in part on divergent and analogical thinking [3]. To be able to support such activities well, it is important to gain a deep understanding of the cognitive processes used by designers, and, in the context of today's complex engineered systems, of the social interactions among multiple experts on diverse design teams. Besides a normative foundation in decision theory and economics, design research should therefore build on a foundation of psychology and sociology.

In this paper, we aim to develop a conceptual framework for design and systems engineering rooted in normative decision theory, but expanded to fold in psychological and sociological

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Nomenclature

π_A	Artifact-Focused Value
π_P	Process-Focused Value
π_o	Organization-Focused Value
a	Artifact Specification
A	Set of Considered Artifact Specifications
$\mathcal{A}$	Artifact-Focused Design Problem
p	Sequence of Process Actions
P	Set of Considered Sequences of Process Actions
$\mathcal{P}$	Process-Focused Design Problem
i	Incentive Structure
I	Set of Considered Incentive Structures
$\mathcal{O}$	Organization-Focused Design Problem
t	Time for Solving a Design Problem
t_p	Duration of a Design Process
C	Cost of Solving a Design Problem
C_p	Cost of a Design Process
C_i	Cost of Incentives
SE	Systems Engineering
VDD	Value-Driven Design

aspects. This is achieved by considering decision making not only from the perspective of the artifact, but also of the design process, and of the organizational structure in which humans perform the process.

2. The Goal of Design: Value Maximization

Design is a systematic process for identifying, exploring and exploiting value opportunities. As is illustrated in Figure 1, such value opportunities continually come and go, within a global context. For instance, given an environmental context of global climate change, an economic context of scarce and expensive gasoline, and a technological context in which powerful electrical motors and increasingly energy-dense batteries are available, there is currently a value opportunity to develop (hybrid-) electric vehicles. As the global context changes, or as the competition catches up, current value opportunities may disappear in the future. There is a constant evolution, due to exogenous influences in the global context, but also due to the participants in the global context introducing new systems and changing the context.

In addition, whether a particular company can take advantage of a value opportunity depends also on its systems engineering capabilities, its ability to generate efficiently and effectively a new system in response to a value opportunity. To maximize its value, a company should therefore not only invest in the creation of new systems, but also into advancing its systems engineering capabilities. Doing so provides it with a competitive advantage, by being able to pursue value opportunities that are not accessible to its competitors. For instance, the systems engineering and design methods and tools of today allow us to handle the development of complex engineered systems that would have been unimaginable only one or two decades ago. But looking forward, the methods and tools will need to be updated for the increased complexity that can be expected in the future. The rate of increase in complexity will be driven by the companies with the most sophisticated systems engineering capabilities. Companies that do not keep up with the technology leaders are bound to fail because they cannot successfully take advantage of value opportunities.

Advances in the state of the art and practice in systems engineering can result from a better understanding and a more rigorous application of the theoretical foundations, as mentioned in the Section 1, but also from taking advantage of new enabling technologies, such as cloud computing, crowd sourcing, data mining, or immersive data visualization. Given this new understanding of the foundations and given these new enabling technologies, a company must update its methods, processes and tools, specific to its global context and application domain, keeping of course the ultimate objective in mind, namely, to maximize value.

The need for a value-driven methodology in systems engineering practice has been the topic of significant research in recent years. Value-Driven Design (VDD) is a systems engineering approach which strives for the maximization of value rather than for the satisfaction of stakeholder needs as in traditional systems engineering [1, 4-5]. The name, "Value-Driven Design," comes from the recent work by a committee of the AIAA [6-10] and by participants of the F6 program at DARPA [11-14]. VDD builds on a foundation of decision theory which prescribes normatively how preferences should be expressed in terms of an objective, value, or utility function (when considering uncertainty [2]). A focus on value is also expressed by Keeney in [15-16].

Accepting the notion that maximization of value is desirable, two questions arise: *"Whose Value?"* and *"Which Value?"* As is discussed in Section 3, the question of whose value to consider is answered in a normative fashion by decision theory: The decision maker should make decisions based on his or her own preferences. We advocate for a normative perspective, because decision makers should *strive* to make rational decisions, even if they not always appear to do so successfully [17]. In Section 3.3, we address the complications that arise when multiple decision makers exist.

The second question, *"Which value?"* is a question about fundamental preferences. In an industrial context, these preferences often map to net present value of the long-term profit stream as reflected in the stock valuation of the company. But in general, they can include anything the decision maker cares about, including environmental impact, or social and humanitarian considerations.

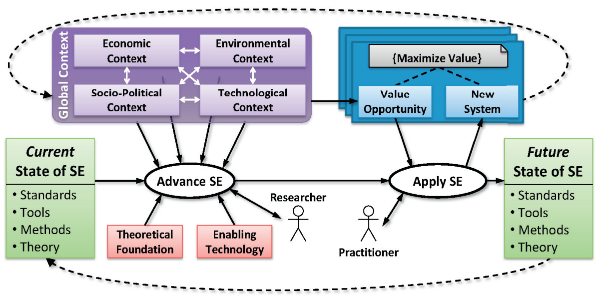

Figure 1. Systems and Systems Engineering Continually Evolve, Driven by a Desire to Maximize Value.

Finally, it is important to recognize that a designer has only a single objective: to maximize value. By definition, a value function rank orders alternatives ordinally or cardinally according to preference. This value may of course (nonlinearly) depend on attributes that represents *means objectives* [15-16], but rather than considering these means objectives separately (as in multi-objective optimization [18]), they should be combined into a single value function. Although it can be a challenge to develop a good model for predicting value comprehensively, aiming to maximize value almost certainly leads to better design choices than ignoring one's overall preference and focusing exclusively on a few means objectives, such as minimizing mass or cost.

3. Decision Making in Design

Based on the premise that the goal of design and systems engineering should be to maximize value under uncertainty, it is clear that the theoretical foundation must include a basis for such decisions. Decision theory provides such a basis, using simple axioms to construct a foundation for rational decision making. The application of decision theory to design goes back at least to the work on Rational Design by Tribus [19], and more recently by Hazelrigg [20-21] and Cook [22]. Decision theory prescribes a process in which a decision maker first describes a driver for their value, and then applies a nonlinear transformation to this value measure to obtain a utility function that incorporates their risk preferences.

In the remainder of this paper, we show how decision theory is broadly applicable to design when considered from three perspectives: artifact-focused, process-focused, and organization-focused decision making. This is different from the traditional focus which was limited to making decisions about the artifact. Broadening the scope to include process and organization leads to several interesting insights into the design process.

3.1. Artifact-Focused Decision Making

When focusing on maximizing the value of the artifact, we acknowledge that a company derives value primarily from producing an artifact that can be sold for profit. This marks a change from the typical focus of design, in which the engineers seek to create an artifact that meets certain benchmarks on consumer attributes. Instead, the consumers' preferences are only important to help the designers understand what will sell, and at what price. As such, while it is important to create value for the customers in a sustainable business model, the focus is on maximizing the company's value. Therefore, from an artifact-focused perspective, a designer is concerned with maximizing the profit, π_A, of a given artifact, a, from the set of possible artifacts, A:

$$\mathcal{A}\colon \max_{a\in A} \pi_A(a) \tag{1}$$

While the conceptual formulation of such an optimization problem is simple, the practical development and implementation is not without difficulties. Hazelrigg [21] provides a framework to guide engineers through the process, but it remains challenging. As an example, consider the evaluation of a gasoline-electric hybrid vehicle, as described in Figure 2. Even for such a simple example, a designer must still consider the following:

- Identify which product attributes impact demand
- Create accurate models for demand, including competition
- Create accurate cost models
- Quantify uncertainty for a diverse range of properties
- Perform a nested optimization to determine a pricing strategy
- Consider how the artifact interacts with the enterprise's other product lines
- Consider financial and human resource constraints

Further, the problem becomes even more complicated when there are additional stakeholders, as in the case when the customer is different from the end user, or when retailers, regulators, activists, etc. are involved. Clearly, numerous research challenges remain.

3.2. Process-Focused Decision Making

It is important to recognize that a decision about the artifact is the implicit outcome of a sequence of decisions made about the process. We obtain a final artifact specification by generating potential artifacts and by then analyzing these alternatives. But there are many possible processes for formulating and solving such a decision problem about the artifact, and we thus need to decide which possible sequences of process steps to follow. A particular process has a corresponding value, which includes the artifact value, π_A, as a function of the artifact but also the time used to solve the design problem, $t(\mathcal{A})$, and the cost of solving the design problem, $C(\mathcal{A})$.

$$\mathcal{A}\colon \max_{a\in A} \pi_A\big(a, t(\mathcal{A})\big) - C(\mathcal{A}) \tag{2}$$

Note that this problem definition is not a traditional optimization problem due to its self-referential nature—the objective function contains a reference to the optimization problem itself. To avoid this self-reference, we can reformulate the design problem from a process-focused perspective. Here, we do not directly specify design alternatives, but rather the actions taken during the design process. The design problem can then be modeled as the following process-focused optimization problem:

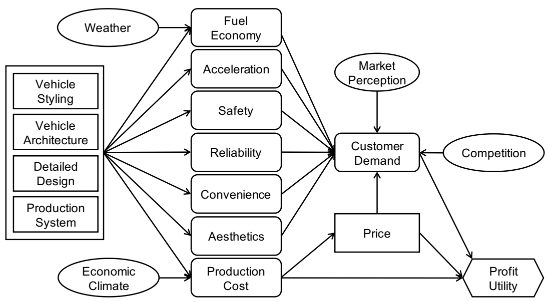

Figure 2. Example of a Value-Driven Framework for Evaluation of a Gasoline-Electric Hybrid Vehicle

$$\mathcal{P}: \max_{p \in P} \pi_P = \max_{p \in P} \pi_A \left(a(p), t_p(p) \right) - C_p(p) \quad (3)$$

reflecting that a designer chooses a sequence of process actions p from a set of considered actions P, resulting in artifact a. Solving this process-focused decision problem is akin to planning the design process. In the planning stage, designers decide which sequence of design actions to pursue, which computational and human resources to apply, and how much time to allocate to each step.

Note that, strictly speaking, $\mathcal{P}$ should again be self-referential, as the process-focused value should reflect the effort and time required to optimize the process-focused value. However, we can justify removing this self-reference as an appropriate approximation by assuming that the process p includes the actions taken during the planning stage. Strictly speaking, the planning stage of p should also be optimized so that it provides the optimal structure for optimizing the process. But then this planning of the planning stage should itself be optimized, and so on. Rather than capturing this infinite regress as self-reference, we consider all of these planning stages to be included in p.

The infinite regress is broken by recognizing that at some point the cost of further planning is larger than the expected benefit. At that point, it is better to resort to heuristics—inexpensive rules of thumb that result in a good decision most of the time. These heuristics may occur already at the artifact level, for instance, when a designer restricts the system alternatives being considered to a small number of common system architectures. Such a heuristic is justifiable if past experience indicates that the small set of architectures is almost certainly going to include the most preferred alternative. The heuristics may also occur at the process level, where based on past experience, a designer may choose to describe and analyze a large set of system alternatives at a particular abstraction level, with a particular analysis formalism and at a particular analysis accuracy. The heuristic then pertains to the process: How to represent and analyze a system alternative? Finally, heuristics may also occur one level deeper still, at the level of selecting appropriate planning actions for planning the design process. For large system development efforts, it may be desirable to take the time to plan the development process: What kind of process should we use? How much time should we allow? What are good milestones or go-no-go points? An example of heuristic at this level may be that for a large effort in which new, unproven technologies are considered, a spiral development approach is appropriate because experience has indicated that it provides a relatively low cost approach for maturing the technologies and eliminating the risks associated with them. However, at some point, this recursive planning loop is guaranteed to end because the expense of additional planning exceeds the expected benefits, so that $C(\mathcal{P}) \approx C_p(p)$ and $t(\mathcal{P}) \approx t_p(p)$, justifying Equation (3).

Even when pragmatically we resort to a heuristic rather than a rigorous solution of a design decision problem, the ultimate objective remains the same: to maximize the overall value, π_P. This is important to recognize when developing new heuristics (as is the focus of much of the ongoing systems engineering and design research). Whether a particular heuristic is good should be evaluated based on its ability to maximize value. As the global context and the enabling technologies change (see Section 1), it is important to regularly re-evaluate existing heuristics, assess whether the underlying assumptions are still valid, and potentially introduce updated and improved heuristics.

Since value can be a challenging metric to measure or predict, other metrics have been proposed as surrogates. For example, consider the metrics of Novelty, Variety, Quality, and Quantity that Shah *et al.* propose to evaluate different ideation processes. In [23], the authors justify each of these metrics independently, but note in their conclusion that directly adding the metrics together is not likely to form a valuable basis for comparing ideation methods. Still, they have set the stage for a value-driven comparison of ideation methods, by posing a set of reasonable metrics that can now be correlated to value. The ultimate value is likely not just a function of these metrics alone, but also includes a consideration of a number of sociological, psychological, and organizational factors. Design is not performed by automatons in a vacuum; it is performed by cognitively limited humans who interact within a social and cultural context. Therefore, methods that purport to be valuable to a designer should be well aligned with the designer's cognitive abilities, as well as his or her social and cultural norms.

3.3. Organization-Focused Decision Making

From an organization-focused perspective, a decision maker may not make decisions about an artifact directly, but only influence artifact decisions indirectly by delegating decision making to others. As is modeled in Equation (4), this decision maker thus designs an incentive structure, i, to encourage others to follow a design process that leads to a valuable artifact:

$$\mathcal{O}: \max_{i \in I} \pi_O = \max_{i \in I} \pi_A \left(a(p(i)), t_p(p(i)) \right) - \sum C_i(i) \quad (4)$$

where the summation includes the costs of the incentives provided to all the stakeholders to whom tasks are delegated. This total cost of the incentives is likely to be higher that than the process cost, $C_p(p)$, in Equation (3) due to the additional cost of agency.

Since, in this model of design, we consider multiple decision makers who mutually have the ability to impact each other's payoff, we must rely on game theory [24] and mechanism design [25] (specifically, principal-agent theory) as a normative foundation to answer the following pertinent questions:

- How should we assign authority and responsibility?
- How should we exchange information?
- How should we measure performance?
- How should we provide incentives?

Organization-focused decision making plays a particularly important role in the context of system-of-systems engineering (SoSE) [26], in which different portions of the system are designed, owned, or operated by different stakeholders.

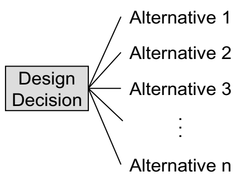

Figure 3. A Design Process Involving All at Once Refinement

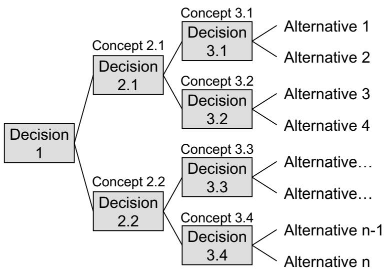

Figure 4. A Design Process Involving Gradual Refinement

When applying game theory to such problems, one would typically assume that it is common knowledge that all players are rational. However, it has been shown in the literature that humans often act irrationally [27]. Therefore, if a decision maker believes that other stakeholders may act irrationally (but predictably so) then he or she should account for this. An interesting area of research extends this principle to consider the possibility of our own irrationality when making decisions. If we want to make good decisions, we should consider that we are subject to biases, and we should take steps to minimize the effect of such irrationality [28-29]. In the end, our goal should be to act as rationally as possible, recognizing our own biases and the likely irrationality of other stakeholders.

4. Characteristics of Valuable Design Processes

Based on the three perspectives of design identified in the previous section, we now consider five characteristics that are typically encountered in design processes. Indeed, we show that each of these characteristics can be justified from a process-focused or organization-focused perspective, but not necessarily from an artifact-focused perspective.

4.1. Characteristic 1: Gradual Refinement of Artifact Specification

In Figure 3, an exhaustive approach for analyzing design alternatives is depicted. In this approach, the decision maker specifies and analyzes the entire set of alternatives in full detail at once, and then selects the most valuable artifact—exhaustive but expensive due to the high cost of both specification and analysis of a large number of alternatives. In Figure 4, a different and more common approach is depicted, in which the specification of the alternatives is refined gradually, allowing a designer to choose which branch in the search tree to follow at each step along the way. Rather than choosing from among a set of completely specified alternatives, the designer now chooses which branches of the search tree to explore, while gradually refining the alternative specification. However, from a process-focused perspective, the second approach is much better. As expressed in Equation (3), besides the artifact value, π_A, the cost of the design process, C_p, must also be considered. Compared to an all-at-once process, a process of gradual refinement tends to require significantly less time and resources for artifact specification and analysis because fewer alternatives are considered in minute detail. Thus, as long as the benefits of a shorter, less expensive design process exceed the loss of value associated with potentially suboptimal artifact specification, gradual refinement adds value. A good example of such a fast-moving and time-critical context would be the development of semiconductor manufacturing equipment.

From an artifact-focused perspective, the second approach is suboptimal. At each decision point, a portion of the space of design alternatives is pruned from further consideration, potentially pruning the most preferred artifact alternative.

4.2. Characteristic 2: Gradual Increase in Analysis Accuracy

To compare and select the most valuable alternative, designers use models to make predictions about the future value of artifacts:

$$\pi_A = f(a) + \varepsilon \tag{5}$$

Because the value, π_A, will be realized at some point in the future, the prediction is inherently uncertain. There are two main sources for this uncertainty: model uncertainty and specification uncertainty. Every model involves abstractions of reality and, therefore, cannot make a perfectly accurate prediction of the future. This *model uncertainty* is illustrated in Equation (5) by including an uncertainty term, ε. Different models include different abstractions and result in different accuracies. In addition, more accurate models also tend to be more expensive.

Besides model uncertainty, there is uncertainty due to the incompleteness of the artifact specification, a. We call this *specification uncertainty*, noting its similarity to Suh's notion of imaginary complexity [30]. Without knowing the additional artifact details that still remain to be specified, the value of the artifact can only be predicted with limited accuracy. Assuming that the artifact specification is refined gradually, as discussed in Section 4.1, the specification uncertainty also becomes smaller over time, as illustrated conceptually in Figure 5.

The two types of uncertainty both impose a bound on the overall accuracy of the value prediction. When the specification uncertainty is large, the overall uncertainty is large also no matter how accurate the model. Similarly, when the model uncertainty is large, the overall uncertainty is large no matter how precisely the artifact is specified.

From an artifact-focused perspective, it is always preferred to perform the most detailed analysis, lest a valuable alternative be mistakenly pruned. However, from a process-focused perspective, when the cost of the analysis is considered as in Equation (3), inaccurate and inexpensive models may be more preferable at the early stages of design when the artifact specification still lacks detail.

This means that throughout the design process, the dominant source of uncertainty alternates between the specification and

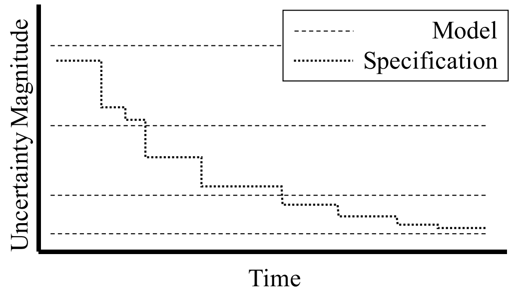

Figure 5. Model and Specification Uncertainty Throughout a Design Process

a variety of increasingly accurate and costly models, as shown in Figure 5. Initially, the specification's uncertainty dominates all but the most abstract of models. At that time, the cost associated with developing and executing very accurate analysis models is greater than the benefit, so that inaccurate, inexpensive models are used. As the uncertainty in the specification is gradually reduced, more accurate models are preferred because the inaccurate models no longer allow one to distinguish between the good and the best design alternatives. Such tradeoffs between costs and benefits of analysis are studied in value-of-information theory [31-33].

4.3. Characteristic 3: Delegation of Design Tasks

As discussed in Section 3.3, a designer, serving as the principal, may delegate design tasks to other individuals, which serve as agents. These agents have their own beliefs and preferences, which are not necessarily aligned with those of the principal. To ensure that these agents take actions according to the principal's beliefs and preferences, the principal needs to communicate what is desired and provide incentives so that, if the agents take actions that maximize their own value, they also maximize the principal's value.

From an artifact-focused perspective, whether to delegate or not has no impact, assuming that the principal provides appropriate incentives—either way the same artifact would be chosen. However, as shown in Equation (4), from an organization-focused perspective, it would be preferable not to offer incentives as they reduce the principal's value. In addition, time and resources are needed for information exchange between the principal and agents, and in that information exchange, miscommunication can occur, resulting in further reduction in value.

Still, it is often desirable to delegate. Delegation allows for division of labor, and hence specialization, so that design tasks can be performed more efficiently. Additionally, the agents may be more skillful in their specialty, resulting in better artifacts. Finally, the principal may be limited in his output capacity, so that the opportunity cost of personally performing all the design tasks may be higher than the cost of delegation.

In practice, the sum of these benefits often exceeds the cost of incentivizing and informing the agents, so that delegation of design tasks can provide significant value to an organization.

4.4. Characteristic 4: Concurrency of Design Tasks

An additional consequence of delegation is that multiple design tasks can be performed concurrently. From an artifact-focused perspective, concurrency has no impact on the end-result, but from a process-focused perspective, we are faced again with a tradeoff. On the one hand, if tasks are performed concurrently, information obtained in one design task is not available to the other concurrent design tasks. This can lead to inefficiencies, for instance, because some tasks are performed unnecessarily [34], resulting in additional time and costs.

On the other hand, concurrency can provide significant benefits. Because artifact value tends to decrease with time (e.g., due to competition), it is often beneficial to get an artifact to market as soon as possible [35]. By performing design tasks concurrently, it is possible to reduce the duration of the design process, resulting in an increase in value. Assuming the expected gains from a shortened design cycle exceed the costs associated with the possible performance of unnecessary work, concurrency is valuable.

4.5. Characteristic 5: Diversity in Teams

In addition to involving multiple designers by delegating separate design tasks, even individual design tasks are often performed by teams. Given the additional cost of labor, it is not directly clear how this practice can be justified from an economic, value-driven perspective. However, a justification can be provided by considering a psychological and social perspective first.

Design involves ideation: ideation of concepts, ideation of systemic consequences, ideation of analysis approaches, etc. These tasks rely on creativity and analogical reasoning. By including individuals with different backgrounds, a wider variety of analogies may be tapped into, resulting ultimately in more valuable concepts. In the literature, diverse groups have been found to be better at complex problem solving tasks [36] and more likely to identify novel and valuable concepts [37]. Thus, the value of an artifact may be improved by using diverse groups that are capable of ideating more valuable concepts, identifying the systemic consequences of these design concepts more comprehensively, and therefore obtaining better predictions of the value of the design alternatives.

Ultimately, even these psychological and sociological arguments need to be framed in the context of the ultimate goal of design, namely, to maximize value. Provided that the benefits of team diversity arising from an improved artifact and streamlined process exceed the losses due to duplication of effort and the additional cost of communication, it is valuable to use diverse design teams for some of the design tasks.

5. Summary and Discussion

In this paper, we have presented a conceptual framework to guide the value-driven design of engineered systems. We started from the premise that design is a purposeful activity, and that designers should act rationally, in accordance with their preferences. Mathematically this can be modeled as value maximization. We applied value maximization from three different perspectives: artifact-, process- and organization-focused. The resulting value-driven model of design allowed us to explain and justify five common characteristics of design processes, none of which could have been explained based on the purely artifact-focused perspective considered in the value-driven design literature previously.

Maybe the most important conclusion derived in this paper is that in terms of value maximization, design is a self-referential optimization problem. From the perspective of value-of-information theory and to break the infinite self-referential regress, it is therefore necessary to resort to heuristics. For instance, rather than rigorously optimizing a global optimization problem over the space of possible design actions, heuristics can provide, at low cost, reasonable guidance as to which design actions to perform. From a process perspective, the use of heuristics is almost certainly more valuable than rigorous optimization, which is likely to require more resources than can be justified based on its benefits relative to heuristics.

However, this poses an interesting problem for design and systems engineering research. Given that heuristics are only applicable in the context for which they were derived, they will need to be updated as the context changes. Since the context is changing increasingly rapidly, the design and systems engineering research community will also need to update the heuristics increasingly often. These heuristics span a broad range:

- *Synthesis heuristics*—e.g., which architectural patterns are appropriate in the current economic, environmental, socio-political and technological context?
- *Analysis heuristics*—e.g., which mathematical formalism, level of abstraction, and accuracy are appropriate for analyzing the system alternatives, taking into account the current state of the art in numerical algorithms and computing infrastructure?
- *Process heuristics*—e.g., how much effort should be allocated to concept ideation? Or how much emphasis should be placed on risk management, given the nature of the system being developed?
- *Organization heuristics*—e.g., which structure? Hierarchical, matrix, or maybe a decentralized structure based in part on crowd-sourcing?

Given that these heuristics will need to be updated frequently, it is important that the research community develop a methodology for determining which heuristics are most appropriate in a particular context. We argue that normative decision theory should be at the foundation for such a methodology, as is illustrated in the value-driven design framework introduced in this paper. But in addition, the quality of a heuristic will also need to be assessed based on non-normative theories. For instance, whether a synthesis heuristic is suitable may depend in part on how well aligned the heuristic is with human psychology and with the social and cultural conventions of the designers applying it. Ultimately, the criterion for assessing heuristics should reflect the ultimate objective of design, namely, to maximize value.

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