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Perception of Complexity in Engineering Design

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Abstract

This paper evaluates perception of complexity in a novel explanatory model that relates product performance and engineering effort. Complexity is an intermediate factor with two facets: it enables desired product performance but also requires effort to achieve. Three causal mechanisms explain how exponential growth bias, excess complexity, and differential perception lead to effort overruns. Secondary data from a human subject experiment validates the existence of perception of complexity as a context-dependent factor that influences required design effort. A two-level mixed effects regression model quantifies differences in perception among 40 design groups. Results summarize how perception of complexity may contribute to effort overruns and outline future work to further validate the explanatory model and causal mechanisms.

1 Introduction

Complex engineering projects face a sustained risk of significant effort overruns on cost and schedule. Overruns of 20–40% routinely occur across diverse domains such as defense acquisition (U.S. Government Accountability Office, 2011), Earth and space science missions (National Research Council, 2010), software (Moløkken and Jørgensen, 2003), and infrastructure and public works projects (Flyvbjerg et al., 2002) and overruns exceeding 100% are not uncommon. Effort overruns destabilize planning exercises, generate waste from descoping or canceling programs, and generally threaten objectives that depend on timely and affordable product deployment.

The systems engineering and design community points to *complexity* as a technical driver for cost growth (Arena et al., 2008; Roberts et al., 2016). Existing literature describes and measures complexity as a nonfunctional attribute correlated with design effort (Calvano and John, 2004; Sheard and Mostashari, 2009; ElMaraghy et al., 2012). However, this analytical perspective leaves a gap to understand how underlying socio-technical mechanisms contribute to effort expenditures and overruns in system design.

For example, Flyvbjerg et al. (2009) explains overruns in infrastructure projects through human factors of delusion and deception rather than complexity itself. Delusion arises from errors in heuristics or biases associated with human decision making. The planning fallacy tends to underestimate task completion times even when past estimates are known to be overly optimistic. Similarly, the anchoring and adjustment effect biases estimates by focusing on the first possible value and only considering insufficient adjustments from it. Deception arises from flawed decision-making practices that reinforce localized objectives. The principal-agent problem considers misaligned behavior between the principal responsible for a decision and the agent acting on his or her behalf where issues such as self-interest, asymmetric information, accountability, and risk preferences influence strategic behavior.

The objective of this paper is to study how two facets of complexity that expose human factors can explain potential sources of effort overruns. Descriptive complexity, the subject of most existing engineering literature, provides an objective measure of an intrinsic property that is correlated with engineering effort. Meanwhile, perception of complexity characterizes its subjective effect on outcomes that is dependent on an individual's abilities. A new explanatory model of complexity in engineering design helps to understand how human limitations to perceive complexity during design activities can contribute to effort overruns via three proposed mechanisms. Secondary data from a prior human experiment validates the hypothesized relationship between complexity and effort for a class of simplified parameter design tasks. Results show perception of complexity varies across design groups as a central model construct that could contribute to effort overruns. Conclusions summarize how the explanatory model of complexity can contribute to future studies relating design performance, complexity, and effort.

2 Complexity in Systems Engineering and Design

Complexity is a long-studied construct that captures diverse perspectives from disciplines ranging from cognition to quantum physics. It is also a defining characteristic of complex systems as a research area in systems engineering and design. Complex systems are typically described by a set of characteristics—numerous components, self-organizing behavior, emergent properties that are not fully explained by hierarchical decomposition, and adaptation to environmental changes—that make design difficult relative to current methods and processes (Sheard and Mostashari, 2009).

Complexity science strives to understand and mitigate challenges of designing complex systems (ElMaraghy et al., 2012). In particular, research on complexity metrics aims to measure an otherwise abstract quantity and causally associate its value with design outcomes such as cost or schedule. Early work in the software domain develops computational complexity metrics based on product attributes such as the number of program statements or paths through a program (Weyuker, 1988; McCabe and Butler, 1989). More recent work adapts complexity metrics to physical systems using functional decomposition or information content approaches to quantify complexity in design (Suh, 1999; Bashir and Thomson, 1999; Summers and Shah, 2010; Sinha and de Weck, 2016; Pugliese and Nilchiani, 2019).

While quantitative metrics are an important part of managing complexity, one must also understand how complexity contributes to outcomes like engineering effort. Darcy et al. (2005) makes a distinction between *internal* and *external* attributes of design artifacts. Complexity metrics are internal attributes that describe the design artifact itself. In contrast, cost, schedule, and required resources are external attributes of the design *process* that carry more direct managerial interest. Schlindwein and Ison (2004) explore similar ideas about descriptive and perceived facets of complexity. Descriptive complexity is an objective measure of an intrinsic, observable property while perceived complexity captures an observer's subjective perspective about it. This point raises questions about whether complexity, as measured by a metric, impacts all observers in the same way. Theoretical and empirical relationships between complexity and effort are of clear importance but are under-studied in literature due, in part, to challenges in data collection.

To summarize, causal linkages of existing work seek to: (1) define an instrument to measure complexity C for a design artifact and (2) associate the measured value to design outcomes such as engineering effort, i.e., $E \propto C$. While substantial work investigates complexity metrics in (1), the association between complexity and effort in (2) has received less attention. The central argument in this paper is that *perception* of complexity is a measurable factor of individuals that influences the relationship between complexity (internal) and effort (external). Furthermore, differential perception of complexity is an unexplored factor that may contribute to effort overrun on engineering projects.

This work asks: how do human limitations to perceive complexity during design activities contribute to effort overruns? There has been some initial discussion of perception of complexity in literature (Manuse and Sniezek, 2017), but it remains a new concept to be explored. The following section presents an explanatory model that relates desired performance and required effort with complexity as an intermediate factor with descriptive and perceived facets. While the proposed relationships remain conjectures at this point, evidence from analysis of secondary data evaluates whether perception of complexity can be observed and if it is of sufficient magnitude to influence design settings.

3 Explanatory Model of Complexity in Engineering Design

This section develops an abstract explanatory model of complexity in engineering design to relate desired performance and required effort. Starting from construct definitions of performance, effort, and complexity, a mathematical model proposes relationships among the three factors. Temporal dynamics extend model results to longer-term horizons to align with research on technology studies.

3.1 Performance and Effort

Framed as "courses of action aimed at changing existing situations into preferred ones" (Simon, 1996), engineering design transforms resources into artifacts that solve problems and generate utility for stakeholders. This section models the relationship between effort (input) and performance (output) in design activities. For clarity in presentation, consider a design outcome to be a product, recognizing design artifacts more broadly include processes and services.

Effort (E) is a holistic measure of costs incurred to realize a product. While primarily conceived of as human labor, it also includes other costs like research, materials, facilities, and administration aggregated to a single factor. Referencing a common effort datum can provide meaningful comparison of alternatives. Time to realize a product can estimate effort assuming constant expenditures, but aggregated design costs or revenues are better estimates over long periods.

Performance (P) is a holistic measure of a product's technical ability to meet its requirements. A performance measure for a product is similar to a utility function in decision theory for a generic preference set where a higher-performance product is preferred to lower-performance one. Given the inherent challenges of formulating a scalar measure of performance, some studies use an inflation-adjusted cost of one "unit" of performance (i.e., performance cost, e.g., cost per Mb of memory) as an inverse measure P^{-1} (Nagy et al., 2013).

Technology studies literature investigates the relationship between performance and effort through the intermediate factor of time. Some models of technological progress use a sigmoid or S-curves to describe decreasing performance returns to effort as a component technology becomes more mature (Christensen, 1992a). Additional effort enables increased product performance but generally at a decreasing rate. Meanwhile, new architectural technologies extend the performance growth region over longer periods (Christensen, 1992b). Over long time periods, technology studies observe exponential growth of functional properties across diverse domains such as information and energy technology (Koh and Magee, 2006, 2008). Other work observes an equivalent exponential decrease in performance cost over time across a broad set of more than 50 technologies (Nagy et al., 2013; Farmer and Lafond, 2016).

While simplified to ignore physical or market limits and other dynamics, the relationship popularized as Moore's law models exponential growth in a performance frontier in Eq. (1) with constant P_0 and positive growth rate r_P.

$$P(t) = P_0 \exp(r_P t), \quad r_P > 0 \tag{1}$$

The exponential growth rate r_P can be expressed as an annual growth rate with $\ln(r_P+1)$ for t in years. Typical annual performance growth rates range from 0.4–0.6 (34–47% per year) for information technology, 0.04–0.10 (4–10% per year) for energy technology, and 0.02–0.12 (2–11% per year) for chemical technology (Farmer and Lafond, 2016).

There is less research on relationships between engineering effort and product performance. Rock's Law, also referred to as Moore's Second Law, observes that microprocessor fabrication facility costs also follow exponential growth in time (Ross, 2003; Rupp and Selberherr, 2011). Augustine's Law XVI provides a similar observation that unit costs for tactical aircraft grow exponentially in time, recognizing unit performance also increases over time (Augustine, 1997). If representative of effort expenditures for engineered products in general, it is reasonable to hypothesize that the effort to implement a product on the performance frontier grows exponentially in time in Eq. (2) with constant E_0 and positive growth rate r_E.

$$E(t) = E_0 \exp(r_E t), \quad r_E > 0 \tag{2}$$

The exponential growth rate r_E can also be expressed as an annual growth rate with $\ln(r_E+1)$ for t in years. The original 15% annual growth in aircraft unit costs observed by Augustine (coincidentally, similar to that of semiconductor manufacturing) corresponds to an effort growth rate of $r_E = 0.140$ while more recent updates showing closer to 6.8% annual growth equate to $r_E = 0.066$ (Johnstone, 2020).

Solving for time and equating performance dynamics in Eq. (1) with effort dynamics in Eq. (2) yields Eq. (3) which relates required effort E to achieve desired performance P as a power law with constant E_0' and positive exponent k_P.

$$E(P) = E_0 \left(\frac{P}{P_0}\right)^{\frac{r_E}{r_P}} = E_0' P^{k_P}, \quad k_P = \frac{r_E}{r_P} > 0 \tag{3}$$

In other words, a relative change in desired performance P requires a proportional change in effort E based on the exponent k_P. For example, consider semiconductor manufacturing where performance measures the number of transistors on an integrated circuit and effort is estimated by fabrication facility cost (Rupp and Selberherr, 2011). A performance doubling time every two years yields $r_P = \ln(2)/2 \approx 0.347$ (30% per year) while an effort doubling time every five years yields $r_E = \ln(2)/5 \approx 0.139$ (13% per year). When combined, the power law exponent $k_P = 0.4$ means a doubling in performance requires $2^{0.4} \approx 1.320$ times the effort or an increase of 32%.

3.2 Two Facets of Complexity

Complexity (C) is as an abstract quality that, in this model, describes objective product features such as degree of coupling, number of components, or solveability (Summers and Shah, 2010). Broader definitions expose two facets of complexity. On one side, complexity *may* enhance performance by adding more capability, for example, by optimizing operations to fine-grained demands (Deshmukh et al., 1998) or tailoring policies to smaller jurisdictions (Oates, 2008). On the other side, complexity *certainly* increases difficulty and associated effort required to design and implement a product (Bashir and Thomson, 2001), whether or not it is effective to actually increase performance. These observations are formalized in performance-complexity (descriptive) and complexity-effort (perceived) relationships below.

First, assume there is a monotonically increasing level of complexity required to achieve a desired level of performance. Here, complexity denotes an objective measure attributed to a design, similar to existing information-, uncertainty-, or energy-based metrics proposed in literature. As it is impossible to adopt a single complexity metric form suitable for all domains and performance measures, Eq. (4) describes a general performance-complexity frontier as a power law with constant C_0 and positive exponent k_C.

$$C(P) = C_0 P^{k_C}, \quad k_C > 0 \tag{4}$$

Values of k_C depend on the performance and complexity metrics selected and the design domain. For example, electro-mechanical products like aircraft exhibit larger k_C values than signal processing products like integrated circuits for a given complexity metric (Whitney, 1996). Furthermore, as a frontier, it is possible to add complexity without seeing a performance return so $C(P)$ reflects the minimum complexity required to realize a product with performance P.

Second, assume there is a monotonically increasing effort required to implement a product of given complexity. This relationship represents the subjective perception of complexity by a design actor realized through an effort expenditure. While specific human factors that contribute to engineering effort is an under-studied problem, existing works point to cognitive factors like limited working memory as effort drivers in solving complex problems (Hirschi and Frey, 2002; Darcy et al., 2005). Similar to the relationship between complexity and performance, Eq. (5) describes a general effort-complexity frontier as a power law with constant E_0'' and positive exponent k_E.

$$E(C) = E_0'' C^{k_E}, \quad k_E > 0 \tag{5}$$

Values of k_E depend on the complexity and effort metrics selected and the design context including knowledge, experience, supporting tools, cognitive abilities, and teamwork. While specific to each design context, averaged k_E values can generalize perception across a target population. Factor values $k_E > 1$ align with study results showing a super-linear relationship between structural complexity metrics and effort (Hirschi and Frey, 2002; Bashir and Thomson, 2001; Sinha and de Weck, 2016). Finally, as a frontier, it is possible to waste effort through inefficient work so $E(C)$ reflects the minimum effort required to realize a product with complexity C.

Composing Eq. (4) with Eq. (5) yields an expanded model of complexity in design in Eq. (6).

$$(E \circ C)(P) = E_0'' \left(C_0 P^{k_C}\right)^{k_E} = E_0' P^{k_C k_E}, \quad k_C > 0, \quad k_E > 0 \tag{6}$$

The resulting expression elaborates on Eq. (3) with $k_P = k_C k_E$, revealing the utility of a power-law relationship for Eqs. (4) and (5). While the domain-specific factor k_C is static for a class of products, the context-dependent factor k_E varies based on a designer's ability to manage complexity.

Returning to the semiconductor manufacturing example from the preceding section, the aggregate observed $k_P = 0.4$ factor combines both domain-specific k_C and context-dependent k_E factors. Decomposing k_P requires a specific complexity metric form. For example, assuming $k_C = 0.333$ (i.e., complexity is proportional to the cube root of the number of transistors) yields an aggregate factor $k_E = 1.2$. Now, consider two hypothetical design organizations in the same domain with different perception abilities. A design context with $k_E = 1.3$ increases to $k_P = 0.433$, meaning a doubling in performance requires $2^{0.433} = 1.35$ times the effort. Alternatively, a design context with $k_E = 1.1$ decreases to $k_P = 0.367$, meaning a doubling in performance requires $2^{0.367} = 1.29$ times the effort.

3.3 Incorporating Time Dynamics

As a final component, the model of complexity in engineering design can incorporate time to show performance-complexity-effort dynamics over strategic horizons. Composing Eq. (6) with Eq. (1) yields Eq. (7).

$$(E \circ C \circ P)(t) = E_0' \left(P_0 \exp(r_P t)\right)^{k_C k_E} = E_0 \exp(r_P k_C k_E t) \quad r_P > 0, \quad k_C > 0, \quad k_E > 0 \tag{7}$$

This expression shows the effort growth rate previously introduced in Eq. (2) decomposes to $r_E = r_P k_C k_E$ such that effort growth depends on technological progress (r_P), design domain (k_C), and design context (k_E).

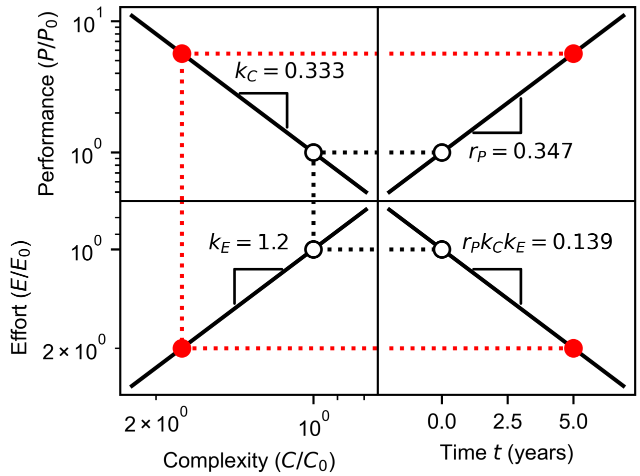


Figure 1: Relation between performance, complexity, effort, and time under the composite model for an example case based on semiconductor manufacturing with $r_P = 0.347$, $k_C = 0.333$, and $k_E = 1.2$ for times $0 \leq t \leq 5$ years.

Figure 1 graphically illustrates relationships between time, performance, complexity, and effort for the semiconductor manufacturing example with datum time $t = 0$ (hollow points) and a notional product planned for $t = 5$ years (solid points). Dotted lines visually connect points on adjacent quadrants. The upper-right plot shows the exponential growth of performance over time following Eq. (1), indicating a 5.67-fold increase in five years. The upper-left plot shows the power law growth of complexity following Eq. (4) with a 1.78-fold increase to achieve the target performance. The lower-left plot shows the power law growth of effort following Eq. (5) with a 2-fold increase to achieve the necessary complexity. Finally, the lower-right plot shows the exponential growth of effort over time following Eq. (7).

Connecting points between the four quadrants helps to trace relationships between performance, complexity, effort, and time. For example, a change in technology progress rate (r_P) modifies the slope in the upper-right quadrant, resulting in different levels of complexity and effort required to achieve a target performance at a specified time. Similarly, changes to the perception factor k_E modifies the slope in the lower-left quadrant, adjusting the resulting effort to achieve a target design. Finally, while simply presented as lines, note that each quadrant reflects a frontier of efficient solutions and additional points exist with lower performance, higher complexity, or higher effort in each quadrant.

3.4 Assumptions and Limitations

As an explanatory model, the model of complexity in engineering design is not intended to predict specific outcomes of any individual design activity or class of activities. Instead, it is intended to generate and evaluate new causal mechanisms to support broad understanding of effort drivers in complex system design. Nevertheless, this section comments on key assumptions and limitations.

Technology studies provide good evidence for exponential growth of product performance over time but exponential growth of effort is less well explored. The power law relationships proposed in Eqs. (4) and (5) were selected for mathematical convenience and ease of presentation rather than strict empirical or theoretical accuracy. While the discussion of Eq. (5) mentions evidence of super-linear relationships between structural complexity measures and design effort, no analogous evidence could be found for the relationship between performance and complexity, which seems to be under-studied. Furthermore, a single relationship form may not exist in general given the variety of complexity and performance metrics used for specific application cases. Alternative definitions allow a degree of freedom for different complexity metrics as long as the function composition in Eq. (6) yields a power law relationship between performance and effort.

Additionally, some factor values cannot easily be compared across cases. Values of r_P depend on time units but can easily be compared across cases. In contrast, values of k_C and k_E depend on the adopted complexity metric which is more application-specific. The model also assumes factors r_P, k_E, and k_C are time-invariant. Realistically, all of these parameters vary in time to some extent in response to contextual factors. For example, Rupp and Selberherr (2011) explore economic limits to Moore's law driven by market capacity constraints that augment the effect of r_P. Other dynamic factors include demand for product innovation, new domain-specific design architectures that exhibit different types of complexity, and new methods or tools that influence designer ability. Ignoring these temporal effects assumes they are secondary to the primary effects of performance, effort, and complexity.

4 Three Mechanisms for Effort Overruns

The proposed explanatory model contributes to three new causal mechanisms that demonstrate potential sources of effort overruns in complex system design driven by exponential growth bias, excess complexity, and differential perception. The following sections explain, illustrate, and analytically evaluate effort overrun for each mechanism.

4.1 Exponential Growth Bias

The first mechanism investigates systematic biases to estimating effort. While product performance follows exponential growth over time with rate r_P, cumulative effort grows exponentially with rate $r_P k_C k_E$, composing factors from drivers for technological progress, product domain, and design context. Estimating required effort to achieve a future product may be subject to human biases to linearize exponential growth (Stango and Zinman, 2009). Linear extrapolation of effort measures such as full-time equivalent staff or allocated budget will under-estimate effort required for a future product because of technological progression compounded by complexity and perception factors.

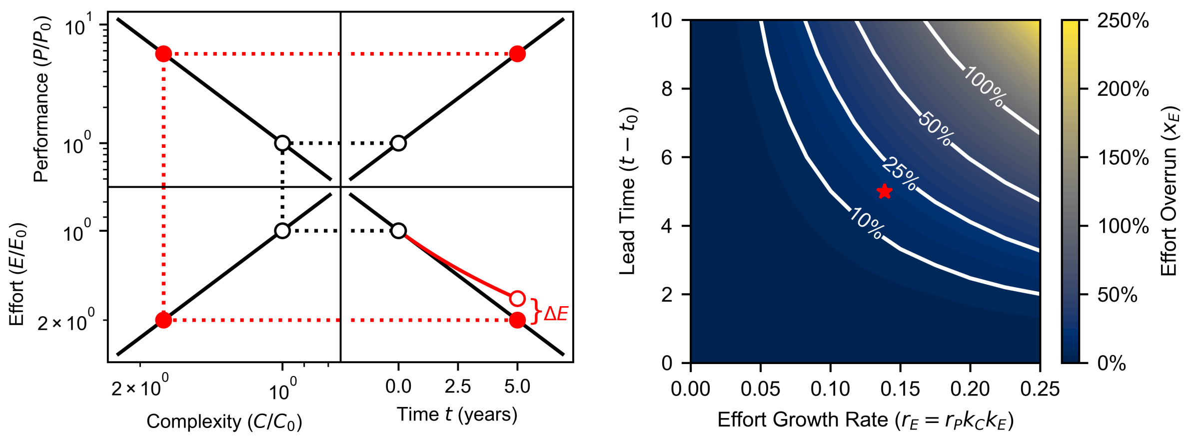
Figure 2a builds on the semiconductor manufacturing example with $r_P = 0.347, k_C = 0.333, k_E = 1.2$ to show linear extrapolation of effort as a red line from $t_0 = 0$ to $t = 5$. It estimates effort (hollow red point) at $t = 5$ as $\hat{E}/E_0 = 1.7$ compared to a true value (solid red point) of $E/E_0 = 2.0$, an apparent 18% overrun. Mathematically, linear effort extrapolation using Eq. (7) from a datum point t_0 yields the approximate effort function $\hat{E}(t)$ in Eq. (8).

$$\hat{E}(t) = E(t_0) + \left.\frac{dE}{dt}\right|_{t_0} (t - t_0) = E(t_0)\left[1 + r_P k_C k_E (t - t_0)\right] \tag{8}$$

Subsequently, Eq. (9) computes effort overruns (x_E) as a fraction of estimated effort as a function of the lead time ($t - t_0$) and composite effort growth rate $r_P k_C k_E$.

$$x_E = \frac{E(t) - \hat{E}(t)}{\hat{E}(t)} = \frac{E(t_0)E(t - t_0)}{E(t_0)\left[1 + r_P k_C k_E (t - t_0)\right]} - 1 = \frac{\exp\left(r_P k_C k_E (t - t_0)\right)}{1 + r_P k_C k_E (t - t_0)} - 1 \qquad (9)$$

A contour plot in Fig. 2b visualizes effort overruns (x_E) computed from Eq. (9) for lead times between 0–10 (years) and annual effort growth rates between 0–0.25 (0–22% per year). Results show projects with a long lead time or rapid effort growth rate are most susceptible to overruns from exponential growth bias.



(a) (b)

Figure 2: Effort overruns from an exponential growth bias (a) traced through performance-complexity-effort-time dimensions and (b) analytically evaluated for variable growth rate and lead time (star shows result from (a)).

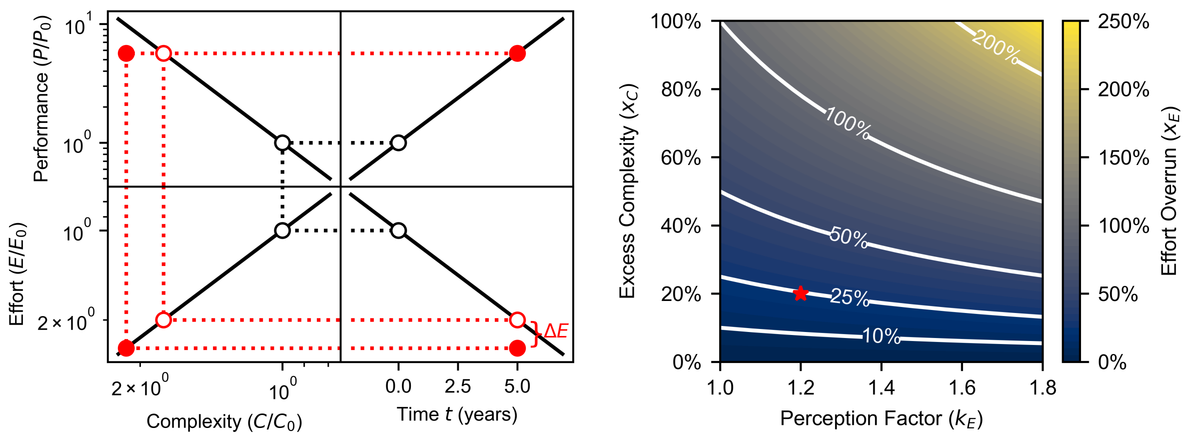
4.2 Excess Complexity

The second mechanism investigates how exceeding the efficient complexity-performance frontier (i.e., adding excess complexity) can contribute to effort overruns. Excess complexity does not improve performance and should generally be minimized (Suh, 1999); however, human limitations ranging from cognitive resources to organizational structures generally prevent “optimal” design from being achieved. Excess complexity is particularly important with respect to overruns because the perception factor k_E acts as an effort multiplier: 20% excess complexity can generate *more* than 20% additional effort for $k_E > 1$ due to perceptual limitations in implementation.

Figure 3a builds on the semiconductor manufacturing example with $r_P = 0.347, k_C = 0.333, k_E = 1.2$ to show a 20% excess complexity incorporated in the design for the new product at $t = 5$. Complexity rises from $C/C_0 = 1.78$ (hollow red point) to $C'/C_0 = 2.14$ (solid red point), subsequently raising effort from $E/E_0 = 2.0$ to $E'/E_0 = 2.49$, an apparent 25% overrun. Mathematically, excess complexity x_C can be expressed as a fraction above the estimated "optimal" complexity (i.e., $C' = (1 + x_C)C$). Equation (10) computes the resulting effort overrun (x_E) as a fraction of the estimated effort with "optimal" complexity from Eq. (5) as a function of excess complexity x_C and the perception factor k_E.

$$x_E = \frac{E(C') - E(C)}{E(C)} = \frac{E_0\left((1 + x_C)C\right)^{k_E}}{E_0 C^{k_E}} - 1 = (1 + x_C)^{k_E} - 1 \tag{10}$$

A contour plot in Fig. 3b visualizes effort overruns (x_E) for excess complexity between 0–100% and for perception factors between 1.0–1.8. While excess complexity is a more influential driver of overruns itself, design contexts with high barriers to perception require substantially more effort to overcome the inefficient application of complexity.



(a) (b)

Figure 3: Effort overruns from excess complexity (a) traced through performance-complexity-effort-time dimensions and (b) analytically evaluated for variable perception and excess complexity (star shows result from (a)).

4.3 Differential Perception

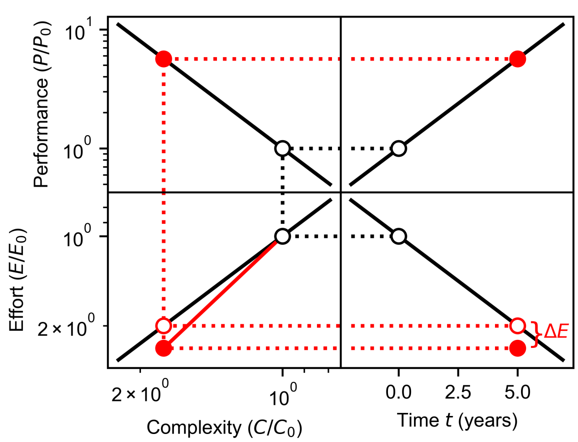
The third mechanism investigates how differential perception of complexity can lead to effort overruns. As the perception factor k_E is unique to the design context, it can vary across individuals and organizations participating in design activities. An increase in this factor results in additional effort to realize a product with a given complexity. Underlying differences in perception may arise from innate cognitive abilities or use of expertise-driven strategies like chunking (Hirschi and Frey, 2002); however, the topic is under-studied. Regardless of its source, differential perception could occur across functional units, levels of hierarchy, or even in response to new technology or organizational policies. Most critically, differential perception between estimators and designers could contribute to apparent effort overruns.

Figure 4a continues the semiconductor manufacturing example with $r_P = 0.347, k_C = 0.333, k_E = 1.2$. The product at $t = 5$ has performance $P/P_0 = 5.67$ and complexity $C/C_0 = 1.78$. An estimator uses the aggregated $k_E = 1.2$ factor to estimate effort (hollow red points) but a designer uses a higher $k'_E = 1.5$ in implementation (red line and solid red point). Assuming a unit constant $C_0 = 1$, effort rises from $E = 2.0$ to $E' = 2.38$ as an apparent 19% overrun. Unlike the previous examples, this result varies based on the scaling factor C_0, reinforcing the mutual dependence between interpretation of differential k_E values and adopted complexity metrics. Large magnitude complexity metrics require smaller differential k_E values to show significant difference in required effort.

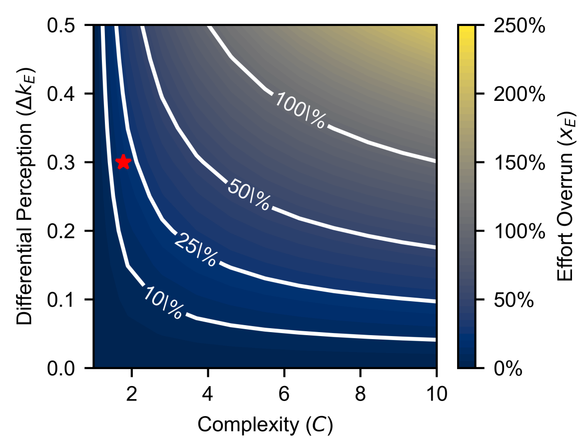
Differential perception can be represented as the difference in perception factors $\Delta k_E = k'_E - k_E$. Equation (11) computes the resulting overrun (x_E) as a fraction of the estimated effort as a function of complexity C from Eq. (5) and differential perception Δk_E.

$$x_E = \frac{E'(C) - E(C)}{E(C)} = \frac{E_0 C^{k_E + \Delta k_E}}{E_0 C^{k_E}} - 1 = C^{\Delta k_E} - 1 \tag{11}$$

A contour plot in Fig. 4b visualizes effort overruns (x_E) for differential perception factors between 0.0–0.5 and for complexity between 1–10. Results highlight the scale dependence between Δk_E and C where large complexity magnitudes only require small differences in Δk_E to yield large overruns.



(a)



(b)

Figure 4: Effort overruns from differential perception (a) traced through performance-complexity-effort-time dimensions and (b) analytically evaluated for variable complexity and differential perception (star shows result from (a)).

4.4 Comments

The three causal mechanisms propose new ways of thinking about effort overruns in engineering design as a step to further understanding and mitigation. Some mechanisms like exponential bias may not be as extreme as presented here while others like excess complexity may be omnipresent. Although presented separately, mechanisms could also work together to amplify effects. For example, a long lead time for a complex product inefficiently designed by an organization with large differential perception between estimating and implementing entities suggests large likely effort overruns.

The proposed model can also help frame other mechanisms contributing to effort overruns. For example, inefficient application of effort away from the complexity-effort frontier clearly contributes to effort overruns. Likewise, the planning fallacy and anchoring and adjustment heuristic may yield outcomes similar to linear extrapolation to explain outcomes from a cognitive psychology perspective. Misjudging other parameters such a k_C or r_P (similar to the differential perception of complexity for k_E) could also contribute to effort overruns.

While the proposed mechanisms remain conjectures at this point, the dual role of complexity as performance enabler and its perception as effort consumer are critical features to be explored further. To study the role of perception and further validate the effort-complexity power law in Eq. (5), the following section measures variation in k_E among a population of design actors working on tasks with variable complexity.

5 Empirical Evidence for Perception of Complexity

In support of the proposed model of complexity in engineering design and, specifically, the relationship between perception of complexity and effort to complete a design task, this section analyzes secondary data from a prior behavioral experiment. Analysis objectives seek to measure the perception of complexity factor k_E across a population of designers, validate the functional form of Eq. (5) for a particular structural complexity metric, and understand how variation in k_E could contribute to differential engineering effort expenditures among individuals.

5.1 Parameter Design Task

A previous study by the author (Grogan and de Weck, 2016) investigated the effect of variable task size (N) and variable team size (n) on required design effort. The study performed a behavioral experiment using an abstract surrogate parameter design task as a linear system of equations in Eq. (12).

$$\text{find}\, x \,\text{s.t.} \left| \sum_{j=1}^{N} m_{ij} x_j - y_i^\star \right| \leq \epsilon \,\forall\, i \tag{12}$$

Design actors select N design parameters $x = \langle x_1, \dots\ x_N \rangle$ (inputs) to meet M target functional requirements $y^\star = \langle y_1^\star, \dots, y_M^\star \rangle$ (outputs). Design parameters and functional requirements are related by an $M \times N$ coupling matrix $[m_{ij}]$. Uncoupled tasks have $m_{ij} = 0$ for all $i \neq j$ such that each design parameter controls exactly one functional requirement. Coupled tasks have $m_{ij} \neq 0$ for all i, j such that all N design parameters affect each functional requirement. All functional requirements must achieve target values within an allowable error tolerance (ϵ) to complete a task.

Unique design problems randomly generate m_{ij} and $y_i^\star$ by composing random orthonormal basis vectors to preserve constant unit distance between the initial condition ($x = 0$) and the solution ($\mathbf{M}x = y^\star$). Control of inputs and outputs is distributed among n designers. Input control means a designer can change the design parameter value and output control means a designer can see if the functional requirement value is within the error tolerance.

A distributed software application implements the parameter design task with purposeful barriers to communication. Each designer uses a graphical user interface to modify assigned inputs and view assigned outputs. Vertical input sliders with randomly-assigned labels like "Diameter" for x_1 and "Flexibility" for x_2 can be modified with a mouse or keyboard shortcuts. Horizontal output sliders with randomly-assigned labels like "Epsilon" for y_1 and "Rho" for y_2 display the valid solution region and automatically update output values. No quantitative information is presented and designers are limited to verbal communication and gestures to complete the design task. The time required to complete a design task is measured from the first input change until all outputs are within the target range.

5.2 Secondary Data

Results from the previous study provide a publicly-available source of secondary data on the surrogate parameter design task (Grogan, 2018). Interested readers should refer to Grogan and de Weck (2016) for methodological details. The data set contains 374 observations of task completion duration from 10 experimental sessions and 30 total participants. Each session administered 24 tasks with $2 \leq N \leq 6$ parameters and $1 \leq n \leq 3$ designers with 9 individual ($n = 1$) tasks performed in parallel (27 samples) and 15 team ($n = 2$ or $n = 3$) tasks. Each individual and team is considered a unique design actor for which a perception of complexity k_E factor can be computed.

To apply the secondary data to study perception of complexity, performance, effort, and complexity must first be operationalized (complexity growth over time is not considered). Assume the number of design parameters N measures performance with $P = N$. Assume the task completion time T (seconds) estimates effort with $E = T$. Finally, Eq. (13) proposes a complexity metric as a function of N with $C_0 = 1$ for all tasks, $k_C = 1$ for uncoupled tasks, and $k_C = 2$ for coupled tasks.

$$C(P) = C_0 N^{k_C} \tag{13}$$

Coincidentally, C equals the number of non-zero m_{ij} factors and is proportional to the task information content. Complexity values range between $C = 2$ for an uncoupled $N = 2$ task and $C = 16$ for a coupled $N = 4$ task.

Preliminary analysis investigates whether complexity and effort follow a power law relationship. The panel in Fig. 5 plots the complexity (C) and effort (E) metrics for all completed parameter design tasks for each of 30 individual (I) and 10 team (T) design groups. An apparent linear relationship in log-log space emphasized by a simple linear regression overlay supports the expected power law relationship between complexity and effort, i.e., the regression slope estimates the k_E factor for each design actor. However, additional statistical analysis must correct for other known contextual factors such as task ordering, team size, and variations in the error tolerance (ϵ) across sessions.

5.3 Analysis and Results

Statistical analysis performs regression to differentiate perception of complexity from other contextual factors. The previous study found the team size (n), task order (O, i.e., sequence in a session), and error threshold (ϵ) to be significant factors influencing effort. Equation (14)

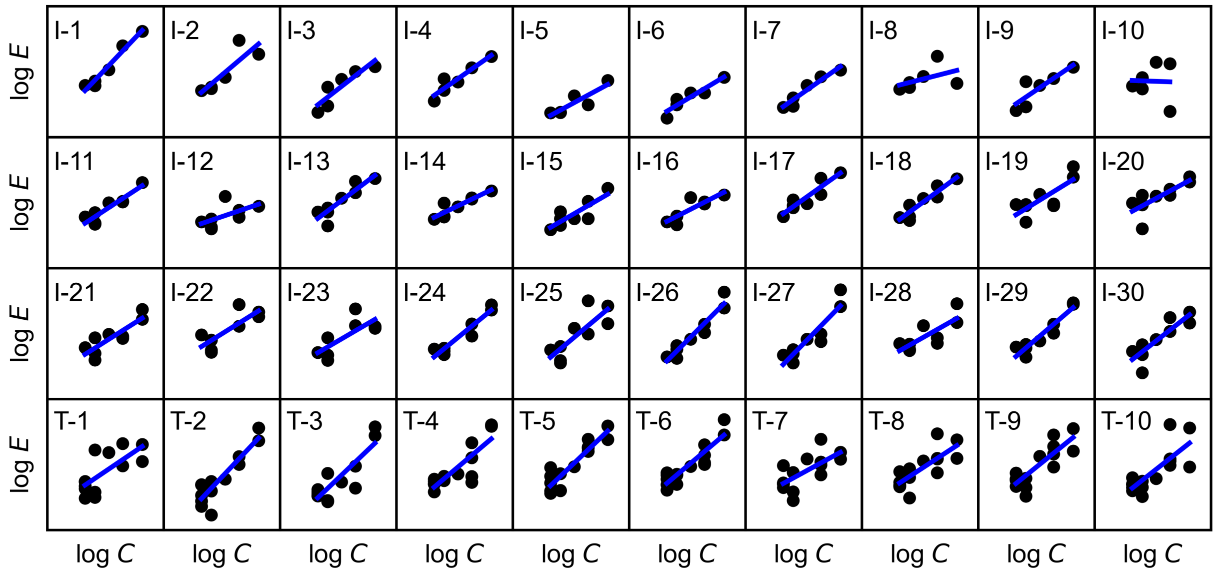


Figure 5: Effort (E) versus complexity (C) on a log-log scale for individuals (I) and teams (T) with simple regression.

isolates the perception of complexity factor k_E as the power law exponent for complexity and aggregates other significant contextual effects to the E_0 factor.

$$E(C) = E_0 C^{k_E} = \left(b_0 n^{b_2} O^{b_3} b_4^{\epsilon_{0.1}} b_5^{\epsilon_{0.11}}\right) C^{k_E} \tag{14}$$

Coefficients to be solved for using regression include a constant b_0, a power law coefficient b_2 for team size n, power law coefficient b_3 for task order O, and constants b_4 and b_5 for dummy variables $\epsilon_{0.1}$ and $\epsilon_{0.11}$ for error tolerance levels 0.1 and 0.11, respectively. The resulting model is similar to that used in Grogan and de Weck (2016).

A two-level mixed effects regression model accommodates correlated samples from designer groups (i.e., individual or team) with factor G (Radenbush and Bryk, 2002). A log-transformation of Eq. (14) assigns $\beta_{0j} = \ln(b_0), \beta_{1j} = k_E$, etc. to yield the level 1 model in Eq. (15) with a design task as the unit of analysis and coefficients for each group j.

$$\ln E = \beta_{0j} + \beta_{1j} \ln C + \beta_{2j} \ln n + \beta_{3j} \ln O + \beta_{4j} \epsilon_{0.1} + \beta_{5j} \epsilon_{0.11} \tag{15}$$

The level 2 model in Eq. (16) considers a design group as the unit of analysis with two effects on level 1 coefficients.

$$\beta_{ij} = \begin{cases} \gamma_{00} + \gamma_{01}(G) + u_{0j} & i = 0 \\ \gamma_{10} + \gamma_{11}(G) + u_{0j} & i = 1 \\ \gamma_{i0} + u_{0j} & \text{otherwise} \end{cases} \tag{16}$$

In other words, group differences can modify the β_{0j} coefficient to tailor E_0 for each group or modify the β_{1j} coefficient to tailor k_E for each group. Group effects on β_{2j} are included due to insufficient data variation and preliminary analysis ruled out group effects on β_{3j} with a backwards stepwise regression procedure.

The linear multiple effects model is computed using the R statistical tool with the `lme4` package using standard maximum likelihood (Bates et al., 2015). Table 1 shows results of a stepwise regression procedure to sequentially eliminate non-significant factors. Each step reduces AIC computed using a maximum likelihood (ML) criterion. The Step 1 model includes random effects of G for both the intercept (E_0) and $\ln C$ (k_E) factors. The Step 2 model eliminates the random effect on the intercept as it explains little variance. Graphical inspection of a profile zeta plot suggests coefficients have good normal approximation and all coefficients are statistically significant based on t values.

Table 1: Stepwise linear multiple effects models for design task time.

		Step 1 Model (AIC=665.97)			Step 2 Model (AIC=641.97)		
Random	**Coef.**	**Factor**	**Var.**		**Factor**	**Var.**	
G	γ_{01}	Intercept	0.000				
G	γ_{11}	$\ln C$	0.018		$\ln C$	0.018	
Residual			0.277			0.277	
Fixed	**Coef.**	**Estimate**	**S.E.**	**t stat.**	**Estimate**	**S.E.**	**t stat.**
Intercept	γ_{00}	1.367	0.119	11.485	1.367	0.119	11.485
$\ln C$	γ_{10}	1.343	0.052	25.865	1.343	0.052	25.865
$\ln n$	γ_{20}	1.215	0.103	11.824	1.215	0.103	11.824
$\ln O$	γ_{30}	−0.175	0.034	−5.119	−0.175	0.034	−5.119
$\epsilon_{0.1}$	γ_{40}	−0.342	0.114	−2.993	−0.342	0.114	−2.993
$\epsilon_{0.11}$	γ_{50}	−0.836	0.153	−5.465	−0.836	0.153	−5.465

5.4 Discussion

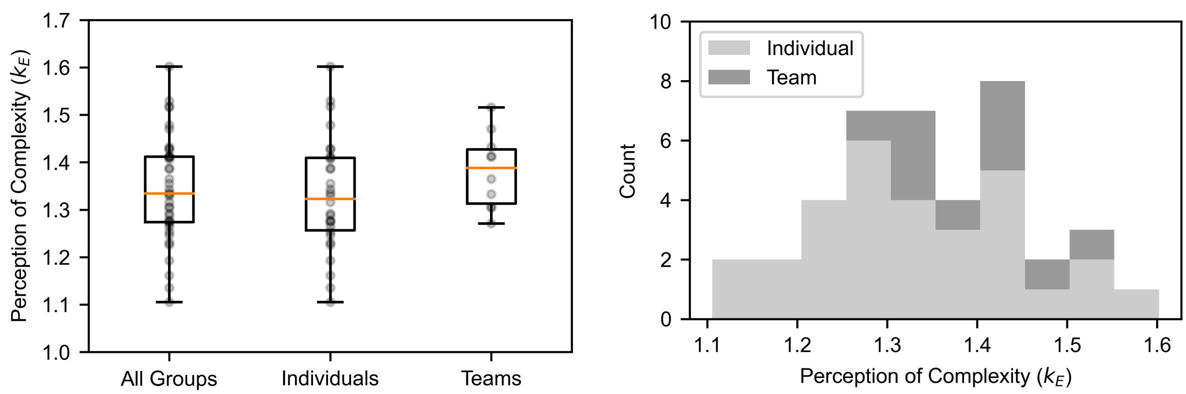
Substituting fitted Level 1 coefficient estimates from the Step 2 model in Table 1 into Eqs. (15)–(16) can estimate effort as a function of contextual factors like team size, order, and error threshold and, most importantly, complexity as defined in Eq. (13). While the fixed effect coefficients are not of primary interest in this analysis, values agree with past results and intuition that completion time increases with team size, decreases with later task order, and decreases with larger error tolerances. Meanwhile, the coefficient value $\gamma_{10} = 1.343$ corresponds to the average k_E value across all design groups. Therefore, analysis results support the hypothesized model in Eq. (5) that a power law governs the relationship between complexity and effort for this simplified parameter design task.

More interesting results appear in the Level 2 coefficients that refine the k_E factor for each design group, confirming the presence of differential perception of complexity. Table 2 reports fitted coefficient $\gamma_{10} + \gamma_{11}(G) = k_E$ for each group G and Fig. 6 shows a box plot and histogram of the resulting distribution. The mean value is $\gamma_{10} = 1.343$ and observed values range from 1.105 to 1.602. The smaller range observed in teams may be attributed to a smaller sample size (10 teams versus 30 individuals) and, although the team mean is slightly larger, Welchs t-test cannot reject the null hypothesis that both group populations have the same mean ($t(23.1) = -1.59, p = 0.13$).

Using coefficients from the Step 2 regression model, the contour plot in Fig. 7 illustrates

Table 2: Level 2 (group-specific) coefficients for perception of complexity (k_E).

Group (G)	k_E	Group (G)	k_E	Group (G)	k_E	Group (G)	k_E
I-1	1.602	I-11	1.275	I-21	1.265	T-1	1.412
I-2	1.478	I-12	1.105	I-22	1.407	T-2	1.516
I-3	1.247	I-13	1.411	I-23	1.275	T-3	1.304
I-4	1.529	I-14	1.292	I-24	1.343	T-4	1.365
I-5	1.136	I-15	1.161	I-25	1.355	T-5	1.471
I-6	1.231	I-16	1.277	I-26	1.386	T-6	1.432
I-7	1.193	I-17	1.518	I-27	1.335	T-7	1.271
I-8	1.330	I-18	1.428	I-28	1.316	T-8	1.333
I-9	1.226	I-19	1.411	I-29	1.388	T-9	1.413
I-10	1.254	I-20	1.429	I-30	1.288	T-10	1.306



(a) (b)

Figure 6: (a) Box plot of k_E by group type with 1.5 inter-quartile range whiskers; (b) Histogram of k_E by group type.

how estimated effort (task completion time) varies as a function of the design task complexity C and the perception factor k_E. Framed within minimum and maximum observed k_E values, the dotted line shows estimated effort for the mean $\gamma_{01} = 1.343$. Dashed lines show estimated effort for values within one standard deviation, $\gamma_{01} \pm \sigma_{\gamma_{01}} = \{1.232, 1.454\}$.

Revisiting the third mechanism for effort overruns, an apparent effort overrun following Fig. 4b appears if designers with lower k_E values estimate effort while designers with higher k_E complete the design. For example, designers within one standard deviation of each other have $\Delta k_E = 0.111$ which, for a simple task with $C = 2$, translates to an apparent effort overrun of $x_E = 2^{0.111} - 1 = 8.0\%$ (estimated at 6.65 seconds, actually 7.18 seconds). However, for a more complex task with $C = 16$, the effort overrun is $x_E = 16^{0.111} - 1 = 36.0\%$ (estimated at 109 seconds, actually 148 seconds).

To further investigate hypothetical effort overruns from flawed k_E values, two error metrics evaluate an effort estimate $\hat{E}$ using the observed data set with $T = 374$ samples. Equation (17) computes a root mean square error (RMSE) as an absolute measure of inaccurate

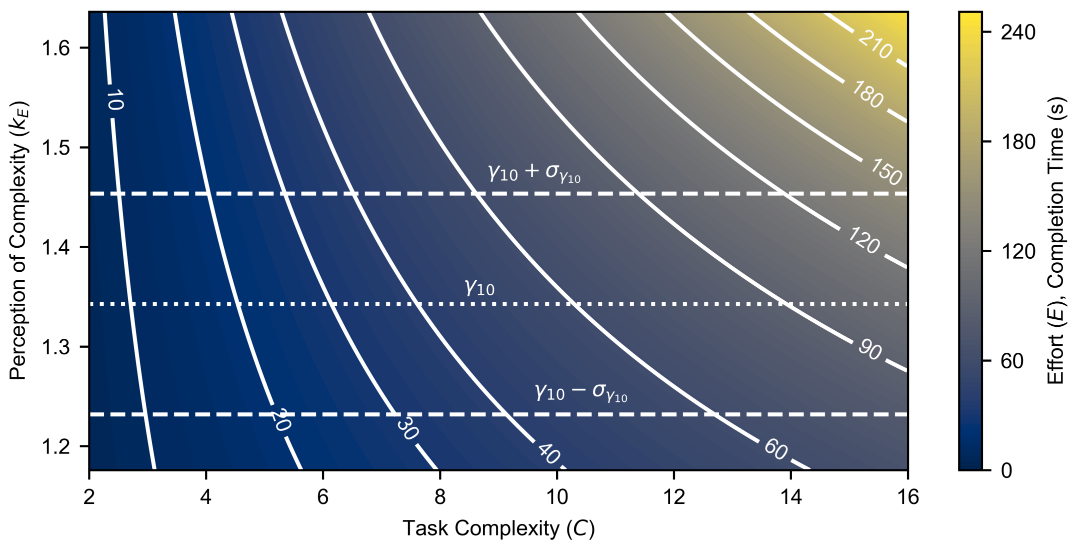


Figure 7: Contour plot of estimated effort (E) as a function of problem complexity C and perception of complexity k_E for a parameter task setting with $O = 10$, $n = 1$, $\epsilon_{0.1} = 0$, and $\epsilon_{0.11} = 0$.

effort estimates.

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\hat{E}_i - E_i\right)^2} \tag{17}$$

Alternatively, Eq. (18) computes the average effort overrun fraction ($\bar{x}_E$), allowing both positive (overrun) and negative (under-run) values to offset each other in the data set.

$$\bar{x}_E = \frac{1}{T}\sum_{i=1}^{T}\frac{\left(E_i - \hat{E}_i\right)}{\hat{E}_i} \tag{18}$$

Table 3 compares RMSE and $\bar{x}_E$ for effort estimates from Eq. (14) under four conditions: 1) using the mean k_E value, 2) using group-specific k_E values from Table 2, and 3–4) using values one standard deviation from the mean k_E value.

Table 3: Hypothetical effort errors and overruns for estimates with alternative perception factors (k_E).

Case	**Estimation k_E Factor**	**RMSE Effort (s)**	**Mean Overrun ($\bar{x}_E$)**
1	$\gamma_{10} = 1.343$	87.8	19.5%
2	$\gamma_{10} + \gamma_{11}(G)$	79.3	14.0%
3	$\gamma_{10} - \sigma_{\gamma_{10}} = 1.232$	99.9	46.4%
4	$\gamma_{10} + \sigma_{\gamma_{10}} = 1.454$	79.3	−2.0%

Results show mean overruns $\bar{x}_E > 0$ in every case which can be explained by the power law relationship between effort and complexity. Model residuals are normally distributed

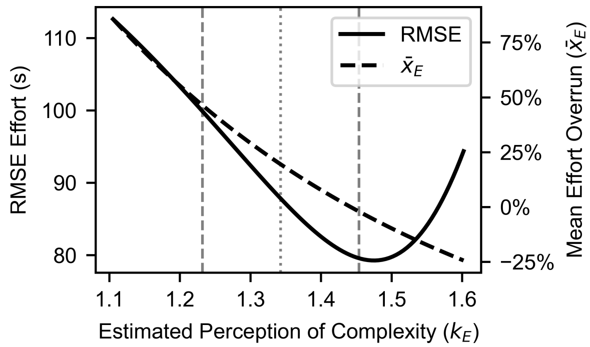


Figure 8: Hypothetical effort errors and overruns for estimates of k_E. Gray lines denote γ_{10} and $\gamma_{10} \pm \sigma_{\gamma_{10}}$.

for log-transformed effort (i.e., $\ln \hat{E} - \ln E \sim \text{norm}(0, \sigma)$) but become a log-normally distributed multiplicative factor when estimating effort (i.e. $E/\hat{E} \sim \text{lognorm}(0, \sigma)$) because of the exponential transformation. Closely related to the more general effect of differential perception, the natural skew of the log-normal distribution produces more frequent overruns than under-runs.

Compared to the baseline mean estimate of k_E in case 1, adopting the group-specific estimates of k_E in case 2 reduces RMSE and mean overrun. Adopting a k_E value one standard deviation below the mean in case 3 substantially increases RMSE and mean overrun effort compared to the baseline. However, adopting a k_E value one standard deviation above the mean in case 4 achieves RMSE similar to the group-level estimates but with near-zero mean overrun, effectively correcting the skewed distribution. Figure 8 plots RMSE and $\bar{x}_E$ values over a wider range of k_E factors, showing the minimum RMSE occurs close to one standard deviation above mean value. If generalizable, this type of insight could help inform effort estimates for broadly-scoped tasks across a diverse set of design actors.

While these results are significantly limited by the nature of the secondary data analysis (including hypothetical effort overruns rather than soliciting actual estimates), follow-up studies should investigate whether differential perception between design groups actually contributes to effort overruns. If similar observations can be replicated for design problems of increasing realism and complexity, results could be used to correct for observed skew or tailor effort estimates to specific design groups based on historical observation of the effort-complexity frontier.

5.5 Limitations

Results of this analysis are subject to several limitations. First, it adopts secondary data from a prior experiment rather than designing a new experiment tailored to specific research objectives. The original study does not solicit effort estimates in advance of each task or measure effort overruns, limiting the strength of some insights provided here. It also does not consider desired performance or temporal dynamics (performance is fixed for each task) and does not permit excess complexity (complexity is fixed for each task), limiting direct validation of Eq. (1) and Eq. (4) as components of the proposed model of complexity in engineering design. However, the prior study provides control over the key variable of interest (complexity) while accounting for key contextual factors like the order, team size, and variable error tolerance to isolate and measure perception of complexity for individuals.

Second, the surrogate parameter design task is a highly simplified representation of design activities. Similar to the objectives of the original study, the abstract nature of the task allows for controlled experimental conditions at the cost of direct generalization to more realistic design scenarios. Its lack of domain-specific context reduces effects of prior knowledge, experience, and supporting tools which are critical in technical activities but also a source of significant variation among design groups. The design task is more of an optimization task than a creative task and has no sources of uncertainty for requirements or mapping between inputs and outputs. The simple tasks in this study also allow many data points to be collected in a design session to improve statistical power. Thus, while the particular results of this study are not intended to directly apply to general engineering design, they do provide supporting evidence of variable perception of complexity between design groups. Research settings with increasing realism should further vet results while advancing measurement of performance, effort, and complexity constructs.

Finally, this study does not directly evaluate the effects of differential perception of complexity. While hypothesized in the third mechanism to contribute to effort overruns, further research is required to understand if there are systematic differences in perception of complexity across disciplinary or hierarchical roles within design organizations and provide further evidence for or against the three proposed mechanisms contributing to effort overruns.

6 Conclusion

Effort overruns on large engineering projects demand new explanations for the role of complexity in design. The proposed model relates desired performance and required effort using two facets of complexity as intermediate factors. Complexity enables desired performance but also contributes required design effort as a function of contextual factors including its perception by design actors. Three mechanisms leading to potential effort overruns include exponential growth biases when using historical effort to project future effort, excess complexity in design which amplifies required effort, and differential perception of complexity which may contribute to poor estimates of required effort.

Secondary data analysis from a previous human subject experiment measures perception of complexity for simplified parameter design tasks. In agreement with the proposed model, results show a power law relates complexity and effort measured as task completion time. Linear regression with mixed effects shows perception of complexity varies across design groups. Results suggest perception of complexity may be a significant driver of effort in design, especially with respect to differential perception across individuals.

While this paper introduces the model of complexity in design and provides supporting evidence, future work must provide further evaluation. First, it is unknown whether a power law governs the relationship between performance and complexity. Evaluating complexity-performance design tradespaces could help identify the Pareto-efficient frontier and determine if it indeed follows a power law. Of course, the functional relationship likely depends on the complexity metric form, so several alternatives may need to be compared with each other.

Second, while this study provides preliminary evidence, it is unknown whether a power law governs the relationship between complexity and effort. Further investigation of historical or experimental data in more realistic design settings would help establish this component of the proposed model. While product performance data is generally available, total effort data including research and development will prove more difficult to acquire or estimate. Building on existing work in technology studies or economics literature may help identify theoretical foundations for this relationship.

Third, the empirical evidence in this study cannot truly assess effort overruns because no effort estimates were collected from design actors. A simple modification of the existing task could ask design actors to estimate required effort before starting a design task which would help evaluate proposed mechanisms for effort overruns. Other future work may augment perception of complexity through various contextual effects. For example, the original study enforced purposeful barriers to design including no quantitative information and limits to verbal communication. Relaxing these constraints or, alternatively, providing improved design tools to facilitate communication or knowledge transfer would be expected to improve perception of complexity and reduce total design effort.

Finally, it may be possible to study the relationship between performance, effort, and complexity in a more realistic design experiment compared to the linear system of equations employed here as a surrogate parameter design task. Future work must balance experimental control with generalization as realistic settings have many uncontrolled effects including prior domain knowledge and experience and challenges to quantify abstract concepts such as performance, complexity, and effort specific to each problem. The two-level random effects regression model provides a strong basis to analyze correlated samples from design actors and should be considered for any future experimental studies.

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