Embodiment Design Cartography: A Conceptual Framework for Design Space Mapping to Support the Development of Physically-Interactive Products

by
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“Focus on the journey, not on arriving at a certain destination.”

— Chris Hadfield, *An Astronaut's Guide to Life on Earth*, 2013 [1]

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Preface

Product design is the act of creating something that is to be used. While the solution to a product design problem is definite, singular—only one new product for a given problem is typically created—there are nearly *infinite options* for alternative configurations that could have been created instead. To get to this singular solution, there are a web of considerations that must be navigated, as well as a variety of success criteria that may be employed. This act of creation—of putting the product out into the real world—inherently challenges the concept of what this product theoretically *is* in a vacuum. Once *embodied*[1] in the real world, the *human element* comes into play; different humans may physically interact with these products and interpret or respond them in some way that is outside of the designer's control. These interpretations can take the form of anything from subjective emotional responses to autonomic bodily responses. Similarly, there is a *situational element* to how humans experience these product interactions, which again can escape direct influence of these designer. All of these *externalities* factor into the considerations that must be navigated, and ultimately shape how the product is received just as much as the technical performance specs it is engineered to achieve in a vacuum. The range of alternative design options that exist within the *design space*[2] may therefore each be measured according to a variety of different, oftentimes *competing outcomes*, which themselves are influenced by a variety of *external factors*. As such, the proposition of selecting a singular solution within this sea of options may become a less than simple affair, in which no one solution is definitively superior.

Systematically navigating these different factors and outcomes across infinite options within the design space is a fundamental issue of product design. Classical paradigms of design typically consider this navigation by a series of *linear decisions*—decisions of which factors to consider, which outcomes are relevant, how to weigh them, etc.—that all culminate in a singular solution, as chosen by the individual values of the designer or firm. However, this linear perspective can

[1] **Embodied**: To be made real, tangible.
[2] **Design space**: A hypothetical space of some dimensionality that contains all of the potential versions of a product that could be created, and the associated considerations that lead to their creation.

have the unintended effect of conceptually burying each of these decisions behind the subsequent solution, such that it may not be apparent as to what other options may be achieved had a different decision been made at any point in this chain. The goal of this dissertation is to develop a *framework*[3] for *mapping* out the options in this design space (i.e., creating a *design space map*), such that the variety of factors and outcomes to be considered may be navigated in a systematic manner, and each design option may be simultaneously conceived as the summation of all of the decisions that lead to their creation. With this framework, two common issues in *new product development* are explored. The first is *'how can the design space map be used to compare tradeoffs between competing outcomes?'*, and the second is '*how can the design space map be personalized to reflect the unique qualities of each individual?'*. The objectives of this research include: 1) defining a *conceptual framework* to support this design space mapping for a general class of design problem, 2) developing modeling, experimental, and design methods for navigating *tradeoffs* between *technical* and *experiential* design outcomes within this framework, and 3) developing modeling, experimental, and design methods for *personalizing* individual design space maps based on users *psychophysiological*[4] measures to improve their overall accuracy. To address these objectives, a conceptual framework is derived around the description and classification of existing design methods in Chapter 2, which is both *flexible* enough to be tailored to specific design problems, and also able to *selectively integrate* advantageous processes of the existing design methods; a case study for the design of a *pneumatic steering column* is conducted in Chapter 3, in which a *linear algebraic* method for identifying and quantifying tradeoffs is developed; and a case study for the design of an *infotainment controller* is conducted in Chapter 4, in which a method for personalizing design space maps according to individual user's *latent emotions* and *cognitions* is developed. This work makes important methodological contributions to the fields of engineering design and design science, and ultimately provides a systematic platform for constructing new design methods for physically-interactive products, which are able to be tailored to the design problem at hand.

[3] **Framework**: A network of interlinked concepts that describe a phenomenon and impart a central philosophy.
[4] **Psychophysiological**: Human physiological responses that provide the basis for psychological processes.

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List of Abbreviations

Acronyms (Uppercase characters; listed alphabetically)

A-A	Actor-Abstraction	MERF	Mixed-Effects Random Forest
ACA	Adaptive Conjoint Analysis	M-L	Mason-Likar
ATC	Analytical Target Cascading	MVIC	Max Voluntary Isometric Contraction
CA	Conjoint Analysis	NIH	National Institute of Health
CBCA	Choice-Based Conjoint Analysis	QFD	Quality Function Deployment
EDC	Embodiment Design Cartography	RTD	Research Through Design
FBS	Function-Behavior-Structure	SCL	Skin Conductance Level
HCI	Human-Computer Interaction	SCR	Skin Conductance Response
HOQ	House of Quality	SHAP	SHapley Additive exPlanation
HMI	Human-Machine Interaction	S-P	Stage-Process
HMIs	Human-Machine Interfaces	TUIs	Tangible User Interfaces
IBI	Inter-Beat Interval	UI	User Interface
KE	Kansei Engineering	UX	User Experience
KES	Kansei Engineering System	VR	Virtual Reality

Numerical/Statistical Notation (Lowercase characters; listed alphabetically)

c	Centered	rms	Root Mean Square
m	Mean (Average)	rmsd	Root Mean Square Deviation
med	Median	sd	Standard Deviation
n	Number of Participants	var	Variance
p	Probability Value		

Variables (Lowercase, bold, italic characters; listed alphabetically)

a	Application	***d***	Diameter/Detent Number
af	Affordability	***ecg***	Electrocardiography Signal
c	Production Cost	***ecu***	Extensor Carpi Ulnaris
d	Detent Number	***eda***	Electrodermal Activity Signal
edc	Extensor Digitorum Communis Activity	***epb***	Extensor Pollicis Brevis Activity
emg	Electromyography Signal	***epc***	Electrocardiography Positive Change

$\boldsymbol{fds}$	Flexor Digitorum Superficialis Activity	$\boldsymbol{sr}$	Structural Rigidity
$\boldsymbol{h}$	Material Hardness	$\boldsymbol{sw}$	Stowability
$\boldsymbol{hr}$	Heart Rate	$\boldsymbol{t}$	Track
$\boldsymbol{hrv}$	Heart Rate Variability	$\boldsymbol{th}$	Wall Thickness
$\boldsymbol{k}$	Torsional Stiffness	$\boldsymbol{v}$	Stowed Volume
$\boldsymbol{l}$	Length	$\boldsymbol{\delta}$	In-Situ Adjustment
$\boldsymbol{m}$	Motor Torque Stiffness	$\boldsymbol{\lambda}$	Experience-Sacrificing
$\boldsymbol{p}$	Pressure	$\boldsymbol{\mu}$	Experience-Maintaining
$\boldsymbol{r}$	Rating	$\boldsymbol{\omega}$	Weighting Coefficient
$\boldsymbol{s}$	Steering Sensitivity	$\boldsymbol{\Theta}$	Angle
$\boldsymbol{sb}$	Stability	$\boldsymbol{\tau}$	Feedback Torque
$\boldsymbol{sc}$	Skin Conductance		

Vectors (Uppercase, bold, italic characters; listed alphabetically)

$\boldsymbol{A}$	(Product) Attributes	$\boldsymbol{E}$	Experiential Responses
$\boldsymbol{A_E}$	Environmental Attributes	$\boldsymbol{E_S}$	Subjective Experiential Responses
$\boldsymbol{A_L}$	Latent Attributes	$\boldsymbol{E_P}$	Physiological Experiential Responses
$\boldsymbol{A_R}$	Responsive Attributes	$\boldsymbol{EC}$	Engineering Characteristics
$\boldsymbol{B}$	Behaviors	$\boldsymbol{EX}$	External Effects
$\boldsymbol{B_E}$	Expected Behaviors	$\boldsymbol{F}$	Functions
$\boldsymbol{B_P}$	Persistent Behaviors	$\boldsymbol{G}$	Customer Groups
$\boldsymbol{B_R}$	Responsive Behaviors	$\boldsymbol{S}$	Structure *or* Semantics
$\boldsymbol{B_S}$	Structure Behaviors	$\boldsymbol{P}$	Properties
$\boldsymbol{C}$	Context	$\boldsymbol{T}$	Technical Functions
$\boldsymbol{CR}$	Customer Requirements	$\boldsymbol{U}$	User
$\boldsymbol{D}$	Design Parameters	$\boldsymbol{R}$	Subjective Ratings
$\boldsymbol{DS}$	Design Sensitivity		

Models (Uppercase, script characters; listed alphabetically)

$\mathcal{E}$	Engineering Model	$\mathcal{I}$	Interaction Model
$\mathcal{F}$	Feature Extraction Model	$\mathcal{P}$	Performance Model

Abstract

Embodiment design is the process of taking an idea for a product and bringing it into the real world by specifying key parameters. In this process, numerous decisions are made that ultimately lead to a solution. By entering the real world, however, a host of complexities are introduced to the design problem by external actors. The different people that physically interact with the product, as well as the situations for these interactions, may all factor into shaping the way this solution is received in a manner that is outside of the designer's control. To truly understand the outcomes of the options that exist within this *solution space*, there is a web of considerations that must be navigated in the *problem space*. Together, the considerations in this problem space and the relations between them, as well as the options in the solution space comprise the overall *design space*. The term 'cartography' refers to the creation of maps—this dissertation presents a conceptual framework for systematically *mapping* out this design space such that the paths along this web of considerations may be navigated, and the resulting outcomes that may be achieved are understood. There are existing methods from different design disciplines that can help understand the solution space, however each imparts a distinct, fixed perspective on how it conceives the problem space and therefore only recognizes the portion it considers to be important. The Embodiment Design Cartography framework developed in this dissertation is illustrated by mapping out these methods on a uniform scale that enables their direct comparison and combination. New design methods are also constructed within this framework, which may be tailored to the problem at hand, and more holistically cover the design space without the limiting preconceptions of existing methods. This practice is employed in two case studies for products that exemplify questions in embodiment design. The first regards how tradeoffs between competing outcomes may be successfully negotiated. The second regards how products may be efficiently personalized on a mass scale. For each case study, a suite of modeling, experimental, and design methods are developed within the framework, which are tailored to the specific needs of the problem. These are used to mathematically model and validate design space maps through empirical user studies. In the first study, the design space map was used to develop a linear

algebraic approach for examining tradeoffs, which informed actionable design adjustments to achieve a more favorable balance. In the second study, the design space map was used to examine how physiological responses may provide latent information on individual differences, which informed the efficient implementation of mass personalizations without conscious engagement from the user. This dissertation has made important contributions in providing designers with the language, tools, and procedures necessary for developing design methods that may be tailored to their specific needs within a structured framework, and promotes a higher level understanding of the various decision paths that may be navigated in the design space. This represents a new paradigm for methodological development in embodiment design.

Chapter 1. Introduction

To take an idea for a product and translate it into the real world, a single solution for exactly how this product is to be configured must be specified. This serves to distinguish the created product from *near-infinite* potential alternative solutions, which were not created. However, it may not be readily apparent as to whether the specified configuration ultimately provides the best possible *outcomes*. If a broad range of different kinds of design outcomes—including how people perceive this product when they use it—are used to measure its success, it can be difficult to know what alternative outcomes are even possible. There are also innumerable different *external factors* that may influence these outcomes once the product is introduced in the real world. All of these factors and outcomes that may be considered, as well as the associated options for how the product may be *embodied*, together comprise a 'design space.' This introductory chapter discusses this concept and motivates the need for 'mapping' out the design space, such that designers can better *understand their options* and make more informed decisions. The specific *class of design problem* that is addressed, as well as the *design tasks* that are supported through this mapping, are each clarified. Existing design methods for creating different types of design space maps of various forms are reviewed, and the associated research issues are established. Finally, the goals, objectives and approach to this research are outlined in depth, and its outcomes are summarized.

1.1. Mapping the Design Journey: An Analogy

Between 1975 and 1977, Will Crowther and Don Woods developed and released *Adventure*, the first text-based adventure game [2]. This pioneering computer game—primitive by today's standards—had players interact with a digital environment that was entirely text-based. Their only insight into this world consisted of brief verbal descriptions, e.g., Figure 1. In *Adventure*, the player is given little initial direction regarding their objective, beyond a vague reference to treasures that may be found within a dark cave. With only limited understanding of the world around them, it is up to the player to enter in text prompts that reveal more about their environment, and to make a series of decisions to navigate through a labyrinth-like cave system. Almost nothing is freely given to the player in the brief text entries; every additional piece of information requires deliberate action to extract. While each decision is made according to the *values* of the individual player, intentional actions such as 'turning on a lantern' can help them determine what *options* may be available to them.

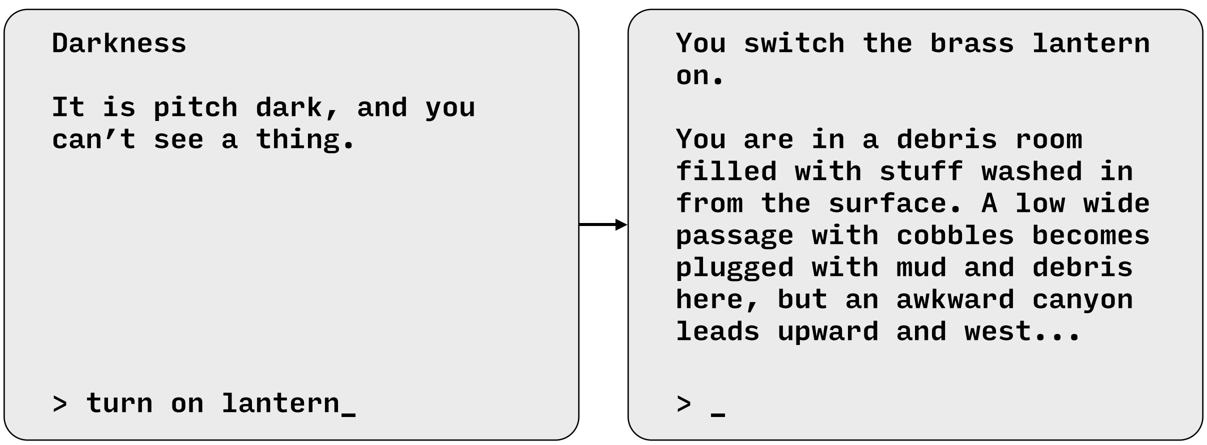

Figure 1. A sequence of passages from *Adventure*. In this text-based computer game [2], players type in prompts (e.g., 'turn on lantern') to interact with and uncover insight about the environment.

In many ways, the process of product design is quite similar to this text-based adventure. The design process may oft be described a *series of decisions* that result in a singular solution [3–9]. In this work, we shall consider this *linear* decision-making to be a sort of journey. The designer assumes the role of the player, who must embark on an adventure through an un-mapped or *ill-structured* problem space (i.e., a dark cave) to determine an outcome within a similarly *ill-structured* solution-space (i.e., abstract treasures), which together form the overall design space [10,11].

> *"At the start of the design process, the designer is usually faced with only a partially defined problem; yet he or she has to come up with a well defined solution. If one thinks of the problem as a space or territory, then it is largely unexplored and un-mapped, and perhaps imaginary in places! It may therefore be appropriate to think of the designer as an explorer, travelling inquisitively through an unknown land, paying attention to unusual finds as well as the mundane. Equally, if one thinks of all potential solutions as occupying a kind of solution space, then that, too, is relatively undefined, and perhaps infinite. Here, the designer is searching for possibilities, and often creating new ones. The designer's task is therefore two-fold; understanding the problem and seeking a solution."*

– Nigel Cross, *Engineering Design Methods: Strategies for Product Design*, 2021 [12]

The Problem Space – Equated to a *dark cave* in this analogy, the problem space contains the set of all *considerations* that the designer could make when developing a product. This space is a model of reality that is only as large and complex as one lets it become. In the simple example of a light switch, for instance, the designer could consider only themselves as a potential user, and only care if the light switch works to turn on/off the light. In this case, the problem space is relatively small and straight foreword; there are minimal decisions to be made. Alternatively, for the same light switch the designer could consider a wide variety of different users—*Are they blind? Do light switches function different in their country?* etc.—and also different contexts of use—*Is it cold out? Is the person wearing mittens?* etc. Additionally, not only does the designer care about whether the light switch works, but now also cares about how it makes you *feel* when you switch it. Now the problem space is much larger and more complex; there are turns and forks in this cave that call for more decisions to be made. In reality, these twists and turns that complicate the problem space exist whether they are considered or not. An adventurer may not observe an alternate passage if it is shrouded in darkness, but this doesn't mean it is not there. Similarly, the designer may not consider alternative factors and outcomes in their decision-making, but these externalities still may exist once the product is placed in the real world. Ignoring these complexities can be strategic, but also limiting in some cases.

The Solution Space – Equated to the *treasures* in this analogy, the solution space contains the set of all the versions or *configurations* of the product that could be developed. This space contains all of the possible configurations that the light switch in the prior example could end up as, and the available solution space is therefore directly tied to the formulation of the product space. Just as there is no definitive formulation of the problem space in ill-structured problems such as design, there is also no definitive option in the solution space; different design solutions can be equally valid and are largely interwoven with the formulation of the design problem [12]. There are multiple treasures that may be discovered in the cave of *Adventure*, and there are multiple design solutions that may be alternatively selected. These treasures are only understood to be found within the cave in an *abstract* sense through vague reference to their existence in the opening lines of *Adventure*; the treasures themselves can be anything. Design options in the solution space are similarly broad and measured in an *abstract* sense, i.e., how they make you *feel*, especially when to the more concrete *design levers*[5] that the designer may directly control. These abstract outcomes can be assessed on a *technical* level (e.g., keeping the sun out of one's eyes [13]) or an *experiential* one (e.g., to "dazzle [one's] senses, touch their hearts and stimulate their minds" [14]), which reflects the potential heterogeneity of viable solutions [15,16].

1.1.1. Systematic Design Space Exploration

While many types of designers may be satisfied with endeavoring through this design journey based solely on their intuition, prior experience [12], personal preference [17], or gut-feelings [18], engineers are decidedly not [12]. An *engineering designer*—the *adventurer* in this analogy—is a sort of hybrid between a traditional designer and an engineer. Engineering design calls for more *rigorous, systematic* approaches to design, in which decisions may be *tested*, *measured*, and *validated*, but still leaves room for a degree of creative problem-solving or *exploration* to tackle these ill-structured problems [12,19]. Systematic engineering design is grounded in fields such as mathematics, physics, and mechanics, and often entails the use of quantitative models [5,19–21] with which some *optimal* design solution may be definitively solved for, e.g., [22–25]. This emphasis on robustness in design research [26] may be largely attributed to the added complexities, risks [12,27], and associated costs [28] of modern engineering design. At its core, to 'design' is to create something *new* [12,29] i.e., "the goal of designers is to change the world through the creation of artifacts" [13]. However, new product development faces an extraordinarily high failure rate

[5] **Design levers**: Any aspect of the product design process that the designer can directly adjust or manipulate to implement immediate change and propagate influence on higher-level outcomes, e.g., an engineering design lever may be the *dimensions* of a component.

[30–32]. Purely relying on intuition or prior experiences may be insufficient if the product is new to the world [12]. While the design process is almost always *iterative* [12], systematic approaches can help reduce or shorten the number of costly, time-intensive iterations [12,19,33], and facilitate more efficient allocation of resources early in this cycle [34]. Efficient, systematic processes can mitigate some of the inherent risks associated with engineering design.

It is therefore up to the engineering designer to systematically *map out* the problem and solution spaces from the *concrete* design levers they may control, through any *external factors* that may be considered, and, ultimately, to the *abstract* design outcomes they may wish to achieve. With a map, the entire 'journey' of linear decisions may be illustrated simultaneously. A map of the dark cave can be used to not only reveal the path that was followed and the treasure that was found, but also the *alternative* paths and treasures that were *not* selected. This reframes the journey that was taken, which—while originally experienced temporally as a series of linear decisions that resulted in the discovery of a single solution—can now be viewed concurrently from a birds-eye-view in terms of all the alternative *options* that could be selected as well. More importantly, this map can now be used as a *tool* for future adventures in this cave—conceivably by different adventurers—as a means for locating potentially superior solutions. It therefore follows that, as a general tool, a greater level of detail and accuracy in reflecting the real-life topology in this map provides a wider range of potential applications and a better ability to lead adventurers to desired treasures. A map of the design space serves an analogous role—to illustrate all the potential design options that may be created in terms of the decisions that lead to their creation. The design space map tells us what influencing *factors* are considered in this design problem, what design *outcomes* are used to measure the available solutions, and how to physically create the associated products using the design levers that are available. Most importantly, this map may be used as a tool for *informing design decisions*, with more robust maps providing more insight in this area.

1.1.2. Intentional Design Decisions: Options and Selections

To make a design decision is to make a selection—to choose one option with the admission that it may come at the expense of the other. Systematic decision-making in engineering design may be based upon two distinct components: *values* and *information*. On the former, decision are based on the *values* or perspectives of the decision-maker [35]. In the case of design, that is the engineering designer (or enterprise), and their individual expertise and domain knowledge can shape these values [36]. Values can take the form of *weights* in an optimization model, for instance. There are a variety of existing support methods for making value-based selections [28], including those grounded in game theory [37], utility theory [38], the analytical hierarchical process [39], or other goal-oriented methods [40,41]. Alternatively, the *information* that the designer may base their decisions on can similarly influence what options are perceived to be available, and the manner in which the design problem is formulated can further shape this information [42]. An adventurer's choice to go left or right at a crossroads within the cave is up to their subjective *values*, but the topology of the cave to split in just this way to afford these two options is a measure of objective *information*, which is independent of anyone's values. However, formulating the problem space in a different manner may uncover *alternative* options, e.g., a third path hidden in the shadows.

This analogy of *Adventure* as a proxy for the design journey is useful not only as a literary device for describing the relatively abstract concept of a 'design space' and motivating the need for a map, but also as a means for emphasizing the level of *intentionality* that is necessary throughout this process. Unlike reality, insights in a text-based adventure are not passively presented to us through our senses. Something that may be automatic or subconscious for us in real-life—to look around and take in information about our environment, for instance—alternatively requires express intent to seek out in systematic design. The designer must take deliberate steps to 'turn on the lantern' so-to-speak—to illuminate the overall design space by strategically formulating the problem space such that the resulting options in the solution space are not only made evident, but truly *understood* on their merits. This understanding can be had by measuring the design outcomes that each option affords on both the *technical* and *experiential* levels.

While individual or institutional values may determine the *selection* of which version of a product shall represent the solution, the deliberately sourced information determines which *options* are available. It is these *options in the design space*—independent of one's values—that are revealed with a design space map. The fundamental axiom of this approach is that, on average, more informed decisions or selections may be made when more information or options are available. Seemingly innocuous decisions could inadvertently preclude the achievement of desirable solutions. The aim of the framework presented in this work is to provide a format for good design decisions to be made, but not necessarily to instruct the designer on what decisions to make. By creating a map, the range of available options for which these decisions are based on may be more rigorously and holistically understood.

1.1.3. Embodiment Design Cartography

To create a design space map, the engineering designer must not only assume the role of the adventurer, but also the *cartographer*, i.e., map-maker. Historically, it was the case that any cartographer who wished to map out uncharted territories must themselves embark on a journey through this space to construct this map by meticulously documenting each twist and turn, each treasure that was discovered. This could be resource intensive process in terms of time, energy, money, etc. For an engineering designer wishing to analogously map out a design space, physically creating every single potential product to construct this map is simply an infeasible proposition. However, just as new technologies have equipped modern cartographers with advanced tools for more efficiently constructing geographic maps (e.g., satellite imaging), existing *design methods* may be leveraged to support design space *mapping* (i.e., the cartographic act of creating of the design space map) in a more efficient manner.

In this dissertation, a *conceptual framework* to support the creation of this design space map is developed. This *Embodiment Design Cartography* (EDC) framework serves to guide these cartographic activities in an efficient, systematic manner, by promoting *strategic formulation of the problem space* and *robust modeling of the solution space*. Aspects of existing design methods are selected and integrated in service of these aims. With this framework, engineering designers may construct design space maps to reveal how concrete design levers should be manipulated to achieve abstract design outcomes. These maps may then be used to identify, compare, and simultaneously consider a holistic set of options for different design configurations in a rigorous manner. These efforts do not expressly emphasize value-based selection of a singular, optimal solution within the design space. Rather, they address the range of feasible solutions on a continuous scale, such that *tradeoffs* between alternatives may be negotiated, and a *broad*, set of abstract design outcomes may be considered. The essence of this framework is grounded within the concept of *embodiment*—the idea of bringing tangible products into the real-world and designing for the externalities that this entails. This idea of embodiment governs both the *class of design problem* that is addressed with this framework, and the specific *design tasks* that it supports.

1.2. Embodiment: Interaction & Design

The design space mapping enabled by the Embodiment Design Cartography (EDC) framework developed in this dissertation is specifically centered around the concept of *embodiment*, in multiple senses of the word. The term 'embodiment' means to make something real in a tangible or *physical* sense. This phenomenon can be applied to both the act of having physical interactions with products, which elicit real consequences or outcomes, and also to the act physically creating products that previously only existed as concepts. Both of these standpoints on 'embodiment' are summarily described, and then detailed in turn.

1. ***Rich, Embodied Interaction*** – The former application of the term represents 'embodiment' from the standpoint of the *user*. This defines the *class of design problems* addressed in design space mapping—those that elicit *rich, embodied interactions*. An *embodied interaction* [43] is simply a physical interaction that a person may have with a product while both are situated in a real environment. The additional qualifier of *'rich'* [44] is included to indicate that: 1) the interaction is based on not only inherent attributes of said product, but also *factors* in the characteristics or predispositions of the person, as well the situated environment for which they interact, and 2) the *outcomes* of said interaction are not only predicated on the technical performance that the product is engineered to achieve, but also the experiential (i.e., emotional, cognitive, or perceptual) responses that its use elicits in a person, or allows them to achieve within the context of some real-world task. Rich, embodied interactions of this nature often involve *haptic feedback* of some kind.

2. ***Embodiment Design*** – The latter application of the term represents 'embodiment' from the standpoint of the *designer*. This defines the *design tasks* that are supported by this framework—those that fall under the umbrella of *embodiment design*. Simply put, *embodiment design* [19] is the act taking an idea for a product and bringing it into the real-world. The idea for the product, i.e., the *concept*, broadly defines what the product is/does, but there are essentially infinite manners in which that idea may be executed. Through the act of embodiment design, the specifics of this *qualitative* idea are determined such that the product may be concretely defined by some set of *quantitative* parameters. These parameters enable the product to be constructed in the real world, and serve to measurably distinguish the selected configuration from the hypothetical alternative options.

1.2.1. Rich, Embodied Interaction: The Artifact, User, and Context

Humans (i.e., *users*) and products (i.e., *artifacts*) both inhabit the physical environment; users may touch, manipulate, and physically interact with artifacts in all manner of ways [45–47]. This physical manifestation is the essence of *embodiment*. *Embodied interactions* are those that are *situated* in the physical world and produce *real* (if not explicitly physical) outcomes [43]. In contrast to 'embodiment', a macro trend of *'dematerialization'* may be observed in product design today. This occurs when artifacts that were previously embodied in the *physical* world become incorporated into a *digital* one, e.g., records/CDs evolving into music streaming services, coins and paper money converting to digital currencies and transactions, books being replaced by tablets and e-readers, etc. [48]. By dematerializing, products are released from their physical bounds and afforded unlimited flexibility and availability in a digital environment [43,48,49]. However, much of our interaction with digital products is reduced to so-called 'picture-under-glass' interactions [50] that lack the level rich, engaging feedback afforded by physical interactions [44,51], which users often prefer, e.g., [52–56]. In fact, physical interactions are unique in the sense that physical touch (i.e., *haptics*) is the only sensory modality that is inherently *interactive*—when you touch a physical artifact, that artifact touches you back [57]. As such, a counter movement against the trend of 'dematerialization' may be observed as well [48], ergo the recent explosion of mechanical keyboard subcultures based around users' common enjoyment of the auditory and haptic feedback, e.g., [58,59]. This movement is, in a sense, a rediscovery of traditional product design [47], akin to the pining for the *rich* interactions afforded by historical instruments of old [60].

> *"For years radios had been operated by means of pressing buttons and turning dials; then as the technology became more sophisticated the controls were made touch-sensitive—you merely had to brush the panels with your fingers; now all you had to do was wave your hand in the general direction of the components and hope. It saved a lot of muscular expenditure of course, but meant that you had to sit infuriatingly still if you wanted to keep listening to the same programme* [sic]*."*
>
> – Douglas Adams, *A Hitchhiker's Guide to the Galaxy*, 1980 [61]

However, this refocusing on rich, embodied interactions certainly holds relevance in modern product design beyond surface-level nostalgia. The haptics afforded by physical interaction provide demonstrable utility in improving design outcomes. *Tactile haptics*[6] [62] in smartphones (e.g., vibration), for instance, may improve operation time, error rate, and overall satisfaction [63–66]. *Kinesthetic haptics*[7] [62] in Human-Machine Interfaces (HMIs) have been shown to aid users in obtaining environmental information through torque or force feedback [67]. For instance, kinesthetic haptics in steering wheels can improve drivers ability to complete maneuvers such as negotiating a curve or maintaining a lane [68,69]. Similar improvements can be seen in the operation of industrial machinery [70,71]. Medical operations have seen improved success rates when implementing haptic feedback in surgical devices [72–74]. The use of haptics have shown benefits for learning and early development [75,76]. Satisfaction or fascination with products can arise due to the aesthetics of these haptics [57,77], and the behavior of consumers may ultimately be influenced by the physical feeling of use [78–81]. The *richness* of these embodied interactions goes beyond their simple existence in the physical world; they engage the user, leverage their natural skills [44,82], stimulate emotional response [83], and impart perceptual meaning into the use of these physically-interactive artifacts [45,46].

While the *technical* performance of an artifact is dictated by its own internal properties, *experiential* responses to its interaction are *not* an inherent property of said artifact [84]. In a rich, embodied interaction, the experience is equally dependent on the qualities of the *user* themself [44] (see also [84]). Furthermore, *embodiment* implies an inherent situatedness within an environment [43]. All rich, embodied interactions may therefore be attributed to *three fundamental actors*: the *artifact*, the *user*, and the *context* of use [85–95], i.e., "a user interacts with some subset of features and affordances [of the artifact], based on location in a context, prior experience, and current emotional state" [96]. In simplistic terms, it comes down to the person, the place, and the thing. These actors serve as the fundamental elements of this phenomenon, for which the EDC framework is *ontologically*[8] derived in Chapter 2. Each of these actors may be used to classify both the *factors*—externalities that influence the rich, embodied interaction—and the *outcomes*—technical or experiential measures to assess the design solution—of which the engineering designer may consider in their formulation of the problem space. Each of these actors is discussed in turn.

[6] **Tactile haptics**: Physical feel relating to surface texture or vibrations; felt through our skin.
[7] **Kinesthetic haptics**: Physical feel relating to motion or force; felt through our muscular effort.
[8] **Ontology**: A system for defining, classifying, and relating concepts on fundamental level.

1.2.1.1. The Artifact

First and foremost, the *artifact*, i.e., the product, is the subject of the design problem. This is something that is *physically-interactive*, and typically imparts some sort of feedback (e.g., haptic feedback) or response to said interaction. When considering rich, embodied interaction from an *industrial design* perspective, one formal description of the artifact characterizes it in terms of three properties [44]: its *'form,'* its *'function,'* and its *'interaction'* (see also [97,98]). In this description, the 'form' represents the physical layout of the artifact, the 'function' represents the tasks that the artifact carries out, and the 'interaction' represents the 'feel' or feedback of physically engaging with the artifact [44]. Unlike dematerialized products, the *coupling* of these properties is inherent to their physical embodiment [93]. A digital product may be able to decouple its 'form,' 'function,' and 'interaction,' such that each property may be designed separately; it is not constrained by physical bounds. The design of physical products, on the other hand, must navigate certain *tradeoffs* that may exist due to these couplings [4,25,44,71,99,100]. Adjustments to one property may incidentally alter another, oftentimes in an indeterminant or detrimental manner [20].

It is in the 'form' or layout parameters that the engineering designer may make these concrete adjustments—this is where the engineering design levers exist. Both the 'interaction' attributes of the artifact, as well as its technical 'function' are ultimately determined by these 'form' parameters (albeit with generally less emphasis on visual aesthetics and more on *structure*), "[t]hat is, the form of products mediates both the interaction and the expression of functionality" [97]. However, while this *industrial design* description is useful for conceiving these couplings, it is ultimately incomplete in capturing all of the properties of the artifact considered in *engineering design*, which extends to both those relating to the interaction, but also those that *persist* outside the scope of the interaction. Some argue that no *direct* coupling exists between 'form' and 'function' [35,101]; rather, this coupling is bridged through intermediary properties. These properties—both those that were already captured in this description and additional, intermediary properties—are discussed in terms of *factors* that contribute to consumer-facing qualities of the artifact, and the *outcomes* of the design problem that are specifically inherent to the artifact.

Artifact Factors – Consumers will oftentimes describe and understand artifacts as 'bundles of attributes' [12,28,102]; these can be continuous or categorical in nature [103]. Attributes of the artifact may be classified as either *responsive* or *persistent*. The former—*responsive attributes*—

are considered to be the *subset* of these attributes that may directly respond to user's interactions [96], i.e., those that describe the feel or reaction of a specific physical interaction (e.g., haptic feedback, system response, etc.). These responsive attributes *factor* into the rich, embodied interaction and ultimately influence design outcomes on the experiential level. However, there are also other attributes of the artifact—*persistent attributes*—that exist outside of this interaction and are relevant for determining engineering design outcomes on a technical level (e.g., strength, weight, cost, etc.). These are attributes that must also be *factored* in when considering the artifact as a complete product, not just as an influence on an interaction. In many cases, both the responsive and persistent attributes are generally not directly adjusted or designed by the engineering designer, but rather result from determinations made to the underlying form or layout parameters.

Artifact Outcomes – The 'function' is the ultimate determinant of why the artifact was created; this may be to meet the needs of the user or the performance objectives of the artifact [104]. However, 'function' is a contentious term in the field of design, the definition of which faces continued scrutiny [105]. In this dissertation, *outcomes* of a design problem may be considered to exist on two levels: 1) the *technical* level, which describes the engineering performance that the artifact is designed to achieve in a vacuum, and 2) the *experiential* level, which describes the responses or uses that the artifact may elicit once it is embodied in the real world. This division of outcomes on a 'technical' and 'experiential' level is commonly echoed in analogous terms throughout various literatures, such as the division of 'quality in design' and 'quality in use' [106,107], the division of 'functional requirements' and 'non-functional requirements' [108,109], or the division of 'technical solutions' and 'user-related features' [110], etc. Only outcomes on the technical level are an inherent property of the artifact, and are considered to be *artifact outcomes*—something that is fundamental to the artifact regardless of any rich, embodied interaction a user may have with it in some context (e.g., durability, affordability, etc.). This distinction therefore attributes the other outcomes, those that exist on the experiential level, to be properties of the other actors in the rich, embodied interaction.

1.2.1.2. The User

The user is the person who is physically interacting with the product in question. The user both *influences*, and is *influenced by* a rich, embodied interaction on an experiential level. These influences on the interaction are considered by *user factors* and *user outcomes*.

User Factors – The user has various inherent qualities that *factor* into their interaction with the artifact, i.e., characteristics that they may have *before* the interaction occurs. These may include emotions, feelings, values, prior experiences, cognitions [96], perceptions [111], motives, abilities, preferences [84], cultural differences [112], moods [113], expectations, goals, [114], concerns, attitudes, standards [115], skills [44], psychological or ideological predispositions [116] and other personal traits [77,117]. These factors serve as *top down information* that influences perception of the product [118] to the point that the user does differentiate it from the artifact itself [119,120]. More objective aspects (e.g., human factors/ergonomics [108,121], or demographic qualities (e.g., age, gender, ethnicity, culture, etc. [86,122]) may reasonably influence their interaction as well. As evidenced by the large number of *user factors* listed here—which, in and of itself is by no means holistic—the intrinsic qualities of the user that factor into the interaction may be quite complex and individualistic in nature. Specific subgroups may be designated as a target audience to narrow the possibilities of these user factors, e.g. [123]. However in practice, these factors are often considered as 'wildcards' that fall beyond the direct control of the designer which, nonetheless, should be accounted for to some degree [96].

User Outcomes – The *outcomes* of the interaction may also be reflected in the user through their experiential responses. In general, 'experience' is typically discussed in terms of *user experience* (UX) or *usability* [124,125] (although other paradigms, like *user acceptance*, exist as well [125–128]). UX is commonly defined as a "user's perceptions and responses that result from the use and/or anticipated use of a product, system or service" [129]; these perceptions/responses can include emotions, preferences, accomplishments, and even physiological responses [84,90,129–134]. However, UX is relatively complex [84,130,135–139] and broad [106], and is considered somewhat difficult to definitively characterize [77,91,94,98,130]. Other definitions exist, such as "the way [an artifact] feels in [a user's] hands, how well they understand how it works, how they feel about it while they're using it, how well it serves its purpose, and how well it fits into the entire context in which they are using it" [140]. Alternatively, usability may be defined as "the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" [141,142]. Additional constructs, such as learnability [143–145], are often considered within this scope as well [125,146]. The relationship between the concepts of 'UX' and 'usability' is fuzzy [139] and has evolved over time [91]. UX has been considered a subset of usability [147], both as distinct concepts [106,148], and more recently, usability as a subset of UX [98,106]; this shift has generally coincided with the rise in popularity of UX [149]. For this dissertation, this line is drawn between those outcomes that are *internal* to that user, and those that are *external*, i.e., those that are only measurable through the completion of a task within the context of use. The former are considered to be the *user outcomes*, e.g., *subjective* perceptions or *physiological* responses that may be measured directly from the user to assess *internal* emotional, cognitive, or perceptual states. The latter are considered to be contextual in nature.

1.2.1.3. The Context

Finally, the context is the situation for which the interaction takes place. Note that while the interaction is embodied in the physical world, its *outcomes* may be reflected in either a *physical or digital environment*. As stated, the outcomes of embodied interaction must be *real*, but not necessarily *physically-so*. For instance, *tangible user interfaces* (TUIs) are devices that afford rich, embodied interactions within the physical world that influence digital environments [150–153]. The context therefore also both influences a rich, embodied interaction, and may be used to assess outcomes of said interaction.

Context Factors – The context for which the interaction takes place shapes the interaction itself, and factors into the resulting experience outcomes. *Context factors* for a rich, embodied interaction may include aspects of the physical environment (or digital in the case of TUIs) [29,117,154], but also may be considered by the social, economic [84], or organizational settings [114] that influence the interaction to take place. The influence of context may by illustrated by the anecdote, “a convertible in one's garage is not the same as driving open-topped through lush hills on a beautiful summer evening” [155]. Consider the differences between having a coffee at a conference versus in a coffee house; the person is the same, the artifact, i.e., the coffee mug, is the same, but the experience can vastly differ; the context differentiates the two [96]. What is designated as the ‘context’ depends entirely on one’s perspective. An artifact may be the subject of the design process for one designer (e.g., the architect of the conference building or coffee house), but may be considered as a context factor by another (e.g., the designer of the coffee mug). What may be a pleasant interaction in one context, may be distinctly unpleasant in another. However, unlike the definite bodies of the artifact and the user, the context can be more ambiguous and less controllable, such that some explicitly omit this component from their consideration, e.g., [130].

Context Outcomes – Some elements of the experiential design outcomes may be considered contextual as well. While subjective and physiological responses are representations of cognitive or emotional states that are explicitly internal to the user, other outcomes—typically those in the realm of usability—are only meaningful within the context of the interaction. Some call for the explicit distinction between measures of emotional stimulation and those of task completion [111]. For instance, measures such as *efficiency* or *effectiveness* are measured in relation to the completion of a task that takes place in an environment, rather than an internal state of the user (e.g., satisfaction). Consider two users who ride two different bikes. One of these users could be an Olympic cyclist, while the other could be a small child; one of their bikes may be a finely tuned instrument, while the other may be a rusted scrap that falls apart after a one-kilometer ride. Naturally, both of these artifacts (the bikes) will perform differently and both users (the riders) will have different internal responses to riding them. However, the overall effectiveness is dependent on the task. If this is to ascend France's legendary Mont Ventoux, (i.e., the 'Beast of Provence'), it is reasonable to infer that one of these combinations of user and artifact may be more predisposed to effectively completing this task than the other. However, if the task is to simply ride down the block, both combinations may ultimately be effective regardless of the internal subjective or physiological responses that are elicited by this interaction. The task completion is assessed through measurements that are *external* to the user, and these are therefore considered to be *context outcomes* in this dissertation.

1.2.2. Embodiment Design: Analysis, Synthesis, and Evaluation

For rich, embodied interactions to occur, the artifacts must first be embodied in the real world. *Embodiment design* is the stage of the design process in which a *qualitative* concept or idea is translated of an into a form that may be physically represented, through the determination of specific *quantitative* parameters [19] (e.g., those relating to the form or layout). This stage is the focus of the work this dissertation. In embodiment design, the engineering designer seeks to answer questions such as "What are the values of key design parameters?" and "What is the configuration of components and assembly precedence relations?" [5]. This conversion from 'conceptual' to 'tangible' is a core skill of a designer [97]. The Embodiment Design Cartography framework is intended to support design tasks in the embodiment design stage of the overall design process. Before this framework may be discussed, it is necessary to first clarify exactly what design tasks pertain to embodiment design, and which tasks fall outside this scope.

There exist a variety of process models that are used to characterize the general steps of determining design solutions, e.g., [12,156–160]. One widely regarded design process model for systematic engineering design categorizes the overarching process in three distinct stages: *conceptual design*, *embodiment design*, and *detail design* [19]. In the conceptual design stage, the engineering designer starts with the assessment of the problem and conducts a search for viable solutions, i.e., concepts. In the embodiment design stage, the engineering designer starts with a selected concept and specifies the layout, form, or structure of the product to best meet objectives related to the design outcomes. In the detail design stage, the engineering designer starts with a definitive embodiment of the product and clarifies all specifications or production documentation to ensure economic feasibility. There is iteration between each of these stages as needed. In general, the embodiment design stage is considered to address the *layout*, while the conceptual and detail design stages are concerned the *principle* and the *production* of the product, respectively [12,19].

Another foundational description of modern, systematic engineering design defines three fundamental processes: *analysis*, *synthesis*, and *evaluation* [161,162]. Design analysis is the process of assessing the current state of some system and determining the needs, problems, or requirements to address. Design synthesis is the process of generating solutions to meet these needs or requirements. Design evaluation is the process of measuring the success of the proposed solutions in addressing the identified problems. These three processes provide a rational basis for systematic design procedures; without their explicit consideration, they may otherwise be circumvented to the detriment of the engineering designer [12].

The latter of these process models describes the activities that are completed in design, while the former prescribes *to what end* they are conducted. In this dissertation, these two seminal process models are overlaid to form the *Stage-Process* (S-P) model of design, illustrated in Figure 2. In the S-P model, the specific tasks of each of the fundamental processes (i.e., analysis, synthesis, and evaluation) are divided across the three stages of the design process (i.e., conceptual, embodiment, and detail design). The processes in the embodiment design stage of this model serve as the fundamental processes for which the Embodiment Design Cartography (EDC) framework is epistemologically[9] and methodologically[10] derived in Chapter 2. The design process generally flows from the conceptual, to the embodiment, to the detail design stages, and within each stage, from analysis, to synthesis, to evaluation. This process is iterative, so the engineering designer may revert back to any prior task as needed. All stages are described here, but *only embodiment design is focused on in this work.*

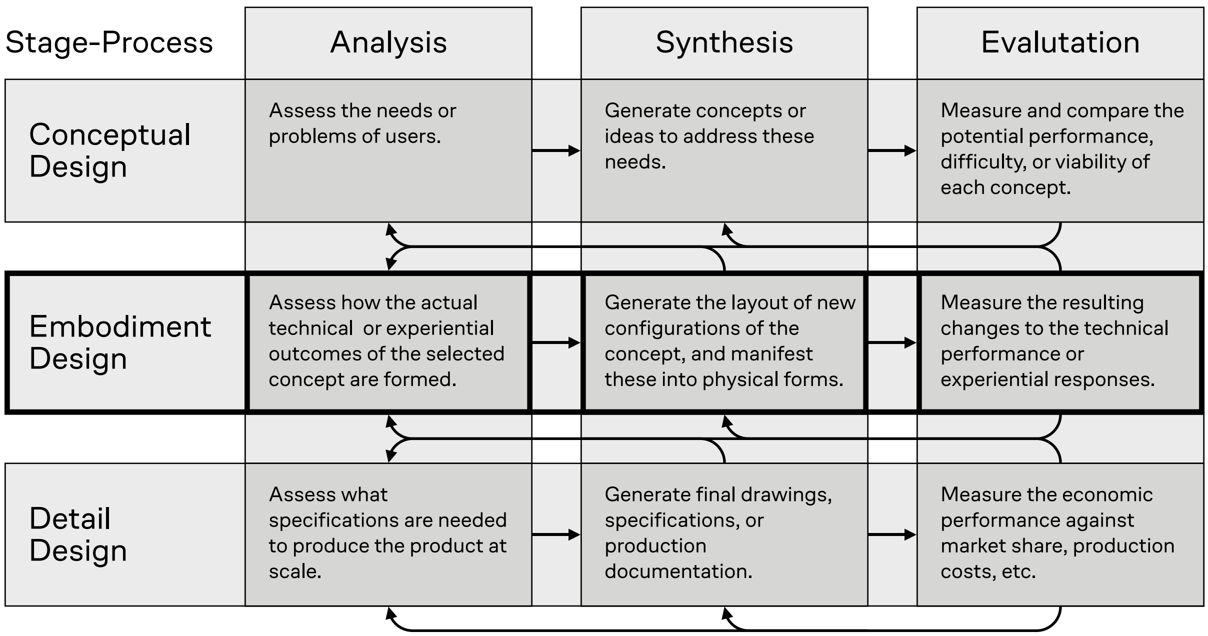

Figure 2. The Stage-Process (S-P) model of design. The overall design process is described by three fundamental processes: *analysis*, *synthesis*, and *evaluation*. These processes are repeated within each design stage: *conceptual design*, *embodiment design*, and *detail design*. The tasks that each process entails for each stage are described in this model. These tasks are iterative such that the designer may revert back to earlier processes or stages at any point. The Embodiment Design Cartography framework is intended to address the three fundamental process within the *embodiment design* stage (highlighted).

The Stage-Process model grounds all discussions of the design process in this work. While the focus of this ultimately centered around embodiment design, this model not only clarifies which specific activities are supported the EDC framework, but also which activities fall outside the intended scope of this framework, in other stages of design. The design problems presented in this work all center around the embodiment design stage. They begin with the principal idea of the concept already determined, and do not address the production of the product after the layout is

[9] **Epistemology**: A system for gathering or constructing knowledge about a phenomenon.
[10] **Methodology**: A system for applying rules or procedures for a particular task.

determined. The design space mapping serves to illustrate all the options for the structural form or layout that the physical embodiment of product may take in the solution space, within the lens of the external factors or outcomes that make up the problem space in a rich, embodied interaction. There are a variety of existing design methods that may be employed to support these processes.

1.3. Current Design Methods State of the Art

A design method is a specification for how the problem space is formulated, what the inputs (i.e., design levers) and outputs (i.e., the design outcomes) are, what tools may be used (e.g., graphical or statistical tools) for modeling the solution space, and what procedures are followed [163]. Design methods are subject to extensive research [108,164,165] across various disciplines [164]. Five established design methods originating across different fields are examined for this review: 1) Function-Behavior-Structure, 2) Quality Function Deployment, 3) Kansei Engineering, 4) Conjoint Analysis, and 5) Axiomatic Design. Each of these methods were selected for this review as representatives of different disciplines or perspectives that participate in design. These include engineering (FBS), project management (QFD), psychology (KE), and marketing (CA). Although not necessarily in name, it may be considered that each of these design methods themselves construct a sort of design space map, in various forms. Each helps to structure some of the considerations made in the problem space, and compare options in the solutions space.

In terms of the *design journey*, each of these design methods could be equated to different maps to the same cave system, which were each created for their own purpose. The treasures, i.e., the solution space, they lead to may differ. For instance, one could be a map of the locations of rare earth metal deposits. Another could be a map of ancient archeological sites. Still another could reveal areas that rare microorganisms inhabit. Each of these maps may therefore emphasize different areas of the cave, i.e., problem space, which are particularly relevant to their specific endeavors. In each of these cases, the map they provide may be drawn to different levels of detail to suit these respective needs—some may necessitate detailed topology, while a rough hand sketch on the back of a napkin may be sufficient for others. Similarly, each design method may consider different factors and outcomes of the rich, embodied interaction, and represent this interaction at different levels of *fidelity*. Furthermore, just as each map of the cave serves a unique purpose, each design method may support unique processes in the Stage-Process model of design (see Figure 2).

Ultimately, each may provide unique cartographic tools for design space mapping, including different conceptual classification systems to formulate the problem space, different quantitative modeling techniques to characterize the solution space, and different numerical or visual systems to compare options in the design space. Each of these design methods considers different factors and outcomes in rich, embodied interaction, and navigates between them through different activities that span the embodiment design processes (as well as other stages of design). These design methods are reviewed in turn.

1.3.1. Function-Behavior-Structure

The Function-Behavior-Structure (FBS) framework [13,166,167] is posed as a generic *engineering* description of the design process for any artifact [168,169]. FBS is centered around the core components of *'function'*—what the artifact is for, *'behavior'*—what the artifact does, and *'structure'*—what the artifact consists of [29,35,170–172]. For instance, a house/shelter could characterize its 'function' to be 'comfortable,' and 'affordable.' Its 'behavior' could then be characterized by the 'strength,' 'weight,' and 'cost'; the 'function' and 'behavior' may be quite closely linked, i.e., the relation between 'cost' and 'affordable' is a simple linear proportionality. Finally, its 'structure' would be characterized by the 'geometry of the floors, walls, ceilings, etc.' [171], i.e., its layout or form. FBS also describes several design processes for maneuvering between these domains [35] to address both the problem space and solution space [11]. *Situated* FBS is an evolution to this original work, which accounts for the perspective of the designer in this process [35,171,173]. FBS has been used to develop general design tools [174], identify cognitive patterns or schemes in design students [11], and support inventive problem-solving [175] or usage-driven innovation [10]. This framework is well established within the design community [176,177] and has been applied as a means for both understanding the design process and supporting applied design endeavors [178].

The procedure detailed by FBS involves propagating the 'function' down through the 'behavior,' into the 'structure.' The 'functions' may either be directly defined by the designer according to desired technical performance [168,170], or propagated by higher level needs/requirements [169]. Some divide these 'functions' between those that are manual and those that are automatic [168]. The 'structure' may then be defined through functional analysis [179,180], and is evaluated according to its ability to meet the criteria defined by the 'function'

[168]. In situated FBS [35,171,173], two distinct versions of 'behavior' are subsequently described—the *'expected behavior'*, i.e., the 'behavior' that was intended to fulfil the 'function', and the *'structure behavior'*, i.e., the 'behavior' that is actually realized by the 'structure.' These two versions of 'behavior' may be directly compared to evaluate the success of the design.

However, FBS is not without criticism, e.g., [10,105,169,178]. The method originated out of engineering and is primarily directed at design outcomes on a technical level, rather than the experiential [108,168]. In this vein, FBS provides limited support of user or context factors. This may be attributed to the framework's lack of *flexibility* in the problem space formulation, i.e., "the need for flexible representation of different levels of abstraction is necessary in capturing problem formulation data [in FBS]… [S]ources (e.g. customer needs, regulations, conditions of the operating environment), and the mating conditions among components help improve capturing more of the formulation space and thus opening potential ways for the discovery of paths to creative outcome" [176]. Several practitioners have noted these absences [181,182], and have proposed different extensions to incorporate the 'user' [168] and 'external effects' [103] into the FBS formulation.

1.3.2. Quality Function Deployment

Quality Function Deployment (QFD) is an organizational planning and *project management* method for relating 'customer requirements' and 'engineering characteristics' [183–188]. The preeminent goal of QFD is to set targets of the 'engineering characteristics' that optimally satisfy the 'customer requirements' [187]. QFD originated in Japan in the 1960-70s and later gained popularity in the US in the 1980s [183,188–198], its original meaning is approximately translated as, "strategic arrangement (deployment) throughout all aspects of a product (functions) of appropriate characteristics (qualities) according to customer demands" [12]. The use of QFD had been reported to reduce development time and costs [17,99], reduce the number of necessary iterations and design changes, improve user's perceptions of quality and reliability, and increase market share [199–204].

The implementation of Quality Function Deployment is primarily built around a graphical matrix known as the House of Quality (HOQ) [99], although additional matrices may be used to further link the 'engineering characteristics' to 'part characteristics,' even further relating those to manufacturing 'process variables' [205,206]. To formulate the problem space in QFD analysis, the dimensions of the ‘customer requirements’ are first determined through market research techniques, and their relative importance is weighted [12,183]. These are entered into the HOQ matrix against the ‘engineering characteristics,’ and the strength of their relation is approximated in the body of this matrix via symbols (e.g., strong, weak, or none) or with numeric scale. The relations between the ‘engineering characteristics’ are also similarly approximated in the head of this matrix. Each ‘engineering characteristic’ may be denoted with a ‘+’ or a ‘–’ according to whether the engineering designer wishes to maximize or minimize the parameter [12,186], if that knowledge is available. The relative importance of each can be used to weigh the priority given to the ‘engineering characteristics’ and ‘customer requirements.’ Users may interact with discrete configurations of the artifact (i.e., configuration A/B) , and provide their ratings on a 5-point Likert scale [207]. Marketing methods such as ‘hall tests’ may be employed in this endeavor, in which users come in an physically interact with a few configurations of a product [12], and possible complete tasks with them to gauge context outcomes, not just user outcomes, i.e., subjective perceptions. Practically, this is feasible as there are only limited configurations/competitors to evaluate. These ratings then help the engineering designer determine ‘engineering characteristic’ targets for a theoretically improved design configuration [12].

This method aims to address the challenge in designing for user’s abstract descriptions of their ‘customer requirements’ by equating them to more concrete ‘engineering characteristics,’ i.e., “the statement ‘Want to use tool continuously’ does not give a designer much useful information, but a desired Tool Mass of 3.0 Ibm and Peak Torque of 200 in lbf make the design problem much better defined” [186]. Additionally, the HOQ explicitly acknowledges the tradeoffs that exist within the design through the head of the matrix [12,186]. QFD provides designers with a useful index of how their current design configuration compares to competing configurations, and allows them to set targets for improvement while serving as a reminder of the couplings that exist within the artifact [186].

However, critiques of Quality Function Deployment are largely centered around the over reliance of intuition and the general vagueness of the insights [187,200,205,208,209]. The notional relations may have dubious mathematical validity [12] and do not always adequately reflect the true functional relations between these constructs [200,209–211], such that their utility for design is limited [186]. The identification and classification of the strength of these relations relies on the implicit knowledge, assumptions, or ‘qualified guesses’ [212] of the engineering designer, rather than empirical measurement [12,204,205,213,214]. Many practitioners have worked to overcome the general impreciseness of QFD through implementation of *fuzzy logic* [215], e.g., [187,202,208,216–227]. In the body of the HOQ matrix, fuzzy regression may be used to characterize more precise functional relations between the 'customer requirements' and 'engineering characteristics' [187,228–230]. In the head of the HOQ matrix, engineering models have been used to augment the relations between the 'engineering characteristics' by characterizing functional relations between them and the underlying 'design parameters,' such that tradeoffs may be more precisely quantified [186].

These inherent limitations in the problem space formulation through Quality Function Deployment, however, have implications on the subsequent solution space. QFD does not afford a complete mapping of the available solution space, but rather enables comparison between discrete configurations or competitors [12]. This direct comparison may not afford the level of intuitive insight in what improvements may be available [190,205], which may be evident through a more robust mapping of the solution space. Engineering designers may use QFD to set individual targets for the 'engineering characteristics,' but it is not always guaranteed that said configuration is achievable [186]. The manual process for positioning new design configurations within the HOQ matrix is quite involved, and cannot be easily updated in real-time [208]. Additionally, the purpose of QFD is only to relate 'engineering characteristics' to 'customer requirements,' which typically preclude the artifact outcomes that are largely addressed by other engineering models. In other words, "the target levels of engineering characteristics are determined by considering ['customer requirements'] in a way to satisfy a single objective, which is maximizing overall customer satisfaction. In general, the satisfaction of ['customer requirements'] is not the only consideration in product design. Other requirements such as cost budget, technical difficulty, and extendibility also need to be considered" [187]. Factors of the context and user are also not expressly incorporated into QFD protocols.

1.3.3. Kansei Engineering

Kansei Engineering (KE, also known as Affective Engineering [213]) is an established method with roots in *psychology* for functionally relating the *'Kansei'*—or emotions—of the user to physical properties of artifact [213,231–235]. KE similarly emerged out of Japan in the 1970s [232]; the term 'Kansei' refers to the users internal emotional, cognitive, or physiological responses [232] that are reflexively prompted through product stimuli [233]. KE has been extensively implemented to promote the emotional design of a wide range of successful products, e.g., the Mazda Miata and its heralded 'joyful driving' [234,235].

The general Kansei Engineering procedure is centered around defining the dimensions of two domains or vector spaces—the 'semantic space' and the 'properties space'—and then characterizing the transformation between them through a Kansei Engineering System (KES) [212,231], e.g., [236–239]. The dimensions of the 'semantic space' are defined by 'Kansei words' [233,240]. Classically, these are *subjective* perceptual descriptors (e.g., 'luxurious'), although this has been expanded to include *physiological* responses as well [213,241–243]. A variety of techniques may be used to determine these dimensions, such as the consultation of experts, pertinent literature, or target users [212]. The dimensionality of this domain can be quite high, reaching up to 600 descriptors in some instances [244]. The 'properties space' is similarly defined; it is generally accepted that the dimensions of this domain already 'exist'—so-to-speak—as observable attributes of the artifact [231]. The task of the designer is to select those that are most influential on the 'semantic space'. Due to lack of necessity, there are comparatively fewer specialized techniques developed to aid the characterization of these 'properties space' dimensions [212,231]. Users then evaluate artifacts that embody the specified dimensions of the 'properties space' over the dimensions of the 'semantic space' through Likert [207] or Semantic Differential scales [245], e.g., [236]. The subsequent KES is quite beneficial for measuring embodied design configurations in terms of user's emotions [243,246], and is primarily used as such [243].

Whereas QFD relies on expert knowledge or assumptions to *notionally* characterize relations between these domains, the KES employs statistical methods to *empirically* characterize these relations, e.g., [213]. A wide variety of statistical methods may be employed in this service [213] (e.g., Quantification Theory Type I [213], II [212,231], or III [213], linear regression [247], generalized linear models [248], discrete choice models [246], neural networks [249], fuzzy logic [213,250], genetic algorithms [251], rough set models [213,252–255], etc.). In fact, KE protocols largely refrain from specifying the statistical methods to use, such that a wide variety of pre-existing statistical techniques may be supported [231]. The use of these statistical methods enables additional consideration of 'customer groups' [212], i.e., user factors, and 'contexts' [256], i.e., context factors, in this analysis. With these mathematical models, a map of the solution space may be graphically visualized (e.g., via density, scatter, or contour plots) to display the positioning of discrete design configurations in relation to more abstract outcomes [213]. For instance, “a three-dimensional contour map is created for the specific Kansei word. Kansei evaluation value for each sample is added as a height value augments the map [sic]. Then a smooth contour that interpolates between the Kansei values of the samples is computed by a local regression method. The proposed methodology creates a three-dimensional contour map that helps researchers to recognize both the linear and nonlinear relationship” between the ‘semantic space’ and the ‘properties space’ [213].

One criticism of Kansei Engineering is that the ‘properties space’ is typically comprised of mainly *categorical* variables (e.g., color, shape) in practice, which precludes the possibilities for innovation or intuitive interpolation of more optimal design configurations within a *continuous* solution space [243,257]. Another criticism is that KE evaluation is either conducted on two-dimensional representations of artifacts [213,231,243,257], or physically-interactive artifacts that *already exist* [246,257]; there are limited mechanisms in KE for actually physically creating *new* design configurations that may be subsequently evaluated [258], especially given the potentially large amount of design configurations necessary to achieve a statistically reliable result [212]. The use of two-dimensional product images to attenuate this issue, e.g., [234], is not commensurate with rich, embodied interaction; a picture/description of a hammer does not provide the same stimulus as physically swinging the actual object [259]. Physically-interactive artifacts are relatively less studied in KE [236], but this is not to say they are incompatible. Several practitioners have successfully applied KE to *evaluate* artifacts that afford haptic feedback (e.g., keyboards [236,260], switches [238,256,261], rotary dials [262], etc.). These studies have found strong correlation between the domains when haptic feedback is involved [236], but have been limited in their creation of new, physically-interactive design configurations, which may be prohibitively costly [231]. Virtual reality (VR) is another avenue that has been explored in this regard [213], but again is insufficient for simulating the physical engagement of rich, embodied interaction (at current technological capabilities).

Additionally, the statistical model must be *validated* before it can be used for embodiment design synthesis [212,231]. However, the high dimensionality of KES domains can be critically detrimental [108,263] to statistical power [264], and introduce issues of multicollinearity in linear models [213]. Post-hoc dimensional reduction techniques can address these issues [213], but from a practical standpoint, this high dimensionality can also be prohibitive to user evaluation due to induced fatigue or boredom [212]. In practice, this dimensionality may be limited or reduced *prior* to evaluation, through various techniques such as pilot studies or factor analysis [212,248]. In spite of these efforts, the resulting model validation still typically comes at the end of the design process—on the finished product [234,244]—but this can result in long, costly iterations [231]. KE can already be quite time intensive, so efficiency and minimizing iterations [108,265,125] in validation is critical.

This method also does not explicitly address the underlying form or layout of the artifact, which likely explains the issues some have raised in translating KE insights into concrete engineering design decisions, e.g., [246]. While factors of the user and context may be considered in this method, they are not typically incorporated directly into the transformations described by the statistical models. KE is also inherently dedicated to outcomes on the experiential, i.e., emotional, level and therefore does not address context or artifact outcomes.

1.3.4. Conjoint Analysis

Conjoint Analysis (CA) is a popular *marketing* method that has since been adopted for product development. This method is used to statistically relate 'product attributes' to users' *utility* through a preference model [266–269]. CA was developed throughout the 1960s and 70s [266,270–272] and has seen continuously growing application since its inception [15]. CA is commonly used to determine *part-worth utilities* and *relative importance weights* of the 'product attributes' (Artifact-What) [16,273]. In engineering design, this method has been widely implemented for optimization, e.g., [274–278]. CA has an extensive track record of promoting innovative engineering design [279].

The Conjoint Analysis protocol generally follows several discrete steps [15,266]:

1. First, the form of the preference model is selected. The part-worth utility function is typically used in modern CA [280]; this is the basis for determining the partial utility for each individual attribute of the artifact [266,281].
2. Second, the relevant attributes of the artifact that define the problem space, i.e., the artifact factors, are parameterized through literature reviews, expert input, interviews/focus groups [280], or simple observations [282], e.g., [34,283–286], although formal support for this parameterization is somewhat limited [287]. These attributes are then discretized across

the span of this continuous space on several levels that comprise the design configurations that are presented to the user, e.g., [34].

3. Third, the evaluation format and experimental design of the Conjoint survey may be selected. This could through basic rankings or ratings [288,289], or more complex formats such as a pair-wise design, i.e., Choice-Based Conjoint analysis (CBCA), in which users select between several alternative design configurations instead of rating each one, or an adaptive design i.e., Adaptive Conjoint analysis (ACA) [267,290,291], in which each subsequent design configuration presented to the user is based off of their responses to the prior [290,292,293]. CBCA is generally favored for determining cost, while ACA is preferred for smaller sample sizes [294].
4. Fourth, the manner in which the artifact is *represented* is determined across a continuum of *fidelity* [34]. The artifact could be presented as a verbal description of the attributes (low-fidelity) [15], a visual representation, e.g., 2D image (medium-fidelity) [15,28,288,295–300], or a physical prototype (high-fidelity) [301–306]. There are advantages and drawbacks to each representation style [266,267,305]. Lower fidelity representations require fewer recourses to produce, but may not adequately communicate the relevant attributes of the artifact to the user [305]. Higher fidelity representations can better forecast real preference [34].
5. Finally, the survey may be conducted and the resulting utilities are subsequently estimated using some statistical model (e.g., logit or probit models for CBCA) over the continuous solution space [280].

In terms of rich, embodied interaction, 'utility' can represent different outcomes depending on the experimental design of the Conjoint survey. For CBCA, the act of choosing a preferred design configuration among alternatives is a simulation of *purchasing* the product in the marketplace. Judgements such as 'purchasing' are aggregate decisions based on design outcomes on both the technical and experiential level [17,34,169,278,307,308], but are not necessarily a direct measurement of either outcome individually. However, other formats—like ratings—are based solely on user's subjective perceptions, and are therefore formatted to capture the user outcomes directly. While CBCA can theoretically encompass all of these multifaceted design outcomes into utility by measuring 'purchase intention,' this aggregation can lead to less accurate preference models across the solution space in comparison to formats that measure outcomes individually, such as through ratings [278,282,288,289]. Additionally, CBCA requires simultaneous evaluation of multiple design configurations, which can cause cognitive overload when the representation of the artifact is of higher-fidelity (e.g., a physically-interactive prototype) and ultimately impede judgements [309–311]. Rating-based formats that measure subjective perceptions are therefore recommended in these applications [34].

The primary benefit of Conjoint Analysis lies not only within the discrete *evaluations* of the parameterized design configurations over the select discretizations, but in the ability to prescriptively apply the estimated preference model to *synthesize* new design configurations over the span of the continuous solution space [15,34,282]. "[S]ince the discrete levels… can represent continuous variables, the extracted preference models can, and often do, result in concept designs that were not presented to the respondents but are interpolated from within the design space. These emergent concept designs match consumer and user preferences but have not yet been seen or assessed by said users and consumers" [282]. With these newly synthesized design configuration, corresponding representations of these artifacts may be generated—*automatically*, if technologically feasible [295]—and subsequently evaluated to validate the preference model's ability to predict user preference over the continuous design space, e.g., [295]. This may be applied to both conceptual design innovations and embodiment design improvements [15], and can help in both reducing design iterations [282] and efficiently allocating resources [34].

However, Conjoint Analysis is limited when dealing with physically-interactive artifacts. Conjoint surveys require a large number of evaluations on different design configurations to construct the preference model across the continuous solution space [15,34,280,282]. For rich, embodied interaction, these design configurations must be represented by physical prototypes to adequately communicate important attributes, i.e., artifact factors, such as haptic feedback to users. In terms of cost, time, and space, physical prototypes are by far the most resources intensive representation of an artifact that may be used in CA [34,279,305], in which a large number of costly prototypes are necessary. This is especially challenging for adaptive experimental designs (i.e., ACA) or validation of preference models, in which newly synthesized design configurations must be rapidly generated. As such, CA is often conducted online/digitally using only visual or descriptive representations of the artifact, e.g., [28,279,288,295,297–300,312]. Similar to KE, virtual reality (VR) has also been explored for CA, e.g., [34,313,314], but again is insufficient for simulating the haptics of rich, embodied interaction [43]. The use of physical prototypes in CA is certainly not non-existent, e.g., [301–304,315], but these endeavors remain quite resources intensive and are generally limited to simple artifacts that may be rapidly prototyped (e.g., 3D-printed coffee mugs) rather than complex devices that afford rich, embodied interaction (i.e., that can provide more complex, information-imbued haptic feedback), for which this method may be infeasible [34].

Another aspect of Conjoint Analysis that is somewhat of a double-edged sword is its lack of direct consideration of the form or layout of the artifact, which the engineering designer may directly control. On one hand, this effectively shields the users from the underlying complexity of this engineering [282]. However, this of course limits the applicability for engineering design. To address this limitation, practitioners have implemented Analytical Target Cascading (ATC) [316,317], a hierarchical engineering optimization method [318], as an extension to CA [28]. In this extension, an engineering model is constructed alongside the traditional preference model to link the concrete engineering design levers of the 'engineering parameters' to the preference model as well. However, this method did not create new physically-interactive prototypes, but rather relied on visual representations [28,282]. Beyond this extension, CA generally does not address user or context factors in the problem space.

1.4. Research Issues

Despite these extensive works on existing design methods, within the context of design space mapping, none of them are: 1) singularly capable of supporting *holistic* consideration of all of the factors and outcomes in rich, embodied interaction, and 2) uniquely advantageous in facilitating a *rigorous* mapping of the design space to not only understand what options are available, but also how to create them with available design levers. This is by no means a knock on these existing design methods; not every design problem requires the full consideration of every aspect of the rich, embodied interaction phenomenon, nor is it always feasible or even prudent to do so. These design methods were developed to address specific problems [163] and are each quite effective in their individual aims. To some extent, it is often possible to combine or integrates these methods such that a broader, more robust design space may be supported. For instance, there have been demonstrable combinations of several of the existing design methods, including KE + QFD [212,213,319,320], CA + KE [273], etc. In general, interest in understanding how different design methods can complement each other has been growing in recent years [10]. However, there is not a clear delimitation of exactly which design methods may be integrated together and which cannot, as well where exactly their potential compatibility points may lie.

> *"Some methodologies cover the whole of the design sequence, others concentrate on important parts of it and may be fitted into other methodologies to improve their probability of aiding the solution of engineering problems."*
>
> – W. E. Eder, *Definitions and Methodologies*, 1966 [321]

This difficulty can be attributed to the fact that these design methods may each be considered as conceptual *'wrappers'* for the underlying considerations they support in their respective design spaces. These 'wrappers' contain the procedures, associated statistical or graphical tools, input/output designations, etc. [163], which are each built upon their own distinct taxonomies and/or ontologies. Design is a multidisciplinary field and nomenclature is often unstandardized; practitioners may use different terminologies to describe similar phenomena [21,171], and critical concepts can often have divergent definitions, e.g., [177]. For instance, it can be unclear as to how terms like 'engineering characteristics' in QFD and the 'properties space' in KE relate to one another, or whether they are actually describing the same concepts. These definitions can shift over time and even tend to be tweaked on a case-by-case basis to fit practitioners' specific needs.

While each these distinctions may have been originally made for independently logical or advantageous rationale, these 'wrappers' also define inherent *boundaries* between design methods [12] that impart difficulties in making direct comparison due to divergent terminologies [172]. As maps of the *design journey*, each design method may detail different passageways and treasures within the same cave system, but they often lack any sort of common landmarks or coordinates to enable their combination. A manner for bridging these boundaries—a *Rosetta Stone*, so-to-speak—is therefore needed to leverage existing design methods as tools in Embodiment Design Cartography.

Overall, the gap between the existing design methods and the desired capabilities for rigorous, holistic design space mapping spans four key research areas: 1) flexible formulation the problem space to capture all relevant considerations in rich, embodied interaction, 2) robust mathematical models to characterize the solution space through the processes of embodiment design, 3) novel experimental techniques and procedures for supporting physical interactions and capturing varied design outcomes, and 4) operational design insights for innovating in real-world design problems. Each of these issues is detailed in turn.

1.4.1. Formulating the Problem Space

The formulation of the *problem space* is a specification of what considerations are made in the design problem. Based on the description of *rich, embodied interaction*, it is evident that are a wide variety of *factors* and *outcomes* that need be considered when translating the conceptual idea of a product into its physical form. Across the various factors and outcomes of the *artifact*, *user*, and *context*, down to the specific *layout* or *form* of the artifact that may be embodied, mechanisms are needed to systematically account for each of these considerations. While each design problem supported in this framework falls under the class of 'embodiment design,' each may also be unique in which considerations are relevant. A manner for *flexibly* formulating the problem space is therefore needed to tailor the design space map to the problem at hand.

1.4.2. Modeling the Solution Space

The model of the *solution space* is a specification for how options of achievable design configurations are understood in terms of the defined problem space. To not only map *what these options are*, but also *how to create them*, a mathematical model is needed to relate abstract design outcomes to concrete design levers, while accounting for any external factors. Modeling techniques for simultaneously supporting a variety of factors and outcomes on both a *technical* and *experiential* level are necessary. Through the processes of *embodiment design*, this model may be characterized according to the relations between these factors and outcomes (i.e., *analysis*), operationalized to create new design configurations (i.e., *synthesis*), and finally validated through user testing (i.e., *evaluation*). Mechanisms for supporting each of these processes are therefore needed to promote the construction of robust models of the solution space.

1.4.3. Developing Experimental Techniques & Procedures

The phenomenon of rich, embodied interaction entails a *physical interaction* with a real product that elicits *experiential* responses from an actual person; this interaction must also be situated in a relevant context or contexts. For this interaction to occur, a *physically-interactive prototype* is necessary, which can be an involved, time intensive process to produce. Additionally, experiential responses are expressed through a wide variety of different channels (e.g., self-report, physiological responses, observation, etc.), which must be each be individually recorded and, if necessary, interpreted. However, the *real-time* generation of new, physically interactive prototypes based on these experiential responses is necessary to utilize adaptive experimental designs or to validate models. A suite of specialized experimental techniques and procedures are therefore needed to empirically measure (and ultimately model) interactions, and to generate high-fidelity prototypes within practical resource constraints (i.e., time, money, space, etc.).

1.4.4. Operationalizing Embodiment Design Cartography

The ultimate aim of embodiment design is to create products that provide the best possible outcomes of benefits in the real-world. *Case studies* for real-world design problems are necessary for bringing each of the prior research issues together—formulating the problem space, modeling the solution space, and developing experimental techniques and procedures—and *operationalizing* them for real design work. There are a variety of insights that that may be explored with design space maps, which each may be supported or extracted though *visualizations* of these maps. For one, different options in the solution space may be compared in terms of the *outcomes* they afford. The *tradeoffs* that may exist between these options in improving one outcome at the cost of another may be negotiated within the design space map. Alternatively, the manner in which different *factors* are brought into consideration may be examined as well. Information about specific users, for instance, could be incorporated to *personalize* the design space map to their specific needs or characteristics. Understanding how to navigate tradeoffs [322,323] and implement product personalizations [324,325] through customer input are two longtime issues that have plagued new product development [326]. A means for putting Embodiment Design Cartography into practice is therefore needed to extract these insights and apply them to address critical issues in real-world design problems.

1.5. Research Goals & Objectives

The goal of this research is to develop the comprehensive practice of *design space mapping* to enable the *holistic*, *rigorous* understanding of the available solutions that *physically-interactive* products may take in terms of a structured design problem. Three key research objectives are crucial to achievement of this goal:

1. ***A Framework for Embodiment Design Cartography*** – The first objective is to derive a *conceptual framework* to support the cartographic activities of design space mapping for design problems rooted in 'embodiment.' This includes supporting a *flexible problem space formulation* that may be tailored to specific design problems, and a *selectively integrative solution space modeling* that may leverage existing design methods.
2. ***A Method for Navigating Tradeoffs in an Emerging Technology*** – The second objective is to apply the EDC framework to develop and demonstrate *modeling*, *experimental*, and *design* techniques within the context of an *emerging* technology. These are needed to negotiate favorable *tradeoffs* between technical and experiential design outcomes using *engineering design levers*.
3. ***A Method for Personalizing Options of an Established Technology*** – The third objective is to apply the EDC framework to develop and demonstrate *modeling*, *experimental*, and *design* techniques within the context of an *established* technology. These are needed to *personalize* the available product options by permitting the user to control their own *psychophysiological design levers*.

By successfully addressing each of these objectives, the conceptual groundwork is laid for the practice of design space mapping, and the utility of such a practice is demonstrated in two distinct applications that are particularly relevant in new product development.

1.6. Research Approach

In order to meet the research objectives and ultimately develop the practice of design space mapping, a 'Research Through Design' (RTD) approach [26,327,328] is employed in this dissertation. RTD stipulates that design knowledge may be generated on two levels: 1) the actual product that is produced, and 2) the general methods for its development [97]. In this way, the understanding of general procedures and methodologies is derived through their application to real-world design problems, e.g., [93,329]. For this approach, a general procedure is defined through the Embodiment Design Cartography (EDC) framework, and is applied to two case studies for the embodiment design of two different physically-interactive products. The operational validity of this framework may therefore be critically assessed in a real-world sense. This validation is conducted *incrementally*, i.e., "the validation of methods has to be an iterative process, whereby different aspects of the method need to be assessed separately. At each stage, it is necessary to look at the scope, coverage and potential benefits of a method" [163]. Each case study is centered around a different aspect of the EDC framework, in which each problem space is formulated differently, and the associated solution space is modeled accordingly. This incremental development and validation allows for the assessment of intermediary results, which may be subsequently addressed [212]. Each chapter therefore aligns to a respective research objectives, and addresses a subset of the noted research issues.

1.6.1. A Framework for Embodiment Design Cartography

To derive the *conceptual framework* for Embodiment Design Cartography in Chapter 2, an *ontology*, an *epistemology*, and a *methodology* are each defined around the phenomenon of 'embodiment' for design space mapping. These three components, which provide the philosophical basis for any conceptual framework [330], are summarized in turn:

1. The EDC *ontology*—the classification of concepts and relations—is grounded on two core perspectives. First, every rich, embodied interaction may be described by an artifact, a user, and a context. Second, the description of these actors may be deconstructed across three different levels of *abstraction*: 1) *how* they are composed, i.e., the form/layout of the artifact, 2) *what* they are, and 3) *why* the product was created, on both a technical and experiential level. Every consideration in the problem space may be mapped onto an *Actor-Abstraction* (A-A) matrix, in which the two dimensions of this matrix are given by the respective actors and abstraction levels.

2. The EDC *epistemology*—the construction of knowledge—establishes four principles for how data is treated in this framework, including how it is: 1) *directed* across the A-A matrix, 2) *collected* from different sources, 3) *propagated* between abstraction levels, and 4) ultimately *validated*. These principles serve to define how the options in the solution space are determined.

3. The EDC *methodology*—the manner for which it is operationalized—is based off of the embodiment design processes within the Stage-Process (S-P) model (see Figure 2). The specific steps of constructing a design space map are categorized within each of these core processes (i.e., analysis, synthesis, and evaluation). These activities dictate how the EDC

ontology and epistemology are applied in practice, and enable the solution space to be constructed for real-world design problems.

This framework is constructed to serve as a *boundary object* for existing design methods. A boundary object is a flexible tool that may be both broadly structured to support different perspectives that lack taxonomic consensus (i.e., the different design methods), but also precisely structured such that it may be tailored to a specific design problem. The derivation of this conceptual framework, the complete details of which are given in Chapter 2, addresses several key research issues.

Formulating the Problem Space – A system is defined for *graphically* mapping out the problem space formulation for a specific design problem within the broader structure of the A-A matrix. The problem spaces that are formulated by the existing design methods are each translated into the language of the EDC ontology and mapped out using this matrix. This serves to place each of the existing design methods in common terms—where they previously deviated—and allows for the identification of areas of overlap, therefore bridging their inherent boundaries. In terms of the *design journey*, these disparate maps of the cave system are redrawn to align to a common scale, such that they may then be overlaid. This highlights the flexibility of the A-A matrix to not only support each of these different existing design methods, but also opens the door for formulating *new* design methods.

Modeling the Solution Space – The solution space is constructed by modeling the relations defined in the problem space map within the A-A matrix. The characterization of these models is achieved through the principles of the EDC epistemology and steps of the EDC methodology. The former clarifies when *empirical study* is necessary versus when *analytical* modeling is appropriate based on the different sources of data for this model. The latter describes the several specific activities that may be conducted to facilitate the processes of analysis, synthesis, and evaluation of this model.

Developing Experimental Techniques & Procedures – The EDC methodology is used as a lens to critically examine each of the activities prescribed by existing design methods. By breaking each method down on this scale, it can be determined which embodiment design processes they support, and of these, which activities may be specifically advantageous in the context of design space mapping. These identified activities are *selectively integrated* into the EDC methodology as tools to promote the efficient modeling of the solution space. Additionally, a technique for the efficient generation of physically-interactive prototypes is enabled by the *modularization* that the A-A matrix affords. In the EDC framework, prototypes are only used to elicit experiential design outcomes that require the rich, embodied interaction to occur for their manifestation. As such, only the *responsive attributes* (e.g., haptic feedback) of the product are necessary to product for said interaction to occur. These attributes may be replicated for design space mapping using alternate means or technological solutions than they would in the real-world. These alternative technological solutions may be *adaptive*, in that they can replicate multiple different configurations across the solution space without necessitating the resource-intensive construction of each configuration individually.

Operationalizing Embodiment Design Cartography – The EDC framework is employed to retroactively construct the design space maps given by existing design methods within a uniform structure. In this common scale, these design methods may be directly compared against each other to illustrate how their conceptions of the problem space, as well as their protocols for modeling the solution space, may vary. Additionally, this mapping can illustrate gaps that could suggest future work, and in some cases have already been addressed by extensions to these methods. This mapping can also reveal specific points compatibility between these existing design methods. However, this exercise does not yet address the creation of *new* design methods that are tailored to specific design problems, nor does it demonstrate utility of design space mapping for informing actionable design decisions.

1.6.2. A Method for Navigating Tradeoffs in an Emerging Technology

To develop a method (including modeling, experimental, and design techniques) for putting the EDC framework into practice, a case study for the design space mapping of a *pneumatic steering column* is conducted. The pneumatic steering column is a device that would be outfitted onto autonomous vehicles and allow for a limited-use steering wheel to be stowed or deployed by regulating pressure in a hollow, inflatable steering column. This *emerging* technology would be used to relinquish manual control back to the driver in emergency situations. However, while this technology would enable a novel stow/deploy functionality, it would also impart a unique feel to steering the vehicle. Both the *kinesthetic haptic feeling* of steering the vehicle, as well as its technical ability to be stowed (among other functions) would be impacted by the underlying form/layout of the steering column itself. Given the emerging nature of this technology, is not immediately evident as to what *tradeoffs* between these technical and experiential design outcomes may exist, nor is it apparent how to determine an option in the available solution space the provides a favorable balance. The EDC framework is therefore employed to map out the design space of this real-world design problem and provide rigorous, holistic insight to these specific challenges. This method, the complete details of which are given in 0, addresses several key research issues.

Formulating the Problem Space – Using the Actor-Abstraction matrix developed in the prior chapter, the problem space for this case study was formulated to bring experiential considerations into a technical design problem. Typical engineering design problems will take an 'artifact-centered' focus, in which the technical objectives relating to the artifact are propagated to—and generally, optimized by—adjustments to the parameters of its form/layout. In this formulation of the problem space, both the technical function (i.e., artifact outcomes) and the experiential response (i.e., user outcomes) were considered as equally critical outcomes to the design problem. External, environment attributes (context factors) were also considered to be especially relevant. The abstract design outcomes were both functionally related to the underlying form/layout of the device, where the concrete engineering designer levers were located. This ultimately represented a new problem space formulation within the A-A matrix, which is distinct from existing design methods.

Modeling the Solution Space – In order to model the solution space across the levels of abstraction, multiple mathematical models were characterized and a technique for *composing* these models was developed based on their natural functional forms. An *interaction model* was used to characterize how the rich, embodied interaction (i.e., twisting with the steering column) elicited experiential responses. This statistical model, which was based on perception to physical stimuli was composed on a *logarithmic scale* in accordance with the *psychophysical*[11] principle described in the Weber-Fechner law [331,332]. An *engineering model* was used to relate the responsive attributes of the steering column that were relevant to the rich, embodied interaction to the layout/form of said device. This mathematical model was based on *power law sensitivities*. When these power law sensitives were mapped into the logarithmic scale of the interaction model, the experiential design outcomes were related to the engineering design levers, and the power law

[11] **Psychophysical**: The psychology that pertains to how humans perceive physical stimuli.

sensitives became linear within this logarithmic scale. This enabled a *linear algebraic*-based exploration of the tradeoffs in the solution space.

Developing Experimental Techniques & Procedures – A user study (n = 57) was conducted to empirically construct and validate the solution space model. Using the prototyping technique afforded by the EDC framework, an *interaction prototype* for the pneumatic steering column was constructed, which could replicate a continuous range of potential design configurations across the solution space with high fidelity. This prototype was outfitted to a driving simulator, which simulated the physical environments in which the rich, embodied interaction of steering the vehicle occurred. Participants of the user study interacted with the prototype and provided their subjective responses. An *adaptive, self-validating* experimental design was employed, in which new design configurations were predicted based on participants prior responses and generated in real-time with the interaction prototype. These new design configurations were then immediately evaluated to validate the solution space model.

Operationalizing Embodiment Design Cartography – With the solution space model validated, the linear algebraic approach for exploring the solution space was employed to negotiate tradeoffs between design outcomes on the technical and experiential levels. The former power law relations of the engineering model—now linear in the logarithmic space—were represented as vectors on a contour plot for the interaction model. These overlayed vectors represented changes to the experiential design outcomes that would be achieved through relative adjustments to the concrete design levers. With this graphical system, *actionable* design insights for this emerging technology were uncovered with regards to how make adjustments that resulted in favorable tradeoffs between design outcomes, i.e., mitigating negative impacts on either the technical or experiential level in order to improve outcomes on the other.

1.6.3. A Method for Personalizing Options of an Established Technology

To develop another method (including modeling, experimental, and design techniques) for putting the EDC framework into practice, a case study for the design space mapping of an *infotainment controller* is conducted. The infotainment controller is a device that is used to navigate applications on the infotainment system, which is itself located on the dashboard of a vehicle. The rich, embodied interaction of rotating the dial on this controller provides *tactile haptic feedback* as it is used to scroll through menu items in various applications (e.g., contacts, volume).

This *established* technology is already employed several models of the Cadillac, however future variants may afford the potential for *personalizing* the feeling of rotating the dial to each individual. Despite the established nature of this technology, however, it remains unclear as to how individual preferences for this feeling may differ, nor is it apparent as to how these individual preferences may vary between different contexts (i.e., between different infotainment applications). The EDC framework is therefore employed to again map out the design space of this real-world design problem and provide rigorous, holistic insight to these specific challenges. This method, the complete details of which are given in 0, addresses several key research issues.

Formulating the Problem Space – The Actor-Abstraction matrix was used to formulate the problem space for this case study such that *user* was incorporated more directly into the design problem (in terms of both user *factors* and *outcomes*). In this formulation, multiple different kinds of experiential responses to the interaction were considered, including responses that were *subjective*, as well as those that were *physiological* in nature. The physiological responses were used to extract information on users' *latent* emotions/cognitions that distinguish their preferences. This latent information was captured by *psychophysiological* measures that were treated as design levers that the *user* could directly adjust to personalize the infotainment controller according to their individual differences. Additionally, the *context* for this interaction was given not by a physical environment, but rather by a *digital* one—the different infotainment applications factored into the rich, embodied interaction as well. Unlike physical contexts, the digital infotainment applications could fall under the control of the designer, and therefore be directly designed alongside the controller itself. As such, multiple different design levers could be adjusted in this formulation, including those relating to the controller (i.e., the artifact), those relating to the application (i.e., the context), and even those relating to latent emotions/cognitions (i.e., the user). This ultimately represented a new problem space formulation within the A-A matrix, which is distinct from existing design methods.

Modeling the Solution Space – To enable the solution space to be personalized in an efficient manner, modeling techniques were developed which allowed individuals to directly input their own psychophysiological measures. This technique was based off of a controls loop (i.e., a biocybernetic loop) that is commonly employed in physio-adaptive systems. In this loop, physiological responses to an interaction are measured and the product is adapted accordingly. However, whereas these adaptations are typically limited *pre-defined* adaptations to physiological triggers, this loop is modified allow the physiological responses to be entered into an interaction model (i.e., a statistical model to predict the perception of physical stimuli) and used to generate new, personalized design configurations for each user. These personalized design configurations were then presented to the user for their evaluation. This modeling technique enabled individual users to personalize their model of the solution space in real-time without requiring them to expressly communicate their preferences. The latent information provided by psychophysiological measures could be passively collected with in-vehicle sensing capabilities, and therefore this could be scaled to large populations without increasing the effort of the designer.

Developing Experimental Techniques & Procedures – A user study (n = 60) was conducted to empirically construct and validate the solution space model. This study was conducted in two phases, each with a different study population. In the first phase (n_1 = 40), participants interacted with the different configurations of the infotainment controller to complete tasks on several applications. Both subjective and physiological responses to this interaction were recorded and used to characterize the interaction model. Two versions of this model were made—one that *included* psychophysiological features, and one that *omitted* them. Infrastructure was developed to record, process, and interpret the physiological data (i.e., extract psychophysiological features) on-the-fly, and a technique for to selecting relevant metrics to include in the interaction model was developed using both machine learning algorithms and researcher-defined heuristics. In the second phase (n_2 = 20), participants again completed tasks with the infotainment controller. Their individual physiological responses were processed and used to predict and generate new design configurations of the controller in real-time, which were then evaluated; new design configurations were also generated based off of the alternate interaction model that omitted physiological predictors, which were evaluated as well. A validation test was employed to compare these two models, and the one that was personalized with individual psychophysiological features was demonstrated to improve the overall accuracy of the solution space map.

Operationalizing Embodiment Design Cartography – With the model of the solution space, it was made evident as to how individual differences altered the solution space, and personalizations should be implemented. The formulation of the problem space for this case study permitted *multidisciplinary* design insights to be tied into the different design levers that were available. For the hardware designer who would control design levers relating to the infotainment controller, for instance, contour plots for the personalized solution space models were examined to determine which attributes of the haptic feedback were worth personalizing (through individual design levers), and which should instead be coupled to the specific application. These insights, however, also exposed how to design levers of the infotainment *applications* could be adjusted. This informed how the software designer who would control these design levers could adjust the number of menu items to best fit the feeling of the controller, instead of the other way around. These explorations highlighted the variety of actionable design insights that could be made for this established technology.

1.7. Research Outcomes

Overall, each of the chapters in this dissertation contributed to addressing the overarching research issues in different ways. These contributions are summarized in turn.

1. To address the need for a flexible manner of conceptualizing design problems, a framework was constructed with a broad organizational structure that could systematically describe any rich, embodied interaction. It was demonstrated how this could be used to precisely formulate the general usage of existing design methods, and also be tailored to new design problems that varied greatly in which considerations were relevant.

2. To address the need for robust modeling approaches for understanding the range of design options, knowledge from a wide variety of different sources was permitted to be used, and the conceptual rules for analyzing, synthesizing, and evaluating this knowledge were defined. Within this framework, techniques were developed for composing multiple models to couple abstract design outcomes and concrete design levers, and for augmenting the models with additional, latent information to improve their overall accuracy.

3. To address the need for practical experimental techniques of date collection, prototyping, and model validation, the procedures used in existing design methods were examined through the lens of the proposed framework to identify useful techniques that may be adapted for these aims. These were then applied and expanded upon in the two case studies, which each employed unique experimental designs and infrastructure to efficiently construct design space maps.

4. To address the need for translating these conceptual, modeling, and experimental foundations into useful design work, the framework was first applied as a tool for enabling

a comparative meta-analysis of existing design methods from a design research standpoint. It was then applied to two case studies of real-world technologies to inform actionable decisions from an industry standpoint. Visualizations were used in both cases to support the identification of useful innovations.

Overall, this dissertation lays the groundwork for establishing this practice of design space mapping, and supplies the engineering designer with a host of knowledge, techniques, and—most importantly—the *tool* of the design space map itself for tackling their own design problems within this new paradigm. Within this new paradigm, the design process may be viewed as a singular, top-down representation of all the decisions that are made and not made, rather than as a series of multiple decisions that are made to reach a solution. The potential impacts of the paradigm shift promoted by the contributions of this work could extend to both industry and academia.

Systematic Design Space Explorations – The engineering designer seeks to engage in the design problem in a rigorous, *systematic* manner, but also apply their creativity to *explore* different solutions. With a systematic manner for *formulating the problem space*, each aspect of the design problem must be expressly considered, and the problem itself may therefore be better understood. Misunderstanding the problem is one of the preeminent causes of failure in new product development [333], which this approach may help alleviate. Alternatively, with the combination of a *robust model of the solution space* to inform how a variety of different outcomes may be created, and *efficient techniques for prototyping* these new designs, the engineering designer is able to feasibly explore a wide variety of different configurations of the product with little resource expenditures. Reducing the time between iterations is another key issue facing new product development [326], which this approach may again help counter.

Data-Driven Product Innovations – The engineering designer ultimately aims to achieve *innovative* design insights through these systematic explorations. A common pitfall in new product development is focusing attentions on how to best deliver a current product, rather than how to deliver the best possible benefits [333]. By promoting a more *holistic formulation of the problem space*, supporting a wide variety of *different knowledge in the solution space model*, and developing *experimental techniques for collecting and processing multiple data channels*, product innovations may be *driven by data* on variety of different benefits, i.e., outcomes. This includes determining how to favorably balance technical and experiential benefits, and how to tailor products based on physiological predispositions. By holding different types of data with equal regard, these innovations could reflect a more ‘maximal use’ of relevant information [333].

Multidisciplinary Collaboration – The engineering designer does not create products on their own, but rather works jointly with multiple different designers from various disciplines or perspectives. By *formulating the problem space* to hold technical and experiential outcomes as equally important, the different disciplines that deal with each are given equal footing in the decision-making process. It is unfortunately the case in many industrial settings that technical sciences are institutionally favored of experiential sciences for new product development [333]. This framework could not only promote more equitable participation, but could also help to remove communication barriers and structure *multidisciplinary collaboration* around clearly assigned design levers.

Methodological Research & Development – Overall, the engineering designer’s core goal is to formalize new design methods to be used for specific problems that are not optimally serviced by the methods that already exist. In *formulating the problem space*, *modeling the solution space*, *developing experimental techniques and procedures*, and *operationalizing the framework* to construct tailored design space maps, the engineering designer is in fact formalizing a new design method through this process. The Embodiment Design Cartography framework as a whole may therefore be conceived as a *planform* for *methodological research & development*. With this platform, engineering designers could be better equipped to systematically develop unique design methods that are tailored to any specific design problem they may address.

1.8. Chapter 1 Conclusion

In this chapter, the design journey—and the need for *mapping* it—is introduced. In a classical paradigm, design is often conceived as a process of linear decision-making that ultimately leads to a solution. However, in the selection of any single solution, there is a near-infinite range of potential alternatives that are *not* selected. This range of alternative options comprises a *design space*—which itself may be decomposed into a *problem space* and a *solution space*. Any change along the series of decisions made in this journey could lead to a different solution in the design space. However, the linear perspective of this classical paradigm effectively serves to *bury* each prior decision behind the subsequent one, which makes it difficult to determine where exactly in the design space these changes would lead, or even what possibilities may exist.

This dissertation suggests an alternate paradigm—one in which a design solution is not conceived as the *end* of the design process, but rather as the entire *journey* that was taken. By recontextualizing the design process in this way, each decision that is made—which *factors* are considered to influence the problem, which *outcomes* are considered to measure the success of the solution, etc.—may be *simultaneously* conceived in terms of all the other possibilities that could have been selected instead. The aim of this work is to create a map of this journey—a *map of the design space*—that designers may use as a tool for understanding the options that comprise this space. This is akin to taking an *adventure* that one may have while traversing through a *dark cave* to discover some *treasure*, and plotting out the course that was taken from an overhead perspective, onto a map that shows the other passageways in this cave that may have been traveled down instead, as well as the locations of other treasures that could have been discovered had changes to this route occurred.

However, there may be a wide range of considerations that can influence the design process when taking the conceptual idea for a product and *embodying* it in the real world, especially if this product is *physically-interactive*. To holistically and rigorously determine which of these considerations are pertinent to include in this map, a *systematic* approach is needed. Many different disciplines participate in the design process, and each may have their own method for supporting these needs. While each of these existing design methods can be useful in their own right, no single method is capable of addressing every consideration that may present itself in embodiment design, which is itself an ill-defined problem. New contributions to this field are therefore necessary establish the practice of design space mapping, which relate to: 1) conceptually formulating the problem space, 2) modeling the solution space, 3) employing experimental techniques and procedures, and 4) operationalizing design innovations. The first step is addressing these issues is to define a *framework* to provide the basis for how the task of Embodiment Design Cartography may be undertaken.

Chapter 2. A Framework for Embodiment Design Cartography

To map the design space of an ill-structured problem, the designer must act as a *cartographer*—they must systematically explore this design space and document the options within in a manner that is useful for design. In this chapter, the Embodiment Design Cartography framework is presented. The objective of this chapter is to derive this *conceptual framework* to support the cartographic activities of design space mapping for design problems rooted in 'embodiment.' This includes supporting a *flexible problem space formulation* that may be tailored to specific design problems, and a *selectively integrative solution space modeling* that may leverage existing design methods. This framework is structured as a *boundary object* to bridge existing design methods and the differing disciplines behind them. This concept of a boundary object is first discussed in terms of design, and it is then used as a lens to separately define an *ontology*, *epistemology*, and *methodology*. These interrelated components define the overall philosophy of this framework, and are each defined here in general terms to establish their theoretical basis. With this framework defined, an exercise is conducted to test its flexibility by applying it to retroactively map *existing* design methods. Not only does this illustrate its flexibility for supporting methods from different disciplines, but these mappings may be used to directly contrast these methods on a uniform scale. This highlights their potentially advantageous techniques that could be selectively integrated into the framework.

2.1. Boundary Objects

The purpose of a framework for mapping the embodiment design process is to impose a degree of structure onto an ill-structured problem. Navigating an ill-structured or ill-defined problem to determine a well-defined solution, i.e., finding hidden treasures within the dark cave, necessitates a *systematic* method. An engineering designer seeks to define systematic methods in a rational manner, such they may be *formalized* and ultimately *generalized* [3,12]. Design is not a one-off activity; the utility of a design method is derived not from its unique usefulness in one singular instance, but rather from its broad applicability to a general *class* of problems. Formalizing these methods helps *operationalize* them in practice [334–337]. Despite this, however, many practitioners are still mistrustful of formal design methods; *over-formalization* imparts rigid guidelines that can unintentionally limit the general utility of a method [12]. There are a spectrum of opinions on this matter [163]. While some have treated design methods similar to scientific methods—precise, strict, rigid, e.g., [338]—others have taken the opposite stance, e.g., [339], and still others fall somewhere in between, e.g., [19].

Ultimately, engineering designers must be *flexible* to adapt formal methods to their specific needs [340]. Design encourages *multidisciplinary* or intersectional actions [21,330,341], as a variety of different disciplines participate in this process [342]. The reviewed design methods, for instance, were each developed through the lens of a different discipline (e.g., engineering, marketing, project management, etc.). However, the implication of this divergent development is that these methods each have implicit boundaries imparted by the conceptual 'wrappers' around the underlying considerations they regard. A *boundary object* is the general term for a flexible formalization that may be used to span such boundaries [341,343,344] and link these individual perspectives or disciplines [345]. Boundary objects may come in many forms [346], but are commonly identified by three characteristics: 1) their *flexibility* to adapt to different perspectives or problems, which is 2) achieved by defining an *looser* organizational structure that may then be more *precisely formulated* for specific problems, and 3) a resulting methodology that may be commonly employed by various practitioners who lack conceptual or taxonomical *consensus* [344].

> *"Boundary objects are objects which are both plastic enough to adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites. They are weakly structured in common use, and become strongly structured in individual-site use. They may be abstract or concrete… The creation and management of boundary objects is key in developing and maintaining coherence across intersecting social worlds."*

– Susan Leigh Star & James R. Griesmer, *Institutional Ecology, 'Translations' and Boundary Objects: Amateurs and Professionals in Berkeley's Museum of Vertebrate Zoology*, 1989 [341]

The notion of boundary objects has been adopted in a variety of disciplines, including ecology [347–350] and information systems [351–356], yet they are still relatively foreign in the realm of design *methods*. Some have recently considered the activity of 'design' itself to be a sort of natural boundary object [21]. Different designers *do* collaborate in spite of—and often, *because of*—their disciplinary differences. This collaboration is attributed to an implicit *reflexivity* that designers possess. They recognize that their perspectives are not all encompassing, and that any formal method of design from a singular perspective is inherently incomplete. This implies a unique difference in boundary objects for design. In contrast to the original intent of boundary objects, which was often to enable coordination *without* collaboration, a collaboration between disciplines is desirable in design [21].

However, boundary objects are only effective at the scale and scope for which they were developed [344]. The broad conceptualization of all of 'design' as a boundary object is not refined to the specific scale and scope of 'embodiment.' It is therefore necessary to define the Embodiment Design Cartography (EDC) framework as a boundary object at the scale of embodiment design for rich, embodied interaction. With this framework, the boundaries of the existing design methods may be bridged and the level of *flexibility* necessary for its general applicability to this class of design problems may be achieved.

2.2. The Elements of a Conceptual Framework

A framework is a "network, or a 'plane,' of interlinked concepts that together provide a comprehensive understanding of a phenomenon or phenomena. The concepts that constitute a conceptual framework support one another, articulate their respective phenomena, and establish a framework-specific philosophy. Conceptual frameworks possess ontological, epistemological, and methodological assumptions" [330]. Similarly, a framework traditionally "lays out the key factors, constructs, or variables, and presumes relationships among them" [357]. A conceptual framework for Embodiment Design Cartography (EDC) must therefore define the network of relationships between the interlinked factors and outcomes in the phenomenon of 'embodiment,' i.e., the *embodiment* design for product that elicits a rich, *embodied* interaction. The wrinkle to this requirement is that the relationships in this phenomenon are not always static; they can vary according to which factors/outcomes are relevant to the specific design problem at hand. This is where constructing the EDC framework as a *boundary object* comes into play. With the dynamic organizational structure of a boundary object, the framework can loosely presume the relationships in the general class of design problem, and then more precisely structure them for specific design problems.

To achieve this flexibility, the core components of the conceptual framework—the *ontology*, *epistemology*, and *methodology*—must each be defined with these aims in mind. In this chapter, the ontology, epistemology, and methodology are only defined in general terms, in which the emphasis is to establish the *theoretical* basis for each. They are then retroactively applied to the existing design methods. It is in the subsequent chapters that they are applied to real-world design problems. These components are each discussed in turn.

2.2.1. The EDC Ontology

The purpose of the EDC ontology is to define the core concepts considered in this framework, the relations between them, and to specify the terminology used to describe them. This establishes the perspective for how the 'embodiment' phenomenon is viewed. This perspective is based on the viewpoint that—in order to realize the embodiment design of products that afford rich, embodied interaction—low-level, *concrete design decisions* are made to achieve high-level, *abstract design outcomes*. Unfortunately, the engineering designer cannot simply manifest the outcomes that they wish for a product to achieve; they must make decisions according to the design levers available to them and understand how these levers produce desired outcomes.

In embodiment design, the manner in which these high-level outcomes are determined by low-level decisions may conceptualized as a series of transformations between different *levels of abstraction* [358,359]. These levels are given by: 1) *how*, 2) *what*, and 3) *why* [111,360,361], in which *how* is the most concrete and *why* is the most abstract (see also [17,19,329]). These abstraction levels may be used to deconstruct the actors that take part in this phenomenon—the artifact, the user, and the context. Each of the abstraction levels is defined in terms of these actors.

1. ***The How*** – At the lowest, most concrete level is the *how*, i.e., *how* each actor is formed or composed to exist as they do. In this work, this level is especially pertinent to the artifact as it represents *how* the product is engineered. This level specifies the geometric dimensions of its form/layout, which can include its structure, materials, and any other components that may be selected, altered, or interchanged in a measurable manner.

2. ***The What*** – Between the *how* and the *why* is the *what*, i.e., *what* each actor is in this phenomenon, independently of one another. This level specifies the relevant *factors* of the artifact, user, and context that directly influence the rich, embodied interaction, which were each defined in Chapter 1. For the artifact, this refers to its consumer-facing attributes—both those relevant to this interaction (e.g., haptic feedback) and persistent outside of it (e.g., cost)—that are manifested by its underlying form/layout. For the user, this refers to their intrinsic characteristics, demographics, or predispositions they bring to an interaction (e.g., age, gender, cultural expectations). For the context, this refers to the defining aspects of the environment that situate this interaction (e.g., the surrounding architecture).

3. ***The Why*** – At the highest, most abstract level is the *why*, i.e., *why* this product was created in the way that it was. This level specifies the relevant *outcomes* of the artifact, context, and user, which were again each defined in Chapter 1. This includes both the inherent *technical* performance of the product, and also the *experiential* responses that result from its rich, embodied interaction. In terms of the artifact, this refers to the former—its inherent technical performance (e.g., durability, affordability). For the user, this refers to their *internal* experiential responses to the interaction (e.g., subjective perceptions, physiological responses). For the context, this refers to the *external* experiential responses that relate to the completion of some *task* (e.g., efficiency, effectiveness).

This ontology postulates that, together, each of these three actors and three abstraction levels many be used to deconstruct any design problem that addresses this 'embodiment' phenomenon. This imparts a 3×3 grid structure to the ontology, in which each cell represents a domain defined by the pairing of an actor and an abstraction level, e.g., *Artifact-How*, *Context-What*, *User-Why*.

Each of these domains shall be henceforth referred to as *Actor-Abstraction* (A-A) domains, which are summarized in Table 1. It is important to note here that two A-A domains are omitted here—the Context-How and the User-How. This is due the intended audience of this work, i.e., the engineering designer. The engineering designer is principally concerned with *how* the artifact is composed—recall that determining of the form/layout of product is the ultimate goal of embodiment design—rather than considering how the user or context came to be. Although they must account for each of these external actors one the product crosses the threshold from a conceptual idea to an embodied artifact, they are only relevant at the level of the *what* and *why*. That is not to say that these domains do not exist or that they cannot be defined, however for the purposes of this work, their omission does not hinder any discussion.

Table 1. The Actor-Abstraction domains. These domains represent the constructs in the EDC ontology.

Actor	Abstraction	Description	Examples
Artifact	How	*How* the form/layout of the artifact is composed.	Geometric dimensions, structure, materials, components, etc.
	What	*What* the artifact is from a consumer perspective. This describes its attributes (responsive/persistent), which *factor* into the rich, embodied interaction.	Haptic feedback, system response, strength, weight, cost, etc.
	Why	*Why* the product was created in the way it was from a performance standpoint. This describes the technical *outcomes* that are inherent to the artifact itself, regardless of any interaction.	Durability, affordability, etc.
Context	What	*What* the context for the interaction is. This describes environmental attributes, which *factor* into the rich, embodied interaction.	Physical, digital, social environments, etc.
	Why	*Why* the product was created in the way it was from an experiential standpoint, with regard to some task. This describes the experiential *outcomes* that are external to the user, and may be observed in the context of the interaction.	Efficiency, effectiveness, error rate, etc.
User	What	*What* the characteristics of the user are. This describes their personal attributes, which *factor* into the rich, embodied interaction.	Predispositions, demographics, expectations, skills, etc.
	Why	*Why* the product was created in the way it was from an experiential standpoint, with regard to user's elicited reaction. This describes the experiential *outcomes* that are internal to the user, and may be assessed through subjective perceptions or physiological responses	Pleasure, satisfaction, heart-rate, arousal, perceive qualities, etc.

2.2.1.1. Actor-Abstraction Matrix: Broad Organizational Structure

Together, these Actor-Abstraction domains may be *externalized*[12] by the *Actor-Abstraction matrix*, illustrated by Figure 3. Per its namesake, the A-A matrix defines its vertical axis by the *actors* in rich, embodied interaction, and its horizontal axis by the *abstraction* levels in embodiment design, such that each cell represents an A-A domain. On the vertical axis, the artifact and user rows are separated by the context row, which is where the interaction between the two occurs. On the horizontal axis, the abstraction levels are arranged from concrete (i.e., *how*) to abstract (i.e., *why*). This matrix represents the EDC ontology's looser organizational in this boundary object, in which the general nomenclature of the A-A domains may be easily understood by different design disciplines. Within this matrix, however, more specific problem spaces may be formulated in a variety of different ways to provide the precise structure of this boundary object.

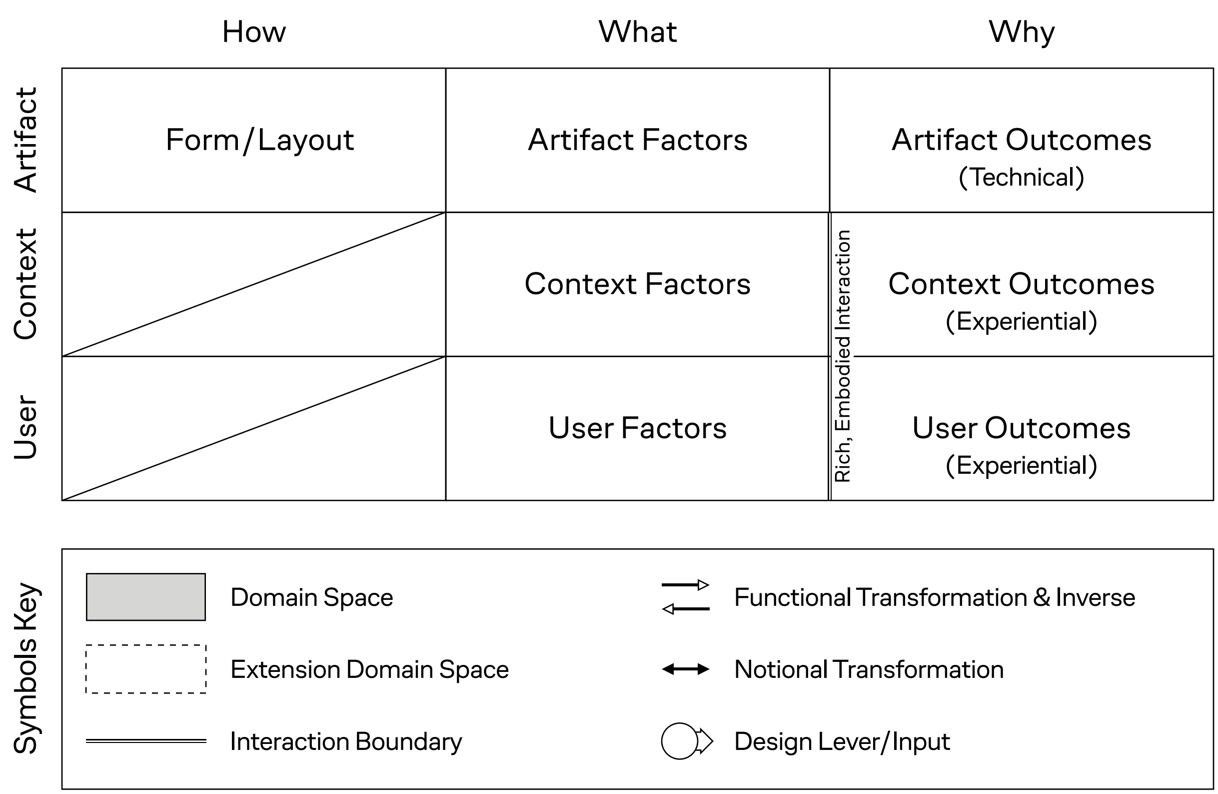

Figure 3. The Actor-Abstraction matrix. The A-A matrix (top) defines its axes according to the three actors and three abstraction levels, and externalizes the *broad* organizational structure of the boundary object. The symbols key (bottom) details symbolic grammar for formulating the *precise* problem space formulation.

[12] **Externalization**: The practice of visualizing design tools through charts or diagrams (see [12]).

2.2.1.2. Actor-Abstraction Symbols: Precise Organizational Structure

The 'symbols key' given in Figure 3 provides a symbolic 'grammar' that may be used to formulate precise problem space maps for specific design problems within the Actor-Abstraction matrix. For now, each of these is defined in general terms according to what they represent and how they may be used. Examples of their application in design space mapping are presented in the latter half of this chapter, and they are subsequently applied throughout the following chapters.

Vector Spaces & Extensions – Within each cell, or A-A domain, specific *vector spaces* may be defined as subsets of relevant considerations within the larger domain. For instance, while the User-Why domain contains all of the perceptions, cognitions, emotions, bodily responses, etc. that may internally result from a rich, embodied interaction, it may be more practical for the engineering designer to only consider their user outcomes by some fixed set of perceptions that they may measure on a sematic differential scale. These ratings would therefore span a discreet vector space defined within the User-Why. Other A-A domains may not be especially relevant or necessary to consider at all in some design problems, such that no vector spaces are defined for the specific problem space formulation. Vector space *extensions* refer to new vector spaces that may be added on to an existing problem space formulation. This could be from practitioners adding on to existing design methods, or from new iterations of a design problem that add new considerations.

Interaction Boundary – The *interaction boundary* defines a specific boundary between domains in the A-A matrix. Located between the Context/User-What and the Context/User-Why, this boundary denotes the area in which it is necessary for a rich, embodied interaction to occur for the *what* to be transformed into the *why*. This essentially serves to differentiate the artifact outcomes—which exist regardless of any interaction—from the context and user outcomes—which do not. From a modeling perspective, any transformation that crosses this distinguishing boundary must be characterized *empirically*. Other transformations that do not cross this boundary may be instead characterized analytically (e.g., through FMEA, etc.). Modeling is further discussed under the umbrella of the EDC epistemology.

Transformations – The relations between vector spaces are given by *transformations*, which are represented here by different types of arrows that may be drawn between the vector space boxes. The type of arrow indicates the manner in which this transformation is characterized.

Functional transformations are characterized through *mathematical models*, and are given by white, unidirectional arrows; these models can have an *inverse* that may describe the transformation in the opposite direction. Alternatively, domains that are related, but not necessarily with the level of specificity provided by a mathematical model, are coupled through *notional transformations*. These are given by bi-directional, black arrows. An example of a notional transformations would be the symbolic relations often used in Quality Function Deployment (e.g., symbols to denote strong/weak relations).

Design Levers – Some vector spaces may be directly adjusted by the designer, while others may only be indirectly influenced by these adjustments. The *design levers* symbol can therefore be used to augment the map of the problem space with information about where the designer may have this direct input. For instance, an engineering designer may be able to manipulate a vector space in the Artifact-How, but generally cannot directly control the user's reaction to that adjustment, which could be described by a different vector space in the User-Why. Ultimately, any design outcomes at the level of the *why* must be linked back to design levers for the map to be operational.

Overall, these symbols may be combined to map the *precise* formulation of the problem space according to which considerations are specifically made in a given design problem. By externalizing this ontology onto the A-A matrix, the considerations are taken out of the head of the engineering designer, and mapped onto this *tool*. This helps free the engineering designer's cognitive processes to focus on creative problem-solving, and enables additional designers or stakeholders to contribute to the process as well [12]. The engineering designer is then able to better consider the unique subtlety of the specific problem, especially when it pertains to determining what considerations may be relevant to the experience of the users [97].

2.2.2. The EDC Epistemology

Whereas the EDC ontology describes the relations between considerations in the formulation of the *problem space*, the EDC epistemology describes how data or information is passed throughout this problem space map to *construct the knowledge of the options in the solution space*. In contrast to the *problem space*, which defines the factors/outcomes that the designer considers when addressing the design problem, the *solution space* contains the range of options for different configurations that the resulting product may take. The solution space is *dichotomous*, as options are selected according to the *abstract* design outcomes, but enacted by the *concrete* design levers. Solutions in EDC are therefore given by neither these outcomes nor these levers alone, but rather by a *model* that characterizes the relation between the two.

To guide the act of modeling the solution space, the three processes of embodiment design—*analysis*, *synthesis*, and *evaluation* (see Figure 2)—are each epistemologically relevant [362]. Mathematical models are characterized in embodiment design *analysis*, used to generate new design configurations in embodiment design *synthesis*, and these new configurations may then be assessed as reflections the model performance in embodiment design *evaluation*. Each of these processes is ultimately reliant on acquisition, usage, and assessment of knowledge—both *of* design and *for* design [363]. In this regard, four epistemological principles for modeling the solution space are specified in Embodiment Design Cartography: 1) the *direction* that data moves across the problem space for each of these processes, 2) the sources that the data for these models is *collected* from, 3) the manner in which it is *propagated* across the abstraction levels, and 4) the tests used to *validate* this data.

The construction of the EDC epistemology as a boundary object ties into a wider debate on the inclusion of formalized epistemologies in design. Some argue that a 'design epistemology' is an inherent contradiction due to the ever presence of *uncertainty* in design—that knowledge cannot be justified when uncertainty exists [364]. On the other hand, total rejection of any formalization in this area is not a suitable solution either; the answer lies in a 'middle ground' [365]—a *broad formalization* that is commensurate with the idea of a boundary object. Each of the principles defined here are, themselves, quite broad in that multiple directions of data flow are permissible, multiple sources of this data may be used, multiple different tools are permitted to collect said data, etc. This enables them to support this requisite level of flexibility.

2.2.2.1. Direction of Data

To couple the *abstract* design outcomes and *concrete* design levers in the solution space, transformations are made between abstraction levels. These transformations can occur in two different directions. In the *natural world*, transformations occur from the *concrete* to the *abstract* (i.e., *how* → *what* → *why*). For instance, the form/layout of an artifact *causes* its consumer-facing attributes to manifest, the factors of an interaction *cause* the outcomes to occur, etc. In the Actor-Abstraction matrix, these *causal transformations* are represented by functions that point to the *right* (i.e., towards the *why* column). A mathematical model that characterizes this causal transformation is considered to be *descriptive* in nature [10,366]. Descriptive modeling is conducted within embodiment design *analysis* to understand how the abstract design outcomes may be influenced by the concrete design levers [362].

In the *designed word*, however, transformations occur in the opposite direction—from *abstract* to *concrete* (i.e., *why* → *what* → *how*); "natural sciences are concerned with how things are. Design on the other hand, is concerned with how things ought to be" [367]. The so-called law of design is that 'form follows function' [368], not the other way around. From the perspective of EDC, this phrase could be updated to read 'the *how* follows the *what* follows the *why*,' although this is admittedly not quite as catchy. To successfully create new designs configurations, the engineering designer must understand how to express abstract outcomes through their concrete design levers [34,96,213]. In terms of the design journey, the designer must be able to not only locate treasures in the dark cave, but also retrace their journey back to the entrance so they may escape with them. In the A-A matrix, these *teleological transformations* are represented by functions that point to the *left* (i.e., towards the *how* column). A mathematical model that characterizes this teleological transformation—oftentimes the inverse of the descriptive model—is considered to be *prescriptive* in nature [10,366]. Prescriptive modeling is employed within embodiment design *synthesis* to implement changes in the concrete design levers based on the abstract design outcomes [362].

> *"A designer and a scientist travel the same road but sometimes in opposite directions. The designer goes from the abstract to the concrete, scientists from the concrete to the abstract."*

– Gordon L. Glegg, *The Science of Design*, 1973 [369]

Overall, the *direction* of knowledge in this epistemology indicates the purpose it serves and the processes it supports. Both *analysis* and *synthesis* are necessary processes for the engineering designer to complete [342]. The A-A matrix provides a clear mechanism for partitioning these processes according to the direction (i.e., right or left) that transformations are symbolically mapped to in this externalization. When rightward facing transformations *descriptively* couple the design levers to the design outcomes, and leftward facing transformations *prescriptively* couple the design outcomes back to the design levers in a closed *circuit*, the formulation of the problem space is considered to be *complete*. A complete formulation is a requisite for modeling the solution space, which incorporates a variety of different data sources.

2.2.2.2. Collection of Data

To construct the model of the solution space, it is necessary to gather information on a variety of different design outcomes. This information may be collected from the artifact, the user, and the context (see Figure 3). However, each of these different sources have associated implications as to how data may be *collected* and *propagated* to the design levers. This impacts the manner in which the solution space model is characterized.

Each of the artifact, context, and user outcomes (see Table 1) at the level of the *why* may be derived or measured in different ways. These differences are detailed in turn.

1. ***Artifact-Why*** – Artifact outcomes are comprised of *technical* metrics that may be measured directly off of the product itself, without any interaction from the user. For instance, the 'durability' may be assessed according to persistent qualities such toughness, waterproofing, or inherent resistance to destructive forces, which are built-in to the product. Similarly, an artifact outcome like 'affordability' may be assessed by qualities such as the production cost, scale, and material scarcity. Ultimately, these outcomes may be derived through known physical properties, calculations, accounting, etc. *before* the artifact is actually embodied in the real-world to be interacted with

2. ***Context-Why*** – Context outcomes are comprised of *experiential* metrics that may be measured in relation to the completion of a *task*. When a person interacts with a product, they most likely have a purpose for doing so. This purpose is to complete some task, and their ability to do so may be measured with respect to the context they are in. For instance, a context outcome like 'efficiency' could be related to the time or effort expended to complete this task with the product. Alternatively, a context outcome like 'effectiveness' could be assessed by how thoroughly they complete said task. Ultimately, these outcomes may be externally measured by an independent observer through timers, counters, checklists, etc. while the artifact is interacted with, and *after* it is actually embodied in the real-world.

3. ***User-Why*** – User outcomes are comprised of *experiential* metrics that may be measured in through the user's reaction to a rich, embodied interaction with the product. These interactions shape users' perceptions of the product, and alter their internal emotional or cognitive states. User outcomes may therefore be given by fundamental emotions like 'stress' or 'arousal,' or could alternatively include abstract perceptual descriptors like 'luxuriousness' or 'sportiness.' Ultimately, these outcomes may be provided by the user themselves—either consciously through surveys or self-reports, or unconsciously through biometric sensors—while the artifact is interacted with, and *after* it is actually embodied in the real-world.

Ultimately, it may be generally concluded that artifact outcomes are derived from the product, context-outcomes are measured by a third-party observer (or system), and user outcomes are provided by the user. The former—the artifact outcomes, which are *technical* in nature—may be derived *analytically*. The latter two, however—the context and user outcomes, which are both *experiential* in nature—must be measured *empirically*. This ties back to the 'interaction boundary' in the Actor-Abstraction matrix, which highlights this same distinction.

This epistemological stance has implications not only for modeling, but also for the experimental techniques and procedures that are employed to collect and process all of this data. Many different data collection techniques may be simultaneously necessary to use. These can include surveys, sensors, independent observers, etc., which can be "rather difficult and expensive to apply because it takes time to gather data from and about users, especially if the idea is to understand the environment in which they will be using the products" [168]. This further motivates the need for efficient techniques and procedures to support these efforts, which are further detailed in subsequent chapters.

2.2.2.3. Propagation of Data

The manner in which objectives for design outcomes (e.g., improve affordability, improve sportiness, etc.) are *propagated* down to the design levers differs according to whether they are *technical* or *experiential* in nature. This duality touches on the fundamental epistemological debate between *rationalism* and *empiricism* that has presided over the last few centuries. "Rationalism claims that knowledge can be obtained deductively by reasoning and empiricism says that knowledge can be attained inductively from sensory experiences" [362].

Analytical models on the technical level may be constructed *deductively*, with a rationalist perspective. For instance, for the 'affordability' of a product to be improved, it may be rationally deduced that the production cost should be decreased. This practice is quite common in engineering, e.g., [5,20,28,186,370,371]. Empirical models on the experiential level, however, must be constructed *inductively*, with an empiricist perspective. For something abstract like 'sportiness,' it may not be clear as to which design levers should be altered and by how much [125]. The users themselves cannot be expected to provide clarity on this relation [186], i.e., "a car buyer may know what 'responsiveness' feels like when driving, but is unlikely to be able to refer to this in terms of engine torque" [12]. The available vocabulary, perspectives, and even the dimensionalities between domains may not directly correspond [168,181,246,329,372]. Empirical study of how these perceptions vary across different design configurations is necessary to characterize these transformations. The EDC epistemology therefore toes the line between rationalist and empiricist perspectives in its continued pursuit of flexibility.

However, simply characterizing the transformation between design levers and outcomes is not sufficient. The different external conditions which may *factor* into the relation must also be taken into account. Design outcomes may greatly differ between these different conditions. Relevant user and context factors at the level of the *what* must therefore be included in the experimental design of any empirical study conducted for solution space modeling. This can provide more insight as to why perceptions are what they are, which can be valuable information for designers.

> *"Design knowledge is not necessarily about knowing what only the final outcome is but (importantly) about the construction of the conditions under which the outcome should be judged. Such judgement relies on factors of human nature and the dynamic between people and the practices that generate these outcomes"* (in reference to *[373,374]*).

Derek Jones et al., *Introduction: Design Epistemology*, 2016 [1]

Ultimately, the logical position taken by the EDC epistemology may be summarized as valuing *utility* over *veracity* [365]. More emphasis is placed on constructing knowledge that is useful than knowledge that is the abject 'truth'. Both *objective* and *subjective* data is equally valued. Rather than taking a hardline stance on rationalism versus empiricism, both perspectives may be employed when pertinent. This, however, does not mean that the *validity* of the models constructed with this data is not rigorously assessed.

2.2.2.4. Validation of Data

While the processes of embodiment design *analysis* and *synthesis* have each been discussed in this epistemology, the third embodiment design process—*evaluation*—is equally critical, especially for models that are characterized empirically. Embodiment design *evaluation* is the process of assessing the design outcomes of the *product*, however this can be used as an indirect assessment of the *model* that was used to create it. By using the solution space model to synthesize a new product configuration that is *predicted* to achieve some specific design outcome, the subsequent assessment of that product may indicate the accuracy of said prediction. It is critical for these assessments to be done on *new* design configurations that were not originally used to characterize the model; the solution space model must be able to predict the outcomes of all options across the continuous span it covers. The evaluation of this predicted design configuration should be based on the same data that was collected to characterize the model in the first place, i.e., if surveys were used to characterize the model, these same surveys would be used again to evaluate the predictions it makes.

In empirical studies, *statistical criteria* may be used to assess the *validity* of these models. A common test could include the synthesis of two different design configurations that are predicted to rank in a certain order according to some design outcome. The user would then evaluate each prediction to validate that the model is able to correctly predict this ordering. This tests the predictive accuracy of the model across a range of the continuous solution space, rather than just testing a single point in this space. Overall, the 'solutions' in Embodiment Design Cartography are not thought of solely by the outcomes, but rather by the coupling between these outcomes and the design levers that is described by the solution space model. It is therefore critical that any empirical models used to characterize these relations are rigorously assessed through significance testing.

2.2.3. The EDC Methodology

Finally, the EDC methodology takes each of these highly theoretical pieces of the framework, and provides a general protocol for how to actually apply design space mapping in practice. Similar to the ontology and epistemology, this methodology is defined through the lens of a *boundary object*. In this way, it is divided into two parts: 1) mapping the *problem space*, which follows a looser protocol, and 2) mapping the *solution space*, which follows a more structured protocol.

These two halves—each discussed in turn—mirror the loose and precise organizational structure given by the boundary object, respectively.

2.2.3.1. Mapping the Problem Space

The first half of the EDC methodology dictates the general protocol for mapping the *problem space* by formulating it within the Actor-Abstraction matrix. This is a more loosely defined protocol as a consequence of dealing with the looser organizational structure given by the A-A matrix. In essence, the role of the engineering designer is to critically examine the design problem at hand and use the symbols key (see Figure 3) to map the *relevant* considerations onto the A-A matrix. This may be performed through a grid-based sweep of each cell in this matrix.

Often times, this may begin with the *why*—every product is created for a reason. Spaces at this level can be defined by setting *objectives* for various design outcomes, which may often be provided to the designer by external specification, or may be deduced by their own intuitions [35,171]. These objectives may each be classified into the vector spaces in Artifact-Why, Context-Why, or User-Why. It is then necessary to work down the levels of abstraction to repeat this process at each stop. At the level of the *what*, the engineering designer may need to consider which qualities of the product are *responsive* to the interaction, and which are persistent outside the interaction in the Artifact-What. It is also critical to consider which external factors in the Context-What and User-What may be most relevant, as it is not feasible to include every possibility in the empirical modeling. Market research or needs-finding activities may be useful for these determinations. Finally, the engineering designer should be able to determine which dimensions of the form/layout may be adjustable in the Artifact-What, although external specifications may impose constraints on these as well.

Ultimately, this is a protocol that must vary on a case-by-case basis, and is where the *creative problem-solving* angle of engineering design comes into play. However, the A-A matrix provides structure to this activity by forcing each cell to be considered individually. The end result of this protocol is a *well-structured* design problem, in which different considerations may be more holistically supported.

2.2.3.2. Mapping the Solution Space

The second half of the EDC methodology dictates the general protocol for mapping the *solution space* by modeling the transformations between the design outcomes and design levers. This is a more precisely structured protocol, as the problem has been well-defined at this point. Here, the role of the engineering designer is to *analytically* and *empirically* characterize this model across the three process of embodiment design—*analysis*, *synthesis*, and *evaluation* (see Figure 2)—to construct the knowledge of how the range of available options for what the product solution may be understood in terms of the defined problem space.

Six activities to construct this map of the solution space are defined across embodiment design analysis, synthesis, and evaluation. These activities include: 1) *parameterizing* the vector spaces in the problem space formulation, 2) characterizing *descriptive models*, 3) applying *prescriptive models* to predict new design configurations, 3) creating physically-interactive *prototypes* of this design configuration, 4) *verifying* that the predicted design configuration elicits the expected design outcomes, and 5) *validating* that the model is able to hold predictive accuracy across continuous range of options in the solution space. These are summarized in Table 2.

Table 2. The methodology for modeling the solution space. Activities span analysis, synthesis, and evaluation.

Process	Activity	Description
Analysis	Parameterizing	Spanning the vector spaces to determine the *dimensions* of the space, as well as the *range* & *discretization* of each.
	Descriptive Modeling	Characterizing the *causal* transformations that naturally exist across the abstraction levels, from the concrete to the abstract (i.e., *how* → *what* → *why*).
Synthesis	Prescriptive Modeling	Inverting the causal transformations across the abstraction levels, such that they may be *teleologically* applied to create new design configurations (i.e., *why* → *what* → *how*).
	Prototyping	Generating physically-interactive prototypes to represent the new design configurations with high fidelity.
Evaluation	Verifying	Comparing the design outcome that a design configuration is *predicted* to achieve, against the *actual* design outcome that is observed.
	Validating	Comparing the performance of *multiple* different design configurations against each other to assess the model's accuracy across the continuous solution space.

The end result of this protocol is the construction of a rigorous and holistic picture of the available options in the solution space, and the application of this methodology is applied in the subsequent chapters. However, experimental techniques and procedures are necessary to complete each of these activities. For instance, existing design methods detail each specific techniques for several of these activities. These design methods may be *retroactively* mapped through the EDC framework to identify how their techniques and procedures may be adopted.

2.3. Mapping Existing Design Methods

The framework for Embodiment Design Cartography was defined as a *boundary object* so that it could be flexibly compatible with multiple design disciplines and perspectives. The best test of this claimed flexibility is to therefore put its ontology, epistemology, and methodology all together to actually construct the design space map the *existing design methods*, which were born out of these different disciplines. Each of these existing design methods already constructs a sort of design space map, as they specify considerations and may be used to assess different design options. However, they do so with a fixed conception of the problem space, and unique terminologies that make direct comparison difficult without any sort of higher-level organizational structure. Through translating these disparate vocabularies into a common vernacular, certain commonalities (and therefore, distinctions) may be identified [21,375].

> *"[E]ngaging in good design is choosing a vocabulary or language to use in defining the design task, generating alternatives, and making judgments of balance, fit, and scale."*
>
> – Richard Boland & Fred Collopy, *Managing as Designing*, 2004 [376]

This mapping exercise can serve two purposes, which are to: 1) demonstrate the EDC framework's effectiveness as a boundary object by flexibly supporting each of these independently developed design methods, and to 2) place each of these design methods onto a uniform scale for which they may be contrasted against not only each other, but also any *new* methods that are created on this same scale. However, this exercise is slightly distinct from mapping the design space of a *new* design problem. Whereas that allows for the map to be *tailored* to the needs of the specific design problem, this exercise involves *retroactively* mapping the entire method, which has been used for innumerable different design problems.

This retroactive mapping therefore relies on a certain degree of *interpretation* to conduct the necessary *meta-analysis* of different works that have applied each method (reviewed in Chapter 1). While the *general usage* of a design method—its scope, coverage, benefits, etc.—can become evident across multiple publications, the lack incentive structures for publishing *failures* can make it more difficult to firmly define its boundaries [163]. Furthermore, due to their relative lack of *formalized flexibility* (compared to EDC), every practitioner who uses these existing design methods may have tweaked or reinterpreted them to better suite their individual needs. This compounds the challenge of constructing definitive maps retroactively.

Nevertheless, the commonality between all these design methods is that they simply describe a *transformation*, which is packaged inside their unique conceptual 'wrappers' (i.e., their terminologies, experimental procedures, visualization tools, etc.). While the *transformation* has an intended input and output domain, the *model* that is often used to characterize such a transformation may be capable of more broadly supporting different inputs/outputs than the individual method may intend; the model itself is not aware of the types of data that comprise its inputs/outputs. This interpretive meta-analysis therefore attempts to map the *intended* usage of these methods, rather capturing all formulations that may be mathematically possible.

The EDC *methodology* is followed for constructing these maps, in which the general *problem space* formulation is mapped onto the Actor-Abstraction matrix (see Figure 3), and protocols for constructing the *solution space* model are mapped across the six activities (see Table 2). Note that the 'design levers' symbol is omitted from these problem space mappings, as it may vary by design problem and these mappings represent general usage. The result of this exercise is the construction of a *uniform, data-dense distillation* of each of these design methods, with which potentially advantageous activities may be adapted for new design problems that are also mapped in this scale.

2.3.1. Mapping Function-Behavior-Structure

Function-Behavior-Structure (FBS) is a design method that was developed from an *engineering perspective* to serve as a uniform description of any artifact that may be designed. The *situated* variant of FBS is mapped here. The problem and solution space maps are each outlined.

Mapping the FBS Problem Space – The problem space of FBS may be mapped to the A-A matrix by classifying the *Function* (***F***), *Behavior* (***B***), and *Structure* (***S***) vector spaces into A-A domains. At the level of the *why*, ***F*** defines why the product was created. Practitioners have stated that 'experience' is taxonomically distinct from 'function' in the manner that it is typically described [377], and consideration of experiential responses in FBS is relatively rare [378]. ***F*** may therefore be mapped into the Artifact-Why domain, as it principally regards the technical artifact outcomes. At the level of the *what*, $\boldsymbol{B}$ describes what the artifact does, and may, of course, be mapped into the Artifact-What. However, in *situated* FBS, $\boldsymbol{B}$ is decomposed into two sub-vector spaces—the *Structure Behavior* ($\boldsymbol{B_S}$) that is casually coupled to $\boldsymbol{S}$ with a functional transformation, and the *Expected Behavior* ($\boldsymbol{B_E}$) that is teleologically coupled to $\boldsymbol{F}$ and $\boldsymbol{S}$ with functional transformations. Finally, at the level of the *how*, $\boldsymbol{S}$ describes how the artifact is composed, and may be mapped into the Artifact-How. One *extension* to this method added 'exogeneous variables' such as temperature to this formulation [103]; an *External Effects* (***EX***) extension vector space may therefore be mapped into the Context-What, which is teleologically coupled to $\boldsymbol{S}$ with functional transformations. Another extension added 'user' factors such as 'profession, experience, expertise, gender, age, etc.' into the formulation [168]; a *User* ($\boldsymbol{U}$) extension vector space may therefore be also mapped into the User-What, and teleologically coupled to $\boldsymbol{S}$ with a functional transformation. The resulting map of the problem space formulated by FBS is given in Figure 4.

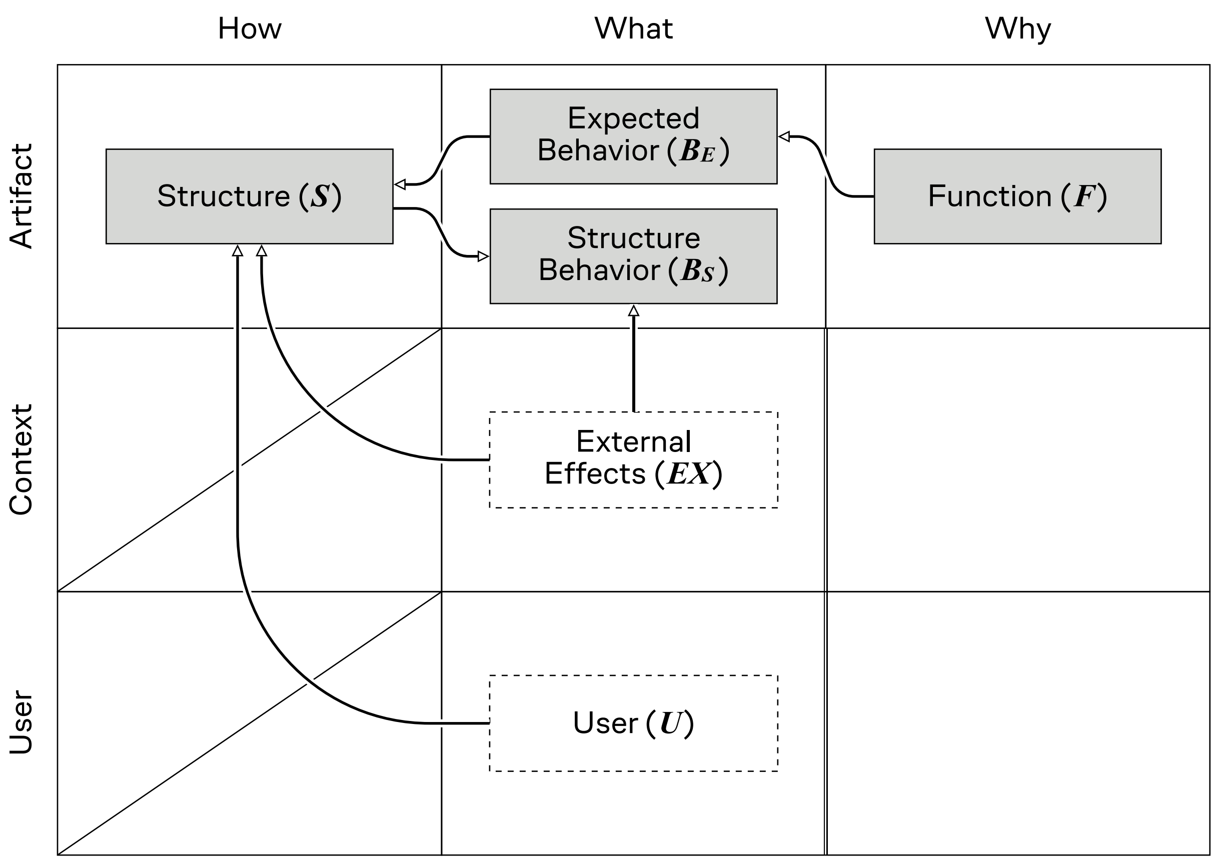

Figure 4. The problem space formulation of Function-Behavior-Structure mapped onto the A-A matrix. Function ($\boldsymbol{F}$) is mapped to the Artifact-Why, Behavior ($\boldsymbol{B_E}$ and $\boldsymbol{B_S}$) is mapped to the Artifact-What, and Structure ($\boldsymbol{S}$) is mapped to the Artifact-How. The extensions External Effects (***EX***) [103] and User ($\boldsymbol{U}$) [168] are mapped to the Context-What and User-What, respectively.

Mapping the FBS Solution Space – The solution space of FBS is mapped through several mathematical models that relate the vector spaces in this formulation. The knowledge for the options in this space is constructed across embodiment design *analysis*, *synthesis*, and *evaluation*.

1. ***Analysis*** – FBS does not give explicitly describe how to the engineering designer should go about *parameterizing* the vector spaces, but it does allow them to be altered for discrepancies between $\boldsymbol{B_E}$ and $\boldsymbol{B_S}$ to be addressed [4,35]. For *descriptive modeling*, FBS characterizes a causal (i.e., rightward-facing) transformation ($\boldsymbol{S} \rightarrow \boldsymbol{B_S}$) [379].
2. ***Synthesis*** – FBS characterizes teleological (i.e., leftward-facing) transformations ($\boldsymbol{F} \rightarrow \boldsymbol{B_E}$ and $\boldsymbol{B_E} \rightarrow \boldsymbol{S}$) for *prescriptive modeling*. Critics have noted, however, that the FBS framework does not provide any theory onto how this teleological transformation is characterized [177,380]. This is likely because they may be analytically derived without empirical study, as the transformations do not cross the *interaction boundary*. For *prototyping*, some have also criticized the utility of FBS as it does not afford a means for generating new design configurations, and instead relies on evaluation of artifacts that therefore do not yet physically exist [178].
3. ***Evaluation*** – Situated FBS is particularly advantageous for *verifying* the solution space through the comparison of $\boldsymbol{B_E}$ and $\boldsymbol{B_S}$ [4,35]. There is, however, not a formalized protocol for *validating* the model across multiple points in the solution space.

2.3.2. Mapping Quality Function Deployment

Quality Function Deployment (QFD) is a design method that was developed from a *project management perspective* to help plan development cycles. The problem and solution space maps are each outlined.

Mapping the QFD Problem Space – The problem space of QFD may be mapped to the A-A matrix by classifying the *Customer Requirements* (***CR***) and *Engineering Characteristics* (***EC***) vector spaces into A-A domains. At the level of the *why*, ***CR***, otherwise commonly known as the 'voice of the customer' [381], defines why the product was created. This vector space could fall into the User-Why, as users are able to provide their subjective rating, or potentially in the Context-Why, as users typically interact with real versions of the product and can complete tasks with them; it is mapped between both A-A domains in this formulation. ***CR*** would *not* cover the Artifact-Why

[187], however, as customers typically have difficulty voicing technical requirements [12] and an traditional engineering approach would be more appropriate for propagating outcomes on this level. ***CR*** is coupled to ***EC*** with a *notional* transformation in the *body* House of Quality (HOQ) matrix; ***EC*** is also coupled back to itself with another *notional* transformation in the *head* of this matrix. At the level of the *what*, ***EC*** describes attributes of the artifact that are relevant to the user, and may therefore be mapped into the Artifact-What. While the name 'engineering characteristics' may sound better suited to the Artifact-How, it is evidenced by later addition of a *Design Parameters* (***D***) extension vector space that is explicitly in this A-A domain [186] (alternatively, see 'part characteristics' [381]), that ***EC*** is correctly attributed to the level of the *what*. ***D*** is then coupled to ***EC*** with functional transformations. The resulting map of the problem space formulated by QFD is given in Figure 5.

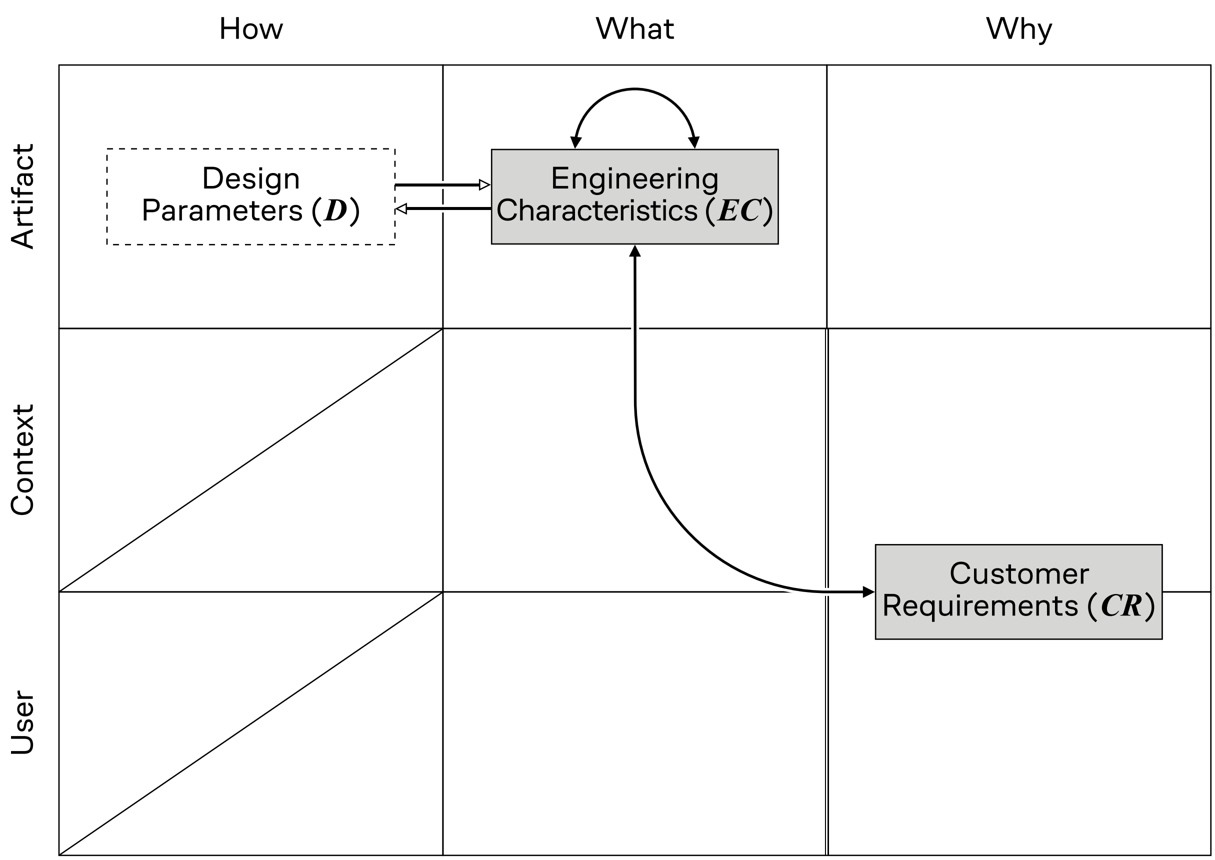

Figure 5. The problem space formulation of Quality Function Deployment mapped onto the A-A matrix. Customer Requirements (***CR***) is mapped across to the Context-Why and User-Why, and Engineering Characteristics (***EC***) is mapped to the Artifact-What. The extension Design Parameters (***D***) [186] is mapped to the Artifact-How.

Mapping the QFD Solution Space – The solution space of QFD is mapped through several mathematical models that relate the vector spaces in this formulation. The knowledge for the options in this space is constructed across embodiment design *analysis*, *synthesis*, and *evaluation*.

1. ***Analysis*** – QFD dictates the use of market research for *parameterizing* the vector spaces. Unlike FBS, QFD does describe the *descriptive modeling* of the notional transformation (***EC***↔***CR***), which is characterized empirically (via surveys, interviews, etc. [381]) as it crosses the interaction boundary—albeit only through a rough notional index.
2. ***Synthesis*** – The notional transformation (***EC***↔***CR***) may be theoretically applied for *prescriptive modeling*, however its notional form is less useful for continuous refinement of new design configurations [205]. QFD does also not provide support for prototyping, and typically relies on premade products for testing.
3. ***Evaluation*** – QFD does not provide explicit means for *verifying* whether a generated design configuration performs as predicted. It is, however, able to support comparison of multiple different design configurations, which may be used for *validating* the solution space model across a range of options.

2.3.3. Mapping Kansei Engineering

Kansei Engineering (KE) is a design method that was developed from an *engineering* and *psychology perspective* to imbue products with emotional considerations. The problem and solution space maps are each outlined.

Mapping the KE Problem Space – The problem space of KE may be mapped to the A-A matrix by classifying the *Semantics* (***S***) and *Properties* (***P***) vector spaces into A-A domains. At the level of the *why*, ***S***, defines the Kansei words (i.e., emotions) that the product was created to achieve. These emotional responses are internal to the user, so ***S*** may be mapped into the User-Why. At the level of the *what*, ***P*** describes observable, influential attributes of the artifact, and may therefore be mapped into the Artifact-What. ***S*** is coupled to ***P*** with a functional transformation that is characterized by a statistical model. Practitioners have added in a *Customer Groups* (***G***) extension vector space [212] and a *Context* (***C***) extension vector space [256] into this functional transformation. These are mapped into the User-What and Context-What, respectively. The resulting map of the problem space formulated by QFD is given in Figure 6.

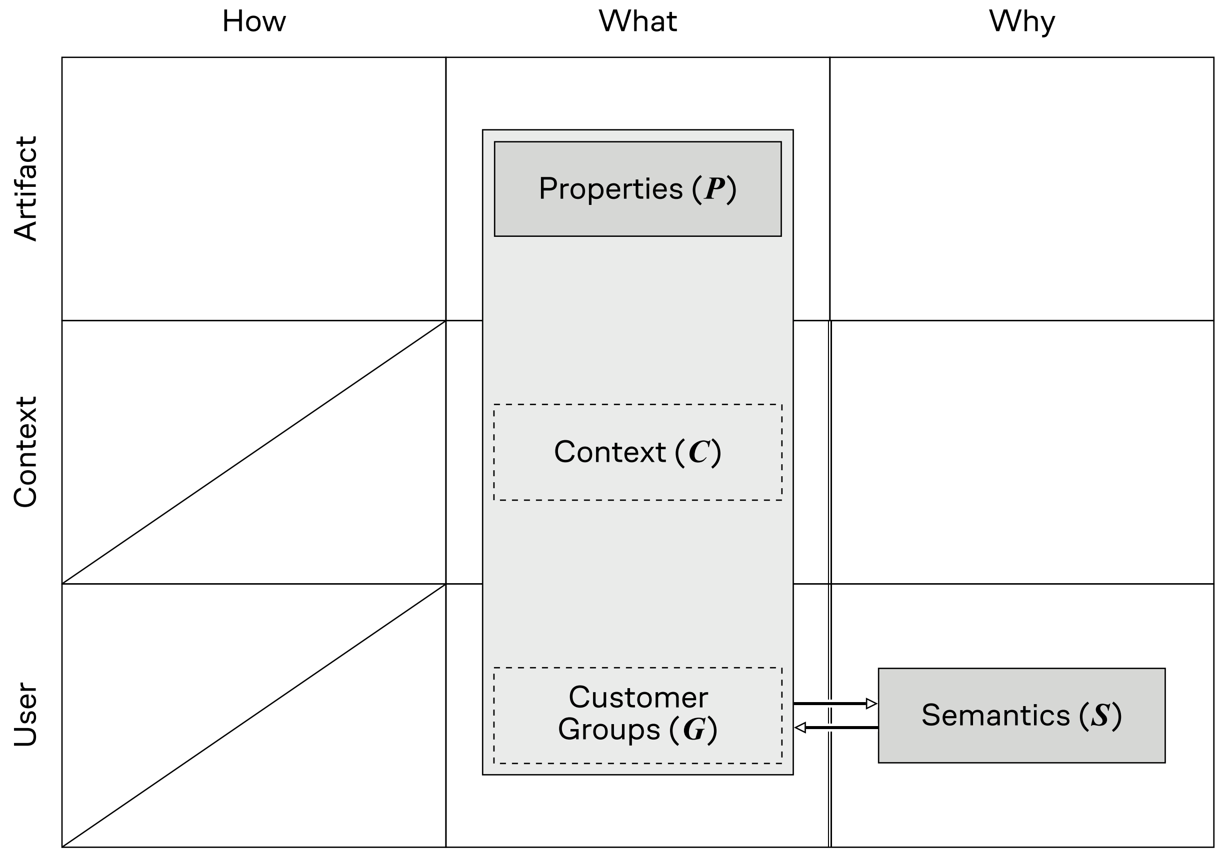

Figure 6. The problem space formulation of Kansei Engineering mapped onto the A-A matrix. Semantics (***S***) is mapped to the User-Why and Properties (***P***) is mapped to the Artifact-What. The extensions Context (***C***) [256] and Customer Groups (***G***) [212] are mapped to the Context-What and User-What, respectively.

Mapping the KE Solution Space – The solution space of KE is mapped through several mathematical models that relate the vector spaces in this formulation. The knowledge for the options in this space is constructed across embodiment design *analysis*, *synthesis*, and *evaluation*.

1. ***Analysis*** – KE provides relatively robust procedures for *parameterizing* the vector spaces, including expert/user consultations, pilot study, literature review [212], or pilot studies [212,248]. It also permits a wide variety of different statistical models to be used for *descriptive modeling*, however the method itself does not specify protocols for characterizing these models [231]. These models also may be graphed with contour plots to better visualize the available options [213].

2. ***Synthesis*** – The inverse of the statistical models may be employed for *prescriptive modeling* [212,213,231], however the common use of categorical data can make it difficult to interpolate new design configurations [243,257]. For *prototyping*, KE does not provide

explicit measures to help make construct physically-interactive prototypes, and is largely limited to products that already exist [246,257].

3. ***Evaluation*** – The protocols of KE do not explicitly discuss *verifying* specific design configurations, but it does describe a process for *validating* the models [212,231]. Dimensional reduction techniques may be used in improve statistical power, however validation testing can require long, costly iterations [231].

2.3.4. Mapping Conjoint Analysis

Conjoint Analysis (CA) is a design method that was developed from a *marketing perspective* to identify how product attributes are valued by customers. The problem and solution space maps are each outlined. A *ratings-based* format for CA is mapped here (as opposed to *choice-based*).

Mapping the CA Problem Space – The problem space of CA may be mapped to the A-A matrix by classifying the *Product Attributes* (***A***) and *Subjective Ratings* (***R***) vector spaces into A-A domains. At the level of the *why*, ***R***, defines the scores that users may subjectively rate the product, which may be mapped into the User-Why. Had this been a *choice-based* format, the problem space would not map as cleanly onto the A-A matrix, as judgements such as 'choice' or 'purchase decision' are a higher level of abstraction that are made based on an aggregation of technical *and* experiential outcomes [17,34,169,278,307,308]. At the level of the *what*, ***A*** describes the attributes of the product that are most relevant to the consumer, and is, of course, mapped into the Artifact-What. ***R*** is coupled to ***A*** with a functional transformation that is characterized by a statistical model. At the level of the *how*, engineers have added in a *Design Parameters* (***D***) extension vector space that describes the underlying form/layout of the artifact [28], which is mapped into the Artifact-How. ***D*** is then coupled to ***A*** with a functional transformation that is characterized by an analytical engineering model. The resulting map of the problem space formulated by CA is given in Figure 7.

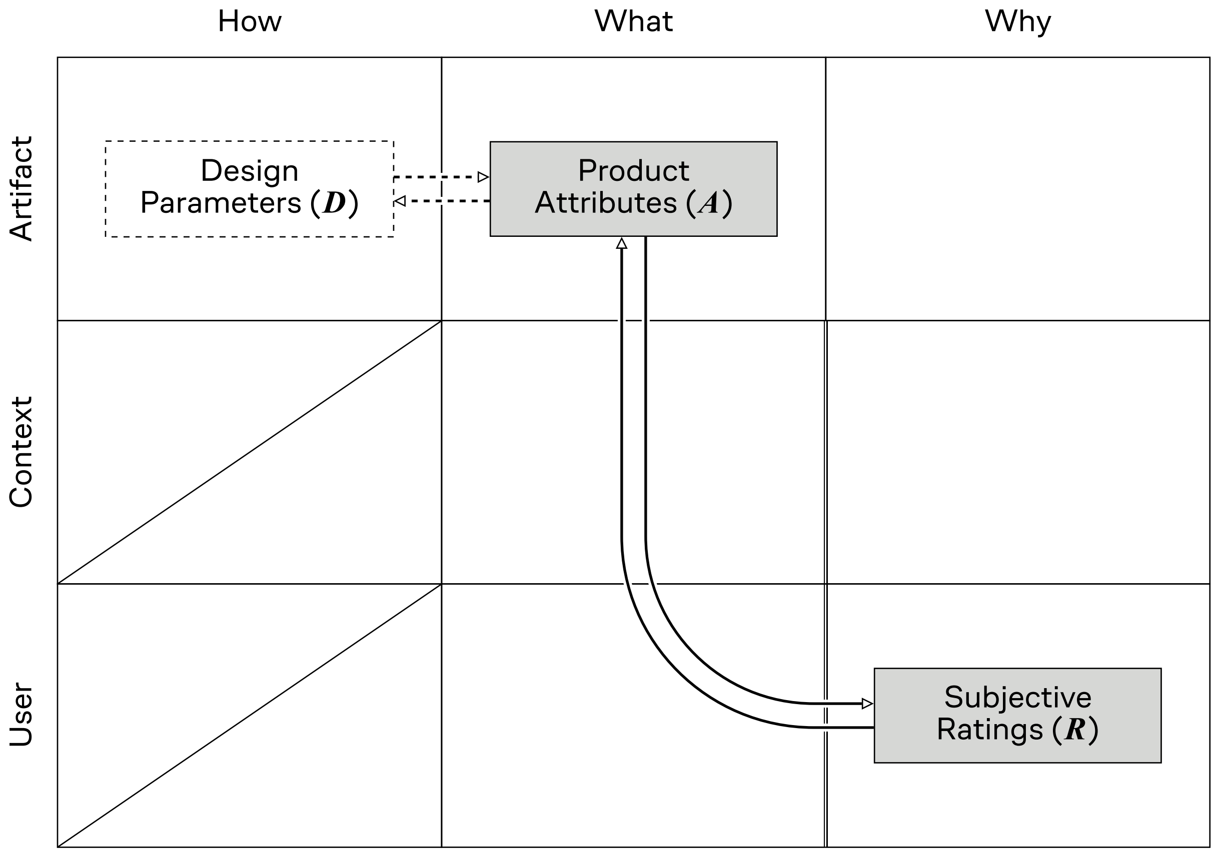

Figure 7. The problem space formulation of Conjoint Analysis mapped onto the A-A matrix. Subjective Ratings (***R***) is mapped to the User-Why and Product Attributes (***A***) is mapped to the Artifact-What. The extension Design Parameters (***D***) [28] is mapped to the Artifact-How.

Mapping the CA Solution Space – The solution space of CA is mapped through several mathematical models that relate the vector spaces in this formulation. The knowledge for the options in this space is constructed across embodiment design *analysis*, *synthesis*, and *evaluation*.

1. ***Analysis*** – CA does not dictate formal protocols for *parameterizing* the vector spaces, but does suggest using literature reviews, expert input, interviews/focus groups [280], or observations [282] to select attributes that thought to be are most relevant to the consumer. CA does, dictate that these dimensions should be discretized across several fixed levels. CA also provides comprehensive support for *descriptive modeling* through protocols to construct the experimental design of the survey, and the characterize the of the statistical model [15,266].

2. ***Synthesis*** – CA is primarily beneficial for *prescriptive modeling*, as new design configurations may be interpolated between the discretizations [15,34,282]. While these

new design configurations may be generated in real-time for low-fidelity representations (e.g., images) [282], it provides limited support for *prototyping* physically-interactive products [34].

3. ***Evaluation*** – The use of adaptive experimental designs can support both *verifying* the individual predictions, and more importantly *validating* the overall model across the continuous solution space.

2.3.5. Selective Integration of Existing Design Methods

Overall, this mapping of existing design methods puts the flexibility of the Embodiment Design Cartography framework to the test across a variety of different perspectives and disciplines. While there are some select instances in which vector spaces fall outside the defined scope of the Actor-Abstraction matrix (e.g., choice-based Conjoint Analysis formats that address higher abstractions), the EDC framework can demonstrably support each of these design methods. While the interpretations to construct these maps may arguably be imperfect, they allow for comparisons to be made that were previously more difficult or impossible to make. In the world of design, functional *utility* reigns supreme over abject *veracity* [365].

Mapping each of these design methods onto this common scale can suggest areas in which they may be *integrated* with each other, a proposition that was previously ambiguous. In terms of boundary objects, a 'boundary' is often misconstrued as a line that differentiates design methods, but in reality is an area in which they *overlap* [344]. This mapping highlights these overlaps, which signal areas in which boundaries may be spanned, i.e., points of compatibility for general usage. For instance, the Design Parameters (***D***) extension vector space defined in both Quality Function Deployment [186] and Conjoint Analysis [28] couples the Artifact-How to the Artifact-What. As Kansei Engineering defines a Properties (***P***) vector space in the Artifact-What—thus overlapping this transformation—it stands to reason that these extensions may also be compatible with KE. Of course, any claims of compatibility for the existing design methods that are suggested by these mappings must be independently validated, which is *not* the specific focus of these efforts.

Rather, the benefit of this exercise for design space mapping is to identify activities that may be leveraged for the creation of *new* maps. As stated in Chapter 1, each of the design space maps given by these existing design methods could be used as tool to support Embodiment Design

Cartography, just as satellite imaging could be used as a tool to support traditional cartography. However, rather than meticulously testing these identified points of compatibility and knitting all of these existing methods together—an act which could create a 'Frankenstein's monster' of stitched-together maps—it is more prudent to *selectively integrate* only what is needed into *new* design space maps. In doing so, EDC may take advantage of the *benefits* of each method, without burdening the engineering designer with their associated *limitations* that may be included in their wholesale adoption.

In terms of modeling the solution space, each of these methods has a different protocol, which could have different numbers of steps that may not directly align. Similar to the problem space in the A-A matrix, this mapping overlayed these protocols onto the six activities that comprise the EDC methodology for constructing the solution space. On this uniform scale, the potentially advantageous techniques that were noted in these mappings are aggregated in Table 3. Each of these techniques from existing methods may then be selectively integrated into the EDC framework to support their respective processes for *new* design problems, which is demonstrated in the subsequent chapters. This therefore allows the EDC methodology to extract desirable pieces of the conceptual 'wrappers' from these methods, and apply them to new transformations that are tailored to the specific design problem at hand—all without relying on any one single method outright.

Table 3. Advantageous techniques of existing design methods that may be used for modeling the solution space.

Process	Activity	Method	Technique
Analysis	Parameterizing	QFD, KE	Using market research, consultations, etc. to define dimensions
		KE	Using pilot studies to set ranges and reduce dimensions
		CA	Discretizing dimensions across fixed levels
	Descriptive Modeling	KE, CA	Supporting a variety of statistical models for empirical studies
		KE	Visualizing models with contour plots
Synthesis	Prescriptive Modeling	CA	Interpolating new design configurations between fixed levels
	Prototyping		
Evaluation	Verifying	FBS	Comparing predicted and realized design outcomes
	Validating	QFD	Comparing multiple different design configurations
		KE	Validating the model across several iterations
		CA	Employing adaptive experimental designs for this model validation

However, this also highlights areas in which *no* existing method provided sufficient processes for this application. Generating new, physically-interactive *prototypes* in a practical and efficient manner remains a persistent challenge for existing design methods, such that no existing activities may be advantageously integrated. This is a limiting factor for empirical modeling, which warrants the exploration of alternative prototyping techniques.

2.3.6. Interaction Prototyping

Embodiment Design Cartography is predicated on the principles of: 1) evaluating numerous options, i.e., different design configurations, within the span of the available solution space, and 2) developing physically-interactive products. These principles inherently hamstring each other. Physically-interactive prototypes are simply the most resource-intensive manner for which an artifact may be represented. To generate new, physically-interactive prototypes in real-time, as is done with lower fidelity product representations, is a complex proposition.

Any transformation that crosses the *interaction boundary* within the Actor-Abstraction matrix (see Figure 3) requires an *empirical* study to characterize. Some formats of these studies can necessitate the on-the-fly generation of new designs, such as adaptive experimental designs (e.g., Adaptive Conjoint Analysis). Real-time prototyping can enable the synthesis and evaluation of new design configurations within a single testing session, and is ultimately key for facilitating this process.

As the existing design methods for describing transformations do not provide sufficient protocols for this task, this presents an opportunity to examine how other prototyping techniques may be integrated into the boundary object that is the EDC framework. In general, prototypes may be utilized for a variety of different purposes. Some can be used to test 'implementation', while others are used to test 'look and feel' [382] (see also [3]). *Product demonstrators* [110] are a specialized class of prototypes that conceptually divides the artifact into two domains that correspond to these aforementioned purposes: 1) the 'technical solutions' that test the 'implementation, and 2) the 'user-related features' that may test the 'look and feel.' These aims are *modularized* in order to break them up into parallel prototyping activities. Modularization allows for 'information hiding' [383], such that the 'look and feel' can be conveyed to the user without revealing the 'implementation.'

This idea of 'modularization' is commensurate with the organizational structure imposed by the EDC framework. The 'technical solutions' (Artifact-How) and the 'user-related features' (Artifact-What) map onto the A-A matrix, however only the latter needs to be represented for the rich, embodied interaction to occur, i.e., to conduct an empirical study of the transformation that crosses the interaction boundary between the *what* and *why*. As such, the 'user-related features' may be prototyped through alternative technologies than the 'technical solutions' that would be actually used in real-life. These alternative technologies could enable the prototype to be *adaptable*, such that multiple different configurations or the 'user-related features' can be replicated in the Artifact-What by a single prototype, and they may conceivably be altered in real-time. This specific class of prototype will henceforth be referred to as an *interaction prototype*.

For instance, a haptic controller could be over-engineered such that the feedback it affords (i.e., its responsive attributes) may be programmatically altered for the sake of empirical study, whereas the actual product would only provide a fixed level of feedback. This interaction prototype could then simulate multiple different design configurations within the Artifact-What domain—which could be altered or generated in real-time—without having to actually adjust the 'technical solutions' in the Artifact-How. This therefore enables a more resource efficient prototyping technique for design space mapping, which is demonstrated in the subsequent chapters.

2.4. Chapter 2 Conclusion

In this chapter, the framework for Embodiment Design Cartography (EDC) was derived in terms of an *ontology*, *epistemology*, and *methodology*, which together define the overall philosophy of design space mapping. Conceptual frameworks ultimately provide *understanding* rather than *explanation* [330]. The philosophy of the EDC framework is summarily to provide an *understanding* of the available *options* in the design space, rather than an *explanation* about why one specific design configuration should be *selected* over another, equally valid solution. With this framework, the design space map for each of the existing design methods reviewed in Chapter 1 was constructed. In terms of the design journey, this mapping exercise is equivalent to taking the existing maps provided by these methods—each of which is used to point adventurers to different treasures, with different levels of detail and different portions of cave system illustrated—and redrawing them all onto a uniform scale such that they may be directly overlaid.

By defining this framework through the lens of a boundary object, the *problem space* may be *flexibly formulated* to support a variety of different design problems. At first, the EDC ontology imparts a looser organizational structure with the Actor-Abstraction (A-A) matrix. This looser structure is important for enabling *multidisciplinary* support, as evidenced by the reverse compatibility of existing design methods from these different disciplines. Even more paramount to this flexibility, however, is the ability it enables to *tailor* precise formulations for any new design problem that addresses the 'embodiment' phenomenon. In this regard, the framework aims provide just the right level of specificity without inadvertently limiting engineering designers through over formalization.

To construct the necessary knowledge of the available design options, the abstract design outcomes and concrete design levers in this formulation may be coupled with the *model of the solution space*. The EDC epistemology clarifies the sources of data that may be used to create this model, which are important to differentiate due to the different manners in which their couplings may be characterized. Artifact outcomes exist on a technical level and may be characterized analytically, while context and user outcomes exist on an experiential level and must be characterized empirically. This is visually denoted by the interaction boundary. The EDC methodology defines a six-step protocol that may be followed to actually characterize this model (i.e., parameterizing, and descriptive modeling), use it to create new design configurations (i.e., prescriptive modeling and prototyping), and assess its predictive accuracy (i.e., verifying and validating). These activities therefore dictate how to conduct the analysis, synthesis, and evaluation of this model.

By mapping the existing design methods with this framework, they may each be commonly examined in terms of the *experimental techniques and procedures* they employ for each of these six activities in the EDC methodology. The meta-analysis of these methods allows for the identification of techniques that are notably advantageous in their general usage, and reveals exactly which processes they may be adapted to support in design space mapping. This is important for improving the efficiency of this practice, as it provides a look into exactly where each of these existing design methods excels, and allows these prospectively advantageous techniques to be *selectively integrated* into the framework without wholesale adoption of any one design method. Additionally, while none of the mapped design methods detail a technique for practically generating physically-interactive prototypes, specific prototyping techniques may be similarly examined through the framework and adapted to support these aims. The A-A matrix informs which aspects of the prototype need be represented (i.e., the Artifact-What), and which are hidden from the user and may therefore be enacted through alternative means (i.e., the Artifact-How).

Overall, this mapping exercise represents how the EDC framework may be *operationalized*. Existing design methods are well understood in their own right (see Chapter 1), but less so in relation to alternative methods from different disciplines or perspectives. This application of the framework is important for facilitating a direct comparison of design methods from different disciplines and revealing how their conceptions of the problem space my differ. By including extensions in this mapping exercise, a picture emerges of why these works were motivated—to fill gaps in these formulations. Other A-A domains that are not addressed in these problem space mappings may therefore suggest additional areas in which these works could serve to be extended. Mapping extensions also illustrates how continued methodological development can be supported by this framework. However, this only represents one half of the manner in which EDC may be operationalized—a retrospective mapping of methods that already exist. It is therefore necessary to explore the other half of this framework's applicability—creating *new* design space maps that are tailored to specific design problems. In the next chapter, this proposition is explored for an emerging technology.

Chapter 3. A Method for Navigating Tradeoffs in an Emerging Technology

Tradeoffs can be present within the design space when different outcomes compete with one another, i.e., to improve one requires the detriment of the other. Design space mapping can be beneficial for understanding these tradeoffs and negotiating a favorable outcome. This is especially pertinent for *emerging* technologies, in which there is a high savings proposition for efficiently navigating said tradeoffs earlier in the new product development cycle. In this chapter, the Embodiment Design Cartography framework is applied to a case study of an *emerging* technology in order to negotiate favorable *tradeoffs* between technical and experiential design outcomes using *engineering design levers*. The objective of this chapter is to develop and demonstrate modeling, experimental, and design techniques in support of these aims. The problem space for this case study is first systematically mapped on the Actor-Abstraction matrix, which results in a unique formulation that is tailored to this specific design problem. The six activities for modeling the solution space are then followed, which are largely undertaken within an empirical user study (n = 57). In this study, an adaptive, self-validating experimental design is employed to characterize the model, generate new protypes in real-time, and then validate its predictive accuracy. With this validated model, a visual system for negotiating tradeoffs is developed, which allows for measurable design adjustments to be informed that achieve a favorable balance between competing design outcomes.

3.1. Tradeoffs in Engineering Design

In ill-structured problems like embodiment design, there is no one single solution that is a definitively superior option [12]. Some design configurations may achieve a high level of *technical* performance, but still elicit negative *experiential* responses. For others, the opposite may be true. There is not necessarily a definitive balance between the two [44,111]. In engineering design, the focus is often centered on the technical level, as this is where engineers specialize [111]. However, it is critical that outcomes on an experiential level are not neglected in this process [127,236]. When purchasing a vehicle, for instance, the experiential responses elicited by attributes such as the 'sound' or 'feel' of closing a car's door can be just as influential to consumer decisions as its technical performance [12]. As both are evidently of critical importance to the success of the solution, a range of viable options may therefore exist in the design space [12,18,109,187,262,384].

> *"Aims, purposes, requirements, functions: these are words for how we see what is needed. But when we name them we tend to exclude the main part, the least predictable: ourselves, our minds, and how they change once we experience something."*

– John C. Jones, *Designing Designing*, 1991 (republished 2021) [385]

Tradeoffs exist in the design problem when different design outcomes are *competing* [4,25,44,71,99,100]—to improve outcomes on one level may detriment outcomes on another, oftentimes in an indeterminant manner [20]. This is a particular ailment for *physically-interactive* products. Whereas *digital* products may be able to *decouple* their attributes such that outcomes on each level may be designed separately, the design of these outcomes in *physical* products is inherently *coupled* [44,93]. This coupling occurs because, at the root level, all of these design outcomes are commonly determined by the underlying form/layout of the product, i.e., they are not independent. Adjustments to the engineering design levers on this level can influence both the *responsive* (i.e., those that influence the rich, embodied interaction) and *persistent* attributes (i.e., those that maintain relevance outside of this interaction) of the product. An example of this may be seen in the design of *haptic controllers*, which must balance tradeoffs between the responsive attributes they afford (e.g., stiffness, manipulability, etc.) and their persistent attributes they achieve (e.g., durability, production cost, etc.), as these attributes are both determined by a common set of form/layout parameters [25,71]. Understanding how to navigate these tradeoffs has remained a longtime issue in new product development, e.g., [322,323,326].

> *"It is quintessential to realize that a consumer product is an optimized solution for a design problem, but always a trade-off between all kinds of conflicting demands… products that are optimized towards one characteristic, for example cost efficiency, often are shallow in other aspects like durability, experience offered, or aesthetics. Good industrial product design is in integrating and balancing all characteristics of a product for a particular application, user group, and context-of-use."*

– Joep Frens, *Designing for Rich Interaction*, 2006 [44]

With a map of the design space, the tradeoffs that exist in a given design problem may be better understood. This map can reveal exactly which outcomes are competing, how the tradeoffs between them are influenced by external factors, and ultimately how to adjust the available design levers to find a favorable balance. Gaining the ability to navigate tradeoffs can be especially beneficial in *emerging* technologies, in which there is little prior understanding for how different outcomes may compete. Between 70-80% of production costs are accrued by decisions made in these earlier stages of development [386], so a more holistic understanding of the design space can pay dividends in this regard. Without a design space map, later corrections to balance these tradeoffs may be necessary, thus incurring costly late-stage adjustments through extensive iterations [110]. Construction of this map through Embodiment Design Cartography may therefore help mitigate these costly mistakes [168] and adjustments [104] by allowing these tradeoffs to be efficiently assessed earlier in the new product development cycle.

3.2. Case Study: The Pneumatic Steering Column

To demonstrate the ability of Embodiment Design Cartography (EDC) to support the navigation of tradeoffs in real-world design problems, the design space map of an *emerging* steering system is undertaken. Physically-interactive products in the form of Human-Machine Interfaces (HMIs) are quite prevalent within automotive settings [387] due to the additional *haptic* information that may provide while driver's visual channels are already dedicated to navigating the vehicle. In the context of steering systems, haptic feedback can afford beneficial experiential outcomes when completing driving tasks (e.g., navigating curves or maintaining lanes) [68,69].

The product in this case study is a *pneumatic steering column*, e.g., [388]. This is an emerging technology that would replace the standard steering column in a vehicle with a hollow, pressurized column composed of an elastic material. It is fixed at one end and may be twisted under torsional shear applied by rotating the steering wheel on the other end; internal constraints prevent bending or lateral deformation, e.g., [389]. The connection to the steering mechanism is a steer-by-wire system, e.g., [390]. This artifact is illustrated in Figure 8.

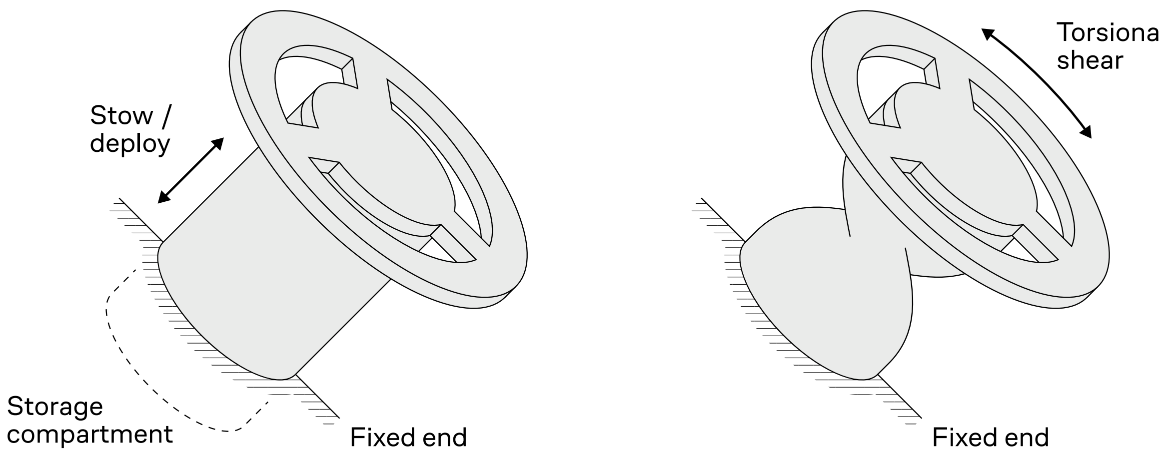

Figure 8. The pneumatic steering column. The steering column in this system is a hollow, pressurized cylinder that is composed of some elastomer. This artifact provides the functionality to be stowed or deployed as needed by inflating the column (left). This, however, impacts the interaction of steering, as the haptics are altered by this new technological approach (right).

The implementation of such a device would enable a *stow/deploy* mechanism for the steering column, which would be used in autonomous vehicles for limited manual-steering scenarios. By decreasing the pressure and contracting internal tendons, the length of the column would compact into a storage compartment at the fixed end. Interest in stowing the steering wheel may increase as greater emphasis is placed on reconfigurability of vehicle interiors, with the advent of autonomous driving. The technological changes to enable this new function, however, would also affect the rich, embodied interaction of rotating the steering wheel. The *kinesthetic haptic feedback* of the pneumatic steering column would likely be stronger over a smaller range of motion. This feedback would also depend solely on the angular displacement of the steering wheel, rather than any motion of the vehicle itself (i.e., steer-by-wire).

It is not immediately apparent as to what this steering interaction should feel like, or how adjustments to the available design levers would influence the experiential responses elicited through its interaction. The tradeoffs that may exist between the *technical* functions (e.g., stowability) and the *experiential* responses (e.g., satisfaction) elicited by the interaction (i.e., rotating the steering wheel) are also not evident. External factors that may influence these tradeoffs need to be considered in the *problem space formulation*. Characterizing *models of the solution space* can be difficult in early development with the limited knowledge base that is available [110]. The costs of constructing multiple *physically-interactive prototypes* that could represent the range of achievable steering feels with high enough fidelity may present barriers. As such, this emerging technology is a suitable candidate for design space mapping to illustrate the manner in which the EDC framework may be *operationalized* to inform design decisions in this area.

3.3. Mapping the Pneumatic Steering Column Problem Space

Following the Embodiment Design Cartography (EDC) methodology detailed in Chapter 2, the first step in design space mapping is to construct the map of the *problem space*. This necessitates a *critical examination* of which considerations may be relevant to this design problem. Each of these considerations will be defined by a vector space that may be mapped within the Actor-Abstraction (A-A) matrix (see Figure 3). As this case study is first and foremost an engineering design problem, language from an existing design method with an engineering perspective (i.e., Function-Behavior-Structure) is used to name these vector spaces. This is simply for the added ease of understanding these designations; the actual naming system of the vector spaces is immaterial as they are ultimately designated by their A-A domains. The resulting mapping is illustrated in Figure 9.

The Why – Starting at the level of the *why*, the aim of this problem is to compare tradeoffs between design outcomes on a *technical* and *experiential* levels. This necessitates the mapping of two different vector spaces in this abstraction. On the technical level, a *Technical Functions* (***T***) vector space, which describes the stow/deploy function and any other technical outcomes that be derived directly from the artifact itself, may be mapped into the Artifact-Why. On the experiential level, this formulation shall include a *Subjective Experiential Responses* (***Es***) vector space, which describes user's subjective perceptions that are specifically elicited by the rich, embodied steering interaction. ***Es*** is mapped into the User-Why. It is between these two vector spaces—***T*** and ***Es***—that the tradeoffs are assessed.

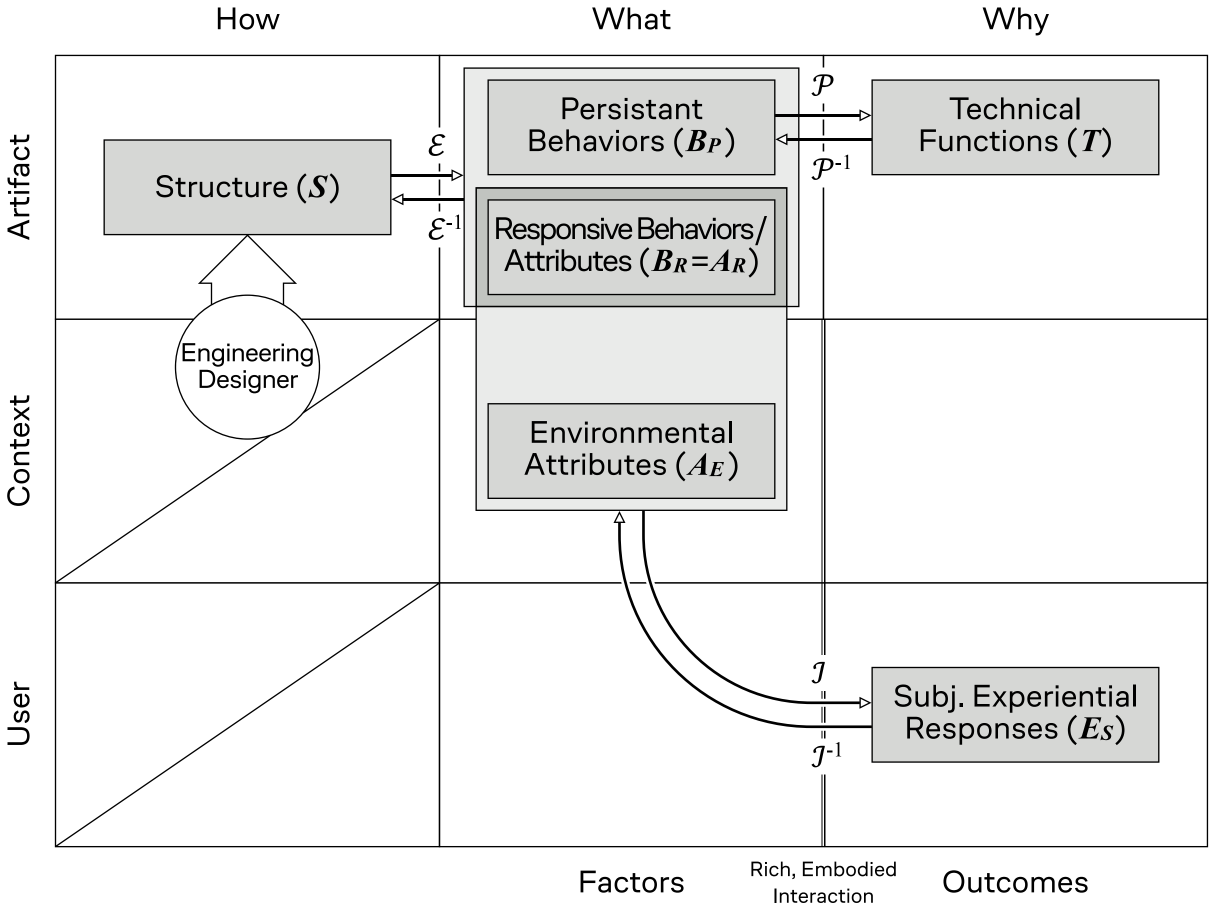

Figure 9. The problem space formulation of the pneumatic steering column mapped onto the A-A matrix. Technical Functions (***T***) is mapped into the Artifact-Why, and Subjective Experiential Responses ($\boldsymbol{E_S}$) is mapped into the User-Why. Persistent Behaviors ($\boldsymbol{B_P}$) and Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$) are both mapped into the Artifact-What, and Environmental Attributes ($\boldsymbol{A_E}$) is mapped into the Context-What. The Structure (***S***) is mapped into the Artifact-How, which is where the engineering design levers preside.

The What – At the level of the *what*, it shall first be considered as to what external factors may influence this tradeoff. One factor that seems to be particularly relevant to the experience of steering with this device is the *physical roads* or *environmental obstacles* that are navigated. In this regard, an *Environmental Attributes* ($\boldsymbol{A_E}$) vector space is mapped into the Context-What. Of course, the attributes of the pneumatic steering column itself may be mapped at this level as well. Out of all the attributes that describe what the artifact is from a consumer perspective, only a *subset* of them may be directly engaged with to elicit experiential responses [96,391]. As such, a *Behaviors* (***B***) vector space (using the FBS schema) is mapped into the Artifact-What, which is decomposed into two sub-vector spaces: 1) a *Persistent Behaviors* ($\boldsymbol{B_P}$) vector space, and a *Responsive Behaviors* ($\boldsymbol{B_R}$) vector space ($\boldsymbol{B} = \boldsymbol{B_P} \cup \boldsymbol{B_R}$). The latter may be alternatively deemed the *Responsive Attributes* ($\boldsymbol{A_R}$) vector space, which itself is a sub-vector space of the overall

Attributes (***A***) vector space ($\boldsymbol{A} = \boldsymbol{A_R} \cup \boldsymbol{A_E}$), which describes the attributes that are relevant to the rich, embodied *steering* interaction. $\boldsymbol{B_P}$ is then coupled to ***T*** [28,186], and ***A*** is coupled to $\boldsymbol{E_S}$ [47,96] across the *interaction boundary*, both with functional transformations. A key assertation is made in these couplings: Persistent Behaviors beget Technical Functions, and Responsive Behaviors beget Subjective Experiential Responses. These couplings are distinct and occur in parallel. For instance, the 'cost' of a toothbrush (i.e., its $\boldsymbol{B_P}$) does not affect its perceived 'comfort' (i.e., its $\boldsymbol{E_S}$) within the specific interaction of 'brushing ones teeth,' but is still highly relevant to the higher level judgments that are made based on the overall design outcomes, i.e., *purchasing* [278].

The Why – This parallel coupling is not to say that $\boldsymbol{B_R}$ may not influence ***T*** and the $\boldsymbol{B_P}$ may not influence $\boldsymbol{E_S}$, they just do so *indirectly*. Both subsets of ***B*** are commonly linked to the underlying form/layout at the level of the *how*. Continuing with the FBS schema for the artifact domains, the *Structure* (***S***) vector space is mapped into the Artifact-How, which describes these parameters of the form/layout that define the pneumatic steering column. It is in this vector space that the engineering *design levers* provide direct input into the design problem. ***S*** is coupled to ***B*** with a functional transformation, such that any adjustments made at this level may alter both $\boldsymbol{B_P}$ and $\boldsymbol{B_R}$, which in turn may impact both ***T*** and $\boldsymbol{E_S}$. The *tradeoffs* that exist between these design outcomes are therefore evidenced by this common coupling at the lowest abstraction level, "[t]hat is, the form of products mediates both the interaction and the expression of functionality" [97].

The resulting problem space formulation couples the concrete design levers (***S***) to the abstract design outcomes (***T*** and $\boldsymbol{E_S}$) in two *closed circuits* that may be traced in both the *causal* and *teleological* directions. Looking at the map, it is evident that the Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$) serves a unique role as a sub-space of two different vector spaces (***B*** and ***A***). It is therefore considered to be an *intermediary vector space*, as it serves as both an *input* and an *output* to different transformations. This allows for the formulation to be 'completed,' as is dictated by the EDC epistemology. Overall, the problem space map that is derived through the systematic examination of these considerations provides a *well-defined* organizational structure that is *unique* from existing design methods and *tailored* to this specific design problem.

3.4. Mapping the Pneumatic Steering Column Solution Space: Analytical Models

Following the Embodiment Design Cartography (EDC) methodology detailed in Chapter 2, once the problem space is formulated, the second step is to construct the map of the *solution space*. The solution space is characterized by modeling the transformations between the vector spaces that contain *design levers*, and those that describe *design outcomes*. This modeling is conducted in order to build a quantitative understanding of the relations within the problem space map, and to then enable rigorous manners for which the resulting design options may be assessed. This map is constructed in a *linear algebraic* sense, and therefore leverages all of the associated machinery (e.g., vectors and vector spaces).

The EDC methodology describes six activities for constructing this map (see Table 2), which include: 1) *parameterizing*, 2) *descriptive modeling*, 3) *prescriptive modeling*, 4) *prototyping*, 5) *verifying*, and 6) *validating*. As the problem space formulation spans the *interaction boundary* (see Figure 3), *empirical* study is necessary for characterizing portions of this overall model. The solution space mapping is therefore discussed across two sections in this chapter, in which this first section pertains to the *analytical* models that may be derived, and the subsequent section then details the characterization of the *empirical* models through a user study. Overall, this mapping spans each of the embodiment design processes (i.e., analysis, synthesis, and evaluation) through each of the six activities in the EDC methodology.

3.4.1. Parametrizing the Pneumatic Steering Column Problem Space

The first activity for the *analysis* process is to *parametrize* each of the vector spaces. Some of these parametrizations are logical or are implied by the design problem, but techniques from Quality Function Deployment or Kansei Engineering may be also leveraged for this purpose, per the meta-analysis conducted on the existing design methods (see Table 3). Expert input was derived for this case study through consultation and collaboration with General Motors (GM) engineers, and ranges were refined with small pilot studies. The parameterized vector spaces are summarized in Table 4 and each detailed in turn.

Table 4. Parametrized vector spaces of the pneumatic steering column problem space. Directional design objectives (increase/decrease) at the level of the *why* are indicated by ±Δ.

A-A Domain	Vector Space	Description
Artifact-How	$\boldsymbol{S} = \{\boldsymbol{l}, \boldsymbol{d}, \boldsymbol{th}, \boldsymbol{p}, \boldsymbol{h}\}$	The *length* (***l***), *diameter* (***d***), *wall thickness* (***th***), *pressure* (***p***), *material hardness* (***h***) of the pneumatic steering column (see Figure 10).
Artifact-What	$\boldsymbol{B_P} = \{\boldsymbol{v}, \boldsymbol{sr}, \boldsymbol{c}\}$	The *stowed volume* (***v***), *structural rigidity* (***sr***), and *production cost* (***c***) of the pneumatic steering column.
	$\boldsymbol{B_R} = \boldsymbol{A_R} = \{\boldsymbol{k}, \boldsymbol{s}\}$	The *torsional stiffness* (***k***) and *steering sensitivity* (***s***) of the pneumatic steering column [390].
Context-What	$\boldsymbol{A_E} = \{\boldsymbol{t}\}$	The *track* (***t***) that the pneumatic steering column is used to navigate, i.e., the *rapid-steering and precision-steering* tracks (see Figure 11).
Artifact-Why	$\boldsymbol{T} = \{\boldsymbol{sw}, \boldsymbol{sb}, \boldsymbol{af}\}$	The *stowability* (+Δ***sw***), *stability* (+Δ***sb***), and *affordability* (+Δ***af***) of the pneumatic steering column.
User-Why	$\boldsymbol{E_S} = \{\bar{\boldsymbol{r}}\}$, $\bar{\boldsymbol{r}} = (\sum_{n=1}^{3} \boldsymbol{r}_n)/3$	The overall *rating* (+Δ$\bar{\boldsymbol{r}}$), averaged between the *satisfaction* ($\boldsymbol{r}_1$), *learnability* ($\boldsymbol{r}_2$), and *controllability* ratings ($\boldsymbol{r}_3$) (5-point scale).

Parametrizing the Structure – The dimensions of the Structure (***S***) vector space physically define the geometry and properties of the pneumatic steering column's form/layout. This device is composed by a pressurized, hollow cylinder, capped at both ends, and made of some elastomer. The dimensions of ***S*** are therefore the *length* (***l***), *diameter* (***d***), and *wall thickness* (***th***), *pressure* (***p***), and *material hardness* (***h***) of this column. These dimensions are illustrated by Figure 10. It is plausible that technical constraints on ***S*** could limit the range of these dimensions, and thus feasible regions of ***T*** and $\boldsymbol{E_S}$. While these are not imposed at this point, various technical constraints that could plausibly be posed are considered when navigating tradeoffs in the design space map. Overall, $\boldsymbol{S} = \{\boldsymbol{l}, \boldsymbol{d}, \boldsymbol{th}, \boldsymbol{p}, \boldsymbol{h}\}$ and each of these parameters may be directly adjusted by the engineering designer.

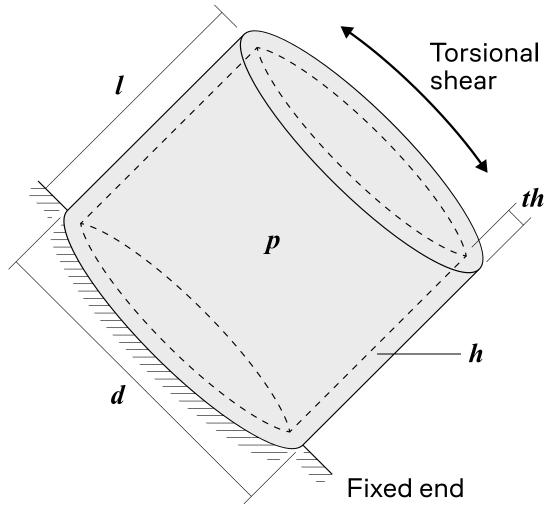

Figure 10. The form/layout of the pneumatic steering column. The Structure (***S***) is conceptualized as a hollow column of length (***l***), diameter (***d***), and wall thickness (***th***), that is inflated to some pressure (***p***), and composed of an elastomer with some material hardness (***h***). It is fixed at one end and torsional shear is applied at the other.

Parametrizing the Responsive Behaviors/Attributes – The dimensions of the Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$) each relate to the specific rich, embodied interaction in question, which in this case is *turning the steering wheel*. Each dimension may be defined in terms of: 1) the user's inputs to this interaction (i.e., the degree they rotate the steering wheel, $\boldsymbol{\Theta_{in}}$), and 2) the haptic feedback or system response that these inputs elicit. For the pneumatic steering column, these dimensions are given by the *effective torque stiffness* (***k***) and *steering sensitivity* (***s***), which together describe the haptic kinesthetic feedback of steering [390]. First, ***k*** is given by Equation (1), in which

$$\boldsymbol{k = \tau/\Theta_{in}} \tag{1}$$

, where $\boldsymbol{\tau}$ is the feedback torque felt by the user, and $\boldsymbol{\Theta_{in}}$ is the degree that they turn the steering wheel. The range of ***k*** was defined to be [1.875e-2, 0.3] $N \cdot m/deg_{in}$ through a small pilot study (see Section 3.5.2). On the other hand, ***s*** is given by Equation (2), in which

$$\boldsymbol{s = \Theta_{out}/\Theta_{in}} \tag{2}$$

, where $\boldsymbol{\Theta_{out}}$ is the degree that the front wheels of the vehicle turn for every $\boldsymbol{\Theta_{in}}$, which again is the degree that the steering wheel is turned. While ***s*** may be directly input or programed in a typical steer-by-wire system, in the pneumatic steering column, the achievable steering angle is greatly diminished by the fact that the column must be *twisted* rather than *rotated*. ***s*** is therefore inversely coupled to this range of motion to maintain the same minimum level of vehicle maneuverability.

Achievable values of $\boldsymbol{s}$ are thusly limited by the maximum torque that users may feasibly apply to the steering wheel for extended periods of time. This range was defined to be [0.7, 11.2] deg_{out}/deg_{in} through a small pilot study (see Section 3.5.2). Overall, $\boldsymbol{B_R} = \boldsymbol{A_R} = \{\boldsymbol{k}, \boldsymbol{s}\}$, in which target levels of $\boldsymbol{B_R}$ are propagated from objectives in the Subjective Experiential Responses ($\boldsymbol{E_S}$).

Parametrizing the Persistent Behaviors – The dimensions of the Persistent Behaviors ($\boldsymbol{B_P}$) relate to qualities of the product that exist outside of the steering interaction. The first is the *stowed volume* ($\boldsymbol{v}$), which describes its volume when fully depressurized and retracted. The second is the *structural rigidity* ($\boldsymbol{sr}$), which describes its stiffness in non-torsional deformations. The third is the *production cost* ($\boldsymbol{c}$), which describes the variable costs, and shall be considered proportional to material volume (for simplicity of the case study). No constraints are imposed on these dimensions. Overall, $\boldsymbol{B_P} = \{\boldsymbol{v}, \boldsymbol{sr}, \boldsymbol{c}\}$, in which target levels of $\boldsymbol{B_P}$ are propagated from objectives in the Technical Functions ($\boldsymbol{T}$), and therefore $\boldsymbol{B} = \{\boldsymbol{k}, \boldsymbol{s}, \boldsymbol{v}, \boldsymbol{sr}, \boldsymbol{c}\}$.

Parametrizing the Environmental Attributes – The rich, embodied interaction of turning the steering wheel requires some *context* for experiences to be meaningful. Drivers' feedback from aimlessly turning the steering wheel would likely be different to what they may provide if they were turning this steering wheel to actually navigate through an environment. Furthermore, the *type* of environment they were navigating through would also affect this interaction, and similarly influence their evaluations. Consider, for instance, the differences in navigating a crowded parking lot, an interstate, and a winding mountain road. In each of these contexts, both the *magnitude* of the steering angle and *frequency* of change in steering angle required to navigate these roads can vary drastically. As such, the Environmental Attributes ($\boldsymbol{A_E}$) in the Context-What are defined by two different categorical *tracks* ($\boldsymbol{t}$) in this case study. $\boldsymbol{t}$ represents two potential extremes of real-world driving scenarios, which are illustrated by Figure 11. The first, *rapid-steering* track is a tightly curved circuit navigated at slow speeds (30 km/h), which requires frequent, large rotations of the steering wheel to successfully traverse. The second, *precision-steering* track is a straight, two-lane road navigated at high speeds (100 km/h) which alternatively requires infrequent, small turns to successfully traverse (i.e., make lane changes). Each of these tracks could be further parameterized by several *continuous* variables (e.g., speed, curvature, etc.), however they are aggregated into a single categorical variable for simplicity of the case study; this aggregation is generally reflected in real life as well. Overall, $\boldsymbol{A_E} = \{\boldsymbol{t}\}$ and therefore $\boldsymbol{A} = \{\boldsymbol{k}, \boldsymbol{s}, \boldsymbol{t}\}$.

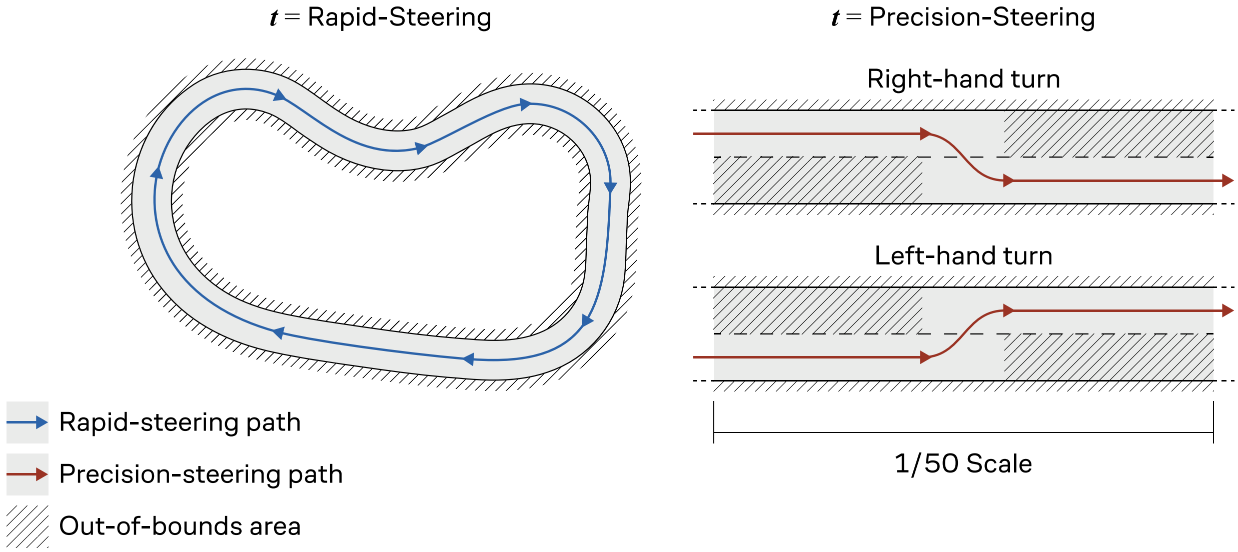

Figure 11. The contexts for the pneumatic steering column interaction. These two different tracks (***t***) define the Environmental Attributes ($\boldsymbol{A_E}$) in this case study. Drivers navigate the *rapid-steering* track (left) at 30 km/h and the *precision-steering* track (right) at 100 km/h. The circuit for the rapid-steering context is looped, while the road of the precision-steering track repeats, alternating between the right-hand and left-hand turns. The diagram of this latter track is pictured in 1/50 scale lengthwise, relative to the width of the track.

Parametrizing the Technical Functions – The dimensions of the Technical Functions (***T***) vector space relate to the stow/deploy mechanism, and other technical requirements common in product development. Each corresponds to a dimension in $\boldsymbol{B_P}$. The first is the *stowability* (***sw***), which describes its ability to be stowed in a storage compartment. The second is the *stability* (***sb***), which describes its ability to resist non-steering-related deformations and retain structural integrity. The third is the *affordability* (***af***), which describes its ability to present low financial barriers for consumers. Overall, ***T*** = {***sw***, ***sb***, ***af***} and a reasonable objective for each of these technical design outcomes would be to *improve* each of them (+Δ).

Parametrizing the Subjective Experiential Responses – The dimensions of the Subjective Experiential Responses ($\boldsymbol{E_S}$) vector space were initially described by five semantic descriptors from an existing questionnaire for automotive HMI evaluation—each of which were each relevant to the steering interaction—which was provided by General Motors. Through a small pilot study (see Section 3.5.2), three semantic descriptions were selected by dropping those that were highly correlated to these remaining three. The selected dimensions were the *satisfaction rating* ($\boldsymbol{r_1}$), i.e., *'how would you rate your satisfaction steering this vehicle?'*, the *learnability rating* ($\boldsymbol{r_2}$), i.e., '*how would you rate your ability to get used to steering this vehicle?*', and the *controllability rating* ($\boldsymbol{r_3}$), i.e., '*how would you rate your ability to control this vehicle?*'. These were evaluated on a 5-point

Likert scale [207]. To reduce this dimensionality such that a *single* objective variable could define $\boldsymbol{E_S}$, the *average rating* ($\bar{\boldsymbol{r}}$) of these three evaluations was calculated; dimensional reduction techniques such as this are common in KE [213] (see Table 3). Overall, $\boldsymbol{E_S} = \{\bar{\boldsymbol{r}}\}$ and reasonable objective for this experiential design outcome would be to improve this average rating (+Δ).

3.4.2. Descriptive Modeling Through Analytical Derivation

With the dimensions of each of these vector spaces defined, the relations between them may be characterized. The second activity of the *analysis* process is to *descriptively model* each of the transformations. There are three mathematical models denoted in the problem space formulation (see Figure 8), which are referred to as the *engineering model* ($\mathcal{E}$), the *performance model* ($\mathcal{P}$), and the *interaction model* ($\mathcal{I}$). Each of these models may have a *distinct functional form*, particularly when addressing the 'embodiment' phenomenon, i.e., physically-interactive products. On the *experiential* level, for instance, humans naturally perceive (e.g., $\boldsymbol{E_S}$) changes to physical stimuli (e.g., $\boldsymbol{A_R}$) on a *proportional*—rather than an *absolute*—scale [331,332]. This principle serves as a basis for the field of *psychophysics* [392], i.e., the *Weber-Fechner law* [393], which states that physical perception is not linear, but rather *logarithmic* in nature. Adjustments to the haptics of an artifact must occur on a *logarithmic* scale to be linearly perceived by the user [394]. However, on a *technical* level, the couplings between an artifact's underlying form/layout (e.g., $\boldsymbol{S}$), its attributes (e.g., $\boldsymbol{B}$), and ultimately, its performance (e.g., $\boldsymbol{T}$), are generally governed by *power law* relations. These differences in functional form—the logarithmic scale on the experiential level and the power law relations on the technical level—come into play when models of these different types are *composed* to couple design levers and outcomes. While the latter of these three models crosses the *interaction boundary*—and is therefore discussed in the subsequent section—the former two may be *analytically* derived.

In a general sense, the *engineering model* ($\mathcal{E}$) characterizes the functional transformation between vector spaces in the Artifact-How (i.e., $\boldsymbol{S}$) to vector spaces in the Artifact-What (i.e., $\boldsymbol{B}$). In this case study, this functional transformation may be given by Equation (3), in which

$$\mathcal{E}: \quad \boldsymbol{S} \rightarrow \boldsymbol{B} \tag{3}$$

$$\mathcal{E}^{-1}: \quad \boldsymbol{B} \rightarrow \boldsymbol{S}$$

, where $\mathcal{E}$ is descriptively characterized in the causal direction, but may be teleologically applied through its prescriptive inverse (i.e., $\mathcal{E}^{-1}$). Similarly, the *performance model* ($\mathcal{P}$) characterizes the functional transformation between vector spaces in the Artifact-What (i.e., $\boldsymbol{B_P}$) to vector spaces in the Artifact-Why (i.e., $\boldsymbol{T}$). In this case study, this functional transformation may be given by Equation (4), in which

$$\begin{aligned} \mathcal{P}: &\quad \boldsymbol{B_P} \rightarrow \boldsymbol{T} \\ \mathcal{P}^{-1}: &\quad \boldsymbol{T} \rightarrow \boldsymbol{B_P} \end{aligned} \tag{4}$$

, where $\mathcal{P}$ is similarly descriptively characterized in the causal direction, but may be teleologically applied through its prescriptive inverse ($\mathcal{P}^{-1}$). Compared to engineering modeling, performance modeling is essentially a measure that translates persistent attributes into layman's terms that comprise the artifact outcomes, which are more meaningful to consumers (e.g., 'affordability' is more directly understandable than 'production costs'). The distinction between '*what* something is' and '*why* something is' can be a fine line when considering a product on a purely technical level, and is largely predicated on *interpretation*. While $\mathcal{E}$ is generally subject to natural laws (e.g., the weight of an artifact is an objective quality), $\mathcal{P}$ generally affords more leeway for the engineering designer in how they wish to specifically define technical design outcomes such as 'durability' or 'affordability.' An outcome like 'durability,' for instance, could refer to its toughness, its waterproofing, or some other inherent resistance to destructive forces, as interpreted by the engineering designer.

Deriving analytical models of relations on this technical level is a well-established process, e.g., [5,20,22–25,28,186,370,395], and there are a variety of existing techniques to support this endeavor (e.g., finite element analysis [396]). In *emerging* technologies, however, the knowledge based required for these more sophisticated techniques may be limited [110]. Techniques for more simply approximating these relations can therefore be necessary to conduct this mapping earlier in the development cycle. In this regard, each of the analytical models on the technical level in this case study are characterized using *proportional sensitivities* that may be approximated with a limited knowledge base. Note that these estimations are not *true* sensitivities in the derivative sense of the word, but rather an index of the relative strength of these dependencies. More robust techniques for sensitivity modeling (e.g., [397,398]) may be employed in later development, but are out of the scope of this case study. This proportional sensitivity model is given in Table 5.

Table 5. Proportional sensitivity model for the pneumatic steering column. An adjustment (Δ) made to any element in the Structure (***S***) will reflect a proportional impact on corresponding elements of the Behaviors (***B***), which will in turn have a proportional impact on corresponding elements of the Technical Functions (***T***). Elements of ***T*** are designated with +Δ to reflect their design objectives (i.e., improve each)

$\boldsymbol{T}$	$\mathcal{P}$	$\boldsymbol{B}$	$\mathcal{E}$	$\boldsymbol{S}$				
$+\Delta \boldsymbol{sw}$	$\propto$	$\Delta \boldsymbol{v}^{-1}$	$\propto$	$\Delta \boldsymbol{l}^{-1}$	$\Delta \boldsymbol{d}^{-1}$	$\Delta \boldsymbol{th}^{-1}$		$\Delta \boldsymbol{h}^{-1}$
$+\Delta \boldsymbol{sb}$	$\propto$	$\Delta \boldsymbol{sr}$	$\propto$	$\Delta \boldsymbol{l}^{-2}$	$\Delta \boldsymbol{d}$	$\Delta \boldsymbol{th}$	$\Delta \boldsymbol{p}$	$\Delta e^{\boldsymbol{h}}$ $(\approx \Delta \boldsymbol{h}^{4})^{*}$
$+\Delta \boldsymbol{af}$	$\propto$	$\Delta \boldsymbol{c}^{-1}$	$\propto$	$\Delta \boldsymbol{l}^{-1}$	$\Delta \boldsymbol{d}^{-2}$	$\Delta \boldsymbol{th}^{-2}$		
		$\Delta \boldsymbol{k}$	$\propto$	$\Delta \boldsymbol{l}^{-1}$	$\Delta \boldsymbol{d}^{4}$	$\Delta \boldsymbol{th}$	$\Delta \boldsymbol{p}^{4}$	$\Delta e^{\boldsymbol{h}}$ $(\approx \Delta \boldsymbol{h}^{4})^{*}$
		$\Delta \boldsymbol{s}$	$\propto$	$\Delta \boldsymbol{l}$		$\Delta \boldsymbol{th}$	$\Delta \boldsymbol{p}$	$\Delta \boldsymbol{h}^{-1}$

For $\mathcal{E}$, the proportional sensitivities between ***S*** and ***B*** are dictated by the power-law relations that are approximated using fundamental principles of static mechanics (e.g., beam-bending, pressure vessel analysis, etc.)—knowledge that would be available for emerging technologies. For instance, a change in the effective torque stiffness (Δ***k***) is assumed to be inversely proportional to a change in the length (Δ***l***) and quartically proportional to a change in the diameter (Δ***d***) according to the second moment of inertia; proportional to changes in the wall thickness (Δ***th***), assuming thin walls; quartically proportional to a change in pressure (Δ***p***), which is the case for pressurized hollow cylinders; and exponentially related to changes in height (Δ***h***), which is a common approximation of the modulus of elasticity in elastomers, e.g., [399]. Although the changes to the steering sensitivity (Δ***s***) may be programmatically enacted in a steer-by-wire system, the range of motion of the steering wheel is limited by both the buckling of the column, and the torque that may be feasibly applied by the user. Δ***s*** is therefore considered inversely proportional to the range of motion, for the driver to maintain the same level of maneuverability. These approximations are largely simplified (e.g., Δ***c*** is equated to change in material volume) and are purely demonstrative for this case study. With a complete sensitivity model, true sensitivity gradients may be readily substituted in here if the technical knowledge is available.

For $\mathcal{P}$, on the other hand, these proportional sensitivities are *rationally* derived. An improvement (i.e., increase) to the stowability (+Δ***sw***) of the pneumatic steering column is interpreted to be inversely proportional to a change in the stowed volume ($\Delta \boldsymbol{v}^{-1}$). An improvement to its stability (+Δ***sr***) is interpreted to be linearly proportional a change in the structural rigidity

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* For simplicity, e^x proportionalities are approximated here by x^4.

($\Delta \boldsymbol{sr}$). An improvement to the affordability ($+\Delta \boldsymbol{af}$) is interpreted to be inversely proportional to a change in the production cost ($\Delta \boldsymbol{c}^{-1}$). $\mathcal{P}$ and $\mathcal{E}$ may be simply composed—where $\Delta \boldsymbol{T} = \mathcal{P}(\mathcal{E}(\Delta \boldsymbol{S}))$—such that the technical design outcomes are coupled to the design levers. This achieves one half of the solution space model through these analytically derived couplings. The other half, however, requires empirical study to characterize.

3.5. Mapping the Pneumatic Steering Column Solution Space: Empirical Models

To conclude the construction of the solution space map, the remaining activities in the Embodiment Design Cartography (EDC) methodology are conducted within an *empirical* user study. The purpose of this study is to characterize (i.e., *analysis*), employ (i.e., *synthesis*), and assess the predictive accuracy (i.e., *evaluate*) of an *interaction model* ($\mathcal{I}$) across the continuous span of the solution space. In a general sense, $\mathcal{I}$ characterizes the functional transformation between vector spaces in the Artifact-What, Context-What, and/or User-What (i.e., $\boldsymbol{A}$) to vector spaces in the Context-Why, and/or User-Why (i.e., $\boldsymbol{E_S}$). In this case study, this functional transformation may be given by Equation (5), in which

$$\mathcal{I}: \quad \boldsymbol{A} \rightarrow \boldsymbol{E_S} \qquad (5)$$
$$\mathcal{I}^{-1}: \quad \boldsymbol{E_S} \rightarrow \boldsymbol{A}$$

, where $\mathcal{I}$ is descriptively characterized in the causal direction, but may be teleologically applied through its prescriptive inverse ($\mathcal{I}^{-1}$). As this transformation crosses the *interaction boundary* in the Actor-Abstraction (A-A) matrix (see Figure 10), its outputs may only be elicited through a rich, embodied interaction, which, in this case, is 'steering with the pneumatic steering column.' A controlled user study was therefore conducted to empirically characterize and validate $\mathcal{I}$, and, ultimately, complete the solution space map. In this study, users (n = 57) assessed different design configurations of the pneumatic steering column (i.e., $\boldsymbol{A_R}$) within different steering tasks (i.e., $\boldsymbol{A_T}$), through trials in which a rich, embodied interaction for this design problem was replicated with an *interaction prototype* in a driving simulator.

3.5.1. Testing Procedure & Infrastructure

Fifty-seven licensed drivers (n = 57; 26 female, 31 male) between the ages of 18 to 74 (m = 33.84, sd = 17.15) were recruited to participate in this study via email listservs and social media advertisements—sixty participants were originally recruited, but three disqualified themselves before completion due to reported motion sickness in the simulator. The following inclusion criteria were specified: participants must 1) possess a valid driver's license, 2) be over the age of 18, and 3) be able to view a screen for 1 hour or more. This study was approved by the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board. Written informed consent was obtained from all participants.

This study took place in a driving simulator, which was constructed by replacing the windshield of a 2004 Cadillac CTS-V with a monitor that displayed the simulated environment. The vehicle's primary controls (i.e., the accelerator, break, and steering wheel) were connected to simulator program (VI-DriveSim) to act as controls for the simulated vehicle. Each of two tracks ($\boldsymbol{t}$) in $\boldsymbol{A_E}$ (see Figure 11) were virtually represented in this simulated environment. Ratings were provided through a Microsoft Surface Tablet that was mounted to the dashboard. This infrastructure is pictured in Figure 12. Lab sessions lasted approximately two hours in total.

After being acclimated to the simulator, the study population was randomly divided into two even groups, with each being assigned to one of the two tracks ($\boldsymbol{t}$; see Figure 11). This was due to practical constraints, as there was only enough time in the study for participants to drive on one track or the other. Participants were then tasked with completing a series of repeated driving maneuvers according to their assigned track. Each trial in this study necessitated the completion of three repeated maneuvers using a given configuration of the pneumatic steering column's responsive attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$), after which participants would provide their subjective ratings ($\boldsymbol{E_S}$). For the *rapid-steering* track, one trial consisted of *three laps of the circuit*. For the *precision-steering* track, one trial consisted of *three lane changes* (alternating between left-hand and right-hand turns). For both tracks, participants were instructed to remain on the road and to avoid the out-of-bounds areas to the best of their ability.

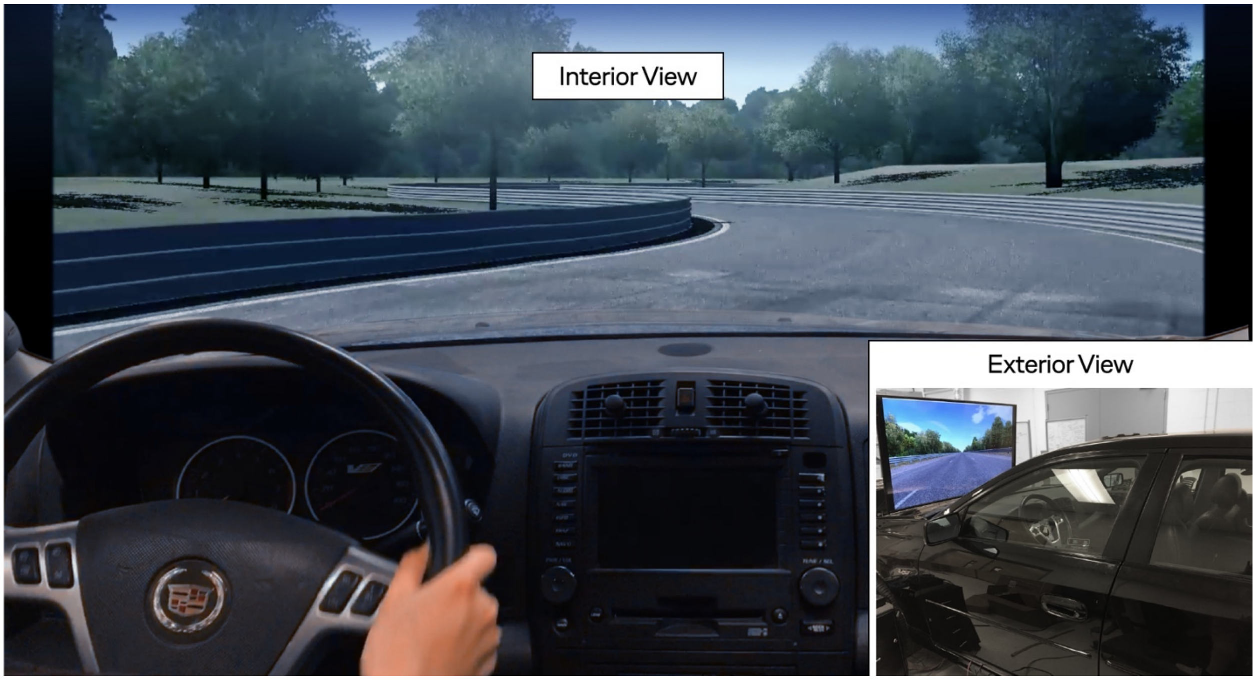

Figure 12. The driving simulator for the pneumatic steering column. From the interior of this vehicle (main), the participant used an interaction prototype that was built into the steering column to control the vehicle in the simulated environment (VI-DriveSim). This simulator was housed in a 2004 Cadillac CTS-V (exterior view; bottom right) to provide an immersive environment. The rapid-steering track is pictured here.

Participants were also outfitted with physiological sensors to measure the skin conductance at their left foot (*electrodermal activity*) and heart rate at their left earlobe (*photoplethysmography*), however this physiological data was *not* used in the construction of this design space map. It must be acknowledged that, although the recording sites of these sensors were selected to avoid interfering with driving maneuvers, these sensors may have influenced participants' ratings in some way.

Prototyping – In this study, participants evaluated *eleven* different configurations of the pneumatic steering column, however eleven different physically-interactive prototypes were not constructed. Rather, a single *interaction prototype* was constructed, which was able to be dynamically replicate any configuration within the span of the continuous solution space. In this case, the interaction prototype was constructed by attaching the traditional, rigid steering column to a harmonic drive motor (AC Servo Motor RSF-14B-50 [400]), which could replicate the kinesthetic haptic feedback in the rich, embodied steering interaction, as defined by $\boldsymbol{A_R}$, but without using the parameters in $\boldsymbol{S}$ to manifest them. An encoder on the steering column streamed the angle of the steering wheel ($\boldsymbol{\Theta_{in}}$) into a Simulink program, which dictated both the feedback torque ($\boldsymbol{\tau}$) that was output to the motor (see Eq. (1)), as well as the steering angle ($\boldsymbol{\Theta_{out}}$) that was output to the simulation (see Eq. (2)). A Python program that communicated with Simulink was then used to input different values for $\boldsymbol{k}$ and $\boldsymbol{s}$, effectively changing the configuration of pneumatic steering column in real time. These values for the eleven different trials were dictated by the experimental design of the study.

3.5.2. Experimental Design

The design of this empirical study was centered around: 1) estimating the coefficients of a regression that characterized (i.e., analysis) the transformation given in interaction model ($\mathcal{I}$; see Eq. (5)), 2) using the resulting model to predict new design configurations (i.e., synthesis), and then ultimately 3) *self-validating* the model (i.e., evaluation), all within same testing session. The form of this regression was given by a *mixed-effects* model, in which the average rating ($\bar{\boldsymbol{r}}$) is estimated ($\hat{\boldsymbol{r}}$) as a function of the Attributes ($\boldsymbol{A}$) vector space. However, as one element of $\boldsymbol{A}$—the track ($\boldsymbol{t}$)—is a categorical variable that is used to *divide* the study population into two groups (i.e., between rapid-steering and precision-steering), this element is pulled out of the model to denote two versions of $\mathcal{I}$ that each correspond to these two populations (and therefore, two different sets of data). These versions are colloquially referred to as the *rapid-steering interaction model* ($\mathcal{I}_{\text{Rap}}$) and the *precision-steering interaction model* ($\mathcal{I}_{\text{Prec}}$). The form of both of these models is given by Equation (6), in which

$$\mathcal{I}:\quad \hat{r} = \begin{bmatrix} a_1 \\ \vdots \\ a_5 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_5 \end{bmatrix} + u_j + e_{ij}, \tag{6}$$

$$a = \{\boldsymbol{k}, \boldsymbol{s}, \boldsymbol{k}\cdot\boldsymbol{s}, \boldsymbol{k}^2, \boldsymbol{s}^2\}$$

, where the *fixed-effects* are given by a, and the *random-effects* for each individual are given by u_j, with some error (e_{ij}) for each prediction. The coefficients (β) are separately estimated for both $\mathcal{I}_{\text{Rap}}$ and $\mathcal{I}_{\text{Prec}}$.

A small pilot study (n = 22) indicated the existence of 2$^{\text{nd}}$ order curvature in this transformation, thus the inclusion of the binomial terms (i.e., $\boldsymbol{k}^2$ and $\boldsymbol{s}^2$). This pilot was conducted prior to the full experiment in order to: 1) identify the ranges of $\boldsymbol{k}$ and $\boldsymbol{s}$ that were likely to contain the optimal $\bar{\boldsymbol{r}}$ (i.e., an *inflection point*), and to 2) downselect the dimensions of $\boldsymbol{E_S}$ (see Section 3.4.1). A wide range of values for $\boldsymbol{k}$ and $\boldsymbol{s}$ were sampled, and the user evaluations in $\boldsymbol{E_S}$ were reviewed. The ranges of $\boldsymbol{k}$ and $\boldsymbol{s}$ that would likely contain the inflection point were determined to be 1.875e-2 $\boldsymbol{k}$ 0.3 (N•m/deg_{in}) and 0.7 $\boldsymbol{s}$ 11.2 (deg_{out}/deg_{in}), respectively (see Section 3.4.1). The inclusion of these binomial terms is particularly useful for *synthesis*, as they allow for the existence of local maxima of $\hat{\boldsymbol{r}}$ to be present within the continuous span of $\boldsymbol{A_R}$, such that new, more optimal design configurations may be interpolated. It is beneficial to identify of the ranges of the dimensions in $\boldsymbol{A_R}$ which contain this inflection point so that this curvature may be reasonably included in $\mathcal{J}$.

Discreet levels across these defined ranges were then specified to further *parameterize* $\boldsymbol{k}$ and $\boldsymbol{s}$ (see Table 3). As this model characterizes user's perceptions ($\boldsymbol{E_S}$) to an interaction involving a *physical stimuli* ($\boldsymbol{A_R}$), these levels were spaced on a *logarithmic scale* in accordance with the psychophysical principle given by the Weber-Fechner law [331,332,392–394]. For each element of $\boldsymbol{A_R}$, three logarithmically space levels were defined (high, medium, low), which were paired to create a full-factorial experimental design (i.e., 3×3 design with nine trials). These nine, randomly ordered trials comprised the *analysis* portion of this study, in which the coefficients of $\mathcal{J}$ (see Eq. (6)) were estimated. This experimental design was therefore the same for each participant (barring the trial order) in this portion of the study. The inverse of this model ($\mathcal{J}^{-1}$; see Eq. (5)) was then used to make two *predictions* in the subsequent *synthesis* portion of this study. These predictions included the design configuration (i.e., pairing of $\boldsymbol{k}$ and $\boldsymbol{s}$) that was predicted to receive the *optimal* average rating ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$), and a configuration that was predicted to receive a *sub-optimal* average rating ($\hat{\boldsymbol{r}}_{\mathrm{Sub}}$), i.e., an average rating that was one root-mean-square deviation (rmsd) lower than the optimal. An *iterative* approach was taken for these predictions, which aimed to address practical challenges such as limited time and sample size. To maximize the statistical power, the coefficients were estimated for each subsequent participant using both their own data *and* the pooled data of all prior participants (who were assigned the same track). The first participant was predicted with n = 1, the second with n = 2, and so forth, until the final participant (n = 57); these data pools were divided between $\mathcal{J}_{\mathrm{Rap}}$ and $\mathcal{J}_{\mathrm{Prec}}$. Both versions of $\mathcal{J}$ therefore varied incrementally for each participant (additional data point for each). The two predictions were made in real-time, and then immediately generated with the interaction prototype. Two *additional* trials—unique for each participant—for $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ and $\hat{\boldsymbol{r}}_{\mathrm{Sub}}$ were then conducted for the *evaluation* portion of this study. The ratings provided by the participants were then used to *verify* the prediction, and then *validate* the model across the solution space. This resulted in eleven total trials in this adaptive, self-validating experimental design, which is summarized by Table 6.

Table 6. The experimental design of the empirical user study of the pneumatic steering column.

Process	Trial ID	Effective Torque Stiffness (k)		Steering Sensitivity (s)	
		Level	**Value** ($N \bullet m/deg_{in}$)	**Level**	**Value** (deg_{out}/deg_{in})
Analysis	1	Low	1.875e-2	Low	0.7
	2	Low	1.875e-2	Med	2.8
	3	Low	1.875e-2	High	11.2
	4	Med	7.5e-2	Low	0.7
	5	Med	7.5e-2	Med	2.8
	6	Med	7.5e-2	High	11.2
	7	High	0.3	Low	0.7
	8	High	0.3	Med	2.8
	9	High	0.3	High	11.2
Synthesis	*Prediction of new design configurations (i.e., prescriptive modeling & prototyping; see Table 2)*				
Evaluation	10	Opt	*Iterative*	Opt	*Iterative*
	11	Sub	*Iterative*	Sub	*Iterative*

To *visualize* the resulting solution space constructed across these processes of *analysis*, *synthesis*, and *evaluation*, contour plots of this model are illustrated in Figure 13 (for the final iteration of $\mathcal{J}_{\text{Rap}}$ and $\mathcal{J}_{\text{Prec}}$). These two predicted configurations—$\hat{\boldsymbol{r}}_{\text{Opt}}$ and $\hat{\boldsymbol{r}}_{\text{Sub}}$—serve as a litmus test for whether $\mathcal{J}$ can correctly predict preference (according to the $\boldsymbol{E_S}$) across $\boldsymbol{A_R}$. To *validate* the model, the prediction was considered to be 'correct' if the *actual* rating given to the predicted *optimal* design configuration ($\bar{\boldsymbol{r}}_{\text{Opt}}$) was rated higher than that given to the predicted *sub-optimal* design configuration ($\bar{\boldsymbol{r}}_{\text{Sub}}$). As a range of design configurations within $\boldsymbol{A_R}$ could be predicted to receive $\hat{\boldsymbol{r}}_{\text{Sub}}$, the point *closest* to the optimal (in Euclidian distance) was selected for each iteration. The importance of the heterogeneity between contexts and users is highlighted by two observations: 1) the predicted optimal design configuration differed for each track, and 2) no two users were predicted to have the same optimal design configuration.

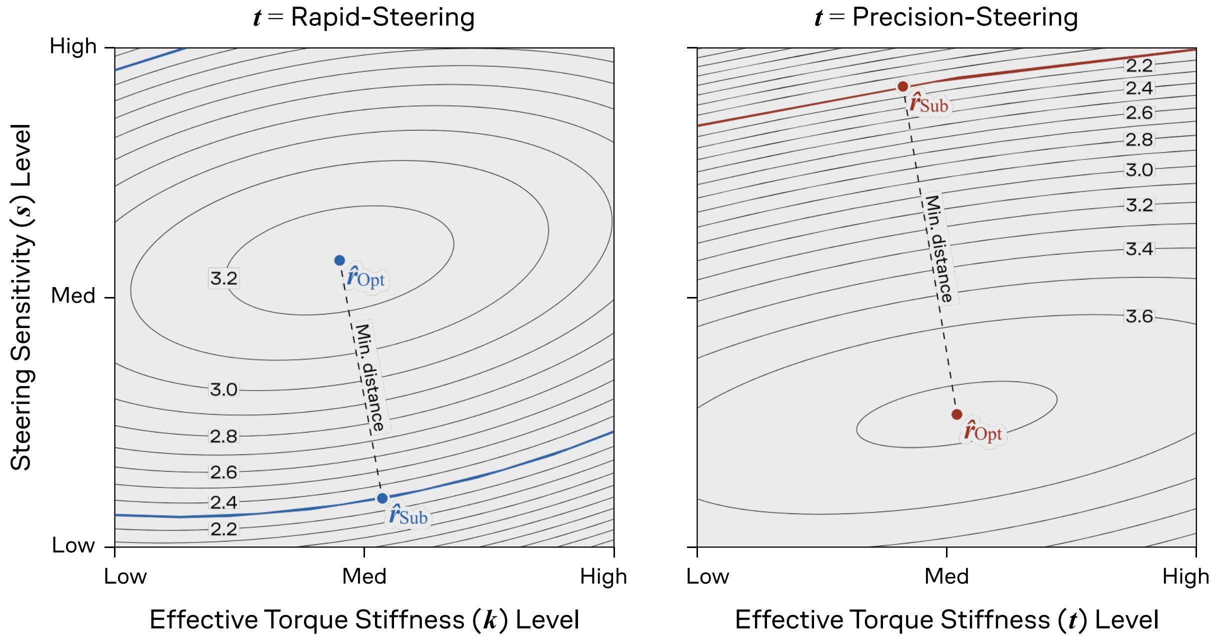

Figure 13. Predictions made in the solution space map of the pneumatic steering column. The interaction models ($\mathcal{J}_{\mathrm{Rap}}$, left; $\mathcal{J}_{\mathrm{Prec}}$, right) are visualized by contour plots, which reveal the range of experiential responses ($\hat{\boldsymbol{r}}$) predicted to be elicited by different options for the configuration ($\boldsymbol{A_R}$) of the pneumatic steering column along a continuous span of the achievable solution space. In this space, $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ represents the configuration of $\boldsymbol{k}$ and $\boldsymbol{s}$ that is predicted to receive the optimal rating. $\hat{\boldsymbol{r}}_{\mathrm{Sub}}$ represents a different design configuration that is predicted to be rated one rmsd lower than $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$. The point closest to $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ along this contour is selected to test the validity of the prediction.

It should be noted that this interpolation of new design configurations is contingent on treating *ordinal* ratings as *continuous* data. Some existing design methods (e.g., Choice-Based Conjoint Analysis) circumvent this by using *choices* to calculate *utility*. This is not feasible in this experiment, as a choice-based approach is too reliant on retaining multiple interactions in memory. Physical interactions of this duration cannot be presented simultaneously or retained in memory with equal fidelity, in the manner that images or descriptions can be.

3.5.3. Experimental Results

This empirical user study was ultimately conducted to characterize and validate the interaction model ($\mathcal{J}$; see Eq. (6)). To construct the model, the coefficients for $\mathcal{J}_{\mathrm{Rap}}$ and $\mathcal{J}_{\mathrm{Prec}}$ were first estimated in the *analysis* portion of the study. The estimates for the *final iteration* of each model are summarized in Table 7. For all results, p-values of < 0.05 are considered significant.

Table 7. Estimated coefficients of the interaction model. Significant p-values are bolded.

Model ($\mathcal{J}$)	Track (t)		k	s	$k{\cdot}s$	k^2	s^2	u_{ij}
$\mathcal{J}_{Rap}$	Rapid-steering	β	0.16	4.01	1.13	-0.90	-3.93	2.06
		p	0.59	**< 0.001**	**< 0.001**	**< 0.01**	**< 0.001**	**< 0.001**
$\mathcal{J}_{Prec}$	Precision-steering	β	0.12	1.34	1.07	-0.39	-3.56	3.50
		p	0.69	**< 0.001**	**< 0.001**	0.15	**< 0.001**	**< 0.001**

The effects of the experimental design may be more plainly examined through a *mixed-effects* model that includes both the effective torque stiffness (***k***), the steering sensitivity (***s***), *and* the track (***t***). Each of these are treated as *categorical* predictors (along with 2 and 3-way interactions) for the *given* average ratings ($\bar{r}$), with a random intercept. An ANOVA (type III) on this model provides significance levels, which are summarized in Table 8.

Table 8. The effects of the experimental design on the average rating. Significant p-values are bolded.

Statistics	Coefficients						
	k	s	t	$k{\cdot}s$	$k{\cdot}t$	$s{\cdot}t$	$k{\cdot}s{\cdot}t$
Sum of Squares	9.72	69.38	33.77	16.87	4.16	38.34	0.64
p-value	**< 0.01**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.05**	**< 0.001**	0.43

The main effects—***k*** ($p < 0.01$), ***s*** ($p < 0.001$), and ***t*** ($p < 0.001$)—were all significant. There were distinct preferences, as indexed by $\bar{r}$, reported across different combinations of the A_R for both tracks. There was also a significant two-way interaction effect between ***k*** and ***s*** ($p < 0.001$). Users generally preferred lower ***k*** paired with higher ***s***, and vice versa. There was a significant two-way interaction effect between ***k*** and ***t*** ($p < 0.001$). Users preferred a higher ***k*** on the precision-steering track and a lower ***k*** on the rapid-steering track. Similarly, there was a significant two-way interaction effect between ***s*** and ***t*** ($p < 0.001$) as well. Users preferred a lower ***s*** on the precision-steering track and a higher ***s*** in the rapid-steering track. These effects are expected, as a higher ***k*** and a lower ***s*** can make precision-steering maneuvers more accurate, but can also require more effort to complete rapid-steering maneuvers. The three-way interaction effect between ***k***, ***s***, and ***t*** was not significant. This model is illustrated in Figure 14.

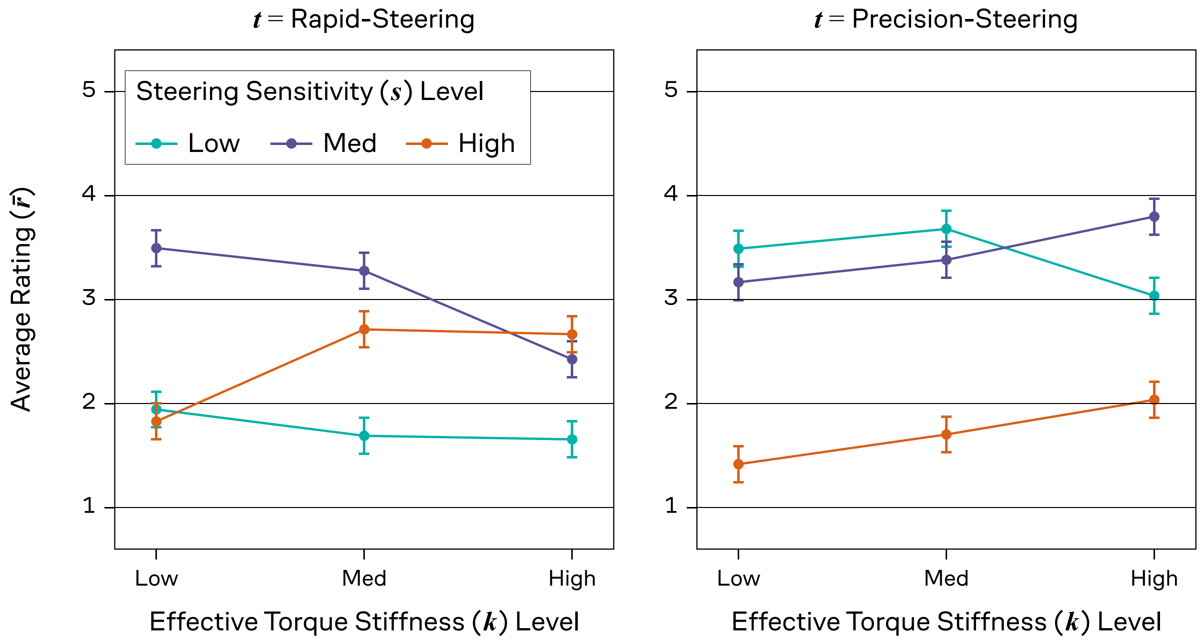

Figure 14. The effects of the experimental design on the experiential response. The mean of the average rating ($\bar{r}$) across all participants is shown for each configuration that was present in the *analysis* portion of the study (9 trials). Interaction effects may be highlighted by intersecting slopes. Both tracks are shown ($\mathcal{J}_{\text{Rap}}$, left; $\mathcal{J}_{\text{Prec}}$, right).

For the *evaluation* process, the average rating ($\bar{r}$) that users *gave* to their optimal ($\bar{r}_{\text{Opt}}$) and sub-optimal ($\bar{r}_{\text{Sub}}$) design configurations may be compared for each context. Despite the fact that the predicted optimal and sub-optimal configurations were *iteratively* updated (i.e., were unique) for each participant, the optimal was consistently preferred over the sub-optimal. Preference was correctly predicted for 50 out of 57 participants, i.e., 87.7% of participants rated the optimal configuration higher than the sub-optimal configuration. Participants significantly preferred their optimal configuration to their sub-optimal one. The optimal configuration ($\bar{r}_{\text{Opt}}$) was rated an average of 1.44 ± 0.19 points higher than the sub-optimal ($\bar{r}_{\text{Sub}}$) on the 5-point scale ($p < 0.001$), which is illustrated by Figure 15. These correct predictions were evenly split between the two tracks, with 25 of 29 participants preferring their optimal to their sub-optimal configuration on the rapid-steering track ($\mathcal{J}_{\text{Rap}}$), and 25 of 28 preferring the same on the precision-steering track ($\mathcal{J}_{\text{Prec}}$). There was no statistically significant difference in the ability to predict between the two contexts. Ultimately, this test may be used validate $\mathcal{J}$ in its ability to correctly predict the preference for *new* design configurations across the solution space. With a validated model, $\hat{r}$ may be used as an index for $\bar{r}$, and any insights in this area may be extended to larger populations.

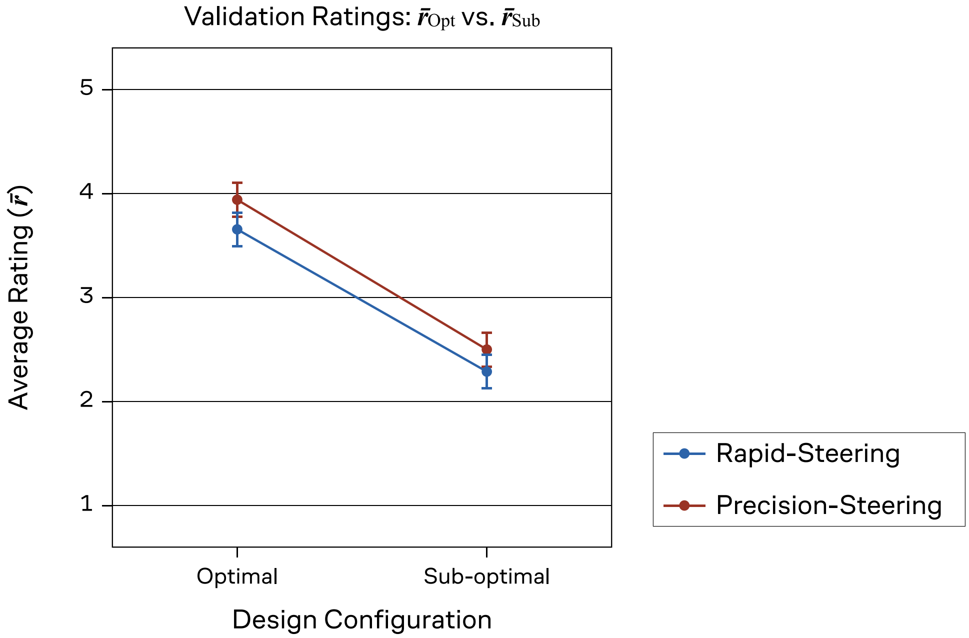

Figure 15. The validation test for the solution space model of the pneumatic steering column. The mean average rating ($\bar{r}$) given to the optimal configuration ($\bar{r}_{Opt}$) is compared to sub-optimal configuration ($\bar{r}_{Sub}$). The optimal configuration was, on average, rated significantly higher than the sub-optimal configuration, thus validating $\mathcal{I}$.

3.6. Navigating Tradeoffs in the Design Space Map

With both the *analytical* and *empirical* models that comprise the solution space model constructed—and that latter being *validated* as well—the complete formulation of the design space map may finally be employed to navigate tradeoffs in this case study. All of the potentially competing design outcomes, including those on the *technical* level and those on the *experiential* level, are mathematically coupled to the design levers, such that adjustments made to the Structure ($\Delta\boldsymbol{S}$) are reflected in the Technical Functions ($\Delta\boldsymbol{T}$) and Subjective Experiential Responses ($\Delta\boldsymbol{E_S}$) through the *composition* of these models. This is represented by

$$\Delta\boldsymbol{T} = \mathcal{P}(\mathcal{E}(\Delta\boldsymbol{S}))$$

$$\Delta\boldsymbol{E_S} = \mathcal{I}(\mathcal{E}(\Delta\boldsymbol{S}))$$

, where the Environmental Attributes ($\boldsymbol{A_E}$) is held constant (i.e., same track). These compositions reflect how the *tradeoffs* that exist between the technical and experiential design outcomes are derived from their common coupling to the underlying form/layout. Both types of outcomes are functions of $\Delta\boldsymbol{S}$, so to alter one implies alterations to the other.

While it could certainly be feasible to assess the tradeoffs in the case study within the format of a multi-objective optimization problem e.g., [401], these models are instead composed in a unique manner that leverages their natural functional forms to facilitate a *systematic exploration* of the solution space. This approach is supported by *visualizations* and *linear algebraic* machinery (i.e., vectors), provides a higher level of nuance to the examination of the solution space, and ultimately affords the potential to discover innovative solutions. Visualizations especially can be useful for representing transformations from experiential outcomes to artifact factors [325].With this system, three different kinds of tradeoffs are examined, which include: 1) the tradeoffs that exist within the *technical* performance if *no concessions* are permitted for impacting the *experiential* response (i.e., maintaining an optimal rating), 2) the manner in which these *technical* tradeoffs can be improved if *minimal concessions* are permitted for impacting the *experiential* response (i.e., sacrificing an optimal rating), and 3) the influence that the context (i.e., the track) has on these tradeoffs, as well as new innovative features can take advantage of this influence. The findings of this endeavor highlight the breadth of quantitative tradeoffs that may be informed through this systematic exploration, using only simple linear algebra.

3.6.1. Model Composition: Leveraging Natural Functional Forms

The composition of the interaction model ($\mathcal{I}$) and the engineering model ($\mathcal{E}$) is a special case, in which each holds naturally distinct functional forms. The latter is typically governed by *power law* relations, while the former may be constructed in a *logarithmic* scale. An *intermediary* vector space exists between $\mathcal{I}$ and $\mathcal{E}$—the Responsive Behavior/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$) is an input of the former and an output of the latter. When these models are simultaneously projected into this intermediary space, the power law relations given by $\mathcal{E}$ (i.e., x^n) become *linear* in the logarithmic scale of $\mathcal{I}$ (i.e., $\log(x^n) = nx$). Each of the proportional sensitives in $\mathcal{E}$ (see Table 5) may therefore be *linearly* represented in a *Design Sensitivity* (***DS***) matrix given by Equation (7), in which

$$\boldsymbol{DS} = \begin{array}{c} \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ -2 & 1 & 1 & 1 & 4 \\ 1 & 2 & 2 & 0 & 0 \\ -1 & 4 & 1 & 4 & 4 \\ 1 & 0 & 1 & 1 & -1 \end{bmatrix} \\ \begin{matrix} \boldsymbol{l} & \boldsymbol{d} & \boldsymbol{th} & \boldsymbol{p} & \boldsymbol{h} \end{matrix} \end{array} \begin{array}{c} \boldsymbol{v} \\ \boldsymbol{sr} \\ \boldsymbol{c} \\ \boldsymbol{k} \\ \boldsymbol{s} \\ \\ \end{array} \tag{7}$$

, where each labeled row/column in this matrix corresponds to the similar row/column in the original sensitivity model (e.g., $\log(\Delta \boldsymbol{l}^{-2}) = -2$; see Table 5). Rows (sub-script) may be indexed by elements of the Behavior ($\boldsymbol{B}$), and columns (super-script) may be indexed by elements of the Structure ($\boldsymbol{S}$), e.g., $\boldsymbol{DS}_{\boldsymbol{k}}^{\boldsymbol{l,d}} = [-1 \quad 4]$ (see columns 1 and 2, row 4 in Eq. (7)).*

$\mathcal{E}$ may therefore be reformulated in the logarithmic space ($\mathcal{E}_{\log}$) according to these linear sensitives in the form given by Equation (8), in which

$$\mathcal{E}_{\log}: \quad \Delta\boldsymbol{B} = \boldsymbol{DS} \times \Delta\boldsymbol{S} \tag{8}$$

$$\mathcal{E}_{\log}: \begin{bmatrix} \Delta\boldsymbol{v} \\ \Delta\boldsymbol{sr} \\ \Delta\boldsymbol{c} \\ \Delta\boldsymbol{k} \\ \Delta\boldsymbol{s} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ -2 & 1 & 1 & 1 & 4 \\ 1 & 2 & 2 & 0 & 0 \\ -1 & 4 & 1 & 4 & 4 \\ 1 & 0 & 1 & 1 & -1 \end{bmatrix} \times \begin{bmatrix} \Delta\boldsymbol{l} \\ \Delta\boldsymbol{d} \\ \Delta\boldsymbol{th} \\ \Delta\boldsymbol{p} \\ \Delta\boldsymbol{h} \end{bmatrix}$$

, where an adjustment to any element in the form/layout ($\Delta\boldsymbol{S}$) has a linear impact on the behaviors of the artifact ($\Delta\boldsymbol{B}$). The impacts of these adjustments on both the Technical Functions ($\Delta\boldsymbol{T}$) and the Subjective Experiential Responses ($\Delta\boldsymbol{E_S}$) may both be determined from $\mathcal{E}_{\text{Log}}$. On the technical level (i.e., $\Delta\boldsymbol{T}$), impacts may be calculated according to the interpreted proportional sensitives of $\mathcal{P}$ (see Table 5), in which a decrease to the stowed volume ($-\Delta\boldsymbol{v}$) will improve the stowability ($+\Delta\boldsymbol{sw}$), an increase to the structural rigidity ($+\Delta\boldsymbol{sr}$) will improve the stability ($+\Delta\boldsymbol{sb}$), and a decrease to the production cost ($-\Delta\boldsymbol{c}$) will improve the affordability ($+\Delta\boldsymbol{af}$). Alternatively, on the experiential level (i.e., $\Delta\boldsymbol{E_S}$), the impacts of adjustments to any element in the form/layout ($\Delta\boldsymbol{S}$) on $\boldsymbol{k}$ and $\boldsymbol{s}$ may be *visually* represented by a linear combination of vectors (e.g., $\boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d}}$). These vectors are projected onto the contour plots of $\mathcal{I}$ to assess the propagated impacts that these adjustments then have on $\hat{\boldsymbol{r}}$. This is illustrated in Figure 16 (for $\mathcal{I}_{\text{Rap}}$).

The slopes of these vectors are given by the linear sensitivities of each element of $\boldsymbol{B_R}$ to each element of $\boldsymbol{S}$. The magnitude of each vector may be scaled according to the scale of the adjustment ($\Delta\boldsymbol{S}$). This visualization illustrates how the adjustments to the design levers in $\boldsymbol{S}$ would relatively impact the design configuration in terms of $\boldsymbol{k}$ and $\boldsymbol{s}$—the axes of this contour plot—which would then impact the predicted rating ($\hat{\boldsymbol{r}}$) that is encoded to the height of these contours. In essence, this therefore provides a visual representation for how adjustments to the design levers allow the

* **Row index**: {$\boldsymbol{v} = 1$, $\boldsymbol{sr} = 2$, $\boldsymbol{c} = 3$, $\boldsymbol{k} = 4$, $\boldsymbol{s} = 5$}
Column index: {$\boldsymbol{l} = 1$, $\boldsymbol{d} = 2$, $\boldsymbol{th} = 3$, $\boldsymbol{p} = 4$, $\boldsymbol{h} = 5$}

engineering designer to navigate throughout the solution space. For instance, $\hat{\boldsymbol{r}}$ is relatively less sensitive to adjustments of the pressure ($\Delta\boldsymbol{p}$), as $\boldsymbol{DS}^{p}_{k,s}$ is directionally aligned with the major axis of the ellipse in the contour plot. With these model compositions, the tradeoffs between $\Delta\boldsymbol{T}$ and $\Delta\boldsymbol{E_S}$ may be navigated in a systematic exploration.

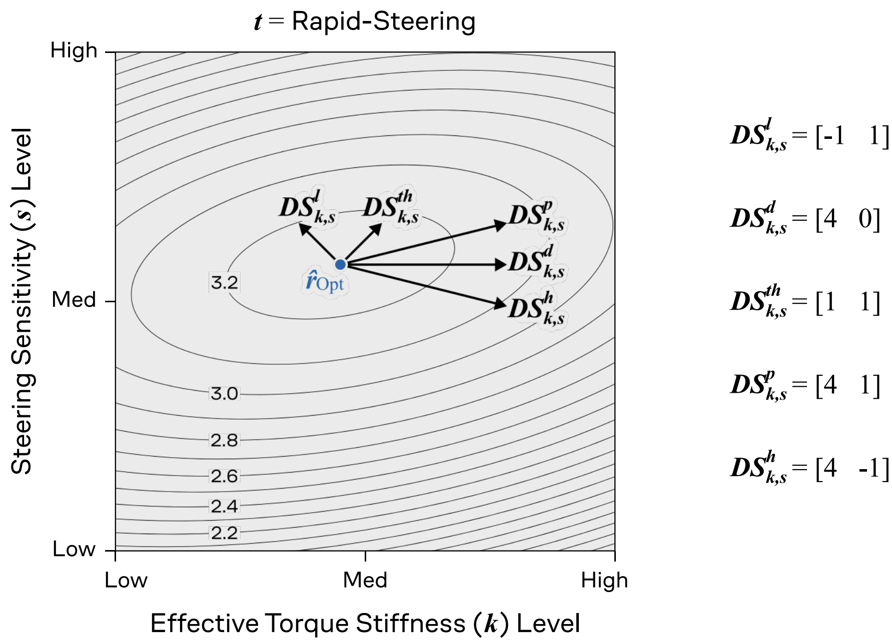

Figure 16. Linear adjustments within the solution space. The composition of $\mathcal{E}_{\log}$ and $\mathcal{J}$ within the intermediary vector space ($\boldsymbol{B_R} = \boldsymbol{A_R}$) permits proportional design sensitivities to become linear in the logarithmic scale. The relative impact of adjustments to the concrete design levers ($\Delta\boldsymbol{S}$) on the predicted experiential responses ($\boldsymbol{E_S}$) may be measured. This is shown for the rapid-steering track ($\mathcal{J}_{\mathrm{Rap}}$), but the vectors remain the same for both contexts.

3.6.2. Identifying Technical Tradeoffs while Maintaining Optimal Experiential Response

When tradeoffs between design outcomes are present, the selection of the configuration that represents the ‘optimal’ balance between them is ultimately predicated on the *values* of the individual designer or firm. Optimizing *experiential* responses ($\boldsymbol{E_S}$) may require concessions to the *technical* performance ($\boldsymbol{T}$). Conversely, sacrificing some ability to optimize $\boldsymbol{E_S}$ may reveal additional avenues for which $\boldsymbol{T}$ may be improved. If the engineering designer is *not willing* to concede any ability to achieve the optimal $\boldsymbol{E_S}$, they would hold the design configuration *fixed* in terms of its Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$) at the predicted optimal configuration ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$; assuming this configuration is achievable). Subsequently, in order to improve $\boldsymbol{T}$—to increase stowability ($+\Delta\boldsymbol{sw}$), increase stability ($+\Delta\boldsymbol{sb}$), and increase affordability ($+\Delta\boldsymbol{af}$)—while making *no* adjustments in $\boldsymbol{B_R}$, the constraints of fixed effective torque stiffness ($\Delta\boldsymbol{k} = 0$) and fixed steering sensitivity ($\Delta\boldsymbol{s} = 0$) may be imposed onto $\mathcal{E}_{\log}$ (see Eq. (8)), along with the desired adjustments to $\boldsymbol{B_P}$, i.e., decreasing the stowed volume ($-\Delta\boldsymbol{v}$), increasing the structural rigidity ($+\Delta\boldsymbol{sr}$) and any decreasing the production cost ($-\Delta\boldsymbol{c}$). This is reflected in

$$\Delta\boldsymbol{B} = \boldsymbol{DS} \times \Delta\boldsymbol{S}$$

$$\begin{bmatrix} -\Delta\boldsymbol{v} \\ +\Delta\boldsymbol{sr} \\ -\Delta\boldsymbol{c} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ -2 & 1 & 1 & 1 & 4 \\ 1 & 2 & 2 & 0 & 0 \\ -1 & 4 & 1 & 4 & 4 \\ 1 & 0 & 1 & 1 & -1 \end{bmatrix} \times \begin{bmatrix} \Delta\boldsymbol{l} \\ \Delta\boldsymbol{d} \\ \Delta\boldsymbol{th} \\ \Delta\boldsymbol{p} \\ \Delta\boldsymbol{h} \end{bmatrix}$$

, where these desirable changes are listed in $\Delta\boldsymbol{B}$. With this equation, the subsequent adjustments to $\boldsymbol{S}$ that can achieve these changes may be solved for.

If each parameter in $\boldsymbol{S}$ is freely adjustable and not subject to any other constraint, the matrix is full rank. The solution for this example is simple, as any combination of $\boldsymbol{B_P}$ is achievable and the desirable adjustments of $\Delta\boldsymbol{S}$ are evident. However, consider the conceivable technical constraint in which the material ($\boldsymbol{h}$) and length ($\boldsymbol{l}$) of the pneumatic steering column were *fixed* ($\Delta\boldsymbol{h} = 0$, $\Delta\boldsymbol{l} = 0$). With two restrictions on the degrees of freedom, the remaining adjustments ($\Delta\boldsymbol{S}$) that may be made while maintaining a fixed $\boldsymbol{B_R}$ may be determined through formulating $\mathcal{E}_{\mathrm{Log}}$ (see Eq. (8)) as

$$\Delta\boldsymbol{B_R} = \boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th,p}} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$$

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 & 1 & 4 \\ 0 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} \Delta\boldsymbol{d} \\ \Delta\boldsymbol{th} \\ \Delta\boldsymbol{p} \end{bmatrix}$$

, where the *null space* of $\boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th,p}}$ dictates the proportional changes that may be made to the remaining parameters of $\boldsymbol{S}$ that may still be adjusted (i.e., $\Delta\boldsymbol{d}$, $\Delta\boldsymbol{th}$, and $\Delta\boldsymbol{p}$) to satisfy this equation. If one of these parameters is adjusted, the others must similarly be adjusted to some degree in order to maintain the configuration of $\boldsymbol{k}$ and $\boldsymbol{s}$ that is predicted to provide the optimal rating ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$). Adjustments to $\Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$ at this specific proportionality are therefore referred to as *'experience-maintaining'* adjustments, which may be scaled to any magnitude ($\boldsymbol{\mu}$) without altering $\boldsymbol{B_R}$. As long as this relative proportion is adhered to when making adjustments to the design levers, changes to the $\boldsymbol{B_P}$ may then be enacted while holding the design configuration fixed within $\boldsymbol{B_R}$. To determine this proportionality, the scale of $\Delta\boldsymbol{S}^{d,th,p}$ that serves as the kernel for $\boldsymbol{DS}_{k,s}^{d,th,p}$ may therefore be solved for, in which

$$\Delta\boldsymbol{S}^{d,th,p} \propto \begin{bmatrix} -0.75 \\ -1 \\ 1 \end{bmatrix}$$

$$\Delta\boldsymbol{S}^{d,th,p} = \boldsymbol{\mu} \begin{bmatrix} -0.75 \\ -1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} \Delta\boldsymbol{d} \\ \Delta\boldsymbol{th} \\ \Delta\boldsymbol{p} \end{bmatrix} = \begin{bmatrix} -0.75\boldsymbol{\mu} \\ -1\boldsymbol{\mu} \\ 1\boldsymbol{\mu} \end{bmatrix}$$

, where $\boldsymbol{\mu}$ represents the overall magnitude of these 'experience-maintaining' adjustments. This shows that—to keep the design configuration fixed at levels providing the optimal rating ($\hat{\boldsymbol{r}}_{\text{Opt}}$) for the rich, embodied steering interaction—the freely adjustable parameters $\Delta\boldsymbol{d}$, $\Delta\boldsymbol{th}$, and $\Delta\boldsymbol{p}$ may be proportionally altered by the ratio of -0.75:-1:1, respectively, to any magnitude ($\boldsymbol{\mu}$). This means that, for an adjustment to the pressure ($\Delta\boldsymbol{p}$) of magnitude $\boldsymbol{\mu}$ to be made, adjustments of the wall thickness ($\Delta\boldsymbol{th}$) of magnitude $-\boldsymbol{\mu}$, and adjustments of the diameter ($\Delta\boldsymbol{d}$) of magnitude $-0.75\boldsymbol{\mu}$ must *also* be made as well.

This imposed proportional constraint on these adjustments has implications for what impacts may be had on the Persistent Behaviors ($\Delta\boldsymbol{B_P}$), which in turn has implications for the impacts that may be had on the Technical Functions ($\Delta\boldsymbol{T}$). These effects may be examined by multiplying this null space of magnitude $\boldsymbol{\mu}$ into $\boldsymbol{DS}_{v,sr,c}^{d,t,p}$ in $\mathcal{E}_{\log}$ (see Eq. (8)), in which

$$\Delta\boldsymbol{B_P} = \boldsymbol{DS}_{v,sr,c}^{d,th,p} \times \Delta\boldsymbol{S}^{d,th,p}$$

$$\Delta\boldsymbol{B_P} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \\ 2 & 2 & 0 \end{bmatrix} \times \boldsymbol{\mu} \begin{bmatrix} -0.75 \\ -1 \\ 1 \end{bmatrix}$$

$$\Delta\boldsymbol{B_P} = \boldsymbol{\mu} \begin{bmatrix} -1.75 \\ -0.75 \\ -3.5 \end{bmatrix}$$

$$\begin{bmatrix} \Delta\boldsymbol{v} \\ \Delta\boldsymbol{sr} \\ \Delta\boldsymbol{c} \end{bmatrix} = \begin{bmatrix} -1.75\boldsymbol{\mu} \\ -0.75\boldsymbol{\mu} \\ -3.5\boldsymbol{\mu} \end{bmatrix}$$

, where $\boldsymbol{\mu}$ represents the magnitude of these 'experience-maintaining' adjustments that impact $\Delta\boldsymbol{v}$, $\Delta\boldsymbol{sr}$, and $\Delta\boldsymbol{c}$. It therefore becomes evident as to what technical tradeoffs exist if no concessions to the experiential response are permitted (i.e., optimal rating is maintained). For adjustments to the freely manipulatable form/layout parameters that conform to the 'experience-maintaining' proportionality dictated by $\boldsymbol{\mu}$ to be made, the stowed volume ($\Delta\boldsymbol{v}$), structural rigidity ($\Delta\boldsymbol{th}$), and production cost ($\Delta\boldsymbol{c}$) may be proportionally impacted by the ratio of -1.75:-0.75:-3.5. Extending these impacts across the proportionalities given by the performance model ($\mathcal{P}$; see Table 5), this means that for the stability to be improved ($+\Delta\boldsymbol{sb}$), both the stowability ($-\Delta\boldsymbol{sw}$) and the affordability ($-\Delta\boldsymbol{af}$) and the will be worsened, or vice-versa; these proportional impacts of $\Delta\boldsymbol{sw}$, $\Delta\boldsymbol{sb}$, and $\Delta\boldsymbol{af}$ are given by the ratio of 1.75:-0.75:3.5, respectively. This systematic exploration of the design space therefore describes both the *existence* and the *relative magnitude* of the technical tradeoffs that exist under these conditions. However, changing how the experiential and technical design outcomes are each *valued* may open the door for a more favorable balance between them.

3.6.3. Improving Technical Tradeoffs by Sacrificing Minimal Experiential Response

The previously identified tradeoffs may become more favorable if additional degrees of freedom are afforded to the negotiation, i.e., if *concessions* for lesser experiential responses are permitted, such that the design configuration is no longer fixed within the Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$). However, if concessions to the Subjective Experiential Responses ($\Delta\boldsymbol{E_S}$) are to be permitted, it stands to reason that the magnitude of these sacrifices should be *minimized*. By constraining the adjustments to the Structure ($\Delta\boldsymbol{S}$), such that the design configuration is allowed to move within $\boldsymbol{B_R}$ only along one *permissible line*, which is parallel to slope of the major axis of the contour of $\mathcal{I}$ (i.e., $\Delta\boldsymbol{s}/\Delta\boldsymbol{k} \propto 1/5.56$ for $\mathcal{I}_{\text{Rap}}$), the relative impact to the predicted rating ($\hat{\boldsymbol{r}}$) may be minimized. This *'permissible adjustments'* line—illustrated in Figure 17—therefore represents the direction in the solution space for which experiential responses are least sensitive to adjustments of the design levers. In effect, if adjustments that alter the design configuration such that it receives a lower-than-optimal rating must be made, this constraint ensures that these experiential detriments are as minimal as possible.

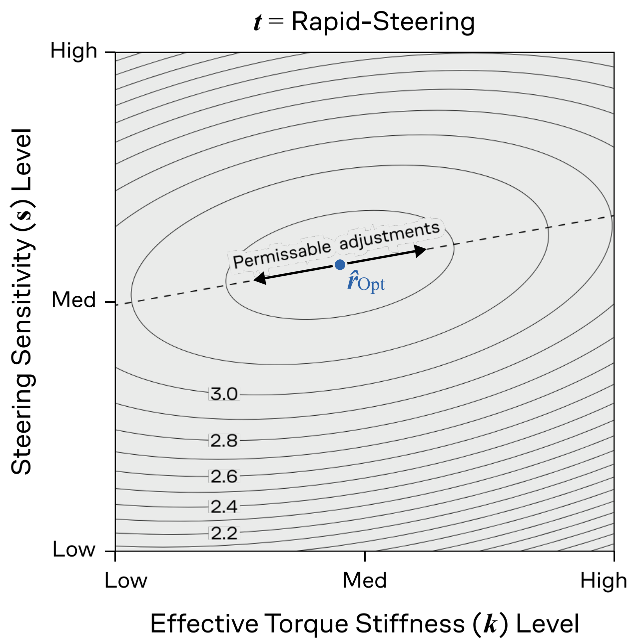

Figure 17. The 'permissible adjustments' line to minimize sacrifices in experiential design outcomes. The line follows the slope of the major axis of the contour of $\mathcal{J}$ to constrain the design configuration within the Responsive Behaviors/Attributes ($\boldsymbol{B_R}$) such that any concessions to the rating ($\hat{r}$) may be minimized if adjustments outside of the specified 'experience-maintaining' ones are to be permitted. The 'permissible adjustments' line for the rapid-steering track is pictured ($\mathcal{J}_{\text{Rap}}$), but this line may be similarly defined for the precision-steering track ($\mathcal{J}_{\text{Prec}}$) as well.

The pneumatic steering system is again considered here under the same imposed technical constraints as before, i.e., fixed length ($\Delta\boldsymbol{l} = 0$) and fixed height ($\Delta\boldsymbol{h} = 0$). An additional degree of freedom in imparted to the non-fixed parameters of the form/layout—the diameter ($\Delta\boldsymbol{d}$), the wall thickness ($\Delta\boldsymbol{th}$), and the pressure ($\Delta\boldsymbol{p}$)—by the introduction of this 'permissible adjustments' line. The proportionality of the permissible adjustments to these parameters ($\Delta\boldsymbol{S}$) may again be determined through formulating $\mathcal{E}_{\text{Log}}$ (see Eq. (8)) as

$$\Delta\boldsymbol{B_R} = \boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th,p}} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$$

$$\Delta\boldsymbol{B_R} = \begin{bmatrix} 4 & 1 & 4 \\ 0 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} \Delta\boldsymbol{d} \\ \Delta\boldsymbol{th} \\ \Delta\boldsymbol{p} \end{bmatrix}$$

, however there are now *two* degrees of freedom for which adjustments to $\Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$ may be made. The first are those that keep $\boldsymbol{k}$ and $\boldsymbol{s}$ fixed within $\boldsymbol{B_R}$—the so-called 'experience-maintaining' ($\boldsymbol{\mu}$) adjustments, i.e., the null space. The second is those that proportionally adjust $\boldsymbol{k}$ and $\boldsymbol{s}$ by the ratio of 5.56:1, i.e., along the slope of the 'permissible adjustments' line (see Figure 17). This second type of adjustments are dubbed '*experience-sacrificing'* adjustments, as they are adjustments of magnitude (λ) that result in *minimal concessions* to the rating ($\hat{\boldsymbol{r}}$). With this additional degree of freedom, both 'experience-maintaining' ($\boldsymbol{\mu}$) and 'experience-sacrificing' (λ) adjustments may be made to $\Delta\boldsymbol{d}$, $\Delta\boldsymbol{th}$, and $\Delta\boldsymbol{p}$, which may allow for a more favorable balance between technical and experiential design outcomes. $\Delta\boldsymbol{B_R}$ may therefore be formulated as a linear combination of these two adjustments, in which

$$\Delta\boldsymbol{B_R} = \boldsymbol{\mu}\begin{bmatrix}0\\0\end{bmatrix} + \lambda\begin{bmatrix}5.56\\1\end{bmatrix}$$

, where the first term represents adjustments of magnitude $\boldsymbol{\mu}$ that can be made while keeping $\boldsymbol{k}$ and $\boldsymbol{s}$ fixed, and the second term represents adjustments of magnitude $\boldsymbol{\lambda}$ while proportionally impacting $\boldsymbol{k}$ and $\boldsymbol{s}$ on the ratio that keeps the design configuration on the 'permissible adjustments' line.

Compared to the previous scenario, this equation now affords engineering designer with the option to sacrifice some degree of their ability to optimize $\hat{\boldsymbol{r}}$ in order improve the technical tradeoffs. If the engineering designer of the pneumatic steering column was unable to meet any of their functional requirements under the constraints of 'experience-maintaining' adjustments, they may consider this path. To determine the proportionality of the adjustments to $\Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$ that may now be made, $\mathcal{E}_{\text{Log}}$ (see Eq. (8)) may be formulated in terms of both types of adjustments, in which

$$\Delta\boldsymbol{B_R} = \boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th,p}} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th,p}} = \boldsymbol{\mu}\begin{bmatrix}0\\0\end{bmatrix} + \lambda\begin{bmatrix}5.56\\1\end{bmatrix}$$

$$\Delta\boldsymbol{B_R} = \begin{bmatrix}4 & 1 & 4\\0 & 1 & 1\end{bmatrix} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th,p}} = \boldsymbol{\mu}\begin{bmatrix}0\\0\end{bmatrix} + \boldsymbol{\lambda}\begin{bmatrix}5.56\\1\end{bmatrix}$$

, where both of these degrees of freedom may be employed for design lever adjustments, but it would generally be desirable to minimize the magnitude of the $\boldsymbol{\lambda}$ in order to minimize the concessions to $\hat{\boldsymbol{r}}$.

Many potential design solutions exist along the permissible adjustments line. For the sake of this example, the simplest—in which the 'experience-sacrificing' adjustments to one of the possible design levers is zero (the third parameter in this case, $\boldsymbol{p}$)—is selected. This is obtained by truncating the third column of the Design Sensitivity (***DS***) matrix (i.e., going from $\boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th,p}}$ to $\boldsymbol{DS}_{\boldsymbol{k,s}}^{\boldsymbol{d,th}}$) and keeping the pressure fixed (i.e., $\Delta\boldsymbol{p} = 0$). $\mathcal{E}_{\text{Log}}$ (see Eq. (8)) may then be formulated as

$$\boldsymbol{DS}^{\boldsymbol{d,th}}_{\boldsymbol{k,s}} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th}} = \boldsymbol{\lambda}\begin{bmatrix}5.56\\1\end{bmatrix}$$

$$\begin{bmatrix}4 & 1\\0 & 1\end{bmatrix} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th}} = \boldsymbol{\lambda}\begin{bmatrix}5.56\\1\end{bmatrix}$$

$$\begin{bmatrix}4 & 1\\0 & 1\end{bmatrix} \times \begin{bmatrix}\Delta\boldsymbol{d}\\\Delta\boldsymbol{th}\end{bmatrix} = \boldsymbol{\lambda}\begin{bmatrix}5.56\\1\end{bmatrix}$$

$$\begin{bmatrix}\Delta\boldsymbol{d}\\\Delta\boldsymbol{th}\end{bmatrix} = \begin{bmatrix}1.14\boldsymbol{\lambda}\\1\boldsymbol{\lambda}\end{bmatrix}$$

, where proportional adjustments of $\Delta\boldsymbol{d}$, $\Delta\boldsymbol{th}$, and $\Delta\boldsymbol{p}$ may therefore be made at the ratio of 1.14:1:0, respectively. The overall adjustments that may be made to $\Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$ may then be represented as the linear combination of these ‘experience-sacrificing’ adjustments of magnitude $\boldsymbol{\lambda}$, and the ‘experience-maintaining’ adjustments of magnitude $\boldsymbol{\mu}$, in which

$$\Delta\boldsymbol{S}^{\boldsymbol{d,th,p}} = \boldsymbol{\mu}\begin{bmatrix}-0.75\\-1\\1\end{bmatrix} + \boldsymbol{\lambda}\begin{bmatrix}1.14\\1\\0\end{bmatrix}$$

$$\begin{bmatrix}\Delta\boldsymbol{d}\\\Delta\boldsymbol{th}\\\Delta\boldsymbol{p}\end{bmatrix} = \begin{bmatrix}-0.75\boldsymbol{\mu}\\-\boldsymbol{\mu}\\\boldsymbol{\mu}\end{bmatrix} + \begin{bmatrix}1.14\boldsymbol{\lambda}\\\boldsymbol{\lambda}\\0\end{bmatrix}$$

, where $\Delta\boldsymbol{p}$ is not used to make any ‘experience-sacrificing’ adjustments, but all three parameters may still be used to make ‘experience-maintaining’ adjustments.

The implications of these combined adjustments on the impacts that may be had on the Persistent Behaviors ($\Delta\boldsymbol{B_P}$), and in turn, the impacts that may be had on the Technical Functions ($\Delta\boldsymbol{T}$) may then be determined. These effects may be examined by multiplying these adjustments into $\boldsymbol{DS}^{\boldsymbol{d,t,p}}_{\boldsymbol{v,sr,c}}$ in $\mathcal{E}_{\log}$ (see Eq. (8)), in which

$$\Delta\boldsymbol{B_P} = \boldsymbol{DS}^{\boldsymbol{d,th,p}}_{\boldsymbol{v,sr,c}} \times \Delta\boldsymbol{S}^{\boldsymbol{d,th,p}}$$

$$\Delta\boldsymbol{B_P} = \begin{bmatrix}1 & 1 & 0\\1 & 1 & 1\\2 & 2 & 0\end{bmatrix} \times (\boldsymbol{\mu}\begin{bmatrix}-0.75\\-1\\1\end{bmatrix} + \boldsymbol{\lambda}\begin{bmatrix}1.14\\1\\0\end{bmatrix})$$

$$\Delta\boldsymbol{B_P} = \boldsymbol{\mu}\begin{bmatrix}-1.75\\-0.75\\-3.5\end{bmatrix} + \boldsymbol{\lambda}\begin{bmatrix}2.14\\2.14\\4.28\end{bmatrix}$$

$$\begin{bmatrix} \Delta \boldsymbol{v} \\ \Delta \boldsymbol{sr} \\ \Delta \boldsymbol{c} \end{bmatrix} = \begin{bmatrix} \text{-}1.75\boldsymbol{\mu} + 2.14\boldsymbol{\lambda} \\ \text{-}0.75\boldsymbol{\mu} + 2.14\boldsymbol{\lambda} \\ \text{-}3.5\boldsymbol{\mu} + 4.28\boldsymbol{\lambda} \end{bmatrix}$$

, where $\boldsymbol{\mu}$ represents the magnitude of these 'experience-maintaining' adjustments and $\boldsymbol{\lambda}$ represents the magnitude of these 'experience-sacrificing adjustments that together combine to impact $\Delta\boldsymbol{v}$, $\Delta\boldsymbol{sr}$, and $\Delta\boldsymbol{c}$. In this form of the equation, it is evident to see that the outcome of the previous scenario—maintaining optimal experiential repones—may be achieved by setting $\boldsymbol{\lambda} = 0$.

As such, the tradeoffs between the technical design outcomes that were previously present when only 'experience-maintaining' adjustments were permitted may now be *corrected* through the use of the 'experience-sacrificing' adjustments, albeit at the cost of a relatively minimal impact on the experiential repones ($\hat{\boldsymbol{r}}$). For instance, if the 'experience-sacrificing' adjustments—which again, are desirable to keep to a minimal magnitude—are specified to be *half* the magnitude of the 'experience-maintaining' adjustments (i.e., $\boldsymbol{\lambda} = 0.5\boldsymbol{\mu}$), then the proportional impacts on $\Delta\boldsymbol{v}$, $\Delta\boldsymbol{sr}$, and $\Delta\boldsymbol{c}$ may be corrected to

$$\begin{bmatrix} \Delta \boldsymbol{v} \\ \Delta \boldsymbol{sr} \\ \Delta \boldsymbol{c} \end{bmatrix} = \begin{bmatrix} \text{-}0.68\boldsymbol{\mu} \\ 0.32\boldsymbol{\mu} \\ \text{-}1.36\boldsymbol{\mu} \end{bmatrix}$$

, where the stowed volume ($\Delta\boldsymbol{v}$), structural rigidity ($\Delta\boldsymbol{th}$), and production cost ($\Delta\boldsymbol{c}$) may now be proportionally impacted by the ratio of -0.68:0.32:-1.36, respectively. Extending these impacts across the proportionalities given by the performance model ($\mathcal{P}$; see Table 5), this means that for stowability (+$\Delta\boldsymbol{sw}$), stability (+$\Delta\boldsymbol{sb}$), and affordability (+$\Delta\boldsymbol{af}$) may all be simultaneously improved with the corrections afforded by this additional degree of freedom; these proportional impacts of $\Delta\boldsymbol{sw}$, $\Delta\boldsymbol{sb}$, and $\Delta\boldsymbol{af}$ are given by the ratio of 0.68:0.32:1.36, respectively.

This represents an improvement from the previous scenario, in that there are now no tradeoffs between technical design outcomes. By making minimal concessions in the experiential responses ($\boldsymbol{Es}$), tradeoffs that were previously present in the performance outcomes ($\boldsymbol{T}$) may be removed. This illustrates how the engineering designer may employ the design space map to precisely quantify the concession to the subjective rating ($\hat{\boldsymbol{r}}$) of steering the pneumatic steering column that they would have to permit in order to achieve the stowability, stability, and affordability that may they desire. Whether these concessions would be considered 'worth it' is a question of their individual *values*, however Embodiment Design Cartography provides the means for them to at least understand what their *options* are.

3.6.4. Examining Experiential Tradeoffs Between Contexts

In the previous exploration, the tradeoffs between technical and experiential design outcomes were navigated within the scope of a *single* context (i.e., the rapid-steering track). These negotiations, of course, may be similarly conducted in the other context (i.e., the precision-steering track), however looking at either one individually ignores the tradeoffs that may exist *between* them. These tradeoffs may be equally important for the product's viability or success. A design configuration suited for a *single* context could be considered more *specialized*. For instance, a configuration of the pneumatic steering column designed for the rapid-steering track may be suited for mountain roads, while a configuration designed for the precision-steering track may be more attuned to highway driving. In practice, the rapid-steering and precision-steering contexts could each conceivably translate into marketing descriptors in an automotive setting. For instance, the vehicle that was tailored for rapid-steering could be designated as 'sporty' (i.e., responsive handling), while the one that was tailored for precision-steering could be designated as 'luxurious' (i.e., smooth handling). Alternatively, a design configuration that is suitable for *multiple* contexts could be more *versatile*. A steering column that is outside of its intended context could provide a negative experience if it is not versatile enough to handle this situation. Versatility, however, may often come at the cost of optimizing *experiential* design outcomes in any one single context. In this case study, the context was certainly impactful on the ratings ($\bar{\boldsymbol{r}}$) that described users' experiential responses. The different tracks were found have significant effect on $\bar{\boldsymbol{r}}$, as well as having significant interactions with both $\boldsymbol{k}$ and $\boldsymbol{s}$ (see Table 8). The manner in which the experiential tradeoffs between these contexts may be navigated with the design space map could take several forms.

If the engineering designer desired some *compromise* between rapid-steering and precision-steering—some balance between 'sporty' and 'luxury'—each track may be considered simultaneously by creating a *convex combination* of the two interaction models (i.e., a weighted average of the coefficients estimated for $\mathcal{J}_{\text{Rap}}$ and $\mathcal{J}_{\text{Prec}}$; see Table 7). The form of this combination is given by Equation (9), in which

$$\mathcal{J}_{\omega} = (1 - \boldsymbol{\omega})\mathcal{J}_{\text{Rap}} + (\boldsymbol{\omega})\mathcal{J}_{\text{Prec}} \tag{9}$$

$$0 \leq \boldsymbol{\omega} \leq 1$$

, where $\boldsymbol{\omega}$ is a weighting coefficient for the relative value placed on each context. As this weighting shifts from the favoring rapid-steering to favoring precision-steering (i.e., as $\boldsymbol{\omega}$ goes from 0 to 1), the optimal design configuration ($\hat{\boldsymbol{r}}_{\text{Opt}}$) moves throughout the solution space in terms of the Responsive Behaviors/Attributes ($\boldsymbol{B_R} = \boldsymbol{A_R}$). This is illustrated by Figure 18. The *average-steering* context represents the equally weighted (i.e., $\boldsymbol{\omega} = 0.5$) convex combination of $\mathcal{J}_{\text{Rap}}$ and $\mathcal{J}_{\text{Prec}}$ (i.e., $\mathcal{J}_{0.5}$). The optimal design configuration in this context therefore represents the configuration predicted to receive $\hat{\boldsymbol{r}}_{\text{Opt}}$ if both interaction contexts are equally important. The path that this optimal design configuration moves within $\boldsymbol{B_R}$ may be plotted as $\boldsymbol{\omega}$ goes from 0 to 1.

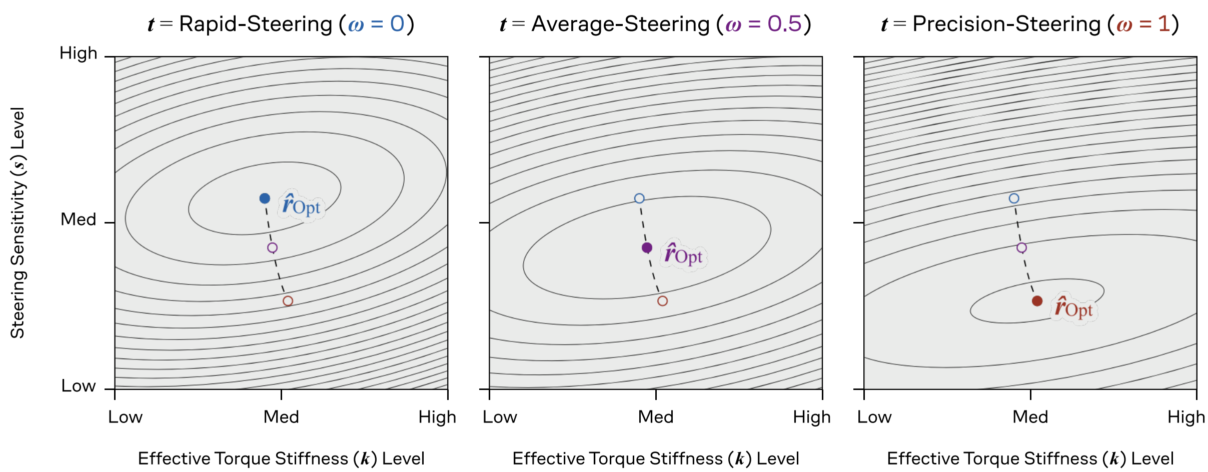

Figure 18. Convex combination of the rapid-steering and precision-steering contexts. The surface and optimal point ($\hat{\boldsymbol{r}}_{\text{Opt}}$) of $\mathcal{J}$ both shift in accordance with $\boldsymbol{\omega}$. Three levels of ω are pictured here: 1) the rapid-steering context ($\mathcal{J}_{\text{Rap}}$; left; $\boldsymbol{\omega} = 0$), the average-steering context ($\mathcal{J}_{0.5}$; center; $\boldsymbol{\omega} = 0.5$), and the precision-steering context ($\mathcal{J}_{\text{Prec}}$; right; $\boldsymbol{\omega} = 1$).

A given configuration along this path may be targeted according to the values of the engineering designer. From this point, the same tradeoffs may then be examined with either 'experience-maintaining' and/or 'experience-sacrificing' adjustments. However, while the resulting design solution would represent some level of compromise between the two contexts, it would not be as successful in achieving the $\hat{\boldsymbol{r}}_{\text{Opt}}$ at either one individually. In this case, it may be observed that the slope of the 'permissible adjustments' line (i.e., the slope of the major axis of the contour) remains nearly constant as $\boldsymbol{\omega}$ goes from 0 to 1. This means that the rating's ($\hat{\boldsymbol{r}}$) relative sensitivity to $\boldsymbol{k}$ and $\boldsymbol{s}$ remains largely consistent—the 'permissible adjustments' line does not drastically vary—and therefore the type of 'experience sacrificing' adjustments that may be made is nearly independent of the context. On the other hand, the path of $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ is approximately orthogonal to the 'permissible adjustments' line, so moving the design configuration along this path has a dramatic negative impact on the experiential response if the device is used outside of its intended context.

If technologically feasible, *in-situ adjustability* may be considered as an alternate means for improving $\hat{\boldsymbol{r}}$ across multiple contexts by providing a more versatile solution. Theoretically, parameters of the Structure ($\boldsymbol{S}$) could be *dynamically adjusted by the user* to adapt an artifact to different contexts. This would effectively enable a single solution to vary within $\boldsymbol{B_R}$, as needed. The parameter that is most effective for in-situ adjustability would be the one which provides a $\boldsymbol{DS_{k,s}}$ vector (see Figure 16) whose slope most closely matches the path of $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ as $\boldsymbol{\omega}$ goes from 0 to 1 (see Figure 18). A combination of multiple design parameters could conceivably be adjusted together to better fit this path, but of course this introduces greater technological complexity. Ultimately, both *effectiveness* and technological *feasibility* must be balanced to make this determination.

In this case study, for instance, the design parameter selected for in-situ adjustability would be the length ($\boldsymbol{l}$). From an effectiveness standpoint, the slope of $\boldsymbol{DS^{l}_{k,s}}$ is the closest to the slope of the path of $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ as $\boldsymbol{\omega}$ goes from 0 to 1 of any single $\boldsymbol{DS_{k,s}}$ vector. From a technological feasibility standpoint, the stow/deploy functionality does enable $\boldsymbol{l}$ to be varied dynamically. When the steering column is depressurized and internal tendons are contracted, its length is decreased as it is compacted into the storage compartment at the fixed end. Assuming that $\boldsymbol{l}$ decreases linearly with the pressure, the internal pressure would remain constant ($\Delta \boldsymbol{p} = 0$) while the length is contracted with internal tensegrity constraints, e.g., [389]. The stow/deploy functionality could therefore serve a second purpose for varying $\boldsymbol{l}$, independent of any other incidental parameter adjustment. This is illustrated by Figure 19.

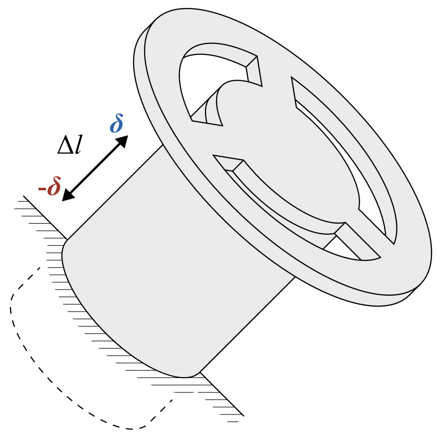

Figure 19. The in-situ length adjustability in the pneumatic steering system. Enabled by the stow/deploy functionality, the length (***l***) may be increased or decreased by some magnitude (δ) to adapt the design configuration for different contexts.

Within the solution space, an *'in-situ adjustability'* line may therefore be defined by the slope of $\boldsymbol{DS^{l}_{k,s}}$. This line determines the path in which the in-situ adjustments may vary the design configuration within $\boldsymbol{B_R}$. Strategically, this line may be situated where it bisects the 'permissible adjustments' line in both the rapid-steering and precision steering contexts, such that the average $\hat{\boldsymbol{r}}$ between both of these intersection points is maximized (i.e., it intersects $\hat{\boldsymbol{r}}_{\mathbf{Opt}}$ in $\mathcal{J}_{0.5}$). This is illustrated by Figure 20, in which the adjustable design configuration is denoted by $\hat{\boldsymbol{r}}_{\mathrm{Adj}}$. In order to adapt the design configuration between each context, the user would increase or decrease ***l*** by some magnitude ($\boldsymbol{\delta}$), thus partially deploying or stowing the column.

The predicted rating ($\hat{\boldsymbol{r}}$) that could be achieved by this *in-situ adjustable* design configuration across the different contexts can be directly compared to *fixed* design configurations that were specifically optimized for either the rapid-steering, average-steering, or precision steering contexts individually (see Figure 18). The predicted ratings for each, summarized in Table 9, are compared as percentages of the optimal ($\hat{\boldsymbol{r}}_{\mathbf{Opt}}$), as this maximum rating also varies across each context. While the in-situ adjustable configuration may afford marginally worse ratings when compared to the design configuration optimized for that specific context, it largely outperforms each of these design configurations within any context they were not tailored for. This suggests that in-situ adjustability on the length (***l***) of the column may be a desirable feature to consider for the pneumatic steering column. However, the benefits that this feature provides on the experiential level must ultimately be weighed against the added technological complexity.

Figure 20. The in-situ adjustability to adapt the design configuration for multiple contexts. By dynamically adjusting the length (***l***) of the pneumatic steering column, its configuration may be altered within the solution space along the 'in-situ adjustability' line, such that it may achieve superior experiential responses ($\hat{\boldsymbol{r}}$) across both contexts

Overall, the design space map constructed in this case study may be demonstrably used for negotiating a variety of different kinds of tradeoffs. While the insights discussed here are admittedly limited to *directionalities* rather than determining specific values—which may be achieved with a more robust engineering model—the tradeoffs explored in this case study illustrate the depth of information that may be ascertained with the design space map, without relying on any complex computational techniques beyond visual analysis of vectors and gradients. Not only were tradeoffs able to be numerically identified and quantified, but new innovation areas (e.g., in-situ adjustability) were identified through this systematic exploration as well. Of course, even more rigorous characterization, modeling, and analysis techniques may certainly be applied here, but the simplicity of this demonstration illustrates how this practice is not necessarily reliant on these advanced techniques. The proposition of easily ascertaining this level of understanding of the design space, with only the limited knowledge base that may be available early in new product development cycle, can be extremely valuable for designers.

Table 9. The rating for each design configurations across each context. Ratings are given as percentages of $\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ across the range of $\hat{\boldsymbol{r}}$ for each contour to emphasize relative experiential response for each configuration. In each context, the in-situ adjustable configuration rates second only to the configuration specifically tailored for that context.

Configuration	**Context (*t*)**		
	Rapid-Steering (ω = 0)	**Average-Steering** (ω = 0.5)	**Precision-Steering** (ω = 1)
Rapid-steering	100%	94.9%	85.1%
Average-steering	95.3%	100%	95.9%
Precision-steering	79.1%	93.7%	100%
In-situ adjustable	99.6%	100%	99.9%

3.7. Chapter 3 Conclusion

In this chapter, the framework for Embodiment Design Cartography (EDC) was applied to construct the design space map of a real-world technology—the pneumatic steering column. This design problem is representative of *emerging* technologies in the realm of rich, embodied interaction, and serves as a case study for one of the primary issues in new product development—navigating *tradeoffs*. In this specific design problem, new technological capabilities provided the opportunity for novel design outcomes on both the *technical* (e.g., stow/deploy) and *experiential* (e.g., perceptions to a new steering feel) levels. However, it was unknown as to how these different design outcomes might *compete* with one another, such that tradeoffs between the would be necessary. With the EDC framework, this *ill-structured* problem was systematically mapped, and the different tradeoffs were numerically explored. This provided a greater understanding of what the available options in this space were, and informed actionable insights as to the available design levers should be adjusted accordingly.

The *problem space* in this case study was *formulated* within the EDC framework in a manner that was tailored to the specific questions surrounding this emerging technology. On its face, the technological innovation being addressed—replacing a traditional, rigid steering column with a pneumatic one that could be stowed or deployed—called for typical engineering analysis for how to how to best achieve the relevant *technical* outcomes of this new functionality. With these technological changes, however, also came a fundamental shift to the *feeling* of interacting with the steering wheel, into a state that was unfamiliar to drivers. This rich, embodied interaction therefore elicited some unknown design outcomes on an *experiential* level, which could also be prospectively influenced by different external factors. To examine these different, competing design outcomes, a *well-defined* formulation was structured within the Actor-Abstraction (A-A) matrix, in which the technical and experiential and outcomes were organized in *parallel*, in a manner that was unique to any of the existing design methods. Through the *critical examination* of the design problem that the A-A matrix calls for, the attributes of the environment that would be navigated with this device were identified as a particularly relevant context factor for influencing the perception of this steering interaction. While these context factors were reasonably considered to be outside the designer's control in this case, this formulation did therefore not address the implications for *design levers in the context* being present. Another notable omission from this formulation was formal recognition of the different user characteristics—outside of random-effects—that may also factor into their rich, embodied interaction. Overall, this formulation demonstrated how new, tailored problem spaces may be precisely defined within EDC, however in doing so it only examined relevant portions of the A-A matrix. It is necessary to further examine these omissions in a real-world design problem for which these other considerations are specifically pertinent.

With this well-defined, yet novel formulation of the problem space, several specialized techniques for *modeling* the associated *solution-space* were developed for problems of this nature. Three distinct transformations were mathematically modeled in this work, including the engineering and performance models, which were *analytically* characterized, and the interaction model, which was *empirically* characterized. Together, these models coupled the concrete engineering design levers at the level of the *how*, and the different abstract design outcomes at the level of the *why*. The parallel formulation of the problem space enabled these transformations to be each be independently characterized, which could be important for modularizing this design task between specialized groups (i.e., engineers versus behavioral scientists), while ensuring their eventual compatibility upon completion. To achieve a *complete formulation*, an *intermediary* vector space was defined as a lynchpin of these models—as both an input and output to these different transformations—which enabled them to be composed. This composition served to close this circuit, so-to-speak, and allowed for multiple models to be projected into a common space. This composition also leveraged the natural functional forms of the different phenomena being characterized—namely the *power law*s that governed the technical relations and the *logarithmic scale* of the experiential relations. In doing so, a systematic exploration of the resulting solution space using *linear algebraic* machinery was made possible, in which the impacts of adjustments to concrete design levers on abstract design outcomes were both easily *visualizable* and *quantifiable*. Overall, this promoted a rigorous, holistic understanding of the available options that comprised this space.

To *experimentally* construct this model of the solution space, *techniques* and *procedures* were developed that were fundamentally based on the core processes of embodiment design—*analysis*, *synthesis*, and *evaluation*. An empirical user study was conducted, which housed the six activities that comprise these processes in the EDC methodology (see Table 3). The vector spaces were first *parameterized* with a combination of expert input, pilot study, and rational derivation. Users then provided subjective ratings on a variety of different configurations of the pneumatic steering column, within different contexts, to *descriptively model* this relation. In the adaptive experimental design of this study, new design configurations of this device were then predicted for each participant through *prescriptive modeling*. Through the use of an *interaction prototype*, these new design configurations were immediately generated in the real world and presented to the user for their interaction. By creating these prototypes in real-time, they were than able to be *verified* by the same participant they were predicted for. Multiple different configurations throughout the solution space were generated for this evaluation, which ultimately enabled to model to be *validated*. Overall, these techniques and procedures helped construct a model that could be reliably used as a tool for negotiating tradeoffs, and made this design space mapping feasible to conduct within practical recourse constraints. However, other types of information could have provided further insight toward these aims. *Physiological* signals, for instance, could provide unique insights that may not be communicated though subjective response alone, and ultimately provide a more holistic description of the experiential response to this interaction. The measurement of physiological signals was included in the procedure of this experiment (see Section 3.5.1), however these measures were not considered in the design space map. The utility of incorporating these signals into the map should be explored further.

Finally, this chapter presented a clear case for how Embodiment Design Cartography may be usefully *operationalized* for design work. The use of a graphical system that was supported by an underlying numerical approach was useful for navigating tradeoffs between technical outcomes, understanding how strategic concessions to experiential outcomes can afford a more favorable balance, and revealing how these tradeoffs were influenced by external factors. Ultimately, this work was important for addressing what represents a core issue in new product development—understanding and negotiating tradeoffs—and did so in a manner that promoted a level of nuance and creative problem solving that is indispensable for *innovations* to be made. The systemic exploration enabled by the design space map not only motivated a new feature (i.e., in-situ adjustability), but did so in a manner that provide actionable insight into how to actually enact said innovation. In the larger 'Research Through Design' (RTD) approach that is taken across this dissertation, this applied case study represents the first incremental validation of the framework as whole. In this regard, EDC was largely successful as a tool for uncovering multiple differed design insights. However, this only represented one potential application of the framework. Further testing and designing with the EDC framework is necessary to continue its incremental validation in other key areas.

Chapter 4. A Method for Personalizing Options of an Established Technology

Personalizing a product can allow it to uniquely suit the needs, preferences, or predispositions of a consumer. However, the designer who is to enact these personalizations must understand what important differences between users exist, and then individually assess these differences on the mass scale of their consumer base. Design space mapping can be beneficial for understanding how to implement these personalizations by considering the *latent* (i.e., unspoken) emotions or cognitions that users may subconsciously communicate. This is especially pertinent for *established* technologies, in which adaptive capabilities to personalize the product are already technologically achieved. In this chapter, the Embodiment Design Cartography framework is applied to a case study of an *established* technology in order to *personalize* the available options by permitting the user to control their own *psychophysiological design levers*. The objective of this chapter is to develop and demonstrate modeling, experimental, and design techniques in support of these aims. The problem space for this case study is first systematically tailored to this design problem within the Actor-Abstraction matrix. Two versions of the solution space are then modeled within an empirical user study (n = 60)—one that includes the latent information provided by *psychophysiological* measures, and one that does *not*. The former is validated to improve predictive accuracy on an out-of-sample population. With this validated model, real-time personalizations may be informed and enacted on mass scales.

4.1. Mass Personalization with Psychophysiology

To be an 'individual' inherently means to be 'different.' People can differ from one another in many ways. With regard to *physically-interactive* products, for instance, the same physical stimuli could elicit vastly different experiential responses according to the user's implicit characteristics or internal state [325]. However, *understanding* each of these unique differences can be a challenging proposition, especially at the larger population scales seen in industrial product development. Individual differences can be quite complex and difficult to determine, even with traditional market research techniques [402,403]. To separately uncover and act on the unique differences of every individual consumer seems an exhausting, infeasible endeavor for a designer to undertake. In the previous case study, these individual differences were only considered by *random-effects* and not formally mapped in the problem space—largely in part due to this challenge. Nevertheless, there is growing consumer demand for increasingly tailored interactions with products [404,405], especially ones that are *embodied*, or physical in nature [93].

Feasibly satisfying this demand is a core issue facing new product development today [324–326]. One manner in which it is at least partially satiated is through product *customization*. Products are considered to be 'customized' when distinct *groups* or segments of users are defined, and each receives a different configuration of the artifact from a *pre-defined* product line or family [324,325]. Customization, however, does not truly address differences at the *individual* level. To make this jump, products may be *personalized* to individual users. Product 'personalization' means to tailor the product to a completely *new* design configuration that is unique to each user, based on information collected about their individual differences [406–408,324,325]. While both approaches involve tailoring the product to the users, *customization* is equated to designing for a 'market-of-*few*' while *personalization* is equated to designing for a 'market-of-*one*' [325,409]. Personalized products can offer better benefits or value to users [410], foster consumer attraction and retention, and ultimately provide design firms with a competitive edge [325,411].

These advantages stem from the fact that personalization effectively *expands the design space* in terms of the experiential design *outcomes* that are considered [324], by imbuing it with additional information about the user *factors* [324]. In essence, more considerations are made on a deeper level, which can allow for the selection of better solutions. However, the design outcomes may in turn become less predictable [324]. This presents both new challenges and new opportunities for applying Embodiment Design Cartography (EDC). To not only personalize a single design configuration, but also the entire range of options in the design space, a host of additional complexities may arise. However, this could also lead to significant improvements to the accuracy of the overall map.

> *"Personalization is to achieve satisfying each customer as an individual. Thus, product differentiation is at individual customer level* [sic]*, as opposed to customization which differentiates products for market segments. The idea of deriving profitability from, and gaining competitive edges through, differentiating products is not new. It often appears as market segmentation, customer-centric, or augmented cognition to exemplify personalization. In terms of design, personalization discerns from customization mainly in two dimensions, expanding product design space, and embracing intangible customer experience."*
>
> – M. M. Tseng, *Design for Mass Personalization*, 2010 [324]

From a product development standpoint, there is an important distinction to be made between 'personalization' and '*mass* personalization' [325]. The former is a longstanding, but costly practice that dates back to primitive crafting. For personalization to be enacted on the mass scales seen in modern product development, it must be done so in manner that is highly resource efficient [409]. For this effort to be worthwhile, personalized products must be generated in *real-time* with *better predictive accuracy* of users' preferences [325]. As such, mass personalization is most commonly employed in *digital* applications (e.g., websites) where it is less resource intensive, rather than on physical products. For *established*, physically-interactive products to similarly afford the option of mass personalization, they must be dynamically adjustable [324]. As such, there are currently relatively few cases in which physically-interactive products are personalized on a mass scale.

A design space map, however, can serve as a useful *tool* for operationalizing mass personalizations of established technologies. For personalization to add value, it is just as—if not *more so*—important that the designer understands *what* to personalize, rather than simply *how* to achieve the technological capabilities of doing so. Investing in the development of an adaptable product is a fruitless endeavor if it remains unknown as to how it is beneficially personalized. Simply stating that a product *should* be personalized does not actually provide the designer with any insight as to *which* product attributes should be adapted, and what these changes should be. With a map of the design space, users' individual differences may not only be understood, but also directly translated into personalized design adjustments. This can also reveal which qualities of the product are actually beneficial to personalize, and which are not. There are several tenets of mass personalization that must be incorporated into the design space map for EDC to be applied in this area. These include: 1) *direct involvement* of the user in the creation *and* navigation of the solution space, and 2) inclusion of *latent* experiential responses when considering the design outcomes in the problem space [325]. Each tenet is discussed in turn.

4.1.1. User Involvement in the Design Process

The involvement of users within the design process is of undisputed value [127,412–415]. To tailor a product according to individual differences, the user must be involved in some way. Their *level* of involvement, however, can vary across a continuous *spectrum*. Along this spectrum, three distinct levels may be defined according to which embodiment design processes (i.e., *analysis*, *synthesis*, and *evaluation*) the user is involved in. These levels include [125,416–419]:

1. ***Informative Involvement*** – At the lowest level of user involvement is *informative involvement* (i.e., design *for* users). At this level, users are only involved in the *analysis* process to help parametrize domain spaces or characterize the descriptive model (e.g., through survey, interview, observation, etc. [420]). The designers then *synthesize* and *evaluate* products without the users' input.

2. ***Consultative Involvement*** – At the intermediary level of user involvement is *consultative involvement* (i.e., design *with* users). At this level, users are involved in both the *analysis* process, and also the *evaluation* process to help *verify* the designs and *validate* the model (e.g., through usability testing after the product is designed [421,422]). The designers, however, still *synthesize* the product completely under their own volition.

3. ***Participative Involvement*** – At the highest level of user involvement is *participative involvement* (i.e., design *by* users). This is also commonly referred to as 'participatory design' [125,415,423–430] or 'co-creation' [402,431]. At this level, users are involved in all three processes—*analysis*, *synthesis*, and *evaluation*. They are given 'genuine' influence [423] on the determination of the resulting design configuration. This means that

they themselves are able to make *direct* adjustments to design levers, rather than just informing designers on how adjustments should be made.

For reference, the previous case study could be placed along this spectrum somewhere around the intermediary level—*consultative involvement*—as users were involved in *analysis* and *evaluation*, but did not have direct control over any design levers for *synthesis*. Enacting mass personalization is ultimately predicated on achieving this highest level of user involvement—*participative involvement*—in which the user is involved in all three embodiment design processes [325]. With this level of involvement, users' *individual differences* may therefore serve as their own *design levers* to the problem. The reason that participative involvement is critical for mass personalization is that it allows users to *directly* influence design decisions with *latent* (i.e., unspoken) information [325,428–430]. Alternatively, the user would have to expressly communicate this information to the designers, so *they* can make adjustments for the user. This is not necessarily feasible at larger scales. Latent experiential responses can provide insight into the *cognitive* or *emotional* reactions that users have difficulty expressing outwardly [324].

> *"[T]he conventional survey or interview often fails to reveal latent customer needs. Furthermore, customers can be reluctant to reveal their inner needs, which may not be known by customers themselves either… It is apparent that not only designers but also customers play crucial roles in expanding the scope of design from customization to personalization."*

– Feng Zhao, *Affective and Cognitive Design for Mass Personalization: Status and Prospect*, 2013 [324]

The manner in which these latent experiential responses are extracted for mass personalization can vary. For instance, Amazon employs mass personalization on its e-commerce sites through *latent* information on users' interests, which are provided by their search and purchase histories. By using the platform differently or changing how they interact with the product, individual users can reconfigure what suggestions are shown to them [409,324,325]. It is therefore important to realize that the *direct* input that users have on mass personalized products is not necessarily *conscious* input. Rather, users may *subconsciously* adjust design levers with their latent experiential responses [432]. To help ensure that these individual adjustments are truly beneficial to the user, it is important for mass personalizations to tap into latent information on *emotional* and *cognitive* responses, not just behavioral [324,325,433–435]. Latent information in these areas may be incorporated into the design space map through measures of *psychophysiology* [436–440].

4.1.2. Psychophysiological Design Levers

Psychophysiological measures are autonomic, or subconscious, *physiological* responses, which may be used to assess latent *psychological* reactions such as emotions or cognitions [441,442]. The physiological responses that may be recorded are not necessarily one-to-one measures of these latent emotions/cognitions [437,442], but can provide a useful index for them, especially when *multiple* different signals are combined (including subjective self-reports, e.g., ratings [443]) [444–448]. There are several notable benefits of such measures. For one, physiological responses can be measured *during* an interaction (i.e., through sensors applied to the body [449]), while subjective responses are limited to *after-the-fact* reporting (i.e., surveys or interviews) [450,439]. To holistically assess design outcomes, experiential responses should be captured both during *and* after an interaction [436,438,451]; physiological responses provide a means for the former. They are also inherently more *objective* than subjective self-reports [452]. Emotions/cognitions reported after an interaction can be subject to bias [453], and may not reflect the same feelings that were originally felt [438]. This may be due to the difficulty of accurately recalling or communicating these feelings after some threshold of time [454–458], or due to the fact that these sentiments may simply change over time [436,459].

The use of such measures to improve design outcomes on the experiential level has therefore seen growing interest [436,438,439]. This growth spans various design disciplines, such as Human-Computer Interaction (HCI) [444,460], Human-Machine Interaction (HMI) [446], and Neurological Information Systems (NeuroIS) [461,462]. In these disciplines, commonly used physiological signals include *electromyography*, *electrocardiography*, and *electrodermal activity* (also commonly referred to as *galvanic skin response*) [436,438]. Each of these signals has previously been demonstrated to provide information on latent emotional/cognitive responses [438,442,444]. For instance, practitioners have identified patterns in these signals to classify discrete emotional states [446,463]. By jointly measuring all three of these signals together, they can the serve as a stronger index to model more complex emotional responses [464,465]. Specific emotional or perceptual labels (e.g., boredom, stress) may then be attached to these *physiological* responses when they are coupled to *subjective* ones [325,437].

In practice, the application of psychophysiological measures is commonly found within *physio-adaptive systems* [466]. This is a type of control system [467] that continuously monitors physiological activity and adapts in real-time according to measured responses [437]. These systems are based on what is known as a *biocybernetic loop* [468–470]. In this loop, discrete emotional/cognitive states are defined in relation to some characteristic physiological activity. When this characteristic activity is detected, a *pre-defined* reaction is triggered [471], and the user's physiological activity is then reassessed as the loop repeats [437,466]. The adaptations afforded by physio-adaptive systems could, for instance, include telling a joke if driver boredom is detected [472] or adjusting a video game's difficulty level according to some threshold of player stress [473,474].

Despite these existing applications, several barriers remain for using psychophysiological measures as *design levers* in mass personalization. The existing application of these measures in product design—physio-adaptive systems—is largely limited to *pre-defined* adjustments in the vein of product *customization*, rather that the creation of *new* configurations that are tailored to the individual, which is the aim of product *personalization*. Ultimately, there is still relatively little understanding of how psychophysiological measures can be effectively applied for *synthesis* of new design configurations [243]. From an *experimental* standpoint, these signals could potentially facilitate *efficient* mass personalizations by informing adjustments in *real-time* [462,466]. However, there are a variety of pain points regarding the techniques and procedures needed to do so. These include the added time and expertise needed to process physiological signals and extract the latent emotional/cognitive information within, as well as the potential intrusiveness of the sensors used to collect this data [436,439,451,462,466,475]. There is also a reported lack of rigorous *validation* on the added value of involving users in the design process at a *participative* level [125,418,476]. The pressing questions in regard to new product development therefore include, "[w]ill this be possible in new design technology? Can product development team [sic] anticipate and adapt to customers' latent needs?… Can personalization be carried out with efficiency?" [324]. Tackling these questions through the framework for Embodiment Design Cartography may provide understanding for how personalizations of physically-interactive products can be efficiently enacted at mass scales, in a manner that most benefits the users.

4.2. Case Study: The Infotainment Controller

To demonstrate the ability of Embodiment Design Cartography (EDC) to support mass personalization in real-world design problems, the design space map of an *established* infotainment controller is undertaken. As noted in the previous chapter, physically-interactive controllers, i.e., Human-Machine Interfaces (HMIs), offer a myriad of functionalities [477] and are quite prevalent within automotive settings [387]. When compared to *digital* user interfaces (UIs), physically-interactive controllers are especially desirable to personalize due to the different the experiential responses that their *haptics* may elicit [93]. However, these devices are more commonly developed with an *informative* or *consultative* level of user involvement [418], rather than reaching the threshold of *participative* user involvement needed for mass personalization.

The product in this case study is an *infotainment controller*. This is an established technology that is currently used to operate the infotainment system on the dashboard of the 2019 Cadillac CT6. This controller, located in the vehicle's center console, is primarily operated using a large rotary dial that may be *rotated* to navigate various different applications, and *pressed* to make selections. This artifact is illustrated in Figure 21.

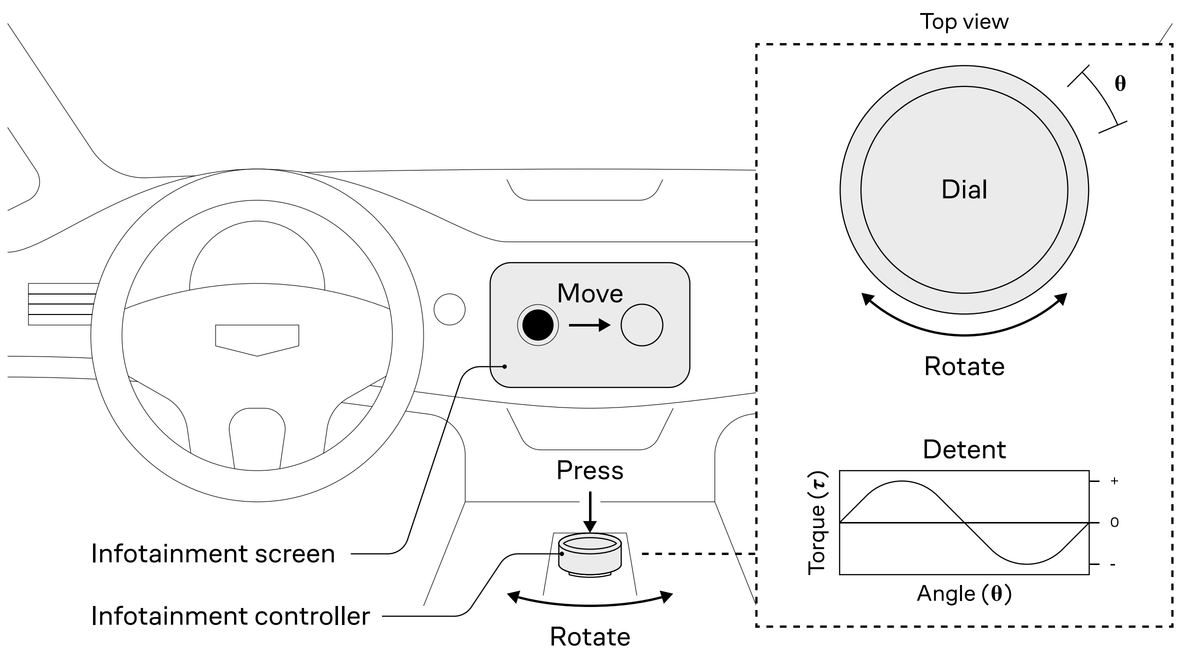

Figure 21. The infotainment controller. The controller is a haptic rotary dial that is used to navigate applications on the infotainment screen, which is located on the dashboard. The dial is rotated to move the selector and pressed to make sections. For every **Θ** degrees that the dial is rotated, the selector is moved one position, and one detent is felt by the user (***τ***). The amplitude and period of the detent profile are both dynamically adaptable.

Through technological capabilities that are already established (proprietary), this device is capable of dynamically adapting the type of *tactile haptic feedback* it provides when it is rotated. The feeling of this feedback is described by *'detents'* (see Figure 21), which vary the feedback torque ($\boldsymbol{\tau}$) that is felt as the dial is rotated to some degree ($\boldsymbol{\Theta}$). Rotating over one detent corresponds to moving the selector on the application screen by one position. Both the *period* of this angular displacement, as well as the *amplitude* of the feedback torque can each be altered in real-time across some range of values. This theoretically enables the profile of this detent to be *personalized*.

It is not immediately apparent, however, as to what personalizations should actually made—which parameters should be adjusted and by how much—in relation to individual differences. The manner in which both designers *and* users can have direct input to these personalizations through different design levers is also not apparent. External factors that may influence these personalizations need to be considered in the *problem space formulation*. Characterizing the *solution space model* can require more sophisticated techniques to support the latent experiential responses. The *experimental infrastructure* and *procedures* needed to collect and process this physiological data can be complex and resource taxing. As such, this established technology is a suitable candidate for design space mapping to illustrate the manner in which the EDC framework may be *operationalized* to inform design decisions in this area.

4.3. Mapping the Infotainment Controller Problem Space

Following the Embodiment Design Cartography (EDC) methodology detailed in Chapter 2, the first step in design space mapping is to construct the map of the *problem space*. This necessitates a *critical examination* of which considerations may be relevant to this design problem. Each of these considerations will be defined by a vector space that may be mapped within the Actor-Abstraction (A-A) matrix (see Figure 3). This process largely echoes the problem space mapping detailed in the previous case study. However, while that problem space was largely formulated from an engineering design perspective, in this case, the underlying form/layout is already established. Instead, a *multidisciplinary* perspective is taken—as is enabled by the framework's construction as a *boundary object*—in which several different types of design levers are defined for different types of designers (and users). The resulting mapping is illustrated in Figure 22.

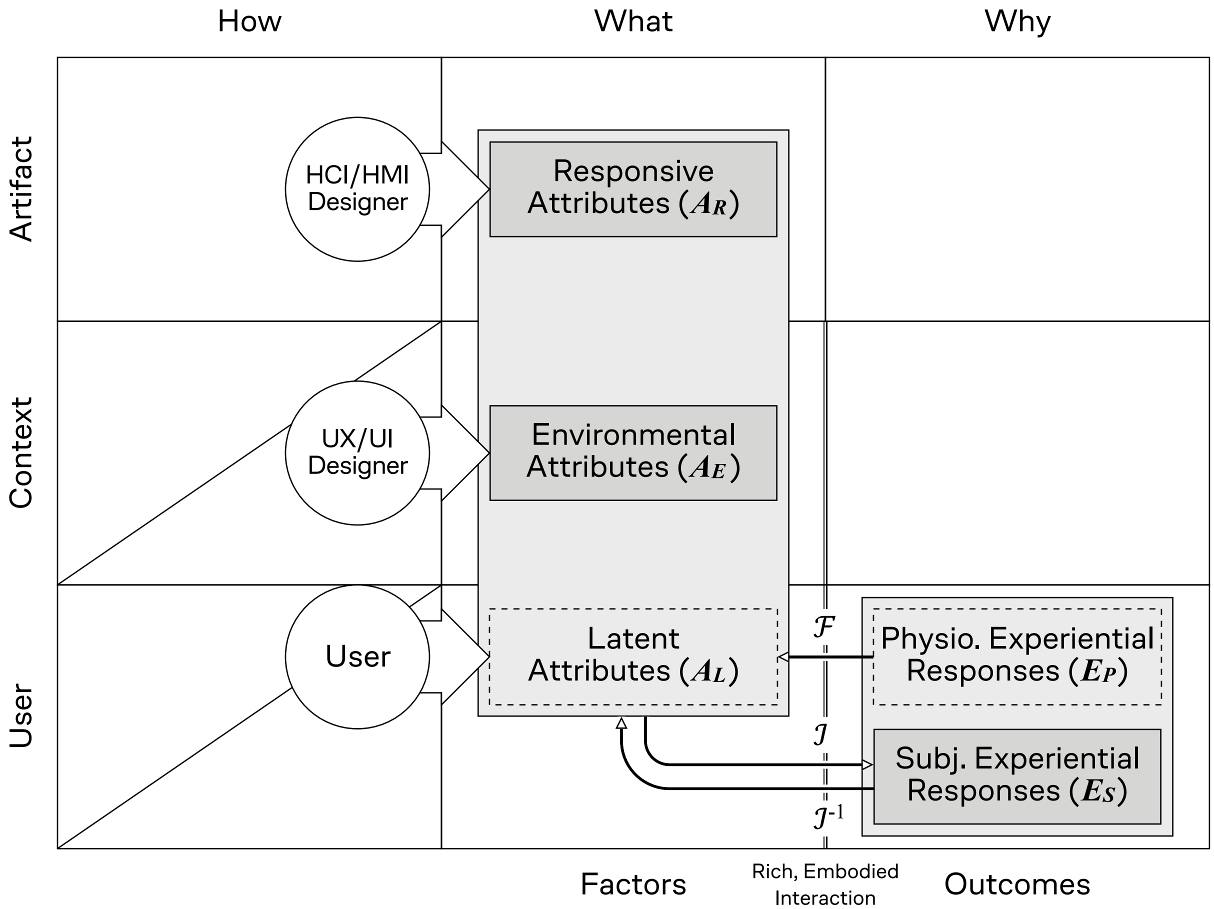

Figure 22. The problem space formulation of the infotainment controller mapped onto the A-A matrix. Physiological Experiential Responses ($\boldsymbol{E_P}$) and Subjective Experiential Responses ($\boldsymbol{E_S}$) are both mapped to the User-Why. Responsive Attributes ($\boldsymbol{A_R}$) is mapped into the Artifact-What, Environmental Attributes ($\boldsymbol{A_E}$) is mapped into the Context-What, and Physiological Attributes ($\boldsymbol{A_P}$) is mapped into the User-What; design levers preside in each of these vector spaces, which may be adjusted by HCI/HMI designers, UX/UI designers, and users, respectively.

The Why – Starting at the level of the *why*, robust consideration of experiential responses is said to be the most important contribution of personalization [324]. This necessitates the mapping of two different vector spaces in this abstraction. First, a *Physiological Experiential Responses* ($\boldsymbol{E_P}$) sub-vector space, which describes the physiological responses elicited *during* the interaction with the controller, may be mapped into the User-Why. This is mapped as an *extension* vector space, as it is only used in one of two versions of this design space map; this is detailed further in the empirical study (see Section 4.4). Second, a *Subjective Experiential Responses* ($\boldsymbol{E_S}$) sub-vector space, which describes the subjective responses elicited *after* the interaction with the controller, may also be mapped into the User-Why. By including both types, the physiological responses may be correlated to the dimensions of the subjective responses and given perceptual labels (e.g., stress). Together, these comprise the overall *Experiential Responses* ($\boldsymbol{E}$) vector space ($\boldsymbol{E} = \boldsymbol{E_P} \cup \boldsymbol{E_S}$), which holistically encompasses experiential responses both during *and* after the interaction.

The What – At the level of the *what*, the qualities of the infotainment controller that may be personalized are first considered. In this regard, a *Responsive Attributes* ($\boldsymbol{A_R}$) sub-vector space, which describes the detent profile of the controller (see Figure 21), may be mapped into the Artifact-What. A designer who works with *hardware* can directly adjust the design levers in this space—this could, for instance, be a Human-Computer/Human-Machine Interaction (HCI/HMI) designer. Like the previous case study, this artifact is also used to navigate some environment, which could factor into the interaction. In this case, however, the environment is *digital* in nature, i.e., the *infotainment screen*. An *Environmental Attributes* ($\boldsymbol{A_E}$) sub-vector space, which describes the *applications* that may be navigated, is thusly mapped into the Context-What. A designer who works with *software* can directly adjust the design levers in this space—this could, for instance, be a User Experience/User Interface (UX/UI) designer. Finally, the individual differences of the user must also be considered. Since these are to be defined by the latent experiential responses that distinguish individuals, it is necessary to first elicit said responses through a rich, embodied interaction. A *Latent Attributes* ($\boldsymbol{A_L}$) sub-vector space, which describes the meaningful *psychophysiological features* that are extracted from the raw physiological signals, may thusly be mapped into the User-What. $\boldsymbol{A_L}$ is therefore coupled to the Physiological Experiential Responses ($\boldsymbol{E_P}$), which is to the right of the *interaction boundary* and therefore results *from* the interaction, but may be used reveal latent individual differences of the user. This space is where the individual user could directly (albeit unconsciously) adjust their own design levers. The overall *Attributes* ($\boldsymbol{A}$) vector space ($\boldsymbol{A} = \boldsymbol{A_R} \cup \boldsymbol{A_E} \cup \boldsymbol{A_E}$) describes the attributes that are relevant to the rich, embodied *rotating* interaction. $\boldsymbol{A}$ is coupled to $\boldsymbol{E_S}$, as each of its sub-vector spaces may contribute to shaping the understanding of *future* interactions.

The How – It should be noted that *no* vector spaces are mapped at the level of the *how* in this formulation. Although there *are* underlying form/layout parameters that enable the dynamic adaptability of the infotainment controller (proprietary), these are already specified and therefore do not need to be ‘designed’ in this case study. If the range of desirable personalizations was found to be smaller or larger than the achievable adaptability, these parameters could be adjusted accordingly in future development.

The resulting problem space formulation couples the *multidisciplinary* design levers (***A***) to the abstract design outcomes (***E***) in several *closed circuits* that may be traced in both the *causal* and *teleological* directions. Looking at the map, there is a controls-like *feedback loop* built-in to this formulation. The Physiological Experiential Responses ($\boldsymbol{E_P}$) that result from the rich, embodied interaction are then used to *prescriptively* extract the Latent Attributes ($\boldsymbol{A_L}$). These then contribute to *descriptively* predicting future outcomes of said interaction ($\boldsymbol{E_S}$). This enables an experimental design that similarly echoes this controls-like format in the subsequent empirical study. Empirical study is necessary as these transformations cross the *interaction boundary*. Overall, the problem space map that is derived through the systematic examination of these considerations provides a *well-defined* organizational structure that is *unique* from existing design methods and *tailored* to this specific design problem.

As no transformations are defined in the formulation that may be analytically derived (i.e., they each cross the *interaction boundary*; see Figure 3), the subsequent *solution space modeling* may be undertaken entirely within an *empirical* study. Before this study is commenced, however, the first activity in the EDC methodology (see Table 2) may be conducted—the *parameterization* of the problem space. The remaining activities are then discussed in the following section.

4.3.1. Parameterizing the Infotainment Controller Problem Space

The first activity for the *analysis* process is to *parametrize* each of the vector spaces. For this case study, the majority of the parameters are implied by the design problem. However, the refinement and selection of these parameters is conducted within the empirical study and guided by the information supplied by the *users*, rather than the being solely determined by the *designers*. This allows the users to select the design levers that are most important to them, as to ensure that the personalizations they enact are those that are truly beneficial. The parameterized vector spaces are summarized in Table 10 and each detailed in turn.

Table 10. Parametrized vector spaces of the infotainment controller problem space.

A-A Domain	Vector Space	Description
Artifact-What	$\boldsymbol{A_R} = \{\boldsymbol{d}, \boldsymbol{m}\}$	The *detent number* (***d***) over a full rotation, i.e., angular period of the detent profile ($16 \leq \boldsymbol{d} \leq 56$), and the *motor torque stiffness* (***m***), i.e., the relative amplitude of the detent profile ($25\% \leq \boldsymbol{m} \leq 75\%$ of max).
Context-What	$\boldsymbol{A_E} = \{\boldsymbol{a}\}$	The *applications* (***a***) that infotainment controller is used to navigate, i.e., the *menu*, *contacts*, and *volume* apps.
User-What	$\boldsymbol{A_L} = \{\boldsymbol{A_{L1}}, \ldots, \boldsymbol{A_{L98}}\}$	A pool of 98 different psychophysiological features ($\boldsymbol{A_{Li}}$) that may be extracted (see Table 11)
User-Why	$\boldsymbol{E_P} = \{\boldsymbol{ecg}, \boldsymbol{eda}, \boldsymbol{emg}\}$	The electrocardiography (***ecg***), electrodermal activity (***eda***), and *electromyography* (***emg***) of the user.
	$\boldsymbol{E_S} = \{\boldsymbol{r}\}$	The *satisfaction rating* (***r***) given by the user (10-point scale).

Parametrizing the Responsive Attributes – The dimensions of the Responsive Attributes ($\boldsymbol{A_R}$) each relate to the specific rich, embodied interaction, which in this case is *rotating the dial*. For the infotainment controller, these dimensions are given by the *detent number* (***d***) and *motor torque stiffness* (***m***), which together describe the 'detent profile' of the controller (see Figure 21). Each detent essentially feels like a bump that provides resistance as the dial is rotated. The detent profile may be defined by a sine wave given by Equation (10), in which

$$\boldsymbol{\tau} = \boldsymbol{m} \sin\left(\frac{2\pi}{\boldsymbol{d}}\boldsymbol{\Theta}\right) \tag{10}$$

$$16 \leq \boldsymbol{d} \leq 56$$

$$25 \leq \boldsymbol{m} \leq 75$$

, where $\boldsymbol{\tau}$ is the feedback torque felt by the user, and $\boldsymbol{\Theta}$ is the degree that they rotate the dial. The number of detents seen in a full, 360° rotation is given by ***d***, which may be adaptably adjusted between the range 16 and 56. This also therefore defines the sensitivity of the controller, as rotating over one detent moves the selector by one position (see Figure 21); increasing ***d*** means the dial must be rotated to a smaller degree ($\boldsymbol{\Theta}$) for each selection, and is therefore more sensitive. The strength of the feedback that is felt is then given by ***m***, which defines the amplitude of this sine wave. This may be adaptably adjusted between the range of 25% to 75% of the total motor power. Overall, $\boldsymbol{A_R} = \{\boldsymbol{d}, \boldsymbol{m}\}$, in which the dimensions of $\boldsymbol{A_R}$ may be directly adjusted and personalized for each user by the HMI/HCI designer.

Parametrizing the Environmental Attributes – The rich, embodied interaction of rotating the dial takes place in the *context* of the infotainment screen. The Environmental Attributes ($\boldsymbol{A_E}$) in the Context-What is therefore defined by three different categorical *applications* ($\boldsymbol{a}$) in this case study. These include a *menu* app, a *contacts* app, and a *volume* app, which are illustrated by Figure 23. The *menu* app has a multi-row list of 8 items per page (16 total). It is scrolled horizontally left-to-right until the end of the row is reached, then vertically to the left-most item on the next row (similar to text on a page). There are two pages that scroll discretely. The *contacts* app has a vertical list of 36 entrees (8 of which are visible at a given time) that scrolls vertically from top-to-bottom. This page scrolls continuously as the selector is moved. The *volume* app has a horizontally scrolling slider that can go from 0 (left) to 100 (right). This page is static and does not move. The current selector position is highlighted on the screen. Each of these applications could be further parameterized by several variables (e.g., list length, scroll direction, items per page, etc.), however they are aggregated into a single categorical variable for simplicity of the case study. Overall, $\boldsymbol{A_E} = \{\boldsymbol{a}\}$, in which dimensions of $\boldsymbol{A_R}$ may be directly adjusted by the UX/UI designer.

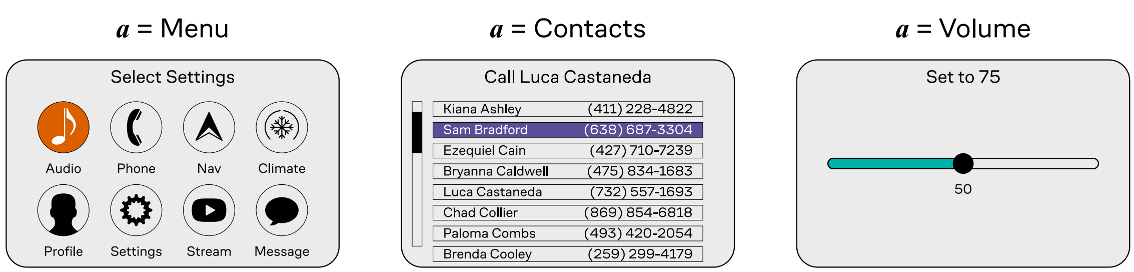

Figure 23. The contexts for the infotainment controller interaction. These three different applications ($\boldsymbol{a}$)—the menu (left), the contacts (center), and the volume (right)—define the Environmental Attributes ($\boldsymbol{A_E}$) in this case study. Task instructions were listed at the top of each (e.g., select settings).

Parametrizing the Latent Attributes – There are a wide variety of *psychophysiological features* that may be extracted from physiological responses. These allow for meaningful information on latent emotions/cognitions to be interpreted from these raw signals [466,478]. These features can be considered to be aggregate descriptors or summary statistics for the continuous signals that are measured during an interaction, e.g., [479–481]. In this case study, 98 psychophysiological features comprise the dimensions of the Latent Attributes ($\boldsymbol{A_L}$). Each of these dimensions represent measures that may be used to differentiate individuals according to their latent emotions/cognitions. These are detailed in Table 11. For every feature, the *squared* (e.g., $\boldsymbol{hrv}^2$), *cubed* (e.g., $\boldsymbol{hrv}^3$), *subject-mean* (e.g., $\boldsymbol{hrv}$-m), *subject-mean-centered* (e.g., $\boldsymbol{hrv}$-c), *centered*

& squared (e.g., $\boldsymbol{hrv}$-c^2), and *centered & cubed* (e.g., $\boldsymbol{hrv}$-c^3) variant was calculated as well. Overall, $\boldsymbol{A_L}$ was therefore comprised of 14 unique psychophysiological features, each with 7 variants (98 total), i.e., $\boldsymbol{A_L} = \{\boldsymbol{A_{L1}}, \ldots, \boldsymbol{A_{L98}}\}$. These dimensions of $\boldsymbol{A_L}$ represent the design levers that *users* have direct (albeit unconscious) control over.

Table 11. The psychophysiological features to inform latent emotions/cognitions. Each feature in $\boldsymbol{A_L}$ may be extracted from one of the signals in $\boldsymbol{E_P}$.

Signal ($\boldsymbol{E_P}$)	Feature ($\boldsymbol{A_L}$)	Description
ecg	$\boldsymbol{hr}_{\text{m}}$	The mean heart rate (inter-beat interval, IBI) over a trial [464,479].
	$\boldsymbol{hr}_{\text{med}}$	The median heart rate over a trial.
	$\boldsymbol{hr}_{\text{sd}}$	The standard deviation of the heart rate over a trial [479].
	hrv	The variability of the heart rate (IBI variance) over a trial [442,444,478,479].
eda	$\boldsymbol{sc}_{\text{m}}$	The mean skin conductance over a trial [479,480].
	$\boldsymbol{sc}_{\text{var}}$	The variance of the skin conductance over a trial [479].
	$\boldsymbol{sc}_{\text{slp}}$	The linear slope of the best-fit line of the skin conductance over a trial. This serves as an index of overall tonic response, i.e., SCL drift.
	$\boldsymbol{sc}_{\text{m-rss}}$	The residual sum of squares of $\boldsymbol{sc}_{\text{m}}$ over a trial.
	$\boldsymbol{sc}_{\text{m-var}}$	The variance of the skin conductance from SC_{m} over a trial. This serves as an index of SCR activity outside of SCL drift.
	epc	Positive change over a trial. This is an index of phasic response, i.e., the frequency and amplitude of SCR activity over this time period [482].
emg	$\boldsymbol{ecu}_{\text{rms}}$	The root mean square of the activity from the *extensor carpi ulnaris* over a trial. This serves as an index for the amount of effort, i.e., muscle activity, required [483–491]. This signal was normalized according to participants' baseline measures [492].
	$\boldsymbol{edc}_{\text{rms}}$	See above, but for the *extensor digitorum communis*.
	$\boldsymbol{epb}_{\text{rms}}$	See above, but for the *extensor pollicis brevis*.
	$\boldsymbol{fds}_{\text{rms}}$	See above, but for the *flexor digitorum superficialis*.

Parametrizing the Physiological Experiential Responses – The dimensions of the Physiological Experiential Responses ($\boldsymbol{E_P}$) are given by three different physiological signals. The first is the *electrocardiography* (***ecg***), which is a measure of the electrical activity of the cardiovascular system, i.e., heart beats [442,444]. This measure has been widely associated with stress or cognitive load [442,444,493–496], often in relation to task difficulty [497–500]. The second is the *electrodermal activity* (***eda***), which is a measure of autonomic activity on the surface of the skin, most commonly the skin conductance, i.e., the electrical potential between two points on the skin. This measure is commonly associated with emotional arousal [501,502]. The third is the *electromyography* (***emg***), which is a measure of the electrical activity that is associated with muscle contractions [442,444]. This is often used to directly measure the physical embodiment of emotion (i.e., facial expressions) [503], however it may also be used to evaluate muscular activity in other areas, such as the forearm [490,491,504]. In this case, ***emg*** is used to assess users' hand/wrist movements [491,505] while interacting with the infotainment controller; similar uses have been previously demonstrated [438]. Overall, $\boldsymbol{E_P} = \{\boldsymbol{ecg}, \boldsymbol{eda}, \boldsymbol{emg}\}$, with each being continuously measured *during* the interaction.

Parametrizing the Subjective Experiential Responses – The dimension of the Subjective Experiential Responses ($\boldsymbol{E_S}$) vector space is described by a single *satisfaction rating* ($\boldsymbol{r}$) to assess preferences in this case study, i.e., "*taking into consideration all aspects of your experience navigating the application during the last task, please rate your overall satisfaction.*" The wording of this survey question was intended to capture the overall rating of both the *feeling* of the controller, as well as its *suitability* for the application (e.g., too sensitive, etc.). This was evaluated on a 10-point Likert scale [207]. This larger scale used to help capture finer differences between subtle personalizations. Overall, $\boldsymbol{E_S} = \{\boldsymbol{r}\}$, with this rating being provided *after* the interaction to help interpret $\boldsymbol{E_P}$, and therefore $\boldsymbol{E} = \{\boldsymbol{ecg}, \boldsymbol{eda}, \boldsymbol{emg}, \boldsymbol{r}\}$.

4.4. Mapping the Infotainment Controller Solution Space

Following the Embodiment Design Cartography (EDC) methodology detailed in Chapter 2, the second step is to construct the map of the *solution space*. The solution space is characterized by modeling the transformations between the vector spaces that contain *design levers*, and those that describe *design outcomes*. This modeling is conducted in order to build a quantitative understanding of the relations within the problem space map, and to then enable rigorous manners for which the resulting design options may be assessed. While the *problem space* was uniformly formulated for each user, the *solution space* is modeled in such a way that the options it contains are *personalized* for each.

Two mathematical models are included in the problem space formulation (see Figure 22)—the *interaction model* ($\mathcal{I}$), and the *feature extraction model* ($\mathcal{F}$). In a similar fashion to the previous case study, $\mathcal{I}$ characterizes the functional transformation between the Attributes ($\boldsymbol{A}$) and Subjective

Experiential Responses ($\boldsymbol{E_S}$) (see Eq. (5)). On the other hand, $\mathcal{F}$ is used in this case study to extract the psychophysiological features that provide latent information on the users' emotions/cognitions. This model transforms the raw signals in the Physiological Experiential Responses ($\boldsymbol{E_P}$) into the psychophysiological features in the Latent Attributes ($\boldsymbol{A_L}$). This functional transformation may be given by Equation (11), in which

$$\mathcal{F}: \quad \boldsymbol{E_P} \rightarrow \boldsymbol{A_L} \tag{11}$$

$$\mathcal{F}: \quad \begin{bmatrix} \boldsymbol{ecg} \\ \boldsymbol{eda} \\ \boldsymbol{emg} \end{bmatrix} \times \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} \boldsymbol{A_L}_1 \\ \boldsymbol{A_L}_2 \\ \boldsymbol{A_L}_3 \end{bmatrix}$$

, where *three* processing functions (f_i) are ultimately selected to extract the three psychophysiological features in $\boldsymbol{A_L}$ that are *most relevant* for predicting individual differences. Many of the dimensions in $\boldsymbol{A_L}$ may be redundant (e.g., 'variance' versus 'residual sum of squares'). The purpose of $\mathcal{F}$ is to allow for *one* psychophysiological feature from *each physiological signal* (i.e., ***ecg***, ***eda***, and ***emg***) to be selected. This ensures that personalizations are limited to the design levers that are most likely to benefit the user (i.e., provide higher satisfaction), while still capturing a holistic understanding of the latent emotional/cognitive information through *combined signals*. The determination of *which* of these processing functions—and therefore, which of these psychophysiological features—are ultimately selected, is determined by the users' own latent information that they provide in an empirical study.

A controlled user study was therefore conducted in *two phases* to extract this latent information, empirically characterize and validate $\mathcal{I}$ and $\mathcal{F}$, and then enact the mass personalizations across the options the solution space map. These phases are each outlined.

1. ***Phase 1 (Analysis)*** – In *phase 1* of this study, users ($n_1 = 40$) assessed different fixed configurations of the infotainment controller (i.e., $\boldsymbol{A_R}$) within different applications (i.e., $\boldsymbol{A_E}$). With the experiential responses provided by these users ($\boldsymbol{E}$), three psychophysiological features ($\boldsymbol{A_L}$) were selected with a *Mixed-Effects Random Forest* (MERF) algorithm to be extracted with $\mathcal{F}$ in real-time. Two versions of $\mathcal{I}$ were then characterized with this information. The first, *full* version contained these psychophysiological features ($\mathcal{I}_{\text{Full}}$), while the second, *reduced* version did not ($\mathcal{I}_{\text{Redu}}$). This first phase therefore encompassed embodiment design *analysis*.

2. ***Phase 2 (Synthesis & Evaluation)*** – In *phase 2* of this study, users ($n_2 = 20$) again assessed these same fixed configurations of the infotainment controller (i.e., $\boldsymbol{A_R}$) within different applications (i.e., $\boldsymbol{A_E}$). This time, the latent information provided by their *individual* psychophysiological features were entered into $\mathcal{J}_{\text{Full}}$ to personalize their solution space. New configurations of the infotainment controller were then synthesized using both $\mathcal{J}_{\text{Full}}^{-1}$ and $\mathcal{J}_{\text{Redu}}^{-1}$. The former were *personalized* to the individual with their own design levers, which represented a *participative* level of user involvement. The latter were *pre-defined*, and therefore represented a *consultative* level of user involvement. Both versions of the model were then evaluated by the users to *verify* the predictions, and to determine the added *validity* provided with mass personalization of the solution space. This second phase therefore encompassed embodiment design *synthesis* and *evaluation*.

Overall, this mapping spans each of the embodiment design processes (i.e., analysis, synthesis, and evaluation) through each of the six activities in the EDC methodology. Both of these phases followed a common testing procedure.

4.4.1. Testing Procedure & Infrastructure

Sixty participants ($n_1 = 40$; 24 female, 14 male, 2 non-binary | $n_2 = 20$; 13 female, 6 male, 1 non-binary) between the ages of 18 to 60 ($m_1 = 39.58$, $sd_1 = 10.80$ | $m_2 = 32.90$, $sd_2 = 11.12$) were recruited to participate in this study via email listservs and social media advertisements. The following inclusion criteria were specified: participants must 1) possess a valid driver's license, 2) be over the age of 18, and 3) be able to view a screen for 1 hour or more. This study was approved by the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board. Written informed consent was obtained from all participants.

This study took place in a testing rig, which was constructed to mimic the interior of the 2019 Cadillac CT6 (for which this infotainment system is used in). A driver's seat, footrest, infotainment screen, and a center console with an armrest and the infotainment controller were all included in a layout that mimicked their analogous positions in the real vehicle. The infotainment controller could be dynamically reconfigured in real-time. The driver seat could also be adjusted forward and backward to accommodate varied participant height (this permitted slight variations in participant's relative position when interacting with the controller, which could have influenced their physiological responses in some way). The three applications (***a***) in $\boldsymbol{A_E}$ (see Figure 23) were displayed on the infotainment screen. Ratings were provided through a Microsoft Surface Tablet that was mounted to the dashboard. This infrastructure is pictured in Figure 24. Lab sessions lasted approximately two hours in total.

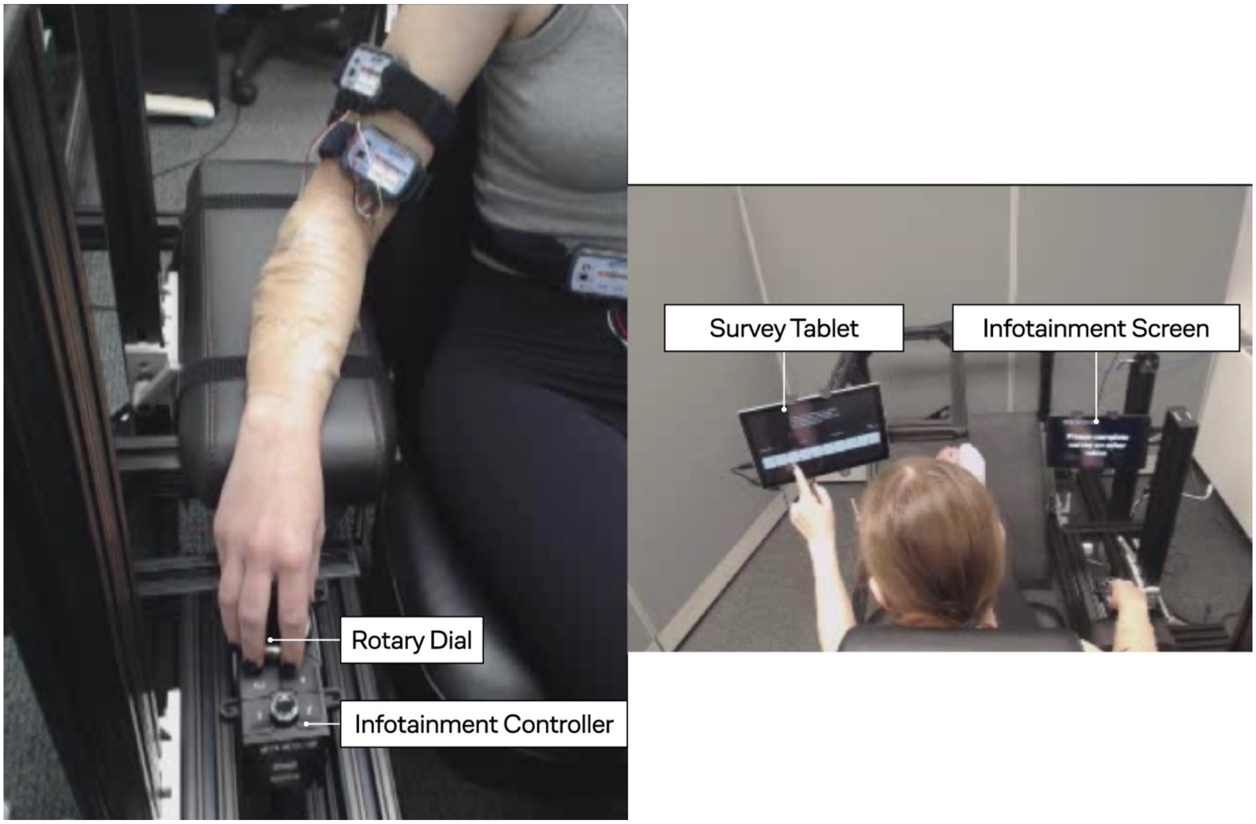

Figure 24. The testing rig for the infotainment controller. The participant sits on the driver's seat and rotates the rotary dial on the infotainment controller with their right hand. The infotainment screen is mounted on the participant's right, and the survey tablet is placed on their left; they operate the latter with their left hand.

4.4.1.1. Sensor Application and Baselines

Physiological signals were recorded using a Biopac MP160 system with BioNomadix wireless transmitters and receiver, and streamed with the associated Acq*Knowledge* (v5.0) software to a central data processing and storage program, written in Python (v3.7). These signals included the *electrocardiography* (***ecg***), *electrodermal activity* (***eda***), and *electromyography* (***emg***). The selection and placement of the associated sensors is highly context dependent, and requires careful consideration of the interaction between the user and the product to ensure that relevant signals are captured and invasiveness and signal noise are minimized. Invasive sensors have the propensity to interrupt the *naturalness* of an interaction to a degree that may be underreported in literature [438]. Each signal is discussed in turn.

1. ***Electrocardiography*** – The measurement of this signal requires the placement of several sensors on the chest [442,506,507]. In this study, a lead II measurement was collected using a Mason-Likar (M-L) lead adaptation, observing the heart from a 60° angle [508]. From this signal, the *inter-beat interval* (IBI), i.e., the time series between heart beats, may be measured by the distance between peaks in the characteristic response of the ***ecg*** signal [444,478]. This signal was sampled at 125 Hz.
2. ***Electrodermal activity*** – The measurement of this signal requires the placement of two electrodes, typically on the hand [438,442,509] (palm or fingers) or foot [509]. These sensors were placed on participant's left foot in this study to mitigate interference from excessive motion (both hands were required for study tasks). The ***eda*** signal itself may be decomposed into its *tonic* (skin conductance *level*; SCL) and *phasic* (skin conductance *response*; SCR) components [480,501,509]. Each of these components provide different information [502,510]. The *phasic* component of this signal exhibits a characteristic response to a single stimuli or event. The *tonic* component is typically used for long-term monitoring and is commonly subject to a drifting baseline [442,501,502,509]. It is therefore necessary to assess the product interaction to determine whether it involves a single stimuli/event, or multiple. For instance, the interaction of rotating the dial on the infotainment controller and feeling the detents may most aptly be described as a *continuous stimuli*. In this case, a single SCR curve for each trial was not expected, but rather a response that contains multiple superimposed SCRs overlayed onto slower SCL deviations [480]. This signal was sampled at 250 Hz.
3. ***Electromyography*** – This signal may be measured on the surface of the skin, or directly within the muscles, i.e., intramuscular; the latter has been shown to improve measurement accuracy [511] at the cost of a significant increase to the level of invasiveness of the sensor. In this experiment, four duotrodes were placed on the surface of forearm in four different positions that corresponded to the primary muscles that were used to rotate the dial on the infotainment controller (these were selected out of seven piloted muscles). These muscles are the *extensor carpi ulnaris* (***ecu***), the *extensor digitorum communis* (***edc***), the *extensor pollicis brevis* (***epb***), and *flexor digitorum superficialis* (***fds***). ***emg*** activity may be observed when each of these muscles is activated. This signal was sampled at 1 kHz.

Upon arrival to the lab, participants were outfitted with biometric sensors to measure each of these signals. Participants were asked to complete several movements with their right hand/arm to palpate muscles in their forearm, such that the locations for the ***emg*** duotrodes could be located. Their skin was gently exfoliated in each of these locations using Nuprep Gel (10 seconds), rinsed with water (no soap), exfoliated again using 3M exfoliation tape (5 seconds), and then the ***emg*** duotrodes were applied. The arch of the user's left foot was then pretreated for the placement of ***eda*** electrodes [509], and two Ag/AgCl monotrode electrodes, wet with an isotonic, 0.05 molar NaCl, electrode gel were applied side-by-side along the site. The electrodes and leads were secured using Transpore Surgical Tape (1527; 3M), and the isotonic gel was given five minutes to be absorbed by the skin before data collection began. These placements are pictured in Figure 25.

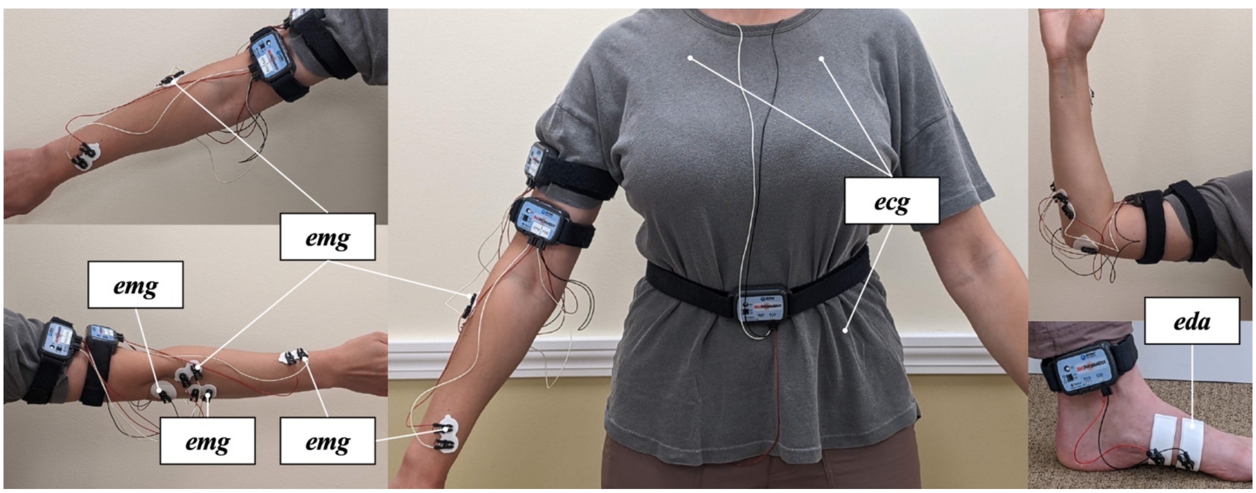

Figure 25. Placements of the physiological sensors. Sensor placements for the ***ecg***, ***eda***, and ***emg*** densors are marked.

Before beginning the study tasks, participants completed several activities designed to establish *baseline measures* to normalize their ***emg*** response [466,512]. A maximum voluntary isometric contraction (MVIC) task [492] was implemented using a dummy infotainment controller, in which the dial was fixed. Participants were instructed to attempt to rotate this fixed dial as hard as they could (using their normal grip) and hold for 5 seconds; this was repeated three times in both the clockwise and counterclockwise directions. The maximum root-mean square (rms) of the ***emg*** activity across these six reptations was selected, and users' subsequent ***emg*** features (see Table 11) were each calculated as a percent of this maximum.

4.4.1.2. Study Tasks

After being acclimated to the infotainment system, participants were then tasked with making a series of selections in each application (i.e., the menu, contacts, and volume). For each trial, the controller was configured to some level of detent number (***d***) and motor torque stiffness (***m***). Users were presented either the menu, contacts, or volume application (***a***) and tasked with making a series of *eight* different selections. For instance, this could entail navigating to, and selecting eight different items/contacts, or setting the volume to eight different levels. Each of these selections was directed by a set of instructions at the top of the screen (e.g., '*Select Settings*'); incorrect selections would not progress the trial. After each correct selection, the screen was reset such that participants began subsequent selections from the same initial position at the beginning of the application. Each of these repetitions required to dial on the infotainment controller to be rotated to a different degree. This was done to ensure that users' experiential responses were based on a variety of different lengths of required rotations (i.e., both fine and large rotations).

After completion of eight selections, participants were given a 10 second break (to allow the ***eda*** signal to return to baseline levels), in which they were instructed to rest and remain still. They were then presented with the survey, where they provided their satisfaction rating (***r***) for the trial. This was then repeated with a different configuration of ***d*** and ***m*** on a different ***a***, as was dictated by the experimental design.

4.4.1.3. Data Collection & Processing

For mass personalizations to be enacted in real-time, an automated data collection and processing pipeline was required for latent emotions/cognitions to be operationalized as design levers. Data in this study was collected from both sensors and surveys, and each needed to be time-synced and processed in real-time. To achieve this, a Python (3.7) program is used to control the experimental design, define the levels of ***d***, ***m***, and ***a*** for each trial, and store all data on a common timescale. The physiological signals were streamed from the sensors to AcqKnowledge 5.0, where researchers could monitor them for interference or abnormalities as they were recorded. These were then streamed to the central computer. The beginning and end of each trial was marked by this computer, and the physiological signals recorded within these time-windows were logged. An additional 10 seconds after the completion of the trial was added for the ***eda*** signal to capture its return to baseline levels. With the trial's time-window defined for each signal, MATLAB (2021b) scripts called from the central Python program were used to extract psychophysiological features ($\boldsymbol{A_L}$) with the processing functions (f_i) contained within the feature extraction model ($\mathcal{F}$; see Eq. (11)). This occurred in a parallel thread while the subsequent trial was commenced. The extracted features (see Table 11) were then available to personalize new design configurations in real-time.

4.4.2. Phase 1 Experimental Design

The design of phase 1 of this empirical study ($n_1 = 40$) was centered around *analysis*, which included: 1) estimating the coefficients of a regression that characterized the transformation given in interaction model ($\mathcal{I}$; see Eq. (5)), and 2) selecting the psychophysiological features ($\boldsymbol{A_L}$) to extract with the feature extraction model ($\mathcal{F}$; see Eq. (11)). The form of this regression is given by a *mixed-effects* model, in which the satisfaction rating ($\boldsymbol{r}$) is estimated ($\hat{\boldsymbol{r}}$) as a function of the Attributes ($\boldsymbol{A}$). However*, two versions* of $\mathcal{I}$ were empirically characterized in this phase—the *full* version ($\mathcal{I}_{\text{Full}}$) *with* psychophysiological features ($\boldsymbol{A_L}$), and the *reduced* version ($\mathcal{I}_{\text{Redu}}$) *without* them. The form of $\mathcal{I}_{\text{Redu}}$ is given by Equation (12), in which

$$\mathcal{I}_{\text{Redu}}:\quad \hat{r} = \begin{bmatrix} b_1 \\ \vdots \\ b_8 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_8 \end{bmatrix} + u_j + e_{ij}, \tag{12}$$

$$b = \{\boldsymbol{d}, \boldsymbol{m}, \boldsymbol{a}, \boldsymbol{d}\cdot\boldsymbol{m}, \boldsymbol{d}\cdot\boldsymbol{a}, \boldsymbol{d}\cdot\boldsymbol{m}\cdot\boldsymbol{a}, \boldsymbol{d}^2, \boldsymbol{m}^2\}$$

, where the *fixed-effects* are given by b, and the *random-effects* for each individual are given by u_j, with some error (e_{ij}) for each prediction. The binomial terms ($\boldsymbol{d}^2$ and $\boldsymbol{m}^2$) provide curvature to the model such that optimal design configurations may be interpolated within the continuous solution space. However, this version precludes the incorporation of the latent information provided by $\boldsymbol{A_L}$, and participants are not afforded with *participative involvement* to adjust these design levers and personalize their own, unique design configurations with this model. Alternatively, the expanded form of $\mathcal{I}_{\text{Full}}$ is given by Equation (13), in which

$$\mathcal{I}_{\text{Full}}:\quad \hat{r} = \begin{bmatrix} b_1 \\ \vdots \\ b_8 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_8 \end{bmatrix} + \begin{bmatrix} q_1 \\ \vdots \\ q_9 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \beta_9 \\ \vdots \\ \beta_{17} \end{bmatrix} + u_j + e_{ij}, \tag{13}$$

$$b = \{\boldsymbol{d}, \boldsymbol{m}, \boldsymbol{a}, \boldsymbol{d}\cdot\boldsymbol{m}, \boldsymbol{d}\cdot\boldsymbol{a}, \boldsymbol{d}\cdot\boldsymbol{m}\cdot\boldsymbol{a}, \boldsymbol{d}^2, \boldsymbol{m}^2\}$$

$$q = \{\boldsymbol{A_{L1}}, \boldsymbol{A_{L2}}, \boldsymbol{A_{L3}}, \boldsymbol{d}\cdot\boldsymbol{A_{L1}}, \boldsymbol{d}\cdot\boldsymbol{A_{L2}}, \boldsymbol{d}\cdot\boldsymbol{A_{L3}}, \boldsymbol{m}\cdot\boldsymbol{A_{L1}}, \boldsymbol{m}\cdot\boldsymbol{A_{L2}}, \boldsymbol{m}\cdot\boldsymbol{A_{L3}}\}$$

, where the *fixed-effects* from the reduced model are given by b, the *additional fixed-effects* of the psychophysiological design levers are given by q, and the *random-effects* for each individual are given by u_j, with some error (e_{ij}) for each prediction. In this model, $\boldsymbol{A_{L}}1$, $\boldsymbol{A_{L}}2$, and $\boldsymbol{A_{L}}3$ represent three psychophysiological features that are selected from the dimensions of $\boldsymbol{A_L}$ (see Table 11) to serve as design levers of the *user*. It is important to note the inclusion of *interaction effects* in q, as these allow for these psychophysiological design levers to adjust and personalize the solution space beyond just shifting the intercept.

This study employs a full-factorial experimental design (i.e., a 3×3×3 design with 27 trials), in which three discreet levels (high, medium, low) of the detent number (***d***) and the motor torque stiffness (***m***) are each specified across their achievable ranges, and every possible combination is paired with each of the three applications (***a***). These 27, randomly ordered trials comprised the *analysis* portion of this study. This experimental design is summarized in Table 12.

Table 12. The experimental design of phase 1 of the empirical user study of the infotainment controller. Each trial listed here (combination of ***d*** and ***m***) is shown for each application (***a***).

Trial ID	Detent Number (*d*)		Motor Torque Stiffness (*m*)	
	Level	**Value** (# in 360°)	**Level**	**Value** (% of max)
1	Low	16	Low	25%
2	Low	16	Med	50%
3	Low	16	High	75%
4	Med	36	Low	25%
5	Med	36	Med	50%
6	Med	36	High	75%
7	High	56	Low	25%
8	High	56	Med	50%
9	High	56	High	75%

With the experiential responses elicited in this design, the coefficients (β) of both models may be estimated. This is done for the entire population ($n_1 = 40$) at the end of phase 1 (as opposed to *iteratively*, as was done in the previous case study). However, there remains to be numerous psychophysiological features that could be included in $\mathcal{J}_{\text{Full}}$. Even the dimensions of $\boldsymbol{A_L}$, while relatively numerous, still represent only a subset of possible features. The incorporation of too many psychophysiological features can detriment the model by expanding the dimensionality

[513,514] with features that do not provide useful latent information, and often hold only minor relevance to the rich, embodied interaction (i.e., rotating the dial). The selection of features to be included in this model must be carefully considered to maintain interpretability and uphold statistical power. *Which* of these features actually enacts beneficial personalizations, however, may not be evident ahead of time [515].

4.4.2.1. Psychophysiological Feature Selection

To combat this, there are a variety of existing techniques that may be applied to reduce dimensionality [516–518]. *Heuristic* (i.e., rule-based) techniques afford designers with more direct influence by enabling them to determine the specific selection rules/thresholds, e.g., [519–524]; they are simple and highly interpretable. Alternatively, more robust machine learning algorithms relinquish this level of control such that decisions are driven more directly be the users' data, e.g., [464,480,525–528]. This enables them to identify more complex, non-linear patterns; they are generally more sophisticated but less interpretable. While algorithms are certainly more powerful, they are *black-box* techniques; they are not necessarily as useful directly off-the-shelf—so to speak—when *understanding* the underlying relations is key for mapping the solution space.

As such, a *hybrid* feature selection technique using both *algorithms* and *heuristics* was therefore employed to define $\mathcal{F}$. This aimed to balance the sophistication and the interpretability in the approach. A *Mixed-Effects Random Forest* (MERF) algorithm [529,530], was therefore used to produce an internally validated *feature importance ranking* of all the psychophysiological features (and their variants) based on each feature's SHAP (SHapley Additive exPlanation) value [531]. MERF algorithms are adept at handling cases with relatively larger feature sets and smaller sample sizes such as this [532]. Non-negligible individual random-effects may be reasonably expected in time-series psychophysiological applications, so the mixed-effects extension is used [529]. In this algorithm, the psychophysiological features acted as the fixed effects, the individual user as a random effect, and the predicted satisfaction rating ($\hat{\boldsymbol{r}}$) was the target variable. The MERF was programmed in Python (3.7) using a combination of the *merf* [533], *shap* [534], and *scikit-learn* [535] packages.

On its own, however, the inner mathematical properties of the MERF are a black-box [532]. The *heuristic* half of this hybrid technique was then employed on the feature importance rankings produced by this algorithm. Specifically, the highest ranked feature from each signal type (i.e.,

eda, ***ecg***, and ***emg***) was selected to be extracted ($\mathcal{F}$). This heuristic ensures the *multi-modality* of the psychophysiological design levers in $\mathcal{I}_{\text{Full}}$ (i.e., $\boldsymbol{A}_{\boldsymbol{L}1}$, $\boldsymbol{A}_{\boldsymbol{L}2}$, and $\boldsymbol{A}_{\boldsymbol{L}3}$). By understanding the underlying relations between of all the features ,and selecting a small set that is most relevant, the black-box conundrum may be avoided [515,536]. This effectively turned the selection of the design levers over to the *users'* latent emotions/cognitions, while allowing the *designer* to retain a degree of control and understanding.

4.4.3. Phase 1 Experimental Results

In phase 1 of this study ($n_1 = 40$), two key results may be examined. First, the relevant psychophysiological design levers that allow the user's latent emotions/cognitions to inform personalized design adjustments were determined; these are to be processed with the feature extraction model ($\mathcal{F}$) in the second phase. Second, the effects of the parameters in the interaction model ($\mathcal{I}$; see Eq. (12) and Eq. (13)) were estimated within a full-factorial experimental design of fixed configurations of the infotainment controller (in terms of discreet levels of detent number (***d***) and motor torque stiffness (***m***)). These are discussed in turn.

4.4.3.1. Psychophysiological Design Levers

The feature importance ranking of the psychophysiological features included in the Latent Attributes ($\boldsymbol{A}_{\boldsymbol{L}}$) was constructed with the *Mixed-Effects Random Forest* (MERF) algorithm. The top-ranked feature from each signal in the Physiological Experiential Responses ($\boldsymbol{E}_{\boldsymbol{P}}$) was selected (see Table 11). The results of this ranking are shown in Table 13, with the top-10 highest ranked features being listed.

Table 13. The psychophysiological feature importance rankings summary. Only the top 10 psychophysiological features are listed (out of a total 98). The highest ranked feature from ***ecg***, ***eda***, and ***emg*** are selected (denoted with >).

	Ranking	Signal (E_P)	Feature (A_L)	Description
>	1	***emg***	***epb***$_{\text{rms}}$-m	The *subject-mean* (-m) of the *root mean square* (rms) of the activity from the *extensor pollicis brevis* (***epb***) over a trial.
	2	***emg***	***edc***$_{\text{rms}}$-m	The *subject-mean* (-m) of the *root mean square* (rms) of the activity from the *extensor digitorum communis* (***epb***) over a trial.
>	3	***eda***	***sc***$_{\text{slp}}$-m	The *subject-mean* (-m) of the *linear slope* (slp) of the best-fit line of *the skin conductance* (***sc***) over a trial.
	4	***eda***	***sc***$_{\text{var}}$-m	The *subject-mean* (-m) of the *variance* (var) of the *skin conductance* (***sc***) over a trial.
	5	***eda***	***sc***$_{\text{m}}$-c^2	The *centered* and *squared* (-c^2) *mean* (m) *skin conductance* (***sc***) over a trial.
	6	***emg***	***ecu***$_{\text{rms}}$-c	The *centered* (-c) *root mean square* (rms) of the activity from the *extensor carpi ulnaris* (***ecu***) over a trial.
	7	***emg***	***ecu***$_{\text{rms}}$-c^3	The *centered* and *squared* (-c^3) *root mean square* (rms) of the activity from the *extensor carpi ulnaris* (***ecu***) over a trial.
>	8	***ecg***	***hrv***-m	The *subject-mean* (-m) of the *heart rate variability* (***hrv***) over a trial.
	9	***ecg***	***hr***$_{\text{sd}}$-m	The *subject-mean* (-m) of the *standard deviation* (sd) of the *heart rate* (***hr***) over a trial.
	10	***eda***	***sc***$_{\text{m}}$-c^3	The *centered* and *cubed* (-c^3) *mean* (m) *skin conductance* (***sc***) over a trial.

Overall, the ***epb***$_{\text{rms}}$-m, ***sc***$_{\text{slp}}$-m, and ***hrv***-m were determined to be the most relevant psychophysiological design levers for providing the latent emotional/cognitive information from each signal. The form of $\mathcal{F}$ may therefore be updated to accommodate these selected features, in which

$$\mathcal{F}\colon \quad \boldsymbol{E_P} \rightarrow \boldsymbol{A_L}$$

$$\mathcal{F}\colon \quad \begin{bmatrix} \boldsymbol{ecg} \\ \boldsymbol{eda} \\ \boldsymbol{emg} \end{bmatrix} \times \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} \boldsymbol{hrv}\text{-m} \\ \boldsymbol{sc}_{\text{slp}}\text{-m} \\ \boldsymbol{epb}_{\text{rms}}\text{-m} \end{bmatrix}$$

, where each of the processing functions (f_{i}) are programmed in MATLAB (see Section 4.4.1.3). With these selections, it is important to note that highest ranked feature from each signal was the *subject-mean* (-m) variant. This indicates that *between-subject* measures of individual differences—not *within-subject* measures of a given user's different responses to various configurations—are more important for personalizations. The selected psychophysiological features may therefore be considered to be representative of users' individual *predispositions*.

The SHAP values [531]—the impact on the satisfaction rating ($\boldsymbol{r}$)—from the MERF output may then provide insight into what latent information is provided with each of these psychophysiological design levers. This is illustrated in Figure 26 through SHAP dependence plots. With these plots, the manner in which this latent information is predicted to influence $\boldsymbol{r}$ may be interpreted.

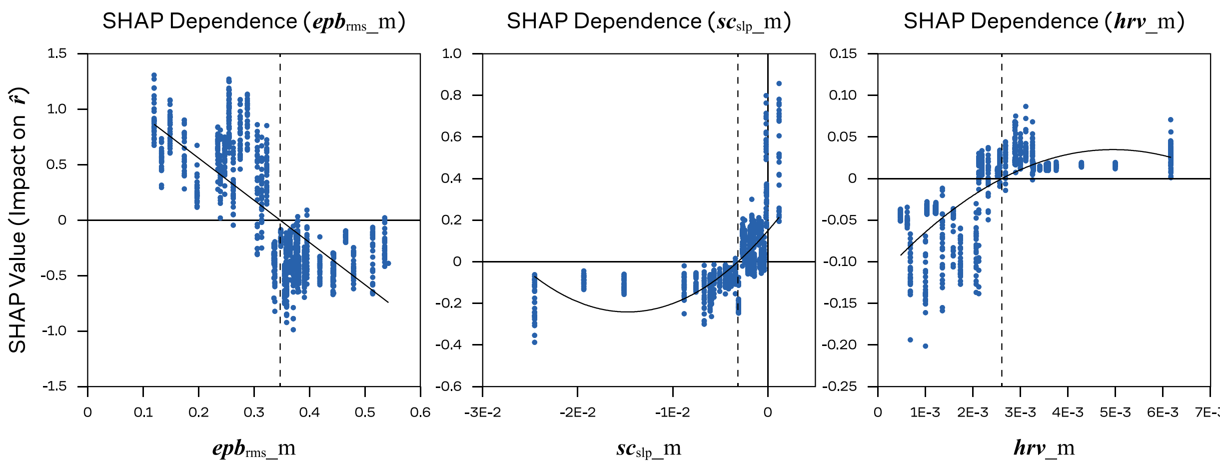

Figure 26. The SHAP dependence plots. The SHAP values for $\boldsymbol{epb}_{\mathrm{rms}}$-m (left), $\boldsymbol{sc}_{\mathrm{slp}}$-m (center), and $\boldsymbol{hrv}$-m (right) show their predicted impact on the satisfaction rating ($\boldsymbol{r}$). The visible vertical clusters represent the 27 trials for each user in phase 1 of this study, as the value of each feature was the subject-mean of these trials. This clusters therefore illustrate individual differences.

For instance, $\boldsymbol{epb}_{\mathrm{rms}}$-m values below ~0.35 tended to have a positive impact on $\boldsymbol{r}$, while values above this threshold had the opposite impact. This can mean that users who use require less muscular activation to rotate the dial find a greater level of satisfaction with this rich, embodied interaction. Alternatively, values of $\boldsymbol{sc}_{\mathrm{slp}}$-m that were at or around 0 tended to increase $\boldsymbol{r}$, while more negative values decreased $\boldsymbol{r}$. This could mean that users with negative drift of their skin conductance level (i.e., low tonic arousal) had lower satisfaction levels, while users with neutral or positive drift to their skin conductance level (i.e., higher tonic arousal) had relatively greater levels of satisfaction. Lastly, lower values of $\boldsymbol{hrv}$-m tended to have a negative impact on $\boldsymbol{r}$, while higher values were more neutral. The impact of this feature is relatively smaller than the other two features, however, as it was only ranked 8$^{\text{th}}$ on the MERF feature importance rankings (see Figure

26). Overall, these plots reveal how individual differences of latent emotions/cognitions can be identified and quantified.

4.4.3.2. Interaction Model Effects

For each version of $\mathcal{J}$, the coefficients of the regressions were estimated with the experiential responses provided from each user in this phase. An ANOVA may be used to determine the fixed effects on the satisfaction rating ($\boldsymbol{r}$) of each parameter in these models. This is summarized in Table 14. A *likelihood ratio test* (LRT) of these two nested models indicated that $\mathcal{J}_{\text{Full}}$ provided a significantly improved fit to the data ($p < 0.001$) over $\mathcal{J}_{\text{Redu}}$.

Table 14. The effects of the experimental design. Significant p-values ($p < 0.05$) are bolded. Tests involving $\boldsymbol{a}$ are two degree of freedom omnibus tests; all other tests are single degree of freedom tests.

	$\mathcal{J}$	$\boldsymbol{d}$	$\boldsymbol{m}$	$\boldsymbol{a}$	$\boldsymbol{d \cdot m}$	$\boldsymbol{d \cdot a}$	$\boldsymbol{m \cdot a}$	$\boldsymbol{d \cdot m \cdot a}$	$\boldsymbol{d}^2$	$\boldsymbol{m}^2$	$\boldsymbol{epb}_{\text{rms}}$-m	$\boldsymbol{sc}_{\text{slp}}$-m	$\boldsymbol{hrv}$-m	$\boldsymbol{d \cdot epb}_{\text{rms}}$-m	$\boldsymbol{d \cdot sc}_{\text{slp}}$-m	$\boldsymbol{d \cdot hrv}$-m	$\boldsymbol{m \cdot epb}_{\text{rms}}$-m	$\boldsymbol{m \cdot sc}_{\text{slp}}$-m	$\boldsymbol{m \cdot hrv}$-m
p-values	$\mathcal{J}_{\text{red}}$	**< 0.001**	0.550	**0.004**	0.465	**< 0.001**	0.882	0.202	**< 0.001**	0.164									
	$\mathcal{J}_{\text{full}}$	**< 0.001**	0.140	**0.003**	0.457	**< 0.001**	0.878	0.190	**< 0.001**	0.156	0.235	0.066	0.204	0.473	0.953	**< 0.001**	0.148	**< 0.001**	**0.001**

There was a significant effect of adjustments to the detent number ($\boldsymbol{d}$; $p < 0.001$), $\boldsymbol{d}^2$ ($p < 0.001$), and the application ($\boldsymbol{a}$; $p < 0.05$), as well as a significant interaction between $\boldsymbol{d}$ and $\boldsymbol{a}$ (omnibus $p < 0.001$) across both versions of the model. On average, participants gave different ratings to different pairings of the $\boldsymbol{d}$ and $\boldsymbol{a}$. Alternatively, there was no significant effect of adjustments to the motor torque stiffness ($\boldsymbol{m}$) or $\boldsymbol{m}^2$. In fact, there were no significant interaction effects with $\boldsymbol{m}$ at all in $\mathcal{J}_{\text{Redu}}$. However, there *were* significant interactions effects with $\boldsymbol{m}$ in $\mathcal{J}_{\text{Full}}$. The interactions that $\boldsymbol{m}$ had with psychophysiological features $\boldsymbol{sc}_{\text{slp}}$-m ($p < 0.001$) and with $\boldsymbol{hrv}$-m ($p = 0.001$) were both significant. The main effects of the psychophysiological features were not significant in $\mathcal{J}_{\text{full}}$, however there was a significant interaction of $\boldsymbol{d}$ and $\boldsymbol{hrv}$-m ($p < 0.001$), along with the noted significant interactions with $\boldsymbol{m}$. These interactions with the Responsive Attributes ($\boldsymbol{A_R}$) suggest the manner in which the psychophysiological design levers may impact the relation between $\boldsymbol{A_R}$ and the satisfaction rating ($\boldsymbol{r}$) on an individual basis, and can therefore personalize these configurations in terms of $\boldsymbol{d}$ and $\boldsymbol{m}$.

4.4.4. Phase 2 Experimental Design

The design of phase 2 of this empirical study ($n_2 = 20$) was then centered around *synthesis* and *evaluation*, which included: 1) predicting and generating both *customized* and *personalized* configurations of the infotainment controller, and 2) assessing their relative performance to validate the added value of involving users at a *participative level* over a more traditional, *consultative level*. With the inverse of the interaction models ($\mathcal{I}_{\text{Full}}^{-1}$ and $\mathcal{I}_{\text{Redu}}^{-1}$), *predictions* may then be made with both. In both cases, these predictions included the design configuration—the pairing of detent number ($\boldsymbol{d}$) and motor torque stiffness ($\boldsymbol{m}$) for a given application ($\boldsymbol{a}$)—that was predicted to receive the *optimal* satisfaction rating ($\hat{\boldsymbol{r}}_{\text{Opt}}$), and a configuration that was predicted to receive a *sub-optimal* satisfaction rating ($\hat{\boldsymbol{r}}_{\text{Sub}}$), i.e., a satisfaction rating that was one root-mean-square deviation (rmsd) lower than the optimal. A different optimal and sub-optimal configuration was predicted for each application (i.e., menu, contacts, volume).

Between these two models, however, the *type* of predictions that were made also varied. For $\mathcal{I}_{\text{Redu}}$, the psychophysiological features, i.e., the design levers of the user, were *not* included in these predictions. This meant that the new population of participants in this phase did not have direct input on these predictions. The optimal design configuration given by $\mathcal{I}_{\text{Redu}}$ is *pre-defined* by the coefficients estimated in the previous phase to be the same for each individual, and may therefore be considered to be a *customization*. Predicting design configurations with $\mathcal{I}_{\text{Redu}}$ therefore represents *consultative involvement* of the user, in that they are involved in the characterization (i.e., *analysis*) and assessment (i.e., evaluation) of design configurations, but do *not* have access to design levers to *directly* influence how the product is configured (i.e., synthesis)

For $\mathcal{I}_{\text{Full}}$, on the other hand, the psychophysiological design levers are used to influence these predictions. In this second phase, this new population of participants again interacted with the infotainment controller in the same 27 fixed trials as the previous phase (see Table 12) to elicit their latent emotions/cognitions. Their individual psychophysiological features (i.e., $\boldsymbol{epb}_{\text{rms}}$-m, $\boldsymbol{sc}_{\text{slp}}$-m, and $\boldsymbol{hrv}$-m) were extracted and entered into $\mathcal{I}_{\text{Full}}$. The optimal design configuration given by $\mathcal{I}_{\text{Full}}$ is completely *new* and *unique* to that specific individual, and may therefore be considered to be a *personalization*. Predicting design configurations with $\mathcal{I}_{\text{Full}}$ therefore represents *participative involvement* of the user, in that they are involved in the characterization (i.e., *analysis*) and assessment (i.e., evaluation) of design configurations, and now *do* have access to design levers to also *directly* influence how the product is configured (i.e., synthesis).

These designations of 'customization' for $\mathcal{J}_{\text{Redu}}$ and 'personalization' for $\mathcal{J}_{\text{Full}}$ can be extended beyond just a single solution provided by each, and may be applied to the entire solution space that they define. With $\mathcal{J}_{\text{Full}}$, *every* option in the solution space is personalized to the specific individual, including the sub-optimal configuration. In total, 12 predictions were made for each participant (i.e., 3 screens × 2 models × 2 predictions for each), and therefore 12 *additional* trials were conducted after the original 27 for each participant in this phase. This experimental design takes a similar format to the controls-like structure of the *biocybernetic loop*. In this design, the latent emotions/cognitions of the user are assessed through their physiological responses, the infotainment controller then adapts accordingly, and their responses to this adaptation are then assessed. The difference, however, is that the 'adaptations' permitted here are not limited to *pre-defined* responses (i.e., *customizations*) used by physio-adaptive systems to regulate the user, but rather represent *new, unique* design configurations (i.e., *personalizations*). This experimental design is summarized by Table 15.

Table 15. The experimental design of phase 2 of the empirical user study of the infotainment controller.

Model ($\mathcal{J}$)	**Trial ID**	**Detent number (*d*)**		**Motor torque stiffness (*m*)**		**Application (*a*)**
		Level	**Value** (#)	**Level**	**Value** (%)	
$\mathcal{J}_{\text{Full}}$	1	Opt	*Personalized*	Opt	*Personalized*	Menu
	2	Sub	*Personalized*	Sub	*Personalized*	
$\mathcal{J}_{\text{Redu}}$	3	Opt	36	Opt	47%	
	4	Sub	*Randomized*	Sub	*Randomized*	
$\mathcal{J}_{\text{Full}}$	5	Opt	*Personalized*	Opt	*Personalized*	Contacts
	6	Sub	*Personalized*	Sub	*Personalized*	
$\mathcal{J}_{\text{Redu}}$	7	Opt	51	Opt	25%	
	8	Sub	*Randomized*	Sub	*Randomized*	
$\mathcal{J}_{\text{Full}}$	9	Opt	*Personalized*	Opt	*Personalized*	Volume
	10	Sub	*Personalized*	Sub	*Personalized*	
$\mathcal{J}_{\text{Redu}}$	11	Opt	55	Opt	25%	
	12	Sub	*Randomized*	Sub	*Randomized*	

While the optimal prediction for each application is pre-defined for $\mathcal{J}_{\text{red}}$, the sub-optimal is *randomly* selected from the contour that represents the set of configurations predicted to be rated one rmsd lower than the optimal. The fixed solution space for $\mathcal{J}_{\text{red}}$ may be visualized with contour plots, as is illustrated in Figure 27. For both models, the two predicted configurations—$\hat{\boldsymbol{r}}_{\text{Opt}}$ and $\hat{\boldsymbol{r}}_{\text{Sub}}$—serve as a litmus test for whether $\mathcal{J}$ can correctly predict preference (according to the rating) across the solution space. To *validate* the model, the prediction was considered to be 'correct' if the *actual* rating given to the predicted *optimal* design configuration ($\boldsymbol{r}_{\text{Opt}}$) was rated higher than that given to the predicted *sub-optimal* design configuration ($\boldsymbol{r}_{\text{Sub}}$). These two models—and therefore, two levels of user involvement—may then be directly compared to determine the value of these personalizations.

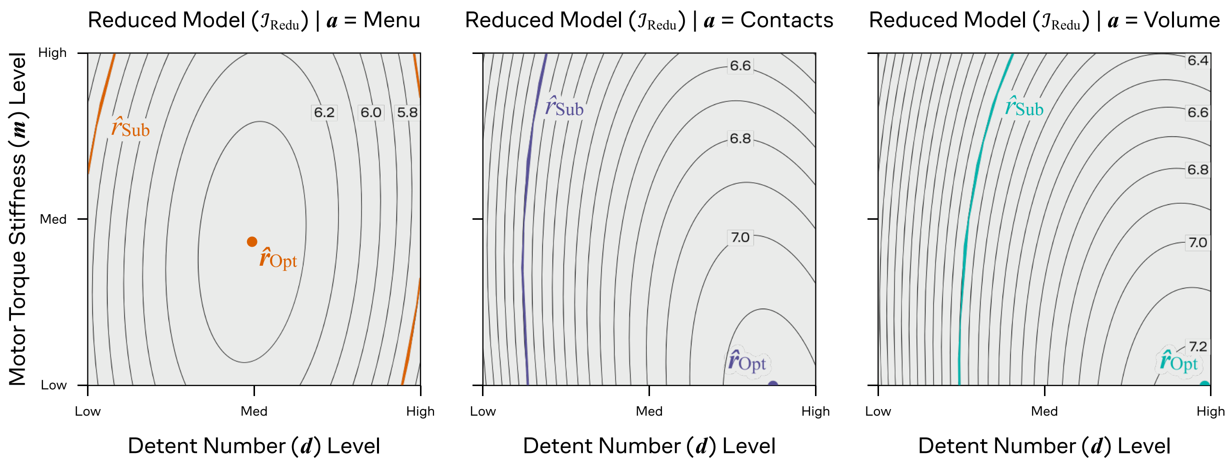

Figure 27. Customization predictions made in the solution space map of the infotainment controller. The reduced interaction model ($\mathcal{J}_{\text{Redu}}$) is visualized by contour plots for each application ($\boldsymbol{a}$). These contours reveal the pre-defined predictions that were made for each participant. In this space, $\hat{\boldsymbol{r}}_{\text{Opt}}$ represents the configuration of $\boldsymbol{d}$ and $\boldsymbol{m}$ that is predicted to receive the optimal rating. $\hat{\boldsymbol{r}}_{\text{Sub}}$ represents a different design configuration that is predicted to be rated one rmsd lower than $\hat{\boldsymbol{r}}_{\text{Opt}}$. $\hat{\boldsymbol{r}}_{\text{Sub}}$ is randomly selected along this contour.

4.4.5. Phase 2 Experimental Results

In phase 2 of this study ($n_1 = 20$), the key result that may be examined is the comparative performance between and $\mathcal{J}_{\text{Redu}}$ and $\mathcal{J}_{\text{Full}}$—between *customization* and *personalization* of the infotainment controller. The ability of each model to predict preference across the solution space may be compared in terms of the two predictions that were made by each. A prediction was considered to be 'correct' if the rating given to the optimal design configuration ($\boldsymbol{r}_{\text{Opt}}$) was greater than that given to the sub-optimal design configuration ($\boldsymbol{r}_{\text{Sub}}$). This is the more conservative approach, in which ties (i.e., $\boldsymbol{r}_{\text{Opt}} = \boldsymbol{r}_{\text{Sub}}$) are considered 'incorrect.' The model that is more successful in this right may be considered to be a more accurate map of the solution space, which can therefore provide better options.

$\mathcal{J}_{\text{Redu}}$ and $\mathcal{J}_{\text{Full}}$ were compared with a *mixed-effects* (accounting for both individual *random-effects* and the *fixed-effects* of ***a***) generalized linear model (GLM) with a binomial distribution, as the dependent variable was a binary term (i.e., correct/incorrect). $\mathcal{J}_{\text{Full}}$ correctly predicted preference 81.6% of the time, while $\mathcal{J}_{\text{Redu}}$ only correctly predicted preference 63.3% of the time; the reduced model had twice as many incorrect predictions as the full model. These results are summarized by Table 16.

Table 16. The results of the interaction model validation test. The full model ($\mathcal{J}_{\text{Full}}$) significantly outperformed the reduced model ($\mathcal{J}_{\text{Redu}}$).

Model ($\mathcal{J}$)	**Correct ($\boldsymbol{r}_{\text{Opt}} > \boldsymbol{r}_{\text{Sub}}$)**	**Incorrect ($\boldsymbol{r}_{\text{Opt}} \leq \boldsymbol{r}_{\text{Sub}}$)**	**Percent correct**
Reduced model ($\mathcal{J}_{\text{Redu}}$)	38	22	63.3%
Full model ($\mathcal{J}_{\text{Full}}$)	49	11	81.6%

The improvement between the models was significant ($p < 0.05$). There was no significant difference in the ability to predict this preference between different applications (***a***), and the interaction effects of ***a*** were also not significant. By personalizing the solution space, a better understanding of the options it contains may therefore be achieved. The *participative involvement* used in $\mathcal{J}_{\text{Full}}$ significantly improved the predictive accuracy over what was achieved with the *consultative involvement* of $\mathcal{J}_{\text{Redu}}$. This provides a rigorous validation to the value of this additional level of user involvement.

4.5. Personalizing Options in the Design Space Map

With the completed map of the design space, including a validated interaction model, the options for personalizing the infotainment controller may be explored. First, the use of each psychophysiological feature as a *design lever* may be examined in terms of how they can each modify the solution space. The personalizations that were enacted in this study may be visualized to better understand how and where these individual adjustments should actually be implemented. These insights may then be propagated to different design levers that may be 'owned' by different disciplines (i.e., hardware or software designers). Finally, the manner in which these personalizations may be extended on a mass scale is discussed.

4.5.1. Adjustments with Psychophysiological Design Levers

The effect that ‘adjustments’ to the psychophysiological design levers ($\boldsymbol{A_L}$) have on the parameters of the infotainment controller ($\boldsymbol{A_R}$) may be individually examined. These adjustments result in a unique solution space for each individual user, such that the combinations of detent number ($\boldsymbol{d}$) and motor torque stiffness ($\boldsymbol{m}$) elicit different responses ($\hat{\boldsymbol{r}}$). To visualize the *isolated* effects that each psychophysiological feature (i.e.,$\boldsymbol{epb}_{\text{rms}}$-m, $\boldsymbol{sc}_{\text{slp}}$-m, and $\boldsymbol{hrv}$-m) has on this solution space, each feature may be individually altered in turn, while the other two are fixed. This is shown by Figure 28, in which each psychophysiological feature is independently varied from the minimum to the maximum value that was recorded, while the other two psychophysiological features are fixed at their respective population means.

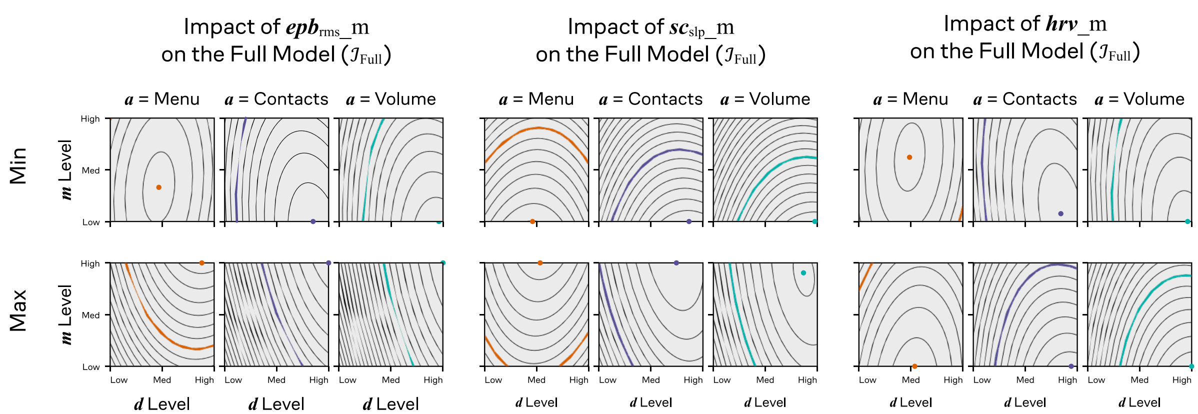

Figure 28. The capacity of personalization afforded by each selected psychophysiological feature. For each contour of $\mathcal{J}_{\text{Full}}$, the impact of $\boldsymbol{epb}_{\text{rms}}$-m (left), $\boldsymbol{sc}_{\text{slp}}$-m (center), and $\boldsymbol{hrv}$-m (right) are illustrated for each $\boldsymbol{a}$. The top row represents the minimum recorded value for each respective psychophysiological feature, while the bottom row represents the maximum value. In each case, the other two psychophysiological features are held constant at the testing population mean. The optimal configuration and sub-optimal contour are highlighted for each plot.

These controlled manipulations illustrate the capacity for the personalization that is afforded by each psychophysiological design lever. As can be seen, the shape of the solution space can look widely different across the ranges of values that were observed in this study. The combinations of $\boldsymbol{d}$ and $\boldsymbol{m}$ that afford $\hat{\boldsymbol{r}}_{\text{Opt}}$ could be drastically different according to an individual’s physiological predisposition. Not pictured in these contours is the effect of these manipulations on the *magnitude* of $\hat{\boldsymbol{r}}$—the peaks of these contours (i.e., $\hat{\boldsymbol{r}}_{\text{Opt}}$) are also impacted by the psychophysiological features. These are summarized by Table 17.

Table 17. The effects of the psychophysiological design levers on the predicted satisfaction rating. The predicted satisfaction rating ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$) is given for each $\boldsymbol{a}$ at the maximum and minimum value of each psychophysiological feature.

Feature (A_L)	Level	Predicted rating for optimal configuration ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$ ± standard error)		
		$\boldsymbol{a}$ = Menu	$\boldsymbol{a}$ = Contacts	$\boldsymbol{a}$ = Volume
$\boldsymbol{epb}_{\mathrm{rms}}$-m	Min	6.75 ± 0.37	7.41 ± 0.38	7.50 ± 0.40
	Max	5.21 ± 1.09	6.24 ± 1.12	6.38 ± 1.13
$\boldsymbol{sc}_{\mathrm{slp}}$-m	Min	4.81 ± 0.84	5.68 ± 0.86	5.78 ± 0.87
	Max	8.62 ± 0.69	8.97 ± 0.70	8.82 ± 0.70
$\boldsymbol{hrv}$-m	Min	6.36 ± 0.24	7.15 ± 0.27	7.24 ± 0.28
	Max	7.73 ± 1.12	8.43 ± 1.14	8.38 ± 1.14

Overall, it is evident that individual differences in latent emotions/cognitions can certainly alter what experiential outcomes are elicited by different options in the solution space. While this highlights the importance of individual design levers, these results alone do not provide insight into how these personalizations should actually be *implemented*, i.e., which aspects of the product need to be altered and which do not.

4.5.2. Understanding the Implementation of Personalizations

With a map of the solution space, the personalizations that are made for each individual may be better understood. Compared to the previous controlled manipulations, the *actual* personalizations were determined by the combination of all three psychophysiological features that each user entered into the interaction model ($\mathcal{I}$). Each optimal design configuration ($\hat{\boldsymbol{r}}_{\mathrm{Opt}}$) that was personalized for an individual participant is illustrated by Figure 29 for all three applications ($\boldsymbol{a}$). In this visualization, the *personalized* optimal points produced by $\mathcal{I}_{\mathrm{Full}}$ are overlayed onto the *static* contours of $\mathcal{I}_{\mathrm{Redu}}$.

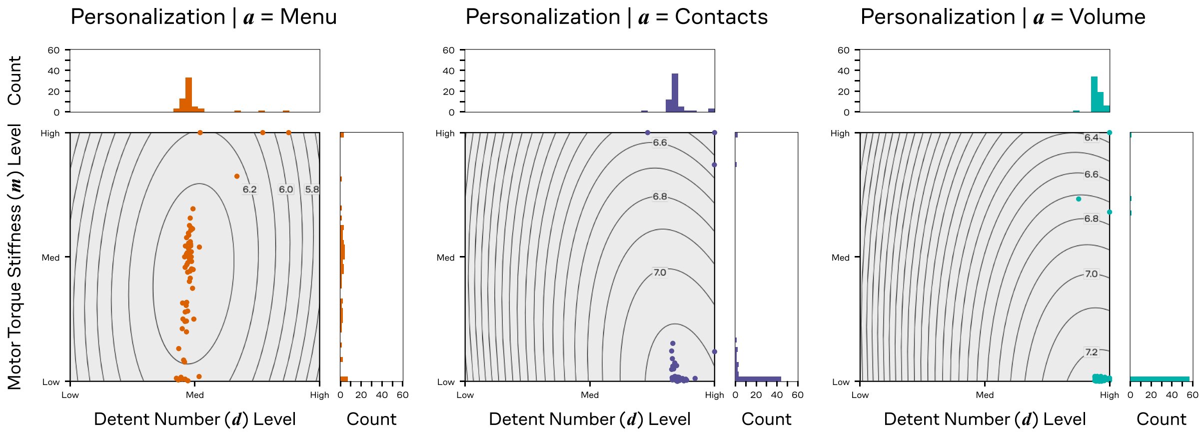

Figure 29. The personalizations of the infotainment controller. The personalized optimal design configurations ($\hat{r}_{\mathrm{Opt}}$) from $\mathcal{J}_{\mathrm{Full}}$ are plotted for each application ($\boldsymbol{a}$). These points are overlaid onto the static contour plots of $\mathcal{J}_{\mathrm{Redu}}$. The histograms on each axis of these contours show the density of these predictions in terms of both detent number ($\boldsymbol{d}$) and motor torque stiffness ($\boldsymbol{m}$).

These plots reveal the distribution of the optimal predictions. It is evident that this distribution differs across each parameter in the design problem (i.e., $\boldsymbol{d}$, $\boldsymbol{m}$, and $\boldsymbol{a}$). For instance, there are distinct clusters of the optimal detent number ($\boldsymbol{d}$) for each application ($\boldsymbol{a}$), which can be seen in the *horizontal* histograms in Figure 29. This suggests that that there is a more *definitive optimal* level for $\boldsymbol{d}$, which is determined more so by the application than by individual differences. The distribution of $\boldsymbol{m}$ on the other hand (i.e., the *vertical* histograms in Figure 29), ranges from widely dispersed on the menu app, to a tightly clustered on the contacts app, to an almost uniform value on the volume app. The latter two are both hitting the boundary of the achievable design space; the distribution of each may be broader if the feasible range of $\boldsymbol{m}$ could have been widened (this device was technologically limited in this way). This ultimately suggests that some product attributes (i.e., $\boldsymbol{m}$) may be more susceptible to personalization than others (i.e., $\boldsymbol{d}$). This also highlights the importance of the inclusion of *interaction effects* between the $\boldsymbol{A_R}$ and the $\boldsymbol{A_L}$ in $\mathcal{J}_{\mathrm{Full}}$. While the effects of $\boldsymbol{m}$ were found to be non-significant in $\mathcal{J}_{\mathrm{Redu}}$, significant interaction effects between $\boldsymbol{m}$ and $\boldsymbol{sc}_{\mathrm{slp}}$-m, as well as between $\boldsymbol{m}$ and $\boldsymbol{hrv}$-m, were evidently some of the primary drivers of the personalization in this case.

It should also be noted that the distributions shown in Figure 29 only represent the *optimal* configurations. It was often the case that this predicted optimal configuration was only *finely tuned* by the additional psychophysiological design levers. As the personalizations were enacted through *latent* information, it is to be expected that any deviations from the optimal design configuration predicted through subjective responses represent the *nuanced* distinctions that users may struggle to expressly communicate. In these instances (e.g., $\boldsymbol{a}$ = volume), it must be remembered that the contour of the solution space *around* that point is impacted as well. This may be exemplified by comparing, for instance, the differences in the contour between the minimum and maximum ***hrv***-m when $\boldsymbol{a}$ = volume (see Figure 28). In this case, the optimal *point* is minimally influence by personalizations, but the overall solution space is quite different. Ultimately, the personalization afforded by the participative involvement in this experiment is not limited solely to the optimal point, but extends across every option in the solution space. These impacts can be critically important to understand, especially when other, potentially *competing* design objectives require deviation from this optimal point to satisfy other requirements (à la the pneumatic steering column). Through design space mapping, the act of 'personalization' may be redefined from an act of altering a *specific* product, to that of altering the entire *range of options* for that product. With this map, the designer can better understand how to actually implement personalization capabilities that have been technologically established.

4.5.3. Informing Multidisciplinary Design Adjustments

By establishing an understanding for how latent individual differences translate into preferences for different configurations of the infotainment controller, *multidisciplinary* design adjustments may be informed. In the problem space, *three* different types of design levers were identified as areas that could be directly adjusted by different designers. Through the personalizations, the *user* assumes the role of 'designer' as well. However, the designation of this *participative* user involvement as 'design *by* users' does not necessarily mean 'design *by* users *alone*.' With the design space map, other design disciplines may still contribute to the design of this infotainment controller as well. The HCI/HMI designer, for instance, could use this map to specify the detent number ($\boldsymbol{d}$) for each application. This could be prudent, as this attribute is less susceptible to individual difference and much more dependent on the context. These contexts, however, could *also* be directly adjusted in this case study. Unlike something like physical roads, the *applications* in the infotainment screen are directly designable. Rather than adjusting the *controller* to match the application, another option would be to adjust the *application* to match the controller. While the design space map in this case study was not expressly constructed for this purpose, it inherently acts as a tool that can be used by different design disciplines (i.e., a boundary object). With this tool, the UX/UI designer could theoretically adjust aspects of these applications (e.g., the number of items) to better suit a fixed configuration of the controller. While $\boldsymbol{A_E}$ was limited to categorical variables in this study (i.e., $\boldsymbol{a}$), the designer could treat each of the application layouts as a *template* that they could use to match *future* screens to set configurations of the controller (e.g., use the 'menu' layout when the level of detents is set to medium). Further parametrizations of $\boldsymbol{A_E}$ into continuous variables could allow the UI of these applications to be precisely tailored to compliment the haptics of the controller.

4.5.4. Personalizing on Mass Scales

Another pressing question in the realm of 'personalization' is how to implement it at mass scales. In this study, the latent information used to inform the personalizations was employed in the construction of the mathematical model in phase 1, which could then be used to generate real-time personalizations in phase 2. By validating the predictive accuracy of this model on an *out-of-sample* population, it may be readily applied to larger audiences. This affords a host of opportunities to identify population-level (or even specific sub-population-level) design insights. In lieu of individual empirical data, simulated distributions may be entered into the model to calculate population averages or joint-distributions. The model may also be entered into a Bayesian network [537]—in which the priors are distributions such as those published by the National Institute of Health (NIH), e.g., [538]—to gain even more insight into the population-level landscape of the design space.

All that would be needed to immediately enact personalizations on any potential user would be information on their physiological *predispositions*, i.e., *between-subject* differences. These are much simpler to capture than *within-subject* differences, and would not even necessarily require a controlled study to do so. In near-future automotive settings, in-vehicle sensing capabilities (or even wearable sensors) could conceivably capture this information *during* the interaction and automatically personalize the infotainment controller accordingly. This prospect has become increasingly achievable as physiological measurement devices have become more reliable [539–541]. Subjective responses—a more time consuming and immersion-breaking type of information—are *not* necessary to inform personalizations made with an already validated model. This means that mass personalizations for this physically-interactive product could by *passively* implemented in a similar fashion to how Amazon personalizes its digital shopping interface, rather than requiring detailed and heavily involved feedback to be expressly communicated by the user. These personalizations could therefore be more feasibly applied at mass scales.

Ultimately, the value of Embodiment Design Cartography in this case study does *not* lie in providing the technological capabilities for personalization. Rather, its value lies in the information it provides on how to enact these personalizations in a beneficial and efficient manner once the technology has been *established*. This is a critical step that may often be relatively ignored when compared to the pursuit of technological capabilities, but is what ultimately ensures that these additional efforts are truly worthwhile in terms of the benefits they provide the user.

4.6. Chapter 4 Conclusion

In this chapter, the framework for Embodiment Design Cartography (EDC) was applied to construct the design space map of a real-world technology—an infotainment controller. This design problem is representative of an *established* technology in the realm of rich, embodied interaction, and serves as a case study for one of the primary issues in new product development—implementing mass *personalizations*. In this specific design problem, the technological capabilities of this controller allowed for it to be dynamically adjusted in real-time. This affords the opportunity for it to be personalized, such that each user may be provided with a *unique feeling* of interacting with the device to best suite their *individual differences*. Each person has *latent emotions* or *cognitions* that distinguish them as an individual and alter their preferences. However, it was unknown as to which aspects of this feeling should be personalized and in what way, in order to provide the most benefit to individual users. With the EDC framework, this *ill-structured* problem was systematically mapped, and the personalizations were numerically explored. This provided a greater understanding of what the available options in this space were, and demonstrated how latent information could inform the manner in which personalizations should be implemented.

The *problem space* in this case study was *formulated* within the EDC framework in a manner that was tailored to the specific questions surrounding this established technology. The focus of this problem was on how the *individual* could inform tailored design adjustments that would provide them with the best *experiential* outcomes on an emotional or cognitive level. To efficiently extract information on these responses—which can be difficult for users to expressly communicate—*psychophysiological* measures may be used. To examine how users may influence the design with these measures, a *well-defined* formulation was structured within the Actor-Abstraction (A-A) matrix, in which these psychophysiological measures were considered as *design levers* that the user may directly (albeit unconsciously) control. Through the *critical examination* of the design problem that the A-A matrix calls for, the applications of the infotainment system (i.e., the menu, contacts, and volume) were identified as a context factor that would also be particularly relevant for influencing the perception of this controller. In this case, the context itself could therefore also be designed. With these different design levers, *multidisciplinary* design insights could be informed. Overall, this formulation demonstrated another instance for how problem spaces may be precisely tailored within EDC, and covered very different considerations from the previous case study.

With this well-defined, yet novel formulation of the problem space, several specialized techniques for *modeling* the associated *solution-space* were developed for problems of this nature. A controls-like modeling approach was taken, which was similar in nature to a *biocybernetic loop*. Physiological responses to an interaction were recorded, and *psychophysiological features* were extracted from these signals. These were then entered into a statistical model to synthesize new design configurations. Where this deviates from a traditional biocybernetic loop is that these new configurations are unique and *personalized* for each individual, while typical adaptations include *pre-defined* responses to specific triggers (e.g., telling a joke if boredom is detected). The latter is more akin to *customization*. This modeling technique therefore enabled personalizations to be synthesized in *real-time* using only latent emotions/cognitions. This increased the level of user involvement towards the *participative* end of the spectrum by allowing them to have direct input to the model. These personalizations were then *visualized* to provide better insight as to what influence these user design levers had, and to understand how they *quantifiably* altered the configuration of the controller. Overall, this promoted a rigorous, holistic understanding of the available options that comprised this space.

Several *techniques* and *procedures* were developed to *experimentally* construct the personalized models of the solution space for each individual in an efficient manner. An empirical user study was conducted in two phases, which followed the processes of embodiment design—*analysis* (phase 1), and *synthesis & evaluation* (phase 2). In the first phase, two models were characterized—one *with* psychophysiological features ($\mathcal{J}_{\text{full}}$), and one *without* ($\mathcal{J}_{\text{red}}$). To construct the full model, a feature selection technique using both *heuristics* and a *Mixed-Effects Random*

Forest (MERF) algorithm was employed. The MERF ranked each feature's importance according to how much latent information they provided on the user's preference (i.e., how much they influenced their rating). As a heuristic, the top ranked feature from each of the three signals (i.e., ***ecg***, ***eda***, and ***emg***) was selected to ensure there was a combination of different channels represented. This technique was therefore able to take advantage the power, sophistication, and scalability offered by the MERF algorithm, while retaining a level of control and interpretability provided by the heuristic. In the second phase, these two models—which each represented different levels of user involvement (i.e., *participative* versus *consultative*)—were used to generate new designs. These were then evaluated by an *out-of-sample* population. The predictions made with $\mathcal{J}_{\text{full}}$ incorporated each individual user's psychophysiological features, and were therefore *personalized* to that person. On the other hand, the predictions made with $\mathcal{J}_{\text{red}}$ did *not*, and were therefore commonly *customized* for the overall population (i.e., *pre-defined*). The personalizations were found to significantly improve the validity of the solution space model, which in turn served to validate the value added by this additional level of user involvement. Overall, these techniques and procedures helped construct a model that was capable of integrating multiple types of experiential responses in the creation of a *tool* for informing how personalizations should be implemented.

Finally, this chapter presented a clear case for how Embodiment Design Cartography may be usefully *operationalized* for a completely different type of design work as the previous case study. The use of a graphical system to visualize how personalized design configurations differed, allowed for the determination of which aspect of the infotainment controller should be personalized (i.e., the motor torque stiffness, ***m***) according to physiological *predispositions*. Alternatively, it also revealed which attribute should instead be coupled to the type of application (i.e., the detent number, ***d***). This latter insight may then but used to inform actionable adjustments of two different kinds of design levers. Either the HCI/HMI designer (i.e., hardware) could then adjust the *controller* to match the application, or the UX/UI designer (i.e., software) could then adjust the *application* to match the controller. Ultimately, this work was important for addressing what represents a core issue in new product development—understanding and implementing personalization—and did so in a manner that promoted a level of nuance and creative problem solving that is indispensable for *innovations* to be made. By constructing the model to use *latent* differences, and then validating it on an *out-of-sample* population, it may be applied on mass scales. The ability to implement mass personalizations with passively collected data is only limited by sensing capabilities (which are continuously improving). While mass personalization on physically-interactive produces remains to be predicated on *adaptable technologies* and *end-user sensing capabilities*, this chapter demonstrates how these personalizations may be beneficially operationalized in practice with technologies that are already established. If the efforts to make a product dynamically adaptable are to be worth that added technological challenges, it is critical that a design space map is employed to inform how the most value may be extracted from these personalizations. In the larger 'Research Through Design' (RTD) approach that is taken across this dissertation, this applied case study represents a second incremental validation of the framework as whole. In this regard, EDC was largely successful as a tool for uncovering multiple differed design insights around a completely different issue than the previous case study.

Chapter 5. Conclusion

In this dissertation, a framework for Embodiment Design Cartography was developed and applied to two real-world design problems involving different technologies. Through these efforts, a new paradigm is promoted—one in which the design solutions are defined by all of the decisions that were both made and not made to lead to their creation, rather than just as results of said decisions. This concluding chapter summarizes this body of work for establishing the practice of design space mapping. First, the research is simply summarized and the manner in which each of the research objectives was met is reviewed. In meeting these objectives, the core research issues that presented barriers to this work were each addressed. An inward reflection of the contributions that each chapter made towards overcoming these issues is then discussed in terms of the value added. Together, these chapters thoroughly addressed each identified gap. The outward impacts that may result from these contributions are then postulated. These impacts extend across different areas of new product development, and provide a basis for new design research. Finally, this discussion turns towards the future and provides several directions that this research may take. Overall, the work presented with these chapters represents a comprehensive body of work for equipping designers with the conceptual basis, modeling techniques, and experimental procedures to implement Embodiment Design Cartography and operationalize product innovations.

5.1. Research Overview

The goal of this research was to develop the practice of *design space mapping* through Embodiment Design Cartography (EDC). This practice shifts the aim of embodiment design from a paradigm of creating a *singular solution*, to that of constructing a *tool* to reveal a range of available options. In the treasure-filled-cave that is the design journey, the design space map grants the 'birds-eye-view' of the decisions that can be made. This new paradigm places greater emphasis on understanding the design journey over just the destination because just as in life, design is a journey, not a destination—it is in the design journey that true insight lies. The 'solution' in EDC is not the *end* of the design journey, per se, but rather that *path* that was chosen to get there. The path that takes the engineering designer from the known—the entrance of the cave, i.e., the concrete design levers in their control—through the labyrinth of twists and turns given by the external factors that they consider, and ultimately to the to the treasures, or abstract outcomes, that they select; the path that is characterized by mathematical models, and may be traversed forwards or backwards for embodiment design analysis or synthesis. A robust map for this journey—one that provides detail on a holistic set of passageways in the cave (i.e., design factors) and treasures to be discovered (i.e., design outcomes), not just the specific solution path that was taken—can serve as a generalizable *tool* for a variety of different purposes, to be used by a variety of different designers.

> *"[A] road map may point the way to a campground for one group, a place for recreation. For another group, this 'same' map may follow a series of geological sites of importance, or animal habitats, for scientists. Such maps may resemble each other, overlap, and even seem indistinguishable to an outsider's eye. Their difference depends on the use and interpretation of the object."*

– Susan Leigh Star, *This is Not a Boundary Object: Reflections on the Origin of a Concept*, 2010 [344]

To establish this practice of design space mapping, both the *conceptual foundations* for how to construct such a map in a general sense, as well as the manner in which these maps may be used to *inform useful design insights in practice*, had to each be developed. As such, a 'Research Through Design' approach was employed, in which both the conceptual and applied aspects of these needs could be developed in tandem through rase studies for real-world design problems.

Through this approach, three core research objectives were met in service of this goal, which are summarized in turn.

5.1.1. A Framework for Embodiment Design Cartography

The first objective was to derive a *conceptual framework* to support the cartographic activities of design space mapping for design problems rooted in 'embodiment,' including supporting *flexible problem space formulation* that may be tailored to specific design problems, and *selectively integrative solution space modeling* that may leverage existing design methods. This objective was met in Chapter 2 of this dissertation through the conceptual derivation of the Embodiment Design Cartography framework. This framework was first defined here in a purely general sense, and then used in the two case studies to demonstrate its specific application in the following chapters.

In this conceptual development, it was first specified that this framework would be constructed as a *boundary object* for design methods. A boundary object is a device that may vary between a *loose* and *precise* organizational structure, such that it may be adapted to different perspectives that may lack taxonomical consensus, but also more specifically formulated for a given problem. As a boundary object, the EDC framework can support each of the different perspectives given by the existing design methods, and be used to span the inherent boundaries between them. Boundary objects in design are unique in that they promote collaboration between different perspectives rather than allow them to work independently. Alternatively, in its more precise structure, this boundary object may then be able to formulate the problem space of a specific design problem.

To derive this conceptual framework, it was necessary to define an *ontology*, an *epistemology*, and a *methodology*, which together establish the overall *philosophy* of the framework. Summarily, this framework-specific philosophy is that comprehensively mapping out all the options in an embodiment design problem can improve decision-making. The EDC ontology defined the classification of concepts and relations through the Actor-Abstraction matrix. The EDC epistemology defined the management of knowledge or data, including how it was directed, sourced, measures/interpreted, and finally validated. The EDC methodology defined the manner for which the framework is operationalized through the processes of embodiment design (i.e., analysis, synthesis, and evaluation) in the Stage-Process (S-P) model (see Figure 2).

Using this framework, each of the existing design methods were mapped through the lens of the EDC ontology, epistemology, and methodology. This interpretive exercise was conducted in order to better understand how these different methods compared to each other on a common scale, and to verify the general compatibility of this boundary object. The problem space of each method was mapped in the A-A matrix to identify their points of overlap. The functions and data collection methods used in each were discussed from an epistemological perspective. Finally, the methodology of each was deconstructed using the S-P model, and activities that were interpreted to be advantageous for design space mapping for selectively integrated into the EDC methodology.

5.1.2. A Method for Navigating Tradeoffs in an Emerging Technology

The second objective was to apply the Embodiment Design Cartography framework to develop and demonstrate modeling, experimental, and design techniques within the context of an *emerging* technology in order to negotiate favorable *tradeoffs* between technical and experiential design outcomes using *engineering design levers*. This objective was met in 0 of this dissertation through the case study of the pneumatic steering column. In this emerging technology, it was unknown as to how improving its *technical* performance (e.g., stowability) would impact—in potentially detrimental manner—the *experiential* responses (e.g., satisfaction) that would be elicited by the rich, embodied interaction (i.e., steering).

The problem space for the pneumatic steering column was formulated in the Actor-Abstraction matrix. On the *technical* level, engineering design levers could be used to make direct adjustment to the artifact's form/layout (Artifact-How). These parameters were directly related to the user-facing qualities of the artifact that were both *responsive*, i.e., providing kinesthetic haptic feedback, and *persistent* (Artifact-What). The latter of these domains was then related to the technical performance of the artifact (Artifact-Why). This 'artifact-centered' formulation is representative of a classical engineering design problem. However, additional considerations were also included on the *experiential* level. The physical environment for which the device was used to steer the vehicle (i.e., the track) was also considered to be an important consideration (Context-What). Both these contextual attributes, as well as the interactive attributes of the artifact, were both considered especially relevant to influencing the rich, embodied interaction. The user's subjective perceptions of this interaction were then measured (User-Why).

The solution space for the pneumatic steering column was modeled both analytically and empirically. The *engineering* ($\mathcal{E}$) and *performance* models ($\mathcal{P}$) were analytical characterized with a *proportional sensitivity* matrix that could be estimated using only the fundamental engineering principles that may be available for emerging technologies with limited knowledge basis. Alternatively, the *interaction* model ($\mathcal{I}$) was empirically characterized with a *mixed-effects* model through an experimental user study (n = 57). In this study, participants provided their subjective ratings to various configurations of the effective torque stiffness and steering sensitivity of the pneumatic steering column, while driving on different tracks in a simulator. New design configurations—and *optimal* and a *sub-optimal*—were then predicted with $\mathcal{I}$, and they were subsequently evaluated by participants. The optimal predictions were rated significantly higher than the sub-optimal predictions, which was used as an index to validate this model.

This validated model, $\mathcal{I}$, was then *composed* with $\mathcal{E}$ to span the problem space and couple the design levers and design outcomes in the solution space. With this composition, the available options in the design space were visually examined using a linear algebraic approach, which was supplemented with graphical tools to visualize this space. With this system, several different types of tradeoffs were navigated under a set of constraints that were imposed to simulate real-world conditions. First, the types of adjustments that could be made without making any concessions to the experiential response (i.e., *experience-maintaining* adjustments) were identified. In this scenario, it was identified that these adjustments had a negative impact on aspects of the technical performance, which could be quantified. Alternatively, the visual system was used to identify the manner in which minimal concessions to the experiential response could be permitted (i.e., *experience-sacrificing* adjustments) to improve the favorability of these tradeoffs. With these minimal concessions freeing up an extra degree of adjustability, the detrimental impacts to the technical performance could then be offset. Additionally, these tradeoffs were compared across the different driving contexts. It was determined that if the length of the column was permitted to be dynamically adjustable, the experiential responses would be more favorable across contexts when compared to any sort of fixed compromise between the two contexts. These insights represented a variety of useful design decisions that could be driven by the design space map.

5.1.3. A Method for Personalizing Options of an Established Technology

The third objective was to apply the Embodiment Design Cartography framework to develop and demonstrate modeling, experimental, and design techniques within the context of an *established* technology in order to *personalize* the available options by permitting the user to control their own *psychophysiological design levers*. This objective was met in 0 of this dissertation through the case study of the infotainment controller. In this established technology, there was opportunity to personalize the haptic feedback of the device, however it was unknown as to how these should be efficiently implemented to best address individual differences.

The problem space for the infotainment controller was formulated in the Actor-Abstraction matrix. In this problem, both subjective and physiological responses to interactions with the controller were measured (User-Why), the latter of which was used to extract *latent*, or unspoken, emotions/cognitions through psychophysiological features (User-What). These were used to define individual differences, and provided the user with the opportunity to directly influence design levers. Another aspect of this problem that differed from the former case study was that the context was given by a *digital* environment, i.e., an app (Context-What), rather than a physical one. Finally, the actual product itself, i.e., the controller, had several interactive attributes that could be directly adjusted to alter its tactile haptic feedback (Artifact-What). The experiential responses were then attributed to the combination of the artifact's haptic feedback, the digital app that provided context, and the user's physiological predisposition. In this way, different designers could either adjust the artifact or the controller to alter design outcomes, and the user themselves could also tacitly *personalize* these outcomes.

Two versions of the solution space for the infotainment controller were empirically modeled—one that included the individual psychophysiological measures ($\mathcal{J}_{\text{Full}}$), and one that omitted them ($\mathcal{J}_{\text{Redu}}$). Both of these models were characterized through an experimental user study (n = 60), in which users provided both their subjective and physiological responses to various configurations of the detent number and motor torque stiffness of the infotainment controller, while using different applications in the infotainment system. This study was conducted in two phases. The first ($n_1 = 40$) was used to characterize $\mathcal{J}_{\text{Full}}$ and $\mathcal{J}_{\text{Redu}}$. The second ($n_2 = 20$) was used to apply these models to create new configurations of the infotainment controller and asses the relative performance of the two models on an out-of-sample population. For both models, an *optimal* and a *sub-optimal* design configuration was predicted at each application. The model which was personalized with physiological measures was found to significantly outperform the other on predicting preferences. $\mathcal{J}_{\mathrm{Full}}$ could therefore be employed to inform mass-personalizations to larger populations.

Each personalized solution space was visualized using contour plots, which were overlaid to identify patterns in preferences. It was observed that individual differences dramatically varied over the motor torque stiffness, but not the detent number. This suggested that the motor torque stiffness should be personalized based on individual physiological predisposition, while the detent number should be coupled with the application. This coupling of the detent number and the application could be used to inform different kinds of design decisions that varied by the discipline of the designer. If the designer was adjusting the infotainment controller, they could adjust the detent number to match the application. Alternatively, if the designer was adjusting the digital applications, they could adjust different parameters, such as the number of menu items, to match a fixed detent number. These insights represented the multidisciplinary design decisions that could be driven by the design space map.

5.2. Research Contributions

This research has made important contributions to the field of *engineering design* and *design science*. In meeting each of the specified research objectives, this work has established the practice of design space mapping. This practice has the potential to revolutionize the manner in which engineering designers navigate the plethora of options and externalities that may be considered when translating a concept into the real world. To do so, however, four identified gaps had to be spanned; these included: 1) a structured manner in which to *conceptualize* these varied design problems had to be derived, 2) an approach for mathematically *modeling* the relation between the available design levers and the various design outcomes, while accounting for any externalities, had to be developed, 3) an array of *experimental* techniques and procedures had to be established to account for these broad problem space formations, and support the empirical characterization of the solution space models, and 4) mechanisms for putting all of these prior efforts together had to be created to *operationalize* real-world design decisions from these conceptual, model-based, and experimentally derived insights. To successfully enable the practice of design space mapping, the work presented in this dissertation has contributed to addressing each of these core research issues, which are each discussed in turn.

5.2.1. Formulating the Problem Space

The first research issue surrounded the manner in which ill-structured design problems that involved the complex phenomenon of rich, embodied interaction could be *formulated* in a structured, yet flexible manner. These problem space formulations required the capability to *variably* support a broad array of different factors and outcomes that may pertain to the design problem at hand. These considerations extend from the concrete design levers to the abstract design outcomes. A mechanism for systematically accounting for relevant considerations across the different actors and abstraction levels was therefore necessary to address this gap. Each chapter in this dissertation addressed different aspects of this issue.

1. In Chapter 2, the conceptual aspect of this research issue was addressed through the derivation of the EDC *ontology*, which was externalized by the Actor-Abstraction matrix. By structuring this matrix as a *boundary object*, it was able to both support the problem space formulations of existing design methods—each independently developed—as well provide a basis for which *new* problem space formulations may be tailored for very different design problems. This problem space mapping not only provided a mechanism for more directly contrasting the considerations that were supported between methods, but also highlighted the *flexibility* of the A-A matrix in supporting all of these varied formulations.
2. In 0, this conceptual groundwork for formulating the problem space was put into practice within the case study of the *pneumatic steering column*. This design problem involved a typical *technical* engineering design problem, but with an added layer of *experiential* considerations on top. A novel problem space formulation, tailored to this specific case study, was able to be constructed within the A-A matrix. This formulation coupled both technical and experiential design outcomes, to the concrete engineering design levers, in a manner that was unique from any existing design method.
3. Alternatively, in 0, the A-A matrix was put into practice for a different case study, this time involving an *infotainment controller*. In this design problem, the novel problem space

formulation centered around the question of how the individual user can influence technological development without expressly communicating their needs. Specifically, both their *subjective* and *physiological* responses to an interaction were considered. This formulation permitted different designers to either adjust the controller or the app to alter design outcomes, but also for the users themselves to tacitly *personalize* these outcomes with their physiological predispositions.

Overall, these different formulations—including both those from existing design methods and those tailored to specific design problems—together serve to illustrate the robustness and adaptability of this conceptual approach for mapping out different problem spaces. This work therefore addressed the research issue by enabling the different factors/outcomes that may be considered in rich, embodied interactions to each be supported as needed.

5.2.2. Modeling the Solution Space

The second research issue involved the mathematical models that were used to relate domains in these problem space formulations—specifically, how they are to be *characterized*, *used*, and *validated*. These *solution space models* must couple the concrete design levers and abstract design outcomes. In accordance with the problem space formulations, they must also include both *technical* models that are analytically characterized, and also *experiential* models that are empirically characterized. The manner in which these models are constructed through embodiment design *analysis*, applied in embodiment design *synthesis*, and validated in embodiment design *evaluation*, were all therefore necessary to develop in order to address this gap. Each chapter in this dissertation addressed different aspects of this issue.

1. In Chapter 2, the conceptual mechanisms for addressing these needs were defined through the EDC *epistemology* and *methodology*. The EDC epistemology specified rules for how data was used for *analysis* or *synthesis* according to direction of transformations on the Actor-Abstraction matrix, as well as how these transformations had to be characterized empirically or analytically according to their source. It also specified the rules for validating models in *evaluation*. The EDC methodology then dictate how to apply these rules through six activities for modeling the solution space, which included parameterizing, descriptive modeling, prescriptive modeling, prototyping, verifying, and validating.

2. In 0, these conceptual foundations were then applied to model the solution space of the pneumatic steering column. In this case study, a modeling technique was developed for composing empirical and analytical models that leveraged their *natural functional forms* (i.e., power-law and logarithmic scale) to enable a *linear algebraic*-based exploration of the available options. This technique proved to be an effective means for identifying favorable *tradeoffs* between different outcomes, while informing exactly how to adjust the engineering design levers to navigate said tradeoffs.
3. In 0, these conceptual foundations were then differently applied to model the solution space of the infotainment controller. In this case study, a technique was developed for *personalizing* the solution space according to individual's *physiological predispositions* based off of a modified *biocybernetic loop*. With this technique, a validation test proved these individual personalizations to be more accurate than a generic solution space created for the entire population.

Overall, these novel modeling approaches represented sophisticated techniques for relating design levers and design outcomes. This work therefore addressed the research issue through detailing efficient manners for characterizing, applying, and validating these models within the EDC framework.

5.2.3. Developing Experimental Techniques & Procedures

The third research issue was based on the need for specialized experimental techniques and procedures for actually empirically characterizing models (i.e., analysis), generating physically-interactive prototypes with these models (i.e., synthesis), and ultimately validating said models (i.e., evaluation). These techniques had to facilitate these processes within *practical resource constraints* of a laboratory setting. Infrastructure was needed to collect and process a wide variety of *different data channels*, often in *real-time*. Similarly, *high-fidelity prototypes* were needed to be rapidly generated with minimal resource use. Each chapter in this dissertation addressed different aspects of this issue.

1. In Chapter 2, the mapping of existing design methods onto the common scale of analysis, synthesis, and evaluation enabled the identification of which processes these existing methods exceed at relative to their peers, and revealed where and how these specific

techniques could be adapted into the EDC methodology. This enabled parts of these existing methods to be *selectively integrated* into the framework, without requiring an single method to be adopted wholesale. In this way, the techniques that were interpreted to be advantages could be leveraged without introducing any perceived limitations associated with the method as a whole. Additionally, a technique for generating physically-interactive prototypes was conceptually posed based off of the *modular* nature imposed by the A-A matrix, which could replicate a *range* of different design configurations across the solution space. This enabled real-time synthesis and validation of new design configurations in experimental studies, which saved valuable resources.

2. In 0, an *adaptive experimental design* was developed for a user study (n = 57) that was conducted to empirically model the solution space of the pneumatic steering column. In this experimental design, subsequent trials contained new design configurations that were predicted based on participants prior responses, and generated in *real-time* using an *interaction prototype*. This enabled the model of the solutions space to be both characterized and validated by the same population of users in an efficient manner.

3. In 0, a different *adaptive experimental design* was developed for another user study (n = 60), which was conducted to empirically model the solution space of the infotainment controller. Two versions of the solution space model were empirically characterized—one *with* physiological measures, and one *without*. This enabled a statistical test to be performed on how these additional measures improved the model's accuracy. Infrastructure was developed to measure, record, and process these physiological measures in *real-time*. A Machine Learning algorithm was employed to select the relevant physiological measures to be included in this model. Ultimately, the model with these additional physiological measures was found to improve the accuracy of the solution space.

Overall, this array of experimental techniques and procedures allowed for the necessary modeling and design work to feasibly take place within practical resource constraints. This work therefore addressed the research issue through developing this array of sophisticated infrastructure to support each process that these models were used for

5.2.4. Operationalizing Embodiment Design Cartography

The fourth and final research issue regarded actually putting all of these conceptual, modeling, and experimental techniques into practice to enact real-world design decisions. The ultimate aim of Embodiment Design Cartography was to support the translation of conceptual ideas for products into their real, embodied selves. The practice of design space mapping had to therefore be put to the test within these real-world scenarios, through case studies for the embodiment design of actual products. Two types of real-world design challenges were specifically targeted here: 1) how to navigate product *tradeoffs* and 2) how to implement product *personalizations*. Furthermore, methods to promote the *exploration* of these maps—via *visualizations* or otherwise—were needed to help locate innovative, desirable solutions among the available options. Each chapter in this dissertation addressed different aspects of this issue.

1. In Chapter 2, Embodiment Design Cartography was employed for an interpretive meta-analysis of the existing design methods. This exercise retroactively mapped each of the existing design methods on to the EDC framework, which made it possible to directly compare them on common grounds. This comparison revealed several useful pieces of information. First, the gaps that were not covered in the Actor-Abstraction matrix suggested potential research gaps, some of which have already been identified and addressed with proposed extensions, while others have not. Additionally, this revealed points of overlap between these methods, which could signal areas in which they may be combined. Alternatively, extensions to one method could be applied to others. This could be beneficial for motivating future research.
2. In 0, Embodiment Design Cartography was successfully applied to the case study of the pneumatic steering column. A visualization system using *vectors* and *contour plots* was employed to survey the available options, and to illustrate the effects of adjustments to engineering design levers. With this graphical system in place, an array of information on the tradeoffs between different outcomes were identified for this emerging technology, all with little prior insight or knowledge basis for which to base these insights. It was shown how different value systems—such as a desire to maintain optimal experience, versus a desire to improve technical performance—could each be imparted onto this tool to influence how design levers should be adjusted. Furthermore, it was also shown how to

adjust these design levers for different driving scenarios, and even suggested a *new feature* that would allow for *in-situ adjustability* of these levers for these different occasions. Ultimately, with a map of the available options, the tradeoffs that exist between them can be made clear.

3. In 0, Embodiment Design Cartography was then successfully applied to the case study of the infotainment controller. Again, contour-based visualizations were used to illustrate the available options, but this time *scatter plots* were overlaid to illustrate *individual differences*. This graphical system specifically revealed which dimensions of the haptic feedback offered by device should be *personalized* for each user, and which should instead be coupled with the context (i.e., the app). Compared to the previous case study, in which only *engineering design* insights were identified, this design space map was used to identify *multidisciplinary* design insights; both the designer of the *physical controller*, as well as the designer of the *digital application*, could make measurable adjustments to improve outcomes based off of this information. Ultimately, not all options in the design space are perceived equally by every individual, but these differences may be accurately reflected in personalized maps.

Overall, these case studies revealed the actionable insights for real-world design problems that may be extracted through design space mapping. This work therefore addressed the research issue by operationalizing the framework conceptualization, modeling approach, and experimental techniques of Embodiment Design Cartography for valuable design work.

5.3. Potential Research Impacts

By addressing each of the core research issues in this work, the primary obstacles for design space mapping have been hurdled. The core outcome of this dissertation can be boiled down into its ability to cast a wide net around the broad range of considerations in embodiment design, and to condense all of this information into a *singular representation*. This in and of itself does not necessarily guarantee product improvements [186]. Just as an unprepared adventurer could stumble through the darkness of a cave system and happen upon a treasure, a designer could certainly create a successful product without a formal plan or map. However, having a map for this process does help these decisions to be made in a more informed manner. The framework for constructing these maps—Embodiment Design Cartography—serves to formalize this philosophy on design space mapping and is designed to provide a *platform* for which a host of modeling, experimental, and design methods may be developed in service of these aims.

> *"A single representation for all product information has long been an unattained ideal in product development research… Using a single representation does not in itself add any new theoretical capability that could not be achieved, however… the real benefit of the unified representation is the change we hope it will cause in the way this information is perceived… We also believe that a unified representation of the information will facilitate bookkeeping, calculations, and other manipulations."*

– Rajah Ramaswamy & Karl Ulrich, *Augmenting the House of Quality with Engineering Models*, 1993 [186]

This singular representation imparts the designer with more *knowledge* of the design space. While knowledge for knowledge's sake can be motivation of its own, the pragmatic benefit of this knowledge could ultimately extend to both *industrial* and *academic* settings. These potential impacts may be thematically organized across four inter-related areas: 1) how design options may be systematically explored, 2) how product innovations may be driven through different kinds of data, 3) how designers from different disciplines or perspectives may collaborate to better address design problems, and 4) how new design methods may be built off of this framework. These impacts could help to counter some of the preeminent reasons that new product development so often fails, and are detailed in turn.

5.3.1. Systematic Design Space Exploration

The archetype of the 'engineering designer' was initially posed in Chapter 1 as hybrid between an engineer—one who addresses design problems in systematic or quantitative manner, typically through mathematical models with which technical performance may be optimized—and a designer—one who addresses design problems in a less rigid manner, through creative explorations of the available solutions. "Superficially it may seem that rigorous method and creativity are incongruous; however, the reality is that quantitative methods can be used to enhance creativity" [326]. The engineering designer therefore seeks to engage with the design process through a combination of these of these drives—to *systematically explore* the options in the design space.

5.3.1.1. Systematic Problem Space Exploration

One of the root causes of failure in new product development can be attributed to a fundamental misunderstanding of the problem—misunderstanding the underlying behavioral science of the user, as well as the factors that influence their experiential responses [333]. To systematically explore a *problem space*, a structured, deliberate examination of what considerations are understood to define it, may be undertaken within the Embodiment Design Cartography framework. Without EDC, there are a multitude of decisions that are baked-in to the selection of an off-the-shelf design method, including what factors/outcomes are considered, how data should be collected, etc.—all the aspects that comprise the conceptual 'wrappers' of these methods. These decisions for how the problem will be understood are therefore implicitly aggregated into this one selection, ignoring any sort of nuance or creative thinking on this manner.

In contrast, the construction of the design space map forces *intentional consideration* of the problem space, which alone may not guarantee a complete understanding, but does at least incentivize the engineering designer to think more deeply about it than they would if they had used an existing design method. As demonstrated in the two case studies, each decision relating to what factors/outcomes are considered, how data is collected, how models are characterized, etc. are all *individually* determined for the problem at hand. Just as in a text-based adventure, each decision or piece of information requires *deliberate* action to enact or extract; the adventurer does not just subconsciously take in their surroundings, they must be intentionally prompted to 'turn on the lantern' to make such observations. The systematic exploration of the design problem may therefore improve the likelihood that the problem is truly understood through the forced intentionality that is imparted by this *flexible problem space formulation*.

5.3.1.2. Systematic Solution Space Exploration

A systematic exploration of the *solution space* involves using sophisticated tools, protocols, and methods, i.e., the Embodiment Design Cartography framework, to not just examine options, but to do so in a way that is somewhat less structured or more creative compared to what may be done in the language of, say, optimization—all while still remaining purpose driven. To 'explore' the solution space is to look around at the many different design configurations that are available, contrast them on a variety of different outcomes before making any sort of value-based down-selections (e.g., setting weights of an optimization model), and ultimately discovering new solutions that may not be obviously selected otherwise. Explorations can allow the engineering designer to look at options without necessarily having a specific solution in mind. For instance, in the case of the pneumatic steering column, the design space map used to compare design configurations in terms of two different types of outcomes (i.e., technical and experiential) to favorably balance the two, the tradeoff of which was previously unknown. Alternatively, in the case of the infotainment controller, the design space map used to compare how individual preference differed—which was again previously unknown to the designer—and ultimately to tailor the solution on both individual and contextual levels.

However, while this unrestricted exploration can certainly uncover promising solutions, it is not the industry norm. The reason for this lies in the practical resource constraints of new product development, e.g., time, money, etc. Exploration in embodiment design implies the creation of many different design configurations, i.e., rapidly *iterating* on the design solution; these iterations can be extremely resource intensive, as embodiment design *synthesis* is the longest stage in the development cycle (followed only by embodiment design *evaluation*) [542]. Minimizing the length of these iterations is therefore another key issue that industry faces in new product development [326]. The beauty of the EDC framework—of documenting the path to each alternative design configuration that is achievable—is that the iterations in these two case studies were made to be extremely efficient with the blueprint provided by the design space map. Unlike the designer who accidently stumbles into a successful product, the engineering designer who systematically maps out this space could more easily retrace their steps and make calculated changes to their decision-making that improve their solution. Not only does the engineering designer prospectively know exactly what alternative outcomes are possible within the design space, but they also know exactly how to manipulate the available design levers to achieve them. They could then use techniques developed within the EDC framework to immediately generate interaction prototypes for these new iterations, thus enabling these iterations to occur extremely quickly (i.e., in real-time). While there is an up-front cost to constructing this map (e.g., running user studies to characterize empirical models, building interaction prototypes, etc.) these ultimately pale in comparison to the potential losses that may be realized in product failures [333], which otherwise remain to be an extremely real and prevalent proposition [30–32]. This seemingly superfluous proposition of systematically exploring design options may therefore pose an astute business case with this *robust solution space model* and *efficient experimental techniques* in hand.

5.3.2. Data-Driven Product Innovations

While understanding the design process itself can be critical, the success of new product development is ultimately based off of the actual *product innovations* that result from said process. Just as in the 'Research Through Design' philosophy taken in the approach to this work, value is generated through the products that are created, just as much as it is through methodological insights. The design space map condenses a broad range of considerations that may be made throughout this process into a singular representation. The results of the systematic exportations that may be made with this singular representation—the products themselves—reflect actionable innovations that are driven by the inclusion of *measurable data* from a wide variety of *different sources* into the solution space model in this work. The suite of modeling, experimental, and design methods developed in the Embodiment Design Cartography framework can therefore help to imbue product decisions with multiple layers of information.

As demonstrated, a wide variety of different types of data may be supported within the EDC framework. Design outcomes may include anything from analytically derived technical performance, to empirically measured experiential response—which itself can be measured through surveys, observations (e.g., timers), and even through sensors. Within the case studies presented in this work alone, experiential responses were collected through self-reports, muscular activity, cardiovascular activity, and electrodermal activity. Because all of these design outcomes were measured *quantitatively* (as opposed to, say, *qualitative* interviews), they could be simply combined to inform measurable decisions about the products. Configurations for the pneumatic steering column, for instance, were simultaneously compared on both a technical and experiential scale; configurations for the infotainment controller were compared on a purely experiential level, but these comparisons were based off of both subjective and physiological measures. In industry, it is not uncommon for new product development to be guided by market research rather than technological or experiential R&D, which can limit the scope of innovation, i.e., "[i]nnovation has become entirely focused on how best to deliver the current product, rather than how best to deliver the benefit consumers seek from it" [333]. Alternatively, the innovations made with the EDC framework in this dissertation were entirely predicated on delivering the best combination of benefits, i.e., positive design outcomes, across all of these different channels.

For instance, a variety of different innovations were able to be drawn from the case studies conducted in this work. The two products that were mapped in these studies differed from one another in almost every discernable manner, except for the fact that they both provided rich, embodied interactions. The pneumatic steering column, for instance, was an *emerging* technology with very little prior insight available as to what types of interactions would even be desirable, let alone what innovations may lead to its improvement. On the other hand, the infotainment controller was an *established* technology that was already in commercial use, but presented an opportunity for future innovation through personalization. In both cases, *benefit-centric* innovations were identified, whether they be *incremental*[13] or 'me-too'-style innovations [326]—such as improving the affordability of the pneumatic steering column while maintaining optimal experience—or even innovations on a more *breakthrough*[14] level [326]—such as identifying opportunities for an in-situ adjustability feature in the pneumatic steering column, or determining how to implement mass-personalization in the infotainment controller. Both types of innovations are valuable in their own right. In each of these case studies, this data-driven approach was also able to validate these innovations through the statistically significant impacts that adjustments had on these different outcomes.

Conceptually, these outcome-based—or *benefit-centric*—innovations are promoted in this format due to the fact that all of these different data types are considered to hold equal design utility within the EDC framework. The act of ontologically placing the three actors (i.e., the artifact, the user, and the context) onto equal levels without imposing a hierarchical structure, inherently places the technical and experiential onto equal footing. The interest and appreciation of the importance of the experiential has been growing across research fields [17,111]. In industry, however, this is not necessarily the case. In fact, it is much more common for technical data to be institutionally overvalued when compared to experiential data—which is therefore underutilized [333]—even if this hierarchy is not necessarily reflected in consumers.

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[13] **Incremental innovation**: Evolutionary improvement to an existing product; also known as a 'me-too' innovation.
[14] **Breakthrough innovation**: Significant departure from an existing product that is based on new technology.

> *"[A] severe imbalance arises between the resources for behavioural* [sic] *and for technological research. A twentyfold bigger annual research budget for technology compared to behavioural science would not be unusual. No wonder that the really big innovations occur in the product field and never occur in the consumer field. Yet these product-technological innovations often lead to unsuccessful products because consumer-relevant aspects are overlooked or simply never sufficiently addressed. When comparing the cost-effectiveness of technological to behavioural research, the latter is likely the more cost-effective of the two by far. The costs of behavioural studies are relatively modest, and they give valuable information…We refer to them here as the 'behavioural sciences', but one could also refer to them as 'experiential sciences' as they aim to understand—and predict—the subjective experience of consumers"*

– Garmt Dijksterhuis, *New product failure: Five potential sources discussed*, 2016 [333]

The underlying conceptualization of the EDC framework could therefore promote the experiential sciences to a higher standing than it may be typically allotted in current practices. There is no prohibitively large cost associated with this promotion. Rather, it is simply countering existing perceptions of the artificial hierarchies that exist between these fields. The resulting product innovations may therefore posed the be better informed by adhering a more 'maximal use' of the product-relevant information that may be provided by a multitude of disciplines [333].

5.3.3. Multidisciplinary Collaboration

By capturing data that tends to fall under different disciplines within this singular representation, the Embodiment Design Cartography framework could also promote *multidisciplinary collaboration*. This collaboration, however, is not just limited to the data that is used for decision-making, but could more broadly describe the potential of this framework to give other disciplines—other types of designers—a metaphorical seat at the table in the design process. Even more so than most endeavors, design is a truly multidisciplinary and collaborative process. This involves disciplines that fall on both the technical and experiential ends of the spectrum.

> *"There are many disciplines that design and that participate in the design process: engineers, industrial designers, architects, software creators, anthropologists, among others. The science part is the systematic study of the structure and behavior of the world. On one hand, the world in this case is synthetic in that it is the world created by people. On the other, the world is natural in that we study how people design. This latter aspect requires participants with knowledge of the social sciences such as cognitive and social psychology, anthropology, and others."*

– Jonathan Cagan, *Design Science: Why, What and How*, 2015 (contributing essay) [342]

However, barriers to multidisciplinary collaboration are quite prevalent. Different disciplines have distinct vocabularies and conceptual maps of the design process, which can make communication difficult. Imposed hierarchies, such as the previously noted asymmetry between technical and experiential sciences (i.e., 'psychophobia' [333]), can present organizational and social barriers to this collaboration. Even the outdated and somewhat derogatory descriptor of 'soft' sciences for those disciplines that *do* address the experiential (i.e., psychology, physiology, etc.) spuriously challenges the rigor of these disciplines in comparison to technical engineering; experiential sciences can, in fact, oftentimes be the 'harder' science [333]. This prevailing attitude implicitly positions these disciplines as somehow less important, even if it is oftentimes exactly the experiential responses that they study which separate product successes and failures. So when these different disciplines are brought together, the nature of their collaboration can be ambiguous or misunderstood.

The EDC framework may be impactful in this regard for several reasons. First, its construction as a *boundary object* helps break down the first obstacle—the communication barrier. By simply reframing the verbiage that is used by one degree of generality, the Actor-Abstraction matrix allows for discipline-specific terminologies (i.e., jargon) to be classified in uniform buckets that are more simply understood (e.g., the Artifact-What). This was illustrated through the mapping of existing design methods, each stemming from different disciplines, onto this uniform ontology. Beyond this, the A-A matrix may again places each actor onto equal levels, in which the technical sciences are centered around the artifact, and the experiential sciences are centered around the user; the context is more of a hybrid between the two. Within the problem spaces that are formulated in this ontology, designers from these different disciplines may be clearly assigned to the role of adjusting their relevant design levers, à la the different design levers assigned in the infotainment controller case study. This could then facilitate the communication between disciplines by structuring the discussion around the clear debate who should adjust their design levers, in which the outcomes of doing so are objectively measurable and evident to all parties. Building this platform for facilitating these conversations and collaborations is key for successful, innovative design, and represents a fundamental building block for ultimately working towards addressing the larger, wicked problems in design.

5.3.4. Methodological Research & Development

All of these interrelated impacts together culminate in the preeminent takeaway of this work—the Embodiment Design Cartography framework may be used as a platform for creating new, tailored, multidisciplinary design methods. The development of design methods is the foundational raisons d'être of both engineering design research [163,366] and design science research [543]. The EDC framework could essentially serve as a blueprint for how design methods are researched, developed, and even taught in academic settings.

Four established design methods from different disciplines were mapped out in this framework—they were each laid out within the Actor-Abstraction matrix and deconstructed according to the processes of embodiment design. From this perspective, it becomes clear just how simplistic many of these decades-old design methods really are. The extensive bodies of research surrounding each of these methods—which have, of course, been instrumental for extending and refining them to the degree that they are today—may arguably reach a point in which they are only doing designers a disservice by further pigeonholing them into fixed structures that may not best suit their individual needs. While there certainly may be use cases for simpler, easily plugin-able design methods, it is ultimately in the best interest of design research and industry alike to continuously improve their sophistication. The EDC framework is not positioned to be a peer to these existing design methods, but rather as a higher-level tool for classifying, comparing, and creating new ones. While it previously may not have been a feasible ask to create a new design method tailored for each new product development cycle, the case studies presented in this work show that, with the conceptual foundation supplied by the EDC framework, it is now certainly within the realm of possibility. Just from these two case studies alone—and by how much they differed from one another—it is apparent that there is a world of new design methods that may be created within this framework.

In fact, that this is not already the norm seems a deep injustice to the field as a whole. Why *should* designers—the creative problem solvers of the world—be limited to such ready-made methods? This research perspective envisages a world in which all embodiment design work starts with a framework such as this. Through a systematic process, a tailored design method is developed, in which the relevant considerations of the problem are intentionally determined, and mapped out with sophisticated modeling and experimental techniques. These mappings then enable an unrestricted exploration of the possible solutions, which are each assessed by a wide variety of different outcomes or benefits that they may provide. A multidisciplinary cohort of designers then adjusts the various design levers to achieve their consensus combination. Ultimately, this leads to improved innovations and an increased likelihood for product success. While this may still be but an ideal to stive for, the framework for Embodiment Design Cartography takes those critical first steps in this direction.

5.4. Future Directions

When discussing a platform for building new design methods and spring-boarding new design research, it is useful to ruminate on future directions that this could take. This is especially true for directions that help address any limitations of the work that has been done so far. There are two separate tracks that may be discussed here: 1) developing new design methods within the existing EDC framework, and 2) further developing the EDC framework itself.

5.4.1. New Method Development within the EDC Framework

On the former track, there is essentially no known limit on the permutations of different design methods that may be developed within this framework. To establish these limits, it is not only important for *successful* applications of the framework be shared, but also for critical for assessments of its *failures* (i.e., where they occurred and why) to be published and disseminated to the research community [163]. This will simply require trial and error to explore; this dissertation does not claim omniscience in this respect. The timescale of methodological development can be quite slow. The 'established' design methods that were reviewed and mapped have each reached this status after decades of development. However, seminal works by the likes of Gero (FBS) [13], Akao (QFD) [188], Nagamachi (KE) [232], Luce and Tukey (CA) [270] have each shown how strong conceptual foundations can lead to extensive future research. This dissertation can only strive for the same. To further this development, new design problems, such as the ones presented in these case studies, must be continuously mapped within the EDC framework. Over time, a slew of new methodological innovations could be built on this groundwork. A better picture of exactly which problems *don't* work in the current format may emerge—which types of problems don't map well to the ontology, which require new modeling techniques, what new practicality constraints may emerge, etc.—and updates or extensions to the framework itself may be proposed to alleviate these issues. Overall, the framework must simply continue to be used for it to continue to evolve. However, the long-term success of this framework is predicated on snowballing adoption rates, which faces obstacles such as the 'user friendliness' and the 'cost' of employing this approach [163]. While the cost of overcoming these is arguably a sound investment in the scheme of new product development, getting this ball rolling may still experience initial resistance. To overcome these obstacles, it is critical that the value proposition of the paradigm shift that is promoted by this framework is continued to be effectively communicated to potential adopters [163].

5.4.2. Further Developments of the EDC Framework

In regard to the latter track—developing the EDC framework itself—this work can perhaps offer more immediate direction. This framework captures a *slice* of the design process; one that covers embodiment design of a rich, embodied interaction, which specifies the actors and abstraction levels that are relevant. The larger process of design, however, extends beyond this 'slice,' both before it and afterwards. The simplest way to define this 'slice'—and, therefore, to identify areas in which to extend it—is through the Actor-Abstraction matrix itself. This matrix could be considered as a *modular component* that represents this 'slice,' which can then leverage the same A-A schema to identify directions for which it may be extended. For instance, the most obvious areas for extension would be in the two cells of this matrix that were omitted in this work—the *Context-How* and the *User-How*. These domains were omitted as they do not typically pertain to the designer of a given product, but could certainly capture influential decisions that are made, i.e., how the context and user were shaped to be the way that they are.

As an example, the former—the Context-How—could involve disciplines such as the *city planners* that design the roads in the case of the pneumatic steering column; clearly, this domain could be quite broad. The User-How, on the other hand, could involve the *marketing* for a product, i.e., how the user was primed to have the expectations or predispositions that they bring to the interaction (i.e., the User-What). This matrix could also be extended beyond the three abstraction levels defined here. For instance, the abstraction level below the Artifact-How could relate to the process variables for *manufacturing* the components of the artifact. As another example, the abstraction level above the User-Why could describe their purchase intention or *demand* for a product. The same goes for different actors; additional rows could potentially be added if other actors were deemed to be relevant in the future. The limits for how far this could be extended are not presently clear. Ultimately, this framework aims to promote multidisciplinary collaboration. These prospective extensions could continue in this stead by bringing in the business, manufacturing, marketing, and even architectural considerations to the design process. Fortuitously, the modular structure of the EDC framework's ontology is primed for such extensions.

5.5. Closing Remarks

Design is an ill-structured problem that has enumerable formulations and even more solutions. This process is something that is simultaneously so prevalent in our daily lives that we are constantly participating in it, but also something that is so important that innovations can change the world and failures can have dire consequences. This work establishes a new paradigm for a process that may be classically conceived as a series of linear decisions—analogous to a first-person perspective of venturing through passageways in a dark cave. This new paradigm shifts this perspective of this process to an overhead viewpoint—a *map* of this dark cave—in which all of the possible options for how to this journey could unfold may be simultaneously viewed and compared. With a design space map, design options may be rigorously and holistically assessed not only in terms of the product itself, but also in regard to the person who interacts with it, and the place or environment that situates their interaction. This map may then be used as a collaborative, multidisciplinary tool for making more informed design innovations, and structuring new methodological research and development.

There are a variety of existing design methods for constructing different types of design space maps, however each serves a fixed purpose. Alone, none have the flexibility to capture all of the different considerations that may be relevant for embodying a physically-interactive product in the real world. Rather than using these ready-made methods, this dissertation has provided the conceptual basis, modeling tools, and experimental techniques for empowering designers to create their own design space maps, which may be tailored to the problem at hand and operationalized uncover innovative solutions. The resulting knowledge base of this work has served to lay the groundwork for establishing the cartographic practice of *design space mapping*. Although much progress has been made, there is still a long path ahead of for further developing this framework, much of which is uncharted. However, there is optimism that the incentive structures for motivating this future work have been laid bare throughout this chapter. Even in the simplest terms of the ‘adventurer’ and the ‘dark cave,’ the value for maps—and the cartographers who create them—are ingrained in our world. For a designer who can serve in this cartographic role, the potential product successes are boundless—as one who can create their own map is never quite lost.

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