Knowledge engineering for additive manufacturing-driven customization

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**KNOWLEDGE ENGINEERING FOR
ADDITIVE MANUFACTURING-DRIVEN
CUSTOMIZATION**

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

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School of Mechanical and Aerospace Engineering
A thesis submitted to the Nanyang Technological University
in fulfillment of the requirements for the degree of
Doctor of Philosophy

2018

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

[12/04/2019]

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Authorship Attribution Statement

This thesis contains material from 6 papers published in the following peer-reviewed journals / from papers accepted at conferences in which I am listed as an author.

Chapter 4 is published as **Ko, H.**, Moon, S. K., "Contradicting Functions with Affordances in Design for Additive Manufacturing," ASME 2017 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Cleveland, Ohio, USA, August 6-9, 2017, Paper No. DETC2017-68157, 2017.

The contributions of the co-authors are as follows:

- I prepared the manuscript drafts.
- The manuscript was revised by me and A/Prof Moon.
- I and A/Prof Moon set the initial project direction and edited the manuscript drafts.
- I conducted literature reviews. A/Prof Moon provided guidance in collecting literature and formulating research problems.
- I set the framework. A/Prof Moon provided guidance in developing it into a formal framework.
- I developed the proposed method. A/Prof Moon provided guidance in comparing the method to the existing methods.
- I developed the proposed model. A/Prof Moon provided guidance in leveraging it in developing a knowledge base.
- This paper's case study was extended in Chapter 7. The contributions of the authors for this paper's case study will be explained in Chapter 7's authorship attribution statement below.

Chapter 5 is published as **Ko, H.**, Moon, S. K., and Otto, N. K., “Design Knowledge Representation to Support Personalised Additive Manufacturing,” Virtual and Physical Prototyping, Vol.10, No.4, pp.217-226, 2015.

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- I conducted literature reviews. A/Prof Moon provided guidance in collecting literature.
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- I developed the proposed method. A/Prof Moon provided guidance in conducting the simulation.
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- I discussed the case study results. A/Prof Moon provided guidance for future work.

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- I set the model and framework. A/Prof Moon and Prof Otto provided guidance in developing the framework.
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- I developed the proposed method and the framework. A/Prof Moon and Prof Wood provided guidance in developing them.
- I selected the case study scenario and compared the results to a relevant study.
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Abstract

The unique tool-less and layer-upon-layer capabilities of additive manufacturing (AM) have largely lessened manufacturing constraints and significantly broadened design freedom. AM offers new opportunities for developing customized products by achieving significant improvements in product performances and lower overall costs. The AM-enabled customization opportunities inevitably challenge traditionally design theories and methodologies (DTMs) that lack design knowledge for AM products. Here, to counteract this limitation, this study presents a novel methodology for constructing knowledge supporting DTMs for AM-enabled customization: customized design for AM (CDfAM). The CDfAM supports two main phases of design for additive manufacturing (DfAM): (1) opportunistic DfAM in a conceptual design phase and (2) restrictive DfAM in an embodiment design phase.

In terms of the knowledge construction for the opportunistic DfAM, it is essential to construct knowledge that supports to explore a customized design space enabled by AM's design freedom from the conceptual design phase. To address the challenge, this study provides a novel method for capturing knowledge of customized AM product behaviors. First, this study proposes an affordance-based DfAM framework by integrating the concept of affordance into three link chain models. Second, an affordance structure is proposed to develop a formal method for representing the knowledge of the customized AM product behaviors utilizing finite state automata.

In terms of the knowledge construction for the restrictive DfAM, this study presents a formal method for representing and reasoning customizable modular knowledge of design rules for AM. First, a novel structured modular hierarchy and associated formalisms of AM design rule elements are presented. Second, machine learning is employed to automatically learn design rules from AM data, which leverages the proposed design rule formalisms.

A knowledge graph is designed and built to demonstrate the proposed methodology. Case studies with AM products such as a transtibial prosthesis leg and AM data such as ex-situ AM measurement data provide illustrations in this study. The case studies show that the proposed methodology explicitly constructs structured and correlated AM design knowledge of customized AM product behaviors, product geometries, and additive manufacturability constraints. It is also shown that qualified design knowledge in the knowledge graph enhances automation of DfAM decision-making and data-driven knowledge constructions.

The proposed CDfAM methodology enables incorporating both customized AM product functionalities and additive manufacturability constraints into product designs. This study provides a foundation for AM knowledge construction and data- and knowledge-driven automation of DfAM decision-making. Validated design rules and representations are expected to contribute to developing international standards on AM design rules.

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List of Abbreviations

3D:	Three-dimensional
AbD:	Affordance-based Design
AM:	Additive Manufacturing
CAD:	Computer-added Design
CART:	Classification And Regression Tree
CDfAM:	Customized Design for Additive Manufacturing
DES:	Discrete Event System
DF:	Design Fundamental
DfAM:	Desing for Additive Manufacturing
DfM:	Design for Manufacturing
DfMA:	Design for Manufacturing and Assembly
DfMC:	Design for Mass Customziation
DfMP:	Design for Mass Personalization
DfX:	Design for X
DG:	Design Guideline
DP:	Design Principle
DR:	Design Rule
DRfAM:	Design Rule for Additive Manufacturing
DTM:	Design Theory and Methodology
EBM:	Elective Beam Melting
FbD:	Function-based Design

FDM: Fused Deposition Material

FSA: Finite State Automata

MC: Mass Customization

ML: Machine Learning

MP: Mass Personalization

OWL: Web Ontology Language

RDF: Resource Description Framework

RP: Rapid Prototyping

SED: Systematic Engineering Design

SLA: Stereolithography

SLS: Selective Laser Sintering

SLS: Selective Laser Melting

SQWRL: Semantic Query-enhanced Web Rule Language

SWRL: Semantic Web Rule Language

Chapter 1. Introduction to Design for Additive Manufacturing in Customized Products

1.1 Background

Additive manufacturing (AM) is a set of manufacturing technologies that join materials to produce three-dimensional (3D) objects from 3D solid models in layer-upon-layer ways, as opposed to subtractive manufacturing methodologies [1]. In product development with AM, the first step is design that develops conceptual and detailed idea of how the product will perform and be structured that will be produced by AM processes based on customer needs [2]. From a design perspective, AM's one of the most significant characteristics compared to the traditional subtractive or formative manufacturing processes is design freedom enabled by AM's unique tool-less and layer-upon-layer natures [3]. AM's advance toward end-use products beyond rapid prototyping (RP) challenges designers to integrate design considerations through product's lifecycle from the early design phase in Design for X (DfX) [4]. As a type of DfX, Design for AM (DfAM) has been proposed with its concentration on both the manufacturability constraints and design opportunities generated by AM processes. AM's uniqueness of design freedom offers new opportunities for DfAM to develop customized products with advanced performances with AM-enabled complex structures and material distributions [4].

Customization is inevitable for industry to survive in fragmented and diversified marketplaces [5]. In product design, there have been many efforts to address customization

issues in various industries [6]. Design for Mass Customization (DfMC) is a strategy that aims at customizing products and achieving mass production efficiency at the same time [7-11]. The design philosophy of DfMC has attracted academia and industry with its rationale to leverage product differentiation in efficient ways [8]. Traditional Mass Customization (MC) has been used the concepts of supply chain to design and manufacture customized products based on existing modules [12]. Product family design is an approach for MC that develops differentiated products from a common platform and designs individual products to diverse market segments [13].

The layer-upon-layer characteristics of AM show alignment with the product characteristics for MC, such as low-cost, high-quality, and design diversity [14] (shown in the Figure 1). AM technologies reduced the entry barrier for both the customer requirement acquisition at the front end and the product manufacturing at the back end [5]. Therefore, new research opportunities are open to designers to address the AM-enabled customization. However, the design theories and methodologies (DTMs) for AM should be different from conventional DTMs due to AM's unique capabilities and design freedom. Therefore, developing new DTMs for AM-enabled customization is a challenge for DfAM in AM applications where conventional methodologies fail to match the advantages and new constraints offered by AM. As AM is now beyond Rapid Prototyping (RP) and for the final product manufacturing, the conventional DTMs are challenged unavoidably [15]. The disadvantages of the conventional DTMs in AM are due to the lack of generic software and design principles rather than the lack of hardware [2]. Therefore, DfAM requires new design principle knowledge for the DfAM theories and methodologies.

Figure 1.1. Manufacturing supply characteristics including AM [14]

1.2 Motivation

In Mass Customization (MC), product variety and cost effectiveness play significant roles for satisfying customers in the market [8]. Companies have put lots of their efforts in developing a new variety of products while reducing production costs and lead-time without the sacrifice of performance and quality of the customized products [16]. To achieve MC from the early product development stage, Design for Mass Customization (DfMC) has been addressed varying customer needs from various the market segments [17]. Based on the varying customer needs from the market segments, DfMC assumes configuration mechanisms such as product architectures and pre-defined configuration models [7]. This is to configure a wide variety of product variants by the tools of modularity with commonalities

embedded in product platforms, with purposes of reusing proven designs among product families [7]. Here, a module is a physical chunk [18]. As such, DfMC has applied different modules to create product family design in order to improve responsiveness and flexibility from customers' needs and share expert knowledge on component and processes modules.

The recent trends of DfAM also seek to include customization for a market-of-one in the AM-enabled open design space with AM's direct digital design and manufacturing workflow and freeform features [19]. Typical markets for AM include bio-medical implants and devices, prostheses, aerospace, and home accessories where AM processes are utilized to satisfy market-of-one preferences and needs. For example, AM is utilized to manufacture personalized products in medical and dental industries such as hearing aids devices [20]. A few selected examples are graphically demonstrated in Figure 1.2.

The industry and academy sectors are looking for design and analysis methods for realizing customized products and seeking optimal solutions utilizing AM. However, so far the existing AM-enabled customization design approaches have been ad-hoc and case-dependent, which leads to the loss of systemicity in their approaches. Also, they have been mostly depending on the commercial Computer-aided Design (CAD), optimization, and 3D scanning tools without relevant common theoretical and methodological backgrounds.

Figure 1.2. Examples of AM-enabled customized products: A prosthetic arm with embedded systems (top), an additively manufactured prosthetic socket with strain gage directly manufactured on it (bottom-left), customized hearing aids (bottom-right)

In this context, the conventional DfMC methodologies have limitations to be directly applied for AM as follows.

First, DfAM is a set of design principles and methodologies centered on AM, therefore, DfAM does not need to deal with the traditional manufacturing's manufacturability constraints as the conventional design methodologies do while being centered on the manufacturability from subtractive and formative processes. The conventional MC's modules are produced with conventional manufacturing technologies and consequently necessitate investments in tooling, i.e., injection molding [21]. Therefore, the nature of the design rules, methods, and constraints for AM should change to ensure not to violate AM's manufacturing constraints that do not require the tooling investment. AM's constraints are

generated from the AM's unique process factors such as orientation, support structures, and tool path planning.

Second, DfAM should aid designers in exploring the new open design spaces resulted from AM's design freedom, which the conventional DfMC cannot support. The design freedom of AM is capable of flexibly producing complex parts with design changes and consequently, furthers the idea to manufacture customized products that efficiently adapt customer profile differences. To address these two limitations, this thesis mainly focuses on developing new systematic engineering methods and methodologies for constructing AM knowledge in customized products.

1.2.1 Exploration of AM-enabled and -restrictive Design Space for Customized Products

The advances in manufacturing capabilities of AM require new design methods and methodologies to take advantage of AM's unique capabilities in the design phase [22]. These unique capabilities of AM include [2]

- Shape complexity: capability to manufacture any shape that realizes the lot size of one, individualized form feature shapes, and performance-oriented shape optimization.
- Hierarchical complexity: capability to produce hierarchical multi-scale structures from the microstructure and mesostructure to the macrostructure at the part level.

- Material complexity: capability to control materials to be processes event at a point level at a time, which enables parts to have complex material compositions or controlled property gradients.
- Functional complexity: capability to product parts with integrated multiple design domain requirements that realize multi-functionalities such as embedded components

While the unique capabilities open new opportunities for DfAM, DfAM approaches can be categorized as two types in design making: (i) Opportunistic DfAM with concentrations on the design opportunities enabled by AM and (ii) Restrictive DfAM with the focus on manufacturability constraints generated by AM processes as shown in Figure 1.3 [4]. Opportunistic DfAM is a type of DfAM that aims to explore a new design space enabled by AM's design freedom with its focus on the unique capabilities offered only by AM. On the other hand, Restrictive DfAM is a type that concentrates on the restrictions of AM such as material properties or product manufacturability.

Figure 1.3. DfAM in customized products as an Opportunistic and Restrictive DfAM

In terms of Opportunistic DfAM, the design goal is to generate new designs with techniques that can search design solutions on the premise of no limit on the AM-enabled open feasible design space [4]. In this point of view, definitions of Opportunistic DfAM have been proposed depending on the approaches and focuses; an example of the definitions is “a methodology to maximize product performance through the synthesis of shapes, sizes, hierarchical structures” [3]. As this definition of DfAM highlights the maximization of product performances, there is a clear difference between DfAM and the most traditional Design for Manufacturing and Assembly (DfMA) that focuses on tailoring designs to achieve minimizations of manufacturing difficulties and cost. Other than aiming at increasing the efficiency of the manufacturing processes, Opportunistic DfAM’s aim of improving functional performances results in designs with complex external or internal hierarchies or consolidated joints that conventional manufacturing processes are not able to achieve [23].

Opportunistic DfAM needs to deal with customized fabrications. AM’s ability to flexibly realize design changes is suitable for products with customized functionalities and shapes [24]. As the tool-less and layer-upon-layer natures of AM do not require additional costs and times to realize an individualized design, AM enables designers to focus on the market-of-one instead of market-of-few. Additionally, while AM is capable of being more energy intensive per unit manufactured compared to the traditional processes, it is able to produce units to precisely match the demand: make-to-order [25]. When AM is used, there are cases wherein AM’s slower cycle time is rewarded by the values of customized products with consolidated parts, reduced material waste, increased demand for customized geometry, and so on [24]. In this context, a challenge for Opportunistic DfAM is to develop design

methods and methodologies that can support to explore large and complex customized design spaces.

On the other hand, in Restrictive DfAM, designers are challenged to identify how to incorporate AM's manufacturability in AM technology differences into the AM part's geometries [26]. To address this challenge, a set of new design theories and methodologies have been proposed with their focuses on process-structure-property (PSP) correlations in AM [27-29]. Then, the correlation studies in DfAM have been related to design rules that can provide designs allowable within constraining correlations of AM feature design, process, and material [30]. The design rules for AM (DRfAM) help to select optimum AM processes settings and relevant materials or enable appropriate designs for a given AM processes [26]. Also, studied on correlations between AM process parameters, process signatures, and product quality enable measuring AM part tolerances, surface roughness, and defects that prevented AM from being accepted in high-value or mission-critical industry applications [31]. Therefore, the DRfAM provides methods to control manufacturing costs and time as well as product qualities in both design and manufacturing life-cycle phases. To provide fundamental principles that are utilizable in different DfAM applications, research on the DRfAM has provided design fundamentals and principles as modular knowledge blocks that designers can customize them as needed by modifying, extending, or reconfiguring the knowledge blocks [30].

1.2.2 Development of DfAM Knowledge for Systematic Engineering Design (SED)

Systematic Engineering Design (SED) is a set of ordered and stepwise design approaches to rationalize the product design and manufacturing processes with different levels of design abstractions from the early design phase to the manufacturing phase in the product development [32]. The advantage of utilizing SED is to structure design problems and tasks in formal and problem-independent ways and to concretize the design processes stepwise, which enables to select and optimize the design solutions from the early stage of the design process. SED approaches have four successive design stages of task clarification, conceptual, embodiment, and detail phases [32].

Even though the adoption of AM provides new challenges to the SED processes for product innovations, as the AM's influence in the SED's different design phases are graphically demonstrated in Figure 1.4, most of the designers and developers have not included the AM's influences in the SED practices so far [4]. Consequently, the previous SED studies fail to adopt AM's capability of shape, hierarchical, functional, and material complexities and AM's process constraints to the customized product designs throughout the whole the product design process.

Most of the current DfAM studies have presented design methods that primarily i) focus on the improvement of parts' functional performance in the macroscale, mesoscale, and microscale [33] or ii) investigate the effects of AM's manufacturability in the design optimization phases [34], while they are commonly conducted at the part-level studies. These part-level studies have a limitation that they focus on design and performance only at the

individual feature level (e.g. minimum wall thickness) in the embodiment and detailed design phases. Therefore, new DfAM knowledge is required for the different phases of SED processes to link AM-enabled designs at the product level from the conceptual design phase to the form feature level the embodiment design phase.

*Source: <http://www.d4am.eng.cam.ac.uk>

Figure 1.4. SED process and product realization with AM: AM's influence on SED phases

DfMC's conventional modular approaches are based on SED. However, there are clear differences between DfAM and DfMC in pursuing customized products as follows. Firstly, DfAM pursues Mass Personalization (MP) that achieves individualized customization based on market-of-one, as the tool-less and layer-upon-layer natures of AM do not require additional costs and times to realize an individualized design and provides advanced design flexibility. MP diversifies products at an individual customer level (market-of-one), while MC accomplishes the product diversification at a market-segment level

(market-of-few). This is in order for MP to increase a product's personal relevance to the individuals at individual levels compared to MC [7]. Secondly, DfAM realizes make-to-order MP beyond MC's configuration-to-order product lines [7]. MP changes the basic design features according to individual customer profile and customer's interactive behaviors. In this point of view, a major design tool commonly used in MP is design of human-product interactions [7]. In this sense, a new DfAM methodology needs to consider human-product interaction knowledge to adopt MP into DfAM.

To sum up, although DfAM provides potential to improve the level of customization in product design with AM's unique capabilities, the conventional design methods and methodologies have had drawbacks to prevent themselves from achieving AM-enabled opportunities. To embrace the AM' capabilities and restrictions in the product design process with the concept of product customization, new DfAM knowledge needs to be considered for SED that can be applied from the early stage of SED's four successive design processes: task clarification, conceptual, embodiment, and detail design phases.

1.3 Research Objective

The principal objective of this thesis is to develop a formal methodology for constructing design knowledge for AM-enabled customization: Customized Design for Additive Manufacturing (CDfAM). A novel methodology for AM, CDfAM, provides designers with quantitative and qualitative knowledge needed in the conceptual design phase to the embodiment design phase of SED for developing AM-enabled customized products. Realizing AM-enabled customization can be achieved by investigating product's desired

functional behaviors driven by AM in the conceptual design phase and link them to physical working structures in the embodiment design phase based on the SED approach. However, current DfAM only emphasizes AM's capabilities and limitations without considering SED's design phases at the product level. At the same time the traditional SED methodologies are not able to embrace AM's characteristics since they were developed for traditional manufacturing processes. Namely, connections between DfAM and SED have not been clear, so that it hinders the product design towards AM-enabled customization. The design knowledge development presented in the thesis will help build clear links between customized product design and AM.

To achieve the main objective, the following sub-objectives are investigated as summarized in Figure 1.5.

- To identify the influence of AM's capability (shape, hierarchical, material, functional complexities) to the design tasks of the conceptual and embodiment design phases of SED
- To provide a novel CDfAM framework to identify systemic links between the heterogeneous domains of performance, design, process, and material in AM to reflect them into design processes
- To compare the two most representative functional behavior representation tools in SED, function [32, 35] and affordance [36], for selecting a functionality modeling tool in DfAM for customized products
- To develop a new concept of functional behavior knowledge representation and a relevant formal method for AM-enabled customization
- To propose a formal method for representing design rules that extends existing

formalisms and language sets

- To construct an ontology as a CDfAM knowledge base by matching the ontology's elements to the proposed hierarchies and associated formalisms that support knowledge representation, extraction, and reasoning in DfAM applications
- To apply the proposed methods to the AM's unique customization product design case studies for model validations and knowledge improvements
- To build CDfAM as a formal design methodology with the adoption of proposed formalisms and systemic analyses that supports to improve the traditional SED processes

Figure 1.5. Research objectives of the thesis supporting product development process with AM

1.4 Research Contribution

The main contribution of this research is to develop a novel knowledge engineering methodology for DfAM in customized product developments. SED's high-level design processes are adopted to identify unique design goals and tasks that DfAM's conceptual and embodiment design phases need to address with newly developed formal methods for constructing DfAM knowledge.

Another contribution of the thesis is to identify existing SED tools' advantages and limitations for the functional behavior modeling phase of DfAM while considering AM-enabled customization opportunities. There have been representative design tools for capturing functional design requirements in formal structures such as function structures or affordance structures. This thesis contrasts function-based methods with affordance-based methods based on their pros and cons in their characteristics when they are applied to AM. Then, this thesis shows how affordance can be leveraged in the conceptual design phase of DfAM to fulfill the objectives of achieving AM-enabled customization with enhanced systematic approaches.

This thesis also proposes novel design methods for representing customizable design knowledge in AM product developments. First, an affordance structure is proposed as a formal modeling technique for representing AM-enabled customized product behaviors. Second, a formal method for representing design rule knowledge is presented as a customizable modular method for incorporating AM's manufacturability into AM feature's geometries. Third, this thesis constructs a knowledge base with reconfigurable CDfAM

knowledge blocks captured in an ontology which allows a semantic representation and automated knowledge reasoning.

1.5 Research Scope

The scope of this study includes literature reviews, a selection of design tools based on the theoretical comparisons and discussions, and a development of new design methods and a system for AM. The literature review includes identifying and refining research problems and research gaps. This process involves identifying the research goals that this research aims to achieve by obtaining the overview of the current situations and existing studies. Through the literature reviews, this thesis understands the fundamental concept of the related studies, finds out research gaps, and sets the research objective.

For selecting design tools and developing methods for AM, design tools in the conceptual and embodiment design phases are considered as shown in Figure 1.4; especially such phases' design techniques are considered mainly in terms of representing product functional behaviors and design rules for AM. Also, this research focuses on formal representation methods that can systemically capture fundamental design knowledge elements and their relationships associated with AM-driven customization.

In terms of DfAM, both of Opportunistic DfAM and Restrictive DfAM are in the scope. A DfAM framework is provided with connected design flows which show how to incorporate AM's capability of shape, hierarchical, material, and functional complexities and additive manufacturability into AM product designs for customization applications (examples are shown in Figure 1.2). The framework connects the AM-enabled product

performances and design constraints from manufacturing processes such as energy source types, build chamber sizes, and material types, which considers both frontend and backend sides of SED processes.

1.6 Overview of the Thesis

This thesis is organized according to the requirements from School of Mechanical and Aerospace Engineering (MAE) of Nanyang Technological University (NTU). This thesis is organized with 8 chapters. The overview of the chapters is represented in Figure 1.6.

Chapter 1 introduces the concept of DfAM in customized product developments and provides the backgrounds, motivations, objectives, and scopes of developing the CDfAM methodology. Chapter 2 elaborates literature reviews of the related state-of-the-art research. The existing design theories, methods, methodologies, and applications are reviewed along with Opportunistic and Restrictive DfAM, AM-enabled customization, and affordance-based SED. The proposed CDfAM framework is illustrated in Chapter 3. Chapter 4 contrasts function-based methods to affordance-based methods based on their advantages and limitations when they are utilized in DfAM to identify design tools suitable from the early phase of DfAM. Chapter 5 introduces an affordance-based formal modeling method as an advanced product functionality knowledge representation method. Chapter 6 presents a systematic method for representing AM design rule knowledge. Chapter 7 demonstrates case studies in that the proposed methodology is performed and evaluated with studies on a seat, a prosthetic leg socket, a thin wall feature, an overhang feature, a honeycomb structure, and analytics on ex-situ measurement AM data. Then, the results are discussed. Chapter 8 is the

final chapter and highlights the summary of the thesis, contributions and limitations of current work, directions of future work, and publications resulting from the thesis.

Figure 1.6. Overview of the thesis

Chapter 2. Literature Reviews

Based on the research focus identified in Chapter 1, literature reviews on relevant studies are presented in this chapter. The relevant studies can break down into many methods and methodologies that support specific AM processes and/or design processes. As shown in Figure 2.1, the relevant studies can be clustered into 5 groups: AM technologies, Opportunistic DfAM, Restrictive DfAM, AM-enabled Customization, and Affordance-based SED.

Figure 2.1. Relevant literature reviewed for CDfAM

2.1 AM Technologies

Contrary to traditional subtractive or formative manufacturing technologies, AM produces parts through successive tool-less and layer-upon-layer fabrication processes. AM processes such as Stereolithography (SLA), Fused Deposition Material (FDM), Selective Laser Sintering (SLS), Selective Laser Melting (SLM), Elective Beam Melting (EBM), and Aerosoljet were invented initially with the purpose of Rapid Prototyping (RP) and they have been gradually advanced toward achieving the final product manufacture [37-41]. The ASTM F42 committee has categorized AM processes into seven areas as shown in Table 2.1.

Table 2.1. ASTM F42 AM process categorization

Categorization	Example
Vat photopolymerization	SLA
Material jetting	Polyjet, Aerosoljet
Binder jetting	Processes by Powder and Binder
Material extrusion	FDM
Powder bed fusion	SLS, SLM, EBM
Sheet lamination	Sheet Forming
Directed energy deposition	Laser Cladding

The generic AM process starts with design requirements and 3D CAD information, and the CAD information is translated into file formats such as STereoLithographic (STL) file format or AM file format (AMF) [42] by slicing the solid CAD models layer-upon-layer. STL has been a traditional way of describing a CAD model's geometry information for AM while AMF extends the STL format to contain more product information such as dimensions, color, and material. A STL or AMF file is sent to an AM equipment where parts are manufactured layer-upon-layer. Then, post-processing could be necessary [43].

The first step of the AM is a design step that generates the idea of how the product are shaped and functioning [2]. In the design phase, designers transform customer needs into parts physical and functional specifications [44]. AM' capability gives designers opportunities to rethink product customization.

2.2 Opportunistic Design for Additive Manufacturing

2.2.1 AM's Unique Capabilities in Product Design

As design is the first step that starts with concepts and requirements of parts, assemblies, and progresses [45], it is significant that the functionality and manufacturability aspects should be considered into the design phase as early as possible [29]. In the viewpoint of Design for X [46, 47], Design for Manufacturing and Assembly (DfMA) is to design products by considering constraints and capabilities of manufacturing and assembly processes [3, 48]. Conventional DfMA mainly requires designers to understand the manufacturing and assembly constraints provided by available manufacturing and assembly methods. Designs

without concerning manufacturing and assembly result in ineffective manufacturing and assembly consequences [29].

From the conventional DfMA perspective, the Handbook for Product Design for Manufacture [49] and Product Design for Manufacture and Assembly [45] well demonstrates the rules and practices of DfMA. In the viewpoint of AM-oriented Design for Additive Manufacturing (DfAM), designers should consider a number of AM process-related parameters in the design process. These are the challenges for Restrictive DfAM as a DfM in AM applications where conventional DfMA fails to embrace manufacturing constraints provided by AM.

In addition, the advances in manufacturing capabilities of AM require new DfX approaches in order to take benefits of AM's unique capabilities. From a design perspective, an advantage from the layer-based additive nature of AM over conventional manufacturing processes is the AM-enabled design freedom that provides new opportunities for customizations, performance improvements, and lower manufacturing costs [3, 15]. AM's unique capabilities that enable the design freedom include the following four categories: shape complexity, hierarchical complexity, material complexity, and functional complexity as presented in Table 2.2 [3, 15, 50].

Table 2.2. AM's unique capabilities

Types	Definition	Descriptions	Examples
Shape complexity	<ul style="list-style-type: none"> • AM's capability to build virtually any shape 	<ul style="list-style-type: none"> • Lot size of one is efficiently achievable. • Customized geometries are efficiently manufactured. • Shape can be better optimized for design requirements. 	<ul style="list-style-type: none"> • Bio-inspired form feature geometries • Form feature with varying thicknesses • Product architecture with custom geometry
Hierarchical complexity	<ul style="list-style-type: none"> • AM's capability to build form features across multiple size scales 	<ul style="list-style-type: none"> • AM can fabricate microstructure, mesostructured, and macrostructure. • AM structures can add other features inside of them 	<ul style="list-style-type: none"> • Lattice structures • Stochastic structures
Functional complexity	<ul style="list-style-type: none"> • AM's capability to produce multi-functional devices in one build 	<ul style="list-style-type: none"> • Surfaces and inside of AM parts can integrate multiple design domains functionalities. • AM can manufacture product mechanisms and embedded components can directly. 	<ul style="list-style-type: none"> • Functional product with embedded electronics or sensors • Integrated heat exchange and cooling systems
Material complexity	<ul style="list-style-type: none"> • AM's capability to process material as a single material or as composite materials at a time 	<ul style="list-style-type: none"> • AM manufactures parts with complex material compositions and designed property gradients 	<ul style="list-style-type: none"> • Multi-materials in a form feature • Functionally graded materials

2.2.2 Functionality-oriented Design Methods and Methodologies

The challenge for Opportunistic DfAM is to develop design methods that can explore AM's large and complex design spaces generated the unique capabilities in Table 2.2. There have

been many research efforts for design optimizations in Opportunistic DfAM so far and they are mostly classified into macroscale, mesoscale, and microscale [19, 33] as shown in Figure 2.2. Mesoscale is for DfAM methods centered on AM feature sizes between 0.1 and 10 mm. Macroscale is for DfAM methods centered on AM feature sizes bigger than 10 mm. Microscale is for DfAM methods centered on AM feature smaller than mesoscale. [33]. Design feature examples in different scales are shown in Figure 2.4. For example, on a mesoscale, Figure 2.3 shows cellular structures that are widely utilized in AM to achieve an improved performance that leverages AM's unique capabilities [33]. According to literature reviews on the design methods for the three scales by Tang and Zhao [33], the design issues in each scale are as follows:

- Macroscale: AM structural optimization (size, shape and topology optimizations) and product customization
- Mesoscale: cellular structure design and optimization
- Microscale: control of the fabrication parameters for certain microstructure to improve the performance of the AM part such as Functionally Graded Materials (FGMs)

Figure 2.2. Classification of opportunistic DfAM

Name	Cell topology
<i>2D Lattice</i>	
Square Cell
Rectangular Cell
Hexagonal Cell
Triangle Cell (Pack of cells)
Mix Cell (Pack of cells)
Kagome Cell (Pack of cells)
<i>3D lattice</i>	
Grid Cell
Octet-truss Cell
X-shape Cell
Face Centered Cubic Cell
Body Centered Cubic Cell
Simplest Foam Model Cell

Figure 2.3. Common cell topologies [33]

Figure 2.4. Design feature examples in (a) macroscale, (b) mesoscale, and (c) microscale [33]

As the previous Opportunistic DfAM studies on the macroscale, mesoscale, and microscale are done only at the part level, there are DfAM issues to be addressed by the DfAM studies at the product level [4, 19, 33, 50, 51] that take into account AM-enabled functionalities. In the product level DfAM, related issues can be as follows:

- Functionality analysis and representation [52]
- Part consolidation [51, 53-55]
- Product with embedded features and electronics [56, 57]
- Direct production of assemblies [19]

The functionality analysis and representation are a starting point of the conceptual design phase of DfAM. In terms of functionality representation in DfAM, Boyard, Rivette [52] proposed a graph-based functionality representation method as shown in Figure 2.5.

The method proposed by Boyard, Rivette [52] is based on a systematic representation of functional behaviors as functionalities utilizing the concept of function. A function from the study of Boyard, Rivette [52] is extracted from functional specifications based on customer needs. Each function is represented as a sphere and the functions' relationships are the nodes in the graphical representation. Boyard, Rivette [52] noted that the functions as spheres are then grouped based on the set of rules that DfAM needs to define, e.g. a geometric appearance. However, their study failed to propose the grouping mechanisms and related DfAM rules that can differentiate itself from the traditional function-based design methods such as function structures [35, 58].

The traditional function structures consist of subfunctions and flows of energy, material, and information between the subfunctions as shown in Figure 2.6. The function's basic expressions are 'active verb-noun objective' pairs and the examples are 'increase pressure', 'transfer torque', and 'reduce speed' [35, 58]. The energy, material, and information flows are defined as follows [35, 58]:

- Energy: an energy-type input/output flows for energy exchanges between functions
- Material: a material-type input/output flows for material exchanges between functions
- Information: data for a device's decision-making or sensory data provided to or by functions

Figure 2.5. An example of function graph [52]

Figure 2.6. A generic function structure format [35]

To reflect the functionalities to the physical form features and geometric/topological entities of additively manufactured parts and products, functional surface (FS) and functional volume (FV) have been proposed [59, 60]. The definitions of FS and FV are as follows:

- FS: an AM feature's surface designed for functionalities such as component interacting surfaces or loading-bearing surfaces
- FV: an AM feature's geometrical volume that links the FSs to support the FSs in achieving the functional requirements

Figure 2.7 shows an example of FSs and FVs. The FSs in Figure 2.7 are designed based on different functional requirements generated from the previous design stages of functionality representations. Tang, Mak [61] utilized FSs and FVs in developing a design methodology to reduce product environmental impacts. They used FSs and FVs for a design optimization to deal with environmental issues with AM.

Figure 2.7. An example of functional surfaces and a functional volume [61]

2.3 Restrictive Design for Additive Manufacturing: Design Rule for AM

2.3.1 Design Rules for Incorporating Manufacturability in AM

While Opportunistic DfAM considers the improvement of parts' functional performance at product and part levels, Restrictive DfAM involves design theories and methodologies that incorporate AM's manufacturability constraints into part designs as a type of AM-oriented Design for Manufacturability (DfM) [4]. DfM considers manufacturing constraints to

identify manufacturing problems in the design phases to reduce the lead time consumed in product development as well as to improve product quality [62]. Mentioning an earlier study on Restrictive DfAM, Hague et al. [63, 64] discuss the consequences of AM constraints on design and on designers from their studies. Hague et al. [63, 64] addressed the possible design and manufacturing issues such as no cost for tolling to amortize into the parts produces, design freedom, material selections, and customer-driven and collaborative design. Hague's group [63, 65, 66] also focuses on studying the impact of AM on DfM by comparing AM and injection molding.

In Restrictive DfAM, to systemically link design, material, and process domains in AM, Rosen [28], Chu et al. [27] and Doubrovski et al. [67] based their approaches on the Three Link Chain Model (3LCM) [68]. 3LCM of which framework is shown in Figure 2.8 studies the relationships among the domains of performances, properties, structures, and processes.

Figure 2.8. 3LCM with linear relationships [68]

The linear structure of the 3LCM provides links between the science and engineering with its i) deductive cause-and-effect logic and ii) inductive goal-means relations. Suh and Albano [69, 70] used the paradigm with their axiomatic design approach in engineering design.

Rosen [28] and Chu et al. [27] proposed a formal DfAM framework based on the Process-Structure-Property-Behavior relationships based upon the 3LCM. In the design of cellular materials, they proposed a hierarchy into their formal DfAM framework in order to capture the geometric complexity at the mesostructured level. They intended to control part behaviors by changing cellular structure geometry as well as material microstructure based on the proposed Process-Structure-Property-Behavior relationships. Figure 2.9 illustrates this approach.

Figure 2.9. DFAM framework that adopts the 3LCM [27]

Rosen [28] also proposed Manufacturable Elements (MELs). MELs represent process planning information with a part's discretized geometric regions and enables form feature-

oriented process simulations. Chen and Wang [71] adopted the Process-Structure-Property-Behavior framework to introduce a DfAM framework to design AM components with AM mesostructures.

Figure 2.10. DfAM system framework [28]

For a knowledge documentation, Yim and Rosen [72] presented an ontology model for AM utilizing Description Logic (DL), ALE. Using the ontology, designers can retrieve DfAM problem knowledge to formulate new problems. Also, a strategy on ontology-based knowledge modeling and reuse was proposed by Liu and Rosen [73] for process planning in AM. They took advantages of ontology approaches that provide reusable and shareable design and process information models. In their study, Liu and Rosen [73] classified design features in AM as shown in Figure 2.11.

Figure 2.11. The classification of design feature in layer manufacturing [73]

Most of the studies on DfM have approaches of feature CAD model decompositions for manufacturability analysis [74, 75]. A design feature is defined depending on given design contexts with corresponding semantic meanings generated from various domains such as design, process planning, manufacture, and cost estimation [76]. Therefore, in feature decomposition-based DfM approaches, manufacturing features are defined based upon manufacturing types. For example, process planning defines machining features [77]. AM requires different manufacturing features due to its unique layer-upon-layer nature. AM features are defined for certain DfM goals in AM such as geometry tolerance and surface quality evaluations [78, 79] or process planning [80]. Then, specific design rules have been identified for AM features for assessing the manufacturability of each feature.

In downstream design processes, identified design rules can be applied to the enhanced geometric freedom associated with AM such as topology-optimized or cellular or consolidated part structures to ensure manufacturability. For example, a design generated using topology optimization can be decomposed into sub-features based on the manufacturable and non-manufacturable geometry regions that are identifiable using validated design rules. Then, redesign of such complex features is done by modifying sub-features' internal and external boundary regions in an iterative design optimization process for a manufacturability evaluation purpose such as a support structure evaluation (see Figure 2.12 [34]).

Figure 2.12. (a) Topology optimized cantilever beam built with support (left) and without support (center), redesigned to be self-supporting (right) using decomposition-based manufacturability analysis for Fused Deposition Modelling process. Arrows indicate two separated geometric regions of build failures if no support strategy is implemented. (b) Decomposed geometric regions where build support strategies are applied: Machine support (left), optimal support. (center), no support – failed (right).

Such design tasks for incorporating AM's manufacturability require fundamental and reusable design rules that are adaptable to design requirement changes generated in various applications and AM contexts. Whether design- and AM process-dependent or independent, design rules are developed based on critical design requirements associated with AM's unique parameters and manufacturing features such as minimum thickness for thin wall features, manufacturable inclination angles and allowable bridging distance for overhangs, and the robust accommodation of heat transfer [74]. For example, Figure 2.13 shows benchmark artifacts with surface roughness for SLM parts with diverse build angles [19]. In this case, design rules are based on the surface geometry of benchmark artifacts, orientation angles, SLM process control parameters and material types and properties.

Figure 2.13. A benchmark study for surface roughness with different build angles

To guarantee the reusability of design rules in DfAM applications, design rules were required to be formally represented and documented by a modular method while explicitly showing the associated relationships of AM parameters and features [26, 30]. For these purposes, the studies of design rules have been conducted to achieve explicit modular representations that enable modifications, extensions, and reconfigurations of design rule knowledge as needed [26, 30].

2.3.2 Design Rule Representation Methods for AM

Design guidelines guide designers to take advantage of the capabilities of AM processes and understand the limitations of them when using AM for product developments. The design guideline knowledge for AM can be achieved from experimental reports [81]. Even though design guidelines at the best provide the best practices to designers, they lack formalisms and methodologies for explicitly representing AM parameters and their relationships relevant to AM features' critical design requirements. Therefore, they have limited themselves from constraining an explicit design space and clearly defining geometry boundaries of a design feature for a given process and material parameters. Formalisms are required for efficiently utilizing them in data analytics, design automation and optimizations, expert systems, etc [26].

On the other hand, design rules provide a common language as a formal structure for describing parametric relationships for critical additive manufacturability-related design requirements; therefore, formal structures interpret design rule knowledge consistently [30]. Designers can dynamically reconfigure the language sets using modular knowledge blocks, rather than creating them by themselves. In this sense, design guidelines and design rules have had a difference in their definitions in AM as follows [30].

- Design guideline: validated text- and illustration-based information for understanding AM categories, processes, operating procedures and best practices.
- Design rule: a prescribed design guide, a valid generation, or a standard of judgment used to influence and constrain a design space

In design rule representations, design rules re-write and represent design guidelines using an expression formalized as [30]

Category (type), if {conditions} then {consequences};

where conditions and consequences consist of two types of modular components: design fundamentals and design principles [26]. The design fundamentals are defined as follows:

- Design fundamentals: basic elements extracted from design guidelines and used to compose design principles and subsequent design rules.

The design fundamentals have had two types: primitives and modules as follows and compared in Table 2.3 [30].

- Primitives: an explicit, single, identifiable concept that new concepts can be generated with
- Modules: a physical chunk, an implicit form feature and geometric entity concept

Table 2.3. Types of design fundamentals and their comparison [30]

	Module	Primitive
Semantic connotation	Implicit (designs)	Explicit (guidelines or constraints)
Methods of generation	Derived or developed	Measured or defined
Dependency	Yes	No

Primitives represent fundamental concepts of physical parameters or variables observed in AM. Among the design fundamentals, primitives include and are classified into three groups, geometry parameters (G), process parameters (P), and material parameters (M). Modules represent AM features ($AM_{Feature}$) [26].

Once the design fundamentals are defined, the design principles relate design fundamentals with one another. The design principles have been defined as follows while the existing ones are formulized as Equation (2.1) based on the sources of generation of primitives shown in Figure 2.14.

- Design principles: foundational and logical correlations between the modules and primitives

$$AM_{Feature}=f(G, P, M) \quad (2.1)$$

Figure 2.14. (a) Three basic elements for function development [82] (b) three different sources of generation of primitives [30]

In Equation (2.1), the relationship function f represents $AM_{Feature}$ by associating relevant G , P , and M . Based on Equation (2.1), design principles have related modules to correlated primitives using functionally specific sets. Primitives provide measurable entities with that design and AM constraints can be represented in Equation (2.1) [26]. Then, modules such as AM features are identified. The modules as implicit design-related entities are explicitly represented by the constraints or guidelines captured in the primitives in design

principles [30]. Design rule representations based on such modules and primitive and their formal relationships have supported reusability, extensibility, readability and computability, as shown in Figure 2.15 [30]. The design principles have been explicitly abstracted with design fundamentals and subsequently, design rules have been interpreted and implemented more explicitly and efficiently, while the implicit $AM_{Feature}$ is represented by the association of the explicit primitives.

Figure 2.15. Design fundamentals, principles and rules in establishing modularity [30]

Deriving design principles based on AM features have enabled relating design rules to feature designs, quantifying part quality in design rules based on feature-based measurements, and utilizing literature on feature-based design of experiments and measurement such as AM benchmark studies [26]. Also, more implementation contexts that are specific to materials, processes, product functionalities, and applications have been added by design rules' variant expressions and conditional "IF-THEN statements". Therefore, the

design principles and rules have enabled synthesizing a context-to-primitive knowledge transformation and vice versa.

Studies on AM knowledge documentation started to focus on design rule knowledge. To name a few, Dinar and Rosen [83] developed a DfAM knowledge base that can emerge from identifying DfAM needs of design rule documentations using the Web Ontology Language (OWL). Then, Kim et al. [84, 85] presented studies that help to retrieve design recommendations for improving manufacturability by reasoning with Semantic Query-enhanced Web Rule Language (SQWRL). The proposed DfAM ontologies represent DfAM knowledge based on the entities of AM event, Manufacturing feature, Design feature, Design parameter, Process parameter, Machine, and Material, Reference entity which point to the source of the information as well as their relationships. The DFAM ontologies can store design and process knowledge and support tutoring systems and CAD tools. Sample models and a network graph from [83] is shown in Figure 2.16.

Figure 2.16. Sample models and fabricated design features using a DfAM ontology
(left), Network graph with entities and instances (right)

2.4 Design for AM-enabled Customization

2.4.1 Design for Mass Customization

As being specified in Chapter 1, AM holds promise in customized products development [21]. In Mass Customization (MC), what traditionally restricts designers is conventional processes' manufacturing flexibility that provides a limited design space for customized parts and products [5]. However, many studies show that the AM's capability of design freedom that is able to realize geometrically [65]. AM enables the transition from mass production to the customization by flexibly changing the ways of delivering the physical products into

layer-upon-layer ways. The product characteristics for MC in Table 2.4 well displays alignment with the characteristics of AM [14].

Table 2.4. Mass customization contrasted with mass production

Mass production	Mass customization
Stable demand	Fragmented demand
Large homogeneous markets	Heterogeneous niches
Low-cost, consistent quality, standardized goods and services	Low cost, high-quality, customized goods and services
Long product development cycles	Short product development cycles
Long product life cycles	Short product development cycles

Now AM technologies are used in Direct Digital Manufacturing (DDM) final components productions [86]. With the advance of AM toward achieving DDM beyond prototyping, the importance of the customization increases while the end-life cycle with product user interactions is considered in the earlier product design phases for AM. There have been many customization applications using AM technologies in DDM. Personalized hearing aid shells were successful applications of DDM [87-89]. Also, there have been applications of AM for custom medical implants and craniomaxillofacial (jaws and skulls) [88]. These represent excellent examples of MC using DDM.

2.4.2 Design for Mass Personalization

Similar to the main concept of Design for Mass Customization (DfMC), the concept of Design for Mass Personalization (DfMP) is to satisfy each customer as an individual [7]. The prevailing practice of MC so far in design is, as Tseng, Jiao [7] addressed, to identify needs at a market-segment level. Such approaches were conducted with families of products. Product family approaches provide common building blocks of modules with product fulfilment design and manufacturing processes. Thus, such approaches reused various elements of design and manufacturing in matching product variety to customer needs [90]. However, a product diverges at an individual customer level in Mass Personalization (MP), while MC achieves product diversification at a market-segment level [91].

Pine [92] initiated the studies of MC while developing a viable strategy. Then, Tseng and Hu [5] showed that MP needs to relate products to individuals more closely compared to MC. Also in terms of customer participants in the design process, personalization involves proactive customer participants in learning, manufacturing, and evaluation stages, while customer participants are passive and limited in customization [5].

MP is a limited scope of MC. MP focuses on a market segment of one while MC is at a market segment of few. To see the differences between MP and MC, this study refers to the research work of Tseng et al. [7]; MP goes beyond configuration-to-order product lines and needs to identify affective and cognitive needs to leverage product functionality to diversity product lines beyond the original products [7].

With the capability of increased design freedoms to fabricate parts with high complexities, the embodiments of AM technologies are appropriate for fabricating

personalized products [24]. Typical markets of AM include aerospace, high-end automotive, and bio-medical. Also, AM processes are used for individual needs such as home accessories [24]. There are AM-enabled opportunities to consolidate parts to reduce material waste for customized geometry [24]. Hence, to realize the AM-enabled personalization, the MP design consideration such as customer profiles and human-product interactive behavior patterns needs to be methodologically integrated with capabilities and/or limitations of possible AM technologies.

One example with increased customer involvements in the AM-related design process is shown in the research work of Campbell, De Beer [93]. To increase the level of customer participation, Campbell, De Beer [93] proposed a design method: Customer Interaction with Functional Prototypes. Their method facilitates customer interactions in product development processes (shown in Figure 2.17). Their customization method enabled the aesthetic and ergonomic aspects for both simple consumer products and more complex products. Such user information is used to optimize the functional aspects of a customized product. In their method, AM models are used to elicit customer feedback. Such study shows the AM's fitness in MP, however, the study of Campbell, De Beer [93] fell short of achieving final products beyond prototypes.

Design evolution through customer interaction

Figure 2.17. Design process of Customer Interaction with Functional Prototypes [93]

To name relevant AM studies more, Tuck et al. [14] present a design method for developing a body-fitting customized seat utilizing 3D laser scanning, reverse engineering, and SLA. They defined the customization process as (a) Geometry capture; (b) Scanning; (c) Data manipulation; and (d) Manufacture. Their study shows a parent model identifying the generic customization process and demonstrates that the pressure distribution under the individual's buttocks can affect the body-fitting design and thus comfort is analyzed. Pallari et al [94] presented their study of foot orthoses for rheumatoid arthritis using SLS. A design and AM process for developing customized medical devices is also shown in Figure 2.18 [95].

Figure 2.18. Design and AM process for developing customized medical device

2.5 Affordance-based Systematic Engineering Design

Traditionally, the majority of SED methods are based on Simon's [96] use of function [97]. Function has been a foundational concept of design and design processes have considered developing desired function models as one of the primary goals [98]. Pahl and Beitz [99] defined SED as a structured design process based on function. In their work, functions are represented as relationships based on system inputs and outputs of energy, materials, and information [98] as shown in Figure 2.6. The main characteristic of Pahl and Beitz's function is that function is a device-centric internal device behavior [97].

While function structures are widely used, Maier and Fadel [100] addressed limitations that function-based design (FbD) has. The limitation is, for example, designers encounter trouble when using FbD approaches to represent user-artifact and artifact-artifact interaction. This is because design problems that do not need the transformation of energy, materials, and information are outside of the scope of FbD methods. Then, Affordance-based

Design (AbD) was introduced based a relational theory for design [100]. Table 2.5 briefly compares the characteristics of FbD and AbD.

Table 2.5. Comparison between function-based design and affordance-based design

Function-based Method	Affordance-based Methods
<ul style="list-style-type: none"> • Device-centric • Transformation-based • Descriptions of internal device behavior 	<ul style="list-style-type: none"> • Relational (e.g., artifact-user) • Artifact-user interaction or artifact-artifact interaction-based • Descriptions of relational behaviors of user-artifact or artifact-artifact

Realizing the different characteristics of FbD and AbD, this section reviews the previous studies on the AbD methods. This is because while there are a variety of needs and preferences for customers who want to manufacture customized products using AM technologies [101]. Understanding and defining individual customer needs is the key to personalization [5]. Individual customer needs should be well matched to relevant product designs. However, the FbD methods have limitations especially on expressing end user's information which is treated as critical evidence to AM-enabled customization. AM-enabled customization requires to figure out the logical relational connections between customer needs, AM-enabled design freedom (enabled by shape complexity, material complexity, hierarchical complexity, and functional complexity), and finally the AM processes. AbD

provides powerful tools for requirement generations in terms of user interaction with the artifacts from the early stages of the design process due to its focus on the end user [97].

The following sub-sections intend to seek the opportunity to increase the completeness of DfAM's design activities by reviewing existing AbD concept ontologies. Section 2.5.1 and 2.5.2 will closely look into existing AbD methods and affordance formulizations.

2.5.1 Affordance in Product Design

There have been many efforts to the study of AbD based on Gibson's [102] and Norman's [103] works of affordance. The term affordance originally comes from perceptual psychology [102]. According to Gibson [102], the affordances are "what the environment offers the animal, what it provides or furnishes, either for good or ill." He introduced affordance as animals' action possibilities offered from the environment. In his study, for example, a step affords a step-ability to users who perceive the existence of the step and are willing to walk on it.

In product design, Norman [103] started to use affordance and its representations in two DfX methodologies (Design for Usability and Design for Error) [103]. In his study, Norman introduced affordance and applies it to design, while adding a perceptual dimension to Gibson's affordance concept. McGrenere and Ho [104] compares affordances of Gibson and Norman as shown in Figure 2.19.

<p>Gibson's Affordances</p> <ul style="list-style-type: none"> • Offerings or action possibilities in the environment in relation to the action capabilities of an actor • Independent of the actor's experience, knowledge, culture, or ability to perceive • Existence is binary – an affordance exists or it does not exist
<p>Norman's Affordances</p> <ul style="list-style-type: none"> • Perceived properties that may or may not actually exist • Suggestions or clues as to how to use the properties • Can be dependent on the experience, knowledge, or culture of the actor • Can make an action difficult or easy

Figure 2.19. Comparison of affordances [104]

After Norman, Maier and Fadel [105, 106] recognized affordance as a fundamental basis for design as the affordance concept is compared to the other concepts such as function. After identifying affordance as a fundamental basis for design [105-108], Maier and Fadel [109]. developed several AbD methods based mainly on Gibson's and Norman's works of affordance [102, 103].

In the works of Maier and Fader, they define the properties of affordances as follows [110]:

- *“Complementarity: an affordance describes an interaction between two subsystems: artifact-user interaction or Artifact-artifact interaction. The affordance is relative to both subsystems and cannot exist in isolation. For example, a single gear cannot transmit power.*

- *Polarity: affordances can be either positive (+) or negative (-), depending upon whether the potential behavior has beneficial or harmful consequences.*
- *Multiplicity: systems can have multiple affordances*
- *Quality: affordances can be of varying quality depending upon how well the subsystems support the potential behavior. The affordance of occupant comfort is of higher quality in a luxury car, for example, than it is in an economy car.*
- *Form dependence: affordances depend on the physical structures of artifacts, unlike functions which are form independent.”*

The studies of Maier and Fadel presented the concepts of Artifact-User Affordances (AUA) and Artifact-Artifact Affordances (AAA), a graphical affordance structure, an embodiment design method, and an affordance-based reverse engineering approach [109, 110]. In AbD, artifacts are categorized into two: one involved in the interaction with the user (artifact-user interaction) and the other which interacts with other artifacts (artifact-artifact interaction) [110]. Depending on the type of interactions, the characteristics of affordances are defined as AUA or AAA. Maier and Fadel argued that the extended concept of AAA, the concept of affordance beyond artifact-user interaction, made the affordance theory applicable in mechanical design, by recognizing the affordances existing between the non-organism subsystems.

The studies of Maier and Fadel study proposed Affordance Structure Matrix (ASM) [110-112]. The ASM is a tool similar to matrix based tools such as Design Structure Matrices (DSMs) [113, 114] and House of Quality (HoQ) matrices [115, 116]. The ASM is a tool to compare affordances by classifying them into three: helpful (+), harmful (-), or no ()

relationship as shown in Figure 2.20. The ASM can serve as a concept exploration tool, because it compares the affordance-structure relations across multiple concepts. Figure 2.20 demonstrates a case of a household vacuum cleaner using the ASM. Maier and Fadel introduce the affordance-based methods as shown in Figure 2.21 and Figure 2.22, using the design tools they developed such as ASM.

Figure 2.20. ASM for a Eureka Bagless vacuum cleaner [110]

Figure 2.21. Overview of the affordance-based design process [110]

Figure 2.22. Procedure for designing individual affordances [110]

Despite their limitations on stating the user's information, Pahl and Beitz's function structures remain one of the main design tools of current engineering design owing to their systematic approaches and applications [97]. This is because the transformation-based function definitions decrease the complexity of design tasks effectively [117]. Also, an overview of how complex devices behave to achieve goals are well shown in function structure diagrams while the diagrams abstract away unnecessary information [97].

Ciavola et al. [97] presented a systematic modeling approach for early-stage design requirements representations. Ciavola et al. [97] presented traditional function-based methods for the benefits of integrating them with affordance-based approaches. Their study demonstrates how affordances add design requirements to the early stages of traditional design processes. The integrated approach takes advantage of both affordance and function concepts.

2.5.2 Formalisms of Affordances

The AbD has formal approaches. In Abd, Maier and Fadel [105] presented the formal adaptation of affordances to engineering. Maier and Fadel [109] then introduced a topical formal relational structure shown in Figure 2.23.

Figure 2.23. Generic affordance structure [110]

Cormier et al. [118, 119] developed a formalization of an AbD approach for capturing user needs: the Desired Affordance Model (DAM). Addressing the shortcomings of the previous studies that does not capture user needs explicitly, they utilized their model to improve affordance model qualities and consistencies. To create and documentate affordances, Cormier et al. [118, 119] developed a formal affordance statement structure as shown in Figure 2.24. For an Artifact-User Affordance (AUA), the structure intends that designers can read the diagram as the principal artifact affords a [user] [affordance] of [target object or environmental entity] [from additional information (optional)]. This structured affordance statement is designed to guide designers to consider the relationship between the artifact, user role, and other objects such as environmental entities [118, 119].

Figure 2.24. Modified affordance model structure [118, 119]

Other than AbD's efforts in formalisms, there have been many research works on formalizing Gibson's affordances since Gibson proposed the affordance concept. Gibson first introduces the term affordances as the following paragraph [102] (p. 127):

“The affordances of the environment are what it offers the animal, what it provides or furnishes, either for good or ill. The verb to afford is found in the dictionary, but the noun affordance is not. I have made it up. I mean by it something that refers to both the environment and the animal in a way that no existing term does. It implies the complementarity of the animal and the environment.”

As Cormier et al. [118, 119] addressed, capturing user needs and user characteristics associated with affordance is significant in AbD. In affordance theory, in terms of representing user's contributions in the interaction, the term ‘capability’ is used by Gibson [102, 120] and ‘effectivity’ is used by Shaw and Turvey [121, 122] to represent the contributions of actors corresponding to affordance of the environment or artifact in the

interaction. Shaw and Turvey [123] provided a formal model based on the “coalition” concept. A “coalition” according to Shaw and Turvey (p.344) is:

“a superordinate system (relational structure) consisting of eight pairs of subsystems (with 1024 states) nested at our exclusive “grains” of analysis (bases, act as reciprocal context of mutual relations, orders, values) and closed at each grain under a (duality) operation that specifies how the two complementary subsystems constraint.”

Turvey [122] formulated the affordance while linking it perspective control (PC) based the definition of affordance in terms of dispositional properties. PC is a control for future events and interpretable with goals, while dispositional properties are the properties that are potential or latent or possible and are not occurrent [122]. Turvey stated that affordance is complemented by effectivity which is a property of the animal’s capability. Additionally, Turvey offered a formal definition for affordance as follows [122].

Let W_{pq} (e.g., a person-climbing-stairs system) $= j(X_p, Z_q)$ be composed of different things Z (person) and X (Stairs). Let p be a property of Z and q be a property of Z (i.e., the complement of p), if and only if there is a third property γ such that

- (i) $W_{pq} = j(X_p, Z_q)$ possesses γ
- (ii) $W_{pq} = j(X_p, Z_q)$ possesses neither p nor q
- (iii) Neither Z nor X possesses γ .

The operator j is the juxtaposition function and is a function that links the environmental affordances to an animal’s effectivity.

Well [124] characterized the affordances as the configurations of Turing machines [125]. His approaches offered a new computational approach that promotes analysis of internal states of perceivers while being consistent with Gibson’s ecological approach. Well

provided an analysis of his formalism and claimed that Finite State Automata (FSA) could be developed to show how the internal states of an agent can be incorporated into ecological theory.

FSA is a formal modeling method of Discrete Event System (DES)s [126]. FSA is capable of representing a language as a set of certain series of states and events with well-defined rules. Kim et al. [127-129] and Rothrock et al. [130] presented affordance-based finite state automata (FSA). Their approach is related to ecological affordances on the basis of atomic models and combined them into a general FSA representation. Affordance-based FSA develops formalisms for formally expressing the affordance's and effectivity's operational properties in state transition models. Fitting dynamic systems into affordance-based FSA, studies mapped the dynamic properties of human-machine and human-environment interaction systems into discrete states and the associating conditions that are expressed with time and physical constraints.

2.6 Limitations and Challenges

The previous research has provided a great background for carrying out DfAM. Generally, most existing DfAM methodologies mainly focus on part-level designs and therefore product-level design approaches are required. In AM, a product-level design methodology needs to simultaneously consider the functionality and manufacturability from product to part scales through design processes, which falls into the scope of the traditional SED's conceptual and embodiment design phases. However, traditional SED methodologies lack AM knowledge and consequently fail to embrace the unique capabilities and constraints of

AM. Thus, a product-level DfAM methodology urgently needs newfound AM knowledge on AM-enabled functionality and AM-restrictive manufacturability constraints. More specifically, the previous research has limitations in three areas that require a methodology to design AM-enabled customization products as follows.

First, for representing AM product's functional behaviors, two representative design tools of function and affordance need to be thoroughly discussed and selected from the early design phase of DfAM. One of the opportunities from AM is personalized fabrications of products such as prosthetic limbs and medical devices. Therefore, the scope and definitions of products are changed in AM compared to the traditional manufacturing technologies. The design freedom of AM is capable of flexibly producing complex parts with design changes and consequently, furthers the idea to manufacture personalized products that efficiently adapt customer profile differences. To achieve personalized product designs and performances, it is required to develop a knowledge representation tool that focuses only on product behaviors for market-of-one segments to take advantage of AM-enabled customization from the early phase of SED processes.

Second, the existing AM design rule studies' focus on broader feature-geometry-material-process correlation lacks explicit AM feature-oriented knowledge that promotes design techniques in that design rules can be utilized for form feature-based product analysis and designs. Novel and fundamental design rule language sets are required to represent relevant additional design contexts generated from AM product, feature, and manufacturing process domains. The lack of such design fundamentals and corresponding design principles and rules is limiting the existing AM design rule studies from being implemented at both

higher design levels for product architecture and complex structures and lower levels for detailed geometric and topological entities.

Third, existing DfAM ontology developments have been not conducted in a coherent manner. The lack of a coherent manner can bring errors and inefficiencies in generating and validating DfAM knowledge mostly captured in formal hierarchical knowledge structures and relationships. There is a lack of a formal methodology that transforms DfAM knowledge formalisms to logic that ontologies constructed based upon. As a result, existing DfAM knowledge construction methodologies have not been yet systematically leveraged in developing machine-processable knowledge stored in DfAM ontologies. Also, most of the existing DfAM ontologies focus on additive manufacturability analysis. Customized AM product behavior knowledge needs to be integrated.

Chapter 3. The Framework of Developing Customized Design for Additive Manufacturing (CDfAM) Knowledge

Due to AM-enabled design capabilities and constraints, designing products for AM requires designers to rethink and redesign the products towards customized way while embracing AM's capabilities of shape, hierarchical, functional, and material complexities as well as AM process constraints. This chapter introduces a framework of building Customized Design for Additive Manufacturing (CDfAM) methodology that constructs AM-driven customization knowledge. Section 3.1 introduces the details of the CDfAM development process along with employed tools and methods. Section 3.2 summarizes the chapter with a recap of the proposed method and a look ahead to the implementation of the proposed method.

3.1 Development of CDfAM Knowledge

The principle contribution of this thesis is to develop a methodology for AM-driven customization knowledge engineering. The proposed methodology extends the concept of SED and DfMP into the DfAM framework and addresses the conceptual and embodiment design phases with formal methods. The steps and associated methods are elaborated in Figure 3.1.

The development process consists of three steps: 1) selection of an SED tool for modeling customized functional behavior, 2) development of an affordance-based method for representing AM-enhanced product behaviors, and 3) development of a method for representing AM design rules. Various tools are utilized in this research to support the proposed three steps. The first step is to select a design tool for modeling customized functional behavior in the conceptual design phase of DfAM. Among the two representative product behavior modeling tools in SED, function and affordance, the first step contradicts function to affordance based on their advantages and limitations when applied in DfAM. After selecting affordance as a design tool based on the first step's contradiction, the second step develops an affordance structure as a formal method for representing customized functional behaviors. In the second step, Discrete Event System (DES) and a language generation [126] is adopted for modeling and parameterizing the affordance structure. For the DES modeling, the second step utilizes and extends Finite State Automata (FSA) [126]: a type of a formal DES modeling technique that has successively modeled affordance into discrete physical states and state transitions [131, 132]. In the third step, this thesis develops a design rule representation method that extends existing modular AM design rule representations based on the concept of design fundamentals and principles. Then, a CDfAM ontology is developed using Web Ontology Language (OWL)/Resource Description Framework (RDF) and design knowledge is captured selectively from the ontology systemically with structured Semantic Web Rule Language (SWRL) and Semantic Query-enhanced Web Rule Language (SQWRL) sets.

Figure 3.1. Overview of constructing CDfAM knowledge and relevant tools

3.1.1 Step 1: Select a Design Tool: Affordance as a SED Tool for Capturing Customized Product Behaviors

Step 1 is to select a design tool for capturing product's customized functional behaviors as functional requirements of AM products in the conceptual phase of the CDfAM. Two representative design tools of SED, function and affordance, are theoretically compared based on their advantages and limitations when applied in DfAM in Chapter 4. In SED, the conceptual design phase starts with capturing desired product behaviors as functional

requirements. In the function-based DfAM, developing function structures is the first task of the conceptual design phase, as the affordance-based DfAM starts with formally modeling the desired product behaviors with affordance structures.

The function structures consist of subfunctions and flows of energy, material, and information between the subfunctions as shown in Figure 2.6. Regarding the properties of subfunctions and three types of input/output flows, function structures commonly show characteristics of

- (i) capture of device-centric product behaviors as functional requirements at market-levels
- (ii) form independence, and
- (iii) input/output-based transformative formal modeling.

On the other hand, affordance has properties of complementarity and form dependence [98] based on its relational properties. The affordance's properties of complementarity and form dependence [98] can address the limitations of the function-based methods at the same abstraction level of function in the conceptual design phase. The affordance-based approaches for DfAM in customized products provide the affordance characteristics of

- (i) capture of relational product behaviors as design requirements at individual levels
- (ii) form dependence, and
- (iii) non-transformative and artifact-user relational formal modeling.

In Chapter 4, the process of contradicting function to affordance in DfAM is described in detail. Also, an affordance-based DfAM domain framework is presented for structured design and analysis processes.

3.1.2 Step 2: Develop an Affordance-based Method for Representing AM Product Behaviors

After addressing capabilities of function and affordance in DfAM and selecting affordance as a DfAM tool, Step 2 proposes a novel knowledge representation method for AM-enabled customized product behaviors as a type of Opportunistic DfAM method in Chapter 5. With the entry barrier reduced in both the customer requirement acquisition at the front end and the product delivery at the back end by AM technologies, new research opportunities are open to designers to address the AM-enabled customization. In the AM-enabled customization, personalization attempts to increase product's personal relevance to the individuals compared to traditional customization [5]. Therefore, a design method is required to represent individualized product functionalities to design and manufacture AM-enabled product architectures.

To address this issue, this step proposes a formal design process framework which provides designers with guidelines to merge Design for Customization (DfC) and Design for Manufacturability (DfM). Then, this step introduces an affordance structure as an affordance modeling technique, where Discrete Event System (DES) modeling [126] is adopted to formally model the affordance structure. This thesis utilizes Finite State Automata (FSA) [126], a type of a formal DES modeling technique that has successively modeled the

affordances into discrete physical states and state transitions [131, 132]. Then, goal-oriented user-product interactive behaviors are presented as formal language sets. The proposed formal representations systemically link customer behavior and preference properties to the design requirements for AM products using the relational properties of affordance, effectivity, and preferences in AbD. In Chapter 5, the development of the framework and the affordance structure is described in detail.

3.1.3 Step 3: Develop a Method for Representing Customizable Modular Design Rules for AM

After new affordance structures are introduced and adopted in a DfAM framework for functionality-oriented product architecture developments in AM, AM's manufacturability needs to be incorporated into the functional and geometrical properties of the additively manufactured parts. To address such challenge, Step 3 develops a method for representing Restrictive DfAM knowledge: customizable modular design rules for AM. Chapter 6 extends a structured modular hierarchy and associated formalisms of existing representations of design rule languages. The proposed method explicitly represents definitions of design rule's fundamental elements in AM's domains of design, process, and material and their correlations. Based on the correlations, the formal method systematically shows how AM's manufacturability constraints are associated with additively manufacturable part structures and how the AM feature designs are recommended as consequences of the AM constraints.

3.1.4 Step 4: Conduct Case Study: Validate Models, Collect Case Knowledge, and Construct CDfAM Ontology

Step 4 validates the proposed methods, constructs a CDfAM ontology using OWL/RDF that captures the ontology's classes, hierarchies, and properties and retrieves CDfAM knowledge with SWRL-based SQWRL. The ontology-based knowledge engineering enables capturing the semantic contents of the CDfAM knowledge. The proposed ontology explicitly represents definitions of CDfAM knowledge elements in AM domains of user, functionality, design, process, and material and their correlations. With the ontology, Step 4 presents a CDfAM knowledge base that is constructed with reconfigurable knowledge blocks. The construction of the knowledge base is demonstrated in Chapter 7 that leverages the proposed affordance structure, design rule language, as well as a Machine Learning (ML) Algorithm, Classification And Regression Tree (CART) algorithm.

3.2 Summary and Preview

Chapter 3 has introduced the development process of the CDfAM that supports customized product designs by considering customized functional behaviors and AM manufacturability.

In summary, the building process of the CDfAM is to:

- Step 1: Select a Design Tool: Affordance as an SED Tool for Capturing Customized Product Behaviors
- Step 2: Develop an Affordance-based Method for Representing AM Product Behaviors

- Step 3: Develop a Method for Representing Customizable Modular Design Rules for AM
- Step 4: Validate Methods and Develop a CDfAM Knowledge Base

The CDfAM can support design processes for AM by integrating the proposed Opportunistic DfAM and Restrictive DfAM methods. The next chapter illustrates the comparison of FbD and AbD and provides a new DfAM domain framework and an affordance structure while leveraging AbD methods.

Chapter 4. Affordance as an SED Tool for Capturing Customized Product Behavior

As Step 1 in the framework of developing the Customized Design for Additive Manufacturing (CDfAM) methodology in Figure 3.1, this chapter presents the selection of affordance as a functional behavior representing tool. For the selection, a theoretical contradiction of Function-based Design (FbD) to Affordance-based Design (AbD) in DfAM is presented to qualify their ability to embrace AM's unique capability in creating customized products. Section 4.1 describes the overview of the selection process in this chapter. The FbD approach's limitations in DfAM is theoretically discussed in Section 4.2. Section 4.3 presents the advantages of AbD approaches in DfAM on the other hand. Section 4.4 proposes a framework of DfAM's design knowledge domains based on the AbD approaches. Section 4.5 proposes a new product behavior representation method. Section 4.6 provides a summary of this chapter and a preview of the next chapter.

4.1 Overview

One of the opportunities from AM is personalized fabrications of products such as shoes, prosthetic limbs, and medical devices. The design freedom of AM is capable of flexibly producing parts with complex geometry changes and consequently, furthers the idea to manufacture personalized products that efficiently adapt customer profile differences. To achieve personalized product designs and performances, it is required to develop design

approaches that are able to focus on product designs at unit levels to take advantage of the design freedom. However, so far, the conventional design theories and methodologies have shortcomings that are not able to embrace the such AM opportunities and thus requires a set of design principles for the theories and methodologies (DTMs) [15].

Therefore, such AM's advance from rapid prototyping (RP) to the end-use products inevitably challenges conventional DTMs. Especially while adopting Systematic Engineering Design (SED) methodologies to DfAM, it is essential to develop new design methods that explore the new design space enabled by AM's design freedom from the early design stage. The conceptual design phase of SED starts with modeling the product's desired functional behaviors as design requirements. To address the challenge of modeling functional requirements in DfAM for customized products, this chapter provides a theoretical comparison on the limitations and advantages on the SED's representative design tools.

Firstly, this study contrasts the FbD methods with the AbD methods based on their unique capabilities in product behavior representations. The device-centric, form independent and input/output-based transformative properties of the FbD methods have capabilities in modeling product's internal behaviors. Nevertheless, the function-based methods show weaknesses in AM-enabled product customization which requires design methods for representing user-centric and physical-structural design requirements as well as their correlations acquirable only by AM's capabilities of shape, hierarchical, material, and functional complexities. On the other hand, the AbD methods can address the limitations of the AbD methods in DfAM based on their user-centric (artifact-user interactive), form dependent, and non-transformative properties. Second, a new formal framework of DfAM

is proposed with four AM domains: the customer domain; the affordance domain; the physical domain; and the process domain. Third, a new formal method for representing customized product behaviors, affordance structure, is proposed, while leveraging the concepts of affordance and Finite State Automata [126]. The contribution of the section is in selecting a design tool for the conceptual design phase of DfAM that fulfills the objectives of achieving AM-enabled customization with SED approaches.

4.2 Limitations of Function-based Design in DfAM

This thesis presents the limitations of the conceptual design phase of DfAM only depending on the function-based methods by categorizing the function's characteristics into as follows:

- (i) capture of device-centric product behaviors
- (ii) form independence, and
- (iii) input/output-based transformative formal modeling.

Note that this section does not aim to criticize the quality of the FbD theories, methods, and methodologies. The purpose is to demonstrate the weaknesses of them when they are applied for the DfAM in customized products.

4.2.1 Capture of Device-centric Product Behaviors as Functional Requirements

Traditionally, the function's basic formal expressions are '[active verb] [noun objective]' pairs [35]. The function's basic formal expressions were developed to transform the customer-centric customer needs into device-centric product behaviors as a start of the conceptual design phase of SED. Once captured in the formal expressions, the design requirements formulized as functions are leveraged in the downstream SED processes such as a design process of mapping them to product's physical working structures at a product level or form features at a part level.

As reviewed in Section 2.4, the major design consideration of the CDfAM is artifact-user interactions (or human-product interactions), and therefore artifact-user interactive product behaviors have to be addressed with proper design tools and methods from the early design phase of DfAM. However, function's formal expressions for product behaviors are only device-centric, and therefore their advantages are not in representing artifact-user interactive product behaviors but in representing device-centric product behaviors. The examples of such function expressions are 'increase pressure', 'transfer torque', and 'reduce speed' [35]. The function's expression of '[active verb] [noun objective]' cannot provide any formal language sets for representing any user-interactive product behaviors and therefore cannot offer any design requirements to be leveraged in mapping them to personalized user data in further DfAM processes [133]. Such device-centric formal expression's lack of languages for representing artifact-user interactions makes the functions inadequate for capturing AM-enabled user-centered product behaviors of which functionalities are

meaningful only when they are customized for the interactions with target customers. In fact, so far in DfAM, user-centric personalized data has been acquired using data acquisition technologies such as 3D scanning and used to modify design features or create new form features [14] for the products such as personalized seats, shoes, prosthetic limbs, and athletic gears. Also, even though design candidates have the same intended device-centric internal behaviors captured by the function, the satisfaction levels of the users can vary individually due to their varying profiles.

In the FbD approaches, developing device-centric function representations is the first step of the conceptual design phase. However, the conceptual design phase of DfAM in customized products needs to clarify how to integrate varying personalized customer data and functional requirements into the corresponding design features with clear design goals methodologically. For example, while more of data acquisition technologies such as XCT scanning are being developed, DfAM approaches for developing customized products are required to clearly explain why certain design process requires personalized design information such as custom fit geometries of fully digitized body scans and how methods can systematically reflect them in the form feature and product architecture designs. Also, DfAM methods need to relate information of the user-related human factors or user interaction patterns to AM artifact designs. As traditional SED has been doing, new formal methods have to support to capture such design knowledge and data, which the FbD methods show limitations in doing so.

4.2.2 Form Independence

The FbD methods such as a function structure are form independent [35]. The form (i.e., structure) independence intends to focus on the functional requirements and function relationships independent of physical form features to create function models of products as shown in Figure 4.1. Due to the form dependence, functional design requirements for form feature geometry have not been clearly captured in the function models so far. However, in DfAM, realizing the structural behaviors enabled by additively manufactured complex structures is considered significant [15]. DfAM requires product behavior or physical conceptual models to present reasons for having intended complex customized design structures. However, the form independent function models prevent themselves from being utilized in resolving such design issues in DfAM where freeform fabrications are important.

It has been observed from literature reviews that the designers identify problems with specific solutions for AM with reference to physical embodiments. Then, the designers attempt to remedy them during the design process. For example, design processes of DfAM for products such as the aforementioned examples of seats, shoes, prosthetic limbs, and athletic gears initialize themselves by conducting user-interactive surface capturing with 3D scanning technologies, instead of constructing the form independent function models. This activity, which is crucial for a successful design outcome in DfAM, cannot be explained by the current FbD approaches due to its form independence. Instead, function-based theories proceed from form-independent function to form, prescribing the function lists that embodiments should have, and therefore stop short of analyzing any other relationships that the embodiments should have [98].

4.2.3 Input/output-based Transformative Formal Representations

Once the product behaviors are defined and expressed using function, the function models are developed and function structures have been in a major use as a formal model. A formal modeling method provides case-independent and structured design techniques and therefore, is a crucial task in engineering design. The function structure Figure 4.1, a representative type of formal function models in FbD, is based on the input/output-based transformative formal modeling approach [32, 35]. Transformative formal model representations have advantages of modeling electromechanical or machine systems with transforming characters based on the input/output flows of energy, material, and information. However, they are not adequate for modeling artifacts, for example, that have an obvious product use but do not have active function transformations based on the three types of inputs/outputs with static structures [98]. The similar motivating examples in DfAM can be considered to address this limitation here again. For a customized stool design, the more significant factors are geometry, volume, size, material, structural feature, and user profiles rather than the functional input/output-based function relations.

Figure 4.1. A generic function structure format [35]

Figure 4.2. A function structure example of electric drill [134]

4.3 Advantages of Affordance-based Design in DfAM

The affordance's properties of complementarity and form dependence [98] can address the limitations of the FbD methods with their artifact-user relational characteristics at the same level of the function models in the conceptual design phase where the FdB methods are utilized. This chapter provides the theoretical discussions of using the AbD methods for DfAM in customized products by categorizing the affordance characteristics into

- (i) capture of user-centric product behaviors as functional requirements at individual levels
- (ii) form dependence, and
- (iii) non-transformative and artifact-user relational formal modeling.

4.3.1 Capture of Relational Behaviors as Functional Requirements at Individual Levels

The affordance has a property of complementarity that defines its relational characteristics [98]. Specifically, the complementarity is the entangled relationships between certain users and certain artifacts, and the affordances capture the relational properties based on the complementarity as shown in Figure 4.3. An implication of the complementarity property is that the affordances depend on specific users thus an artifact can afford different behaviors to different users [98]. Indeed, it has been shown that the advantage of complementarity is to map affordance models to not only artifact design specifications but also related user characteristics at individual levels [135]. The user characteristics include user information related to human factors such as anthropometric dimensions and biomechanical capabilities, knowledge, preferences on usage, and constraints to develop user-specific individualized designs [135].

Figure 4.3. Affordance defined in artifact-user interactions

The complementarity property can be considered for the customized products such as an additive manufactured shoe. When a shoe is customized based on the AbD approach, a customized shoe for a runner is designed to afford an improved running performance to the runner specifically. An improved performance, for example, running for a certain period of time at a certain speed with a certain running pose, is a behavior that can be achieved when the shoe is specifically customized for the runner based on the target runner's physical profiles and capabilities. In other words, the improved running performance is achieved when the shoe is designed to afford certain form shapes and mechanical behaviors and material properties designed based on the interactions between the shoe and the runner. When the affordances are utilized, the designers have an opportunity to consider both the runner's characteristics and the shoe's form features and interactive behaviors based on the complementarity property. As the affordances, in this case, capture the target runner-specific design requirements at the individual level, other runners who have different running patterns, foot sizes, or different preferences cannot achieve the same performance with the shoe.

In DfAM, studies such as [136] show that the customized geometries and user preferences influence decision makings on design optimization and AM process selections.

This type of DfAM studies assumed that custom geometries are given and have started their processes by taking the custom geometries and preferences as inputs for the design process of design optimizations. However, while the design optimizations happen at the downstream design phases such as the embodiment and detailed design phases [137], the capturing of functional requirements happens at the earlier stage. Therefore, adding a conceptual design phase for generating user-specific functional requirements and specifications enabled by the AbD methods can increase the completeness of the DfAM approaches for developing customized products.

4.3.2 Form Dependence

The affordances are form dependent whereas the function is form independent, since it is the form of an artifact that determines what the artifact affords to users [98]. In DfAM, the form matters since the main benefit of employing AM process is the ability to manufacture parts of any geometric complexity without tooling [15] and the AM-enabled personalized products have been achieved based on AM's complex geometries. The form dependence enables designers to explore unexplored design space from the early design process and finally preserves design freedom, which matches AM's unique capability; Maier, Ezhilan [111] present that considering the structures in the earlier phase of the design process preserves design freedom, since it allows the designers to manipulate and refine concept structures and product architectures early in the design process without considering other restrictions.

Another advantage of affordance's form dependence is that it explains how structures influence product behaviors, which the function's form independence fails to do so [106]. It

has been explained by Maier and Fadel [98] that, by noticing that it is the structures of systems that determine their affordances, the analysis on how the affordances describe what behaviors are possible following the knowledge transformation flow as shown in Expression (I)

$$\text{structure} \rightarrow \text{affordance} \rightarrow \text{behavior} \quad (\text{I})$$

In DfAM, a goal of design is to find optimal designs in the conceptual and detailed design phases by taking inputs of behavior requirements from the conceptual design phase. Therefore, the design flow can be described as what structures specifications are possibly achievable based on the input behaviors for the knowledge transformation as shown in Expression (II)

$$\text{behavior} \rightarrow \text{affordance} \rightarrow \text{structure} \quad (\text{II})$$

Expression (II) shows that the affordances act as bridges with direct relations of the artifact-user behavioral requirements to the form features in the design process ,while the functions provide indirect relations due to their form independence. In this way, the AbD not only analyzes but also prescribes the affordances of embodiment designs for AM.

4.3.3 Non-input/output-based transformative and Artifact-User Relational Formal Representations

Unlike the FbD's formal modeling introduced in Chapter 4.2.3, the affordance's complementarity and form dependence properties enable designers to have non-input/output-transformative and artifact-user relational formal representations. An example of affordance's formal modeling formats is 'artifact affords a [user] [affordance] of [target object or environmental entity] [from additional information (optional)]' [119]. For example, an additively manufactured trans-tibial prosthesis with a blade that has been designed for running performance can be represented as 'a trans-tibial prosthesis with blade affords [an amputee] [a running ability] of [the residual limb]'.

The such formal affordance models can capture design knowledge on AM contexts in that there is no active function transforming inputs/outputs and static complex AM structures are important. Not being restricted to the transformative representation, affordance models can also be utilized in a design context where customized design data and artifact uses are obvious. Then, the formal affordance models can be transformed into the other formal design information and knowledge formats in downstream design flows while the rest of the design processes leverage the structured design knowledge in affordance models. In DfAM, the formal affordance models are acceptable as long as

- (i) they focus on the affordance representations that can capture AM-enabled structure behaviors, and
- (ii) they help to integrate customized customer data into the corresponding design features.

As a summary, the affordance-based methods exhibit the advantages when carried out in the conceptual design phase of DfAM in customized design as shown in Table 4.1.

Table 4.1. FbD methods and AbD Methods in DfAM

	FbD Methods	AbD Methods
Capture of Functional Behaviors	The capture of device-centric product behaviors based on the function lacks customization design knowledge and consequently provides little clues for user-centric customized designs uniquely achievable with AM's capabilities.	The affordance's complementarity property enables the designers to capture artifact-user interactive product behaviors at individual. Consequently, artifact-user interactive product behaviors customized design provide customized design knowledge that is directly linked to customized physical space that is uniquely achievable with AM's capabilities.
Form Dependency	Developing form-independent function models can distract the designer's attention to the form structures and structural performances enabled by AM's shape and hierarchical	The affordance's form dependence makes the designers focus on the form structures from the conceptual design phase by providing a direct link between product behaviors and form features. Consequently, the

complexities.

form dependence preserves design freedom in the early design stage and enables exploring a physical design space where the function-based models cannot explore in the conceptual design phase.

**Formal
Representa-
tion**

The formal representation methods based on the transformative input/output nature of the function cannot formally represent the design knowledge of the user variances and static complex structures.

The non- input/output-based transformative and artifact-user relational formal representations provide the conceptual design phase of systematic DfAM with formal language sets that help to capture both personalized customer and physical domain data into structured product behavior models.

4.4 DfAM Knowledge Domain Framework

This section presents a DfAM knowledge domain framework. Before moving on to the methods developments, a goal of developing a formal DfAM framework is to identify systemic links between the heterogeneous domains of performance, design, material, and processes in order to reflect them into designs and design processes [28, 29]. In developing

such frameworks, DfAM has utilized the three link chain model (3LCM) that is originated from the material science domain and is adopted in DfAM to considers the linear relationships between the elements performance, properties, structure, and process [68]. When applied in AM-enabled engineering product designs, the performances in the 3LCM can be considered as product behaviors of an additively manufactured part or an entire product architecture. In this research, the affordance becomes a tool for representing desired product behaviors.

The new formal framework of DfAM is proposed with four domains: the customer domain; the affordance domain; the physical domain; and the process domain. The formal framework is illustrated schematically in Figure 4.4. The *customer domain* consists of a set of elements (noted as U) that represent user characteristics. The most significant characteristic of the proposed customer domain is that it is an individual domain. This is because the AM-enabled customization aims to achieve market-of-one. Using AM technologies for customized products means that the customized parts are additively manufactured in a specific pattern that satisfies a target customer. Therefore, the market-of-one customer domain acquires the user characteristics of a target individual.

The *affordance domain* consists of a set of affordance elements (noted as A). The affordance elements in this domain model customized artifact-user interactive behavior to analyze and represent desired product behaviors. A can represent desired performances for DfAM methodologies such as 3LCM-based DfAM methodology to achieve AM-enabled customization while not utilizing common desired product behaviors based on the FbD methods. To be specific, affordance-based DfAM forms newly proposed mappings as in Expression (III):

user→behavior→affordance→structure & property→process (III)

The *physical domain* contains the physical structures (S) and properties (T) such as an optimal weight or strength, customized width and height, and perceivable form feature surface properties that satisfy specified affordances. Being different from the function-based design frameworks, the physical domain here is defined based on the affordance's form dependence. Here, the features are the form features that directly or indirectly involved in the artifact-user interactions and therefore influence the types of the affordances. In DfAM, the examples of the form features include an inner surface of a prosthesis socket, an upper surface of a navy aircrew ejector seat [14], or a prosthetic ear features in terms of direct interactions. In terms of indirect interactions, an inner structure that affects and supports user interactions can be an example. T contains information about part properties that are derivable from A and S using physical principles, e.g., mechanical, thermal, and electrical properties [29]. In this study, T is a set of physical properties that is derived by the user interactive structural behaviors resultantly. Examples can be fewer stress concentrations and lighter weight that is enabled by the AM and needs to be defined and verified based on the A and S .

Finally, the *process domain* (noted as AM) represents specific AM methods and their process parameters. The process domain as more standard routings for AM processes are being set up, the process platform as a standard routing can be adjusted for different setups needs to be adjusted its process selections and settings. Also, in DfAM, based on the process domain information, it is considered important to incorporate AM manufacturability aspects

such as part orientations, slicing, supports, scan speed, layer thickness, and hatch density on product designs in the physical domain such as custom fit interactive surface and functional surfaces and volumes that influence the product performances or measurements of the level of the user's satisfaction. Based on the proposed design synthesis framework, a DfAM process can be illustrated along the entire spectrum of product realization for AM according to the domain framework.

During the design process, designers/design engines can map the design elements based on the design purposes such as how the designs want to satisfy what requirements, as seen in the arrows in Figure 4.4 that represent the analysis and design information flows. Based on the proposed design framework, the DfAM process can be illustrated along the entire spectrum of design and product realization for AM.

Figure 4.4. Four Domains of DfAM

4.5 Finite State Automata-based Affordance Structure

Based on the proposed design process framework, this section introduces an *affordance structure* as a customized product's functional behavior modeling technique for the CDfAM. The conceptual design phase of the affordance-based CDfAM starts with formally modeling the desired behaviors with affordance structures, as the FbD starts at a conceptual design phase by modeling function structures. Therefore, as a starting point of the conceptual design phase of DfAM, developing the affordance structure is considered significant, since the design processes in the rest design phases proceed while leveraging the behavior models represented by the affordance structure. Also, the purpose of the affordance structure is similar to that of a function structure; the affordance structure organizes affordances in a structured format, whereas a function structure organizes functions [110].

In DfAM, modeling the discrete physical states has been utilized to achieve a detailed behavior model in the conceptual design phase [29]. This chapter utilizes Finite State Automata (FSA) [126], a type of a formal Discrete Event System (DES) modeling technique that has successively modeled affordances into discrete physical states and state transitions [128]. The basic FSA is the Deterministic Finite Automaton (DFA), and it consists of tuples as follows in Equation (4.1) [126].

$$F = \langle S, \Sigma, \delta, s_0, F \rangle, \quad (4.1)$$

S : A set of states,

Σ : A set of transitions among states,

$\delta: S \times \Sigma \rightarrow S,$

s_0 : Initial (starting) state, and

F : A set of final states.

In this research, the formal affordance structure is formulated as Equation (4.2)

$$A = \langle S_a, \Sigma, \delta, s_0, F \rangle \quad (4.2)$$

S_a : A set of states (affordance states), $\{s_0, a_1, \dots, a_n, F\},$

Σ : A set of transitions among states: a set of behavioral realizations of affordances, $\{b_0, b_1, \dots, b_n\},$

δ : A state transition function, $S_a \times \Sigma \rightarrow S_a,$

s_0 : Initial (starting) state, and

F : A set of final states: goal states.

In Equation (4.2), the affordances are represented as a physical state (S_a) and the realization of affordances with the actual behaviors are state transitions (Σ). This is because, in the AbD, the affordances and the behaviors are distinct but closely related [98] as follows. An affordance is an interaction between an artifact and a user in which properties of the artifact offers an opportunity of the artifact use to the user. This means that for example, the affordance of run-ability of a prosthetic leg is one type of interactions that shows a running opportunity, while the act of the amputee's actual running behavior with the prosthetic leg is a different type of interaction as an actual use and the realization of the affordance. However,

still the two are related because the product must first afford the opportunity of running (an affordance, i.e., physical state) before it can ever actually be used for running (a behavior, i.e., state transition) [98]. Therefore, in constructing an affordance structure, this distinction and relationship between the behavior opportunities and actual behaviors should be carefully addressed as physical states and state transitions for capturing multiple affordances and their relationships. In this way, the affordance structure provides a product's multi-functionality representation method based on affordance transformations (affordance state transition in the formal representation, $S_a \times \Sigma \rightarrow S_a$, in Equation (4.2)) triggered by artifact-user interactive behaviors.

In the AbD, goals can be modeled as user's desired situations in product uses to be achieved by performing a sufficient set of behaviors afforded by products [138]. In this sense, the affordance structure defines the set of final states, F , as the goal states. The affordance structure presents a sequence of affordance states and state transitions connected to given goals by putting the affordances into flow-based orders. s_o is the initial state and is a null state that starts the flows. The graphical representation of A is shown in Figure 4.5.

Figure 4.5. A generic graphical representation of FSA-based affordance structure

4.6 Summary and Preview

In the context that AM provides designers with opportunities to develop new design theories and methodologies (DTMs), this chapter presented theoretic contradictions of function to affordance for the conceptual design phase of DfAM. Then, taking advantages of the affordance-based methods, this thesis proposed a DfAM domain framework. While the most of the existing DfAM studies have been applicable in the embodiment and detailed design phases, this study is meaningful that it develops a theoretical background for a new SED framework that is applicable from the conceptual design phase of DfAM.

Although this chapter covers an SED method for DfAM, it is noted that shortcomings exist in the limited current scope of theoretical discussions for product behavior modeling. Also, affordance models at the functional level need to be connected to the specified physical design parameters and parameter values of the AM-manufacturable working structures at the form feature level. In this point of view, this study can be extended to the related future work as follows: 1) Extension of the affordance structure and 2) Development of a formal design method for design rule representations.

Among the two-future work, the next chapter provides a new formal method for modeling customized functional behaviors by extending the proposed affordance structure and generating a language set as functional requirement based on the FSA approach, to address the first future work. The second future work is addressed in Chapter 6. The conceptual design phase of the affordance-based CDfAM starts with formally modeling the desired product behaviors with affordance structures that organize affordances in the affordance domain $\mathcal{A}$. The modeling technique of FSA is again applied to parameterize

affordances while mathematically and graphically representing the affordance structure in the next chapter.

Chapter 5. Affordance-based Knowledge Representation of Customized Functional Behaviors for AM

This chapter as Step 2 of developing the Customized Design for Additive Manufacturing (CDfAM) in Figure 3.1 introduces an affordance representation method that extends the affordance structure in Chapter 4.5. Chapter 5.1 describes the overview of the chapter. A design process framework is represented in Chapter 5.2 that merges Design for Customization (DfC) and Design for Manufacturability (DfM) framework by extending the DfAM domain framework in Figure 4.4 into a process framework. Chapter 5.3 proposes an extended affordance structure. Based on the proposed affordance structure, a formal language sets are proposed as goal-oriented customized product behaviors in Chapter 5.4. Chapter 5.5 provides a summary of this chapter and a preview of the next chapter.

5.1 Overview

The objective of this chapter is to develop an extended affordance structure as a formal representation method that captures functional behaviors of AM-facilitated customization products. This chapter also introduces a design process framework for CDfAM which provides designers with guidelines to merge DfC and DfM. The affordance structure is constructed using Finite State Automata (FSA) that is a formal modelling technique based on Discrete Event Systems (DES) [126]. Based on the FSA-based affordance structure, goal-oriented customized product behaviors are parameterized as formal language sets. The

proposed formal representations systemically link the affordance structure to customized functional behaviors in artifact-user interactions as functional requirements for additive manufactured artifacts leveraging the relational properties of affordance and formal modeling technique of FSA.

5.2 Design Process Framework

This chapter proposes a formal framework of the CDfAM process, a design process for AM-facilitated customization to identify customized functional requirements in the formal affordance structure development. By proposing the novel process formal framework, this study enables to adopt i) the concept of DfC and DfM based on the 3LCM-based CDfAM design knowledge domain framework in Chapter 4.4, and ii) the concept of affordance [139] and effectivity [121] to a formal design process structure that can be incorporated into the design process. Affordance-based Design (AbD) [98], which is based on the relational characteristics of affordance, also provides the concept of effectivity [121]. Effectivity was originally defined by Shaw and Turvey [121] to represent human's contribution in the artifact-user interaction. In this research, the effectivity is defined as user's capability to capture the affordance's relational opportunities that correspond to the matched affordance.

The 3LCM-based DfAM has a Process-Structure-Property-Behavior relationships framework [27, 28]. When the Process-Structure-Property-Behavior relationships are used for a design method instead of material science, the meaning of the model remains the same, however, the context changes [67]. In this sense, in Figure 4.4, Chapter 4.4 added the affordance and customer domains to the 3LCM framework to highlight the customized

functional behavior modeling aspects. In AM-facilitated customization, designing the performance of 3LCM includes design requirements for desired functional behaviors that support product's end-use and provide users with preferable interactions. Based on the proposed four domain framework in Figure 4.4, the proposed design process framework for CDfAM defines both DfC as an Opportunistic DfAM process and DfM as a Restrictive DfAM process, and merges them as shown in Figure 5.1.

The design process defines how an AM part or an AM product design systemically supports customized behaviors in using the additive manufactured-artifacts while considering the user's personal characteristics. DfC considers the customer needs in the market-of-one market segment at an individual customer level and interprets them in terms of user's behavioral intentions in the artifact use, I . In this research, DfC considers an artifact-user interaction framework to transform customer needs into the user and artifact models such as artifact's affordances, F , and user's effectivities, Q , which represent product' and user's capabilities in artifact-user interactions, respectively. Finally, DfC achieves customized functional behavior parameters, PB .

Figure 5.1. Design Process of CDfAM

On the other hand, DfM seeks manufacturing constraints and capabilities that affect the level of customization by defining AM-related parameters, AP . Figure 5.1 the manufacturing process space, P , contains process information with operation sequences and the values of process variables. The structure design space, S , has the geometric, topological, and material structures. The property space, T , consists of part properties that are derivable from S using physical principles such as mechanical, thermal, and electrical properties [28].

In the previous studies, DfAM was defined as $\Delta: (S, B) \rightarrow (S^*, P, T)$ [28]. This explains that the DfAM method takes S (structure) and B (behavior) as inputs to identify AM-related design features. However, in AM-enabled customization, B needs to contain customized behavior features, and formal representations are required for systemic analysis.

In this research, the CDfAM pursues to use personalized behavior parameters, PB , as an input for DfAM instead of using B . To investigate the characteristics of PB at the product level, the formal representations are proposed in the following section.

5.3 Extended FSA-based Affordance Structure

Gibson [139] introduced the affordance as action possibilities offered from the environment to the animals that are capable of seizing these offering. In his study, for example, a step affords a step-ability to users who perceive the existence of the step and are willing to walk on it. Affordance-based design [98], which is based on the relational characteristics of affordance, provides powerful tools to personalization for design requirement generations due to its focus on the user and his interactions with artifacts. The affordances can act as a prescript tool for guiding designers of user experiences which plays an important role for personalization [140].

This research investigates affordance, effectivity, preferences, and user behaviors in the framework of an artifact-user interaction model while viewing user's preferable user behaviors with artifacts as the outcome of the artifact-user interaction. The concept of effectivity was originally defined by Shaw and Turvey [121] to represent human's contribution in the interaction. In this research, the effectivity is defined as user's capability to capture the affordance's relational opportunities for actions and conduct the actions that correspond to the matched affordance.

FSA is a formal modelling technique based on DES that can model the affordances graphically and provide designers with goal-oriented design approaches along with graphical

representation [127]. FSA represented affordances with an overview of how complex human behaviors and environment cooperate to achieve goals, while abstracting away unnecessary low-level information in human-machine corporate system designs [130] and service ecosystem designs [141]. FSA and the concept of affordance were also used to represent the design knowledge on operational properties of Electron Beam Melting (EBM) to identify the interrelations between AM constraints, user's desire and capabilities, and product's customized features [131]. They adopted user's preferences and behaviors, and uses FSA to provide a measurable tool for representing design requirements in AM-facilitated personalization.

This research proposes a formal representation of the artifact-user interaction as Affordance-, Effectivity-, and Preference-based Finite State Automata (AEP-based FSA) as in Equation (5.1). AEP-based FSA consists of tuples that represent artifact's and user's relational features considered for personalized artifact uses. The tuples systematically represent goal-oriented desired user behaviors and the related design features of the artifact and user preference levels.

$$G = \langle S, \Sigma, \delta, s_0, F, \{X, Z, W\}, \{P, Q, PR, PSA\}, Pr, j, \pi \rangle \quad (5.1)$$

where

S : A set of states

Σ : A set of transitions among states: set of user actions in the artifact use,

δ : State Transition Function, $S \times \Sigma \rightarrow S$,

s_0 : Initial (starting) state

F : A set of final states: goal of the artifact-user interaction
 X : Artifact,
 Z : User,
 W : Artifact-user,
 P : A set of affordances, $P = \{p_1, p_2, \dots, p_m\}$,
 Q : A set of effectivities, $Q = \{q_1, q_2, \dots, q_m\}$,
 PR : A set of preferences, $PR = \{pr_1, pr_2, \dots, pr_m\}$,
 PPA : A set of possible actions in the artifact use with preference level labeled,
 $PPA = \{ppa_1, ppa_2, \dots, ppa_m\}$,
 Pr : Perception predicate function, $X_P \rightarrow P, Z_q \rightarrow \{Q, PR\}, W_{pq} \rightarrow PSA$,
 j : Juxtaposition function, $X_P \times Z_q \rightarrow W_{pq}$,
 π : Possible customer action generation function, $P \times Q \times PR \times C \rightarrow PSA$,
 C : Set of physical action conditions, and
 pa : possible user action, $pr \cdot pa \in PPA$ and $pr \cdot pa \in \Sigma$.

Equation (5.1), X , Z , and W represent the artifact, user, and artifact-user interaction respectively. Also, P , Q , PR , and PSA represent the sets of affordances, effectivities, preferences, and preference-labelled user actions, respectively. While the affordance and effectivity exist at the same level [121], the user's preference property is also at the level of where affordance and effectivity are [141]. Existing at the same level, the affordance, effectivity, and preference can represent the artifact-user interaction state and combine themselves to generate preference-labelled user actions, which is represented as $\pi: P \times Q \times PR \times C \rightarrow PPA$ in Equation (5.1).

In FSA, the set of feasible transitions is triggered if and only if a symbol occurs and is defined the transition function. The input symbol is considered a preference-labelled user action in Equation (5.1), which indicates the artifact-user interaction achieves its goals when the users successively take actions by utilizing the artifact. A simple graphical representation of the AEP-based FSA is shown in Figure 5.2. The transition between the states a , b , and c are triggered by the preference-labelled user actions $pr^i \cdot pa^i$, $pr^{i+1} \cdot pa^{i+1}$, and $pr^{i+2} \cdot pa^{i+2}$. In Figure 5.2, the graphical representation also reflects user's preference properties. The preference indicator of the user behavior and its quality can be viewed as goal-directed, which is concerned with possible actions. Using the preference value, designers can compare the difference types of user behaviors in a numerical way.

Figure 5.2. Graphical representation of state transition

The proposed representation corresponds to AM-facilitated personalization for two reasons. First, the representation contains tuples for the user behaviors in the artifact use and corresponding preferences to represent user experiences level which are considered key factors for personalization. Second, by formally representing state transitions (δ) of the artifact-user interaction, which is triggered by preference-labelled user action ($pr \cdot pa$) in the artifact use, the proposed representation demonstrates that the properties of user behaviors

and preferences are systemically represented in the proposed artifact-user interaction and related to the design requirements. The representation can not only deal with static design values but also dynamic ones reflected in state changes.

5.4 Goal-oriented Language Generation

Each actualization of user action is defined as a state transition (δ), which means that a combination of each action represents successive user actions that are defined as user' activity; a finite sequence of operational actions. Mathematically, an activity with a series of n actions is described as a concatenation of the actions. A user activity, UA , is expressed with affordances, effectivities, and preferences as Equation (5.2):

$$UA = \prod_{i=j}^n [\pi(p_i, q_i, pr_i)], j \leq n < \infty, \quad (5.2)$$

where

$\pi(p_i, q_i, pr_i) = a \in \Sigma, i = j, j + 1, \dots, n$, and p_i, q_i , and pr_i is affordance, effectivity, and preference levels in the context of i^{th} sub-state, $i = j, j + 1, \dots, n$, respectively.

The possible action generation function (π) takes sets of affordances (P), effectivities (Q), preference (PR), and conditions (C) as inputs and generates preference-labelled possible user actions (PPA). This research takes the PR values from between 0 to 1 randomly, for the purpose of illustrating interaction mechanisms. For example, if a user's interaction with two seats is considered, the user actions can be generated as Equation (5.3):

$$PPA \quad (5.3)$$

$$= \pi(P, Q, PR, C)$$

$$= \{ppa_1 = pr_1 \cdot pa_1 = p_1 \times q_1 \times pr_1 \times c_1 ,$$

$$ppa_2 = pr_2 \cdot pa_2 = p_2 \times q_2 \times pr_2 \times c_2 \}$$

$$= \{ppa_1 = pr_1 \cdot pa_1 = 0.4 \times \text{customer_sit_on_seat_A},$$

$$ppa_2 = pr_2 \cdot pa_2 = 0.6 \times \text{customer_sit_on_seat_B}\}$$

where,

$$P: \{p_1=\text{seat_A_sit_on_able},$$

$$p_2=\text{seat_B_sit_on_able}\};$$

$$Q: \{q_1=\text{customer_capability_to_sit_on_seat_A},$$

$$q_2=\text{customer_capability_to_sit_on_seat_B}\};$$

$$PR: \{pr_1=0.4, pr_2=0.6\}; \text{ and}$$

$$C: \{c_1=\text{reachable height for the customer} \geq \text{height of seat A},$$

$$c_2=\text{reachable height for the customer} \geq \text{height of seat B}\};$$

In this research, the user behaviour is defined as a set of user activities, where an activity is a series of specific user actions. The goal is the desired states that the user arrives at after performing a series of actions with the artifact. Based on the automata models and

the state transition diagrams, a connection between the formal model and languages [126] can be considered to address the logical relationships between the goal-oriented user behaviour and the related design requirements. From the proposed formal model, all possible user experiences from the initial interaction state can be generated as a language in Equation (5.4):

$$L(G) := \{e \in \Sigma^* : \delta(s_0, e) \text{ is defined}\}, \quad (5.4)$$

where,

$$\delta: S \times \Sigma^* \rightarrow S,$$

$$\Sigma^* = \prod_{i=j}^n [\pi(p_i, q_i, pr_i)], j \leq n < \infty.$$

In Equation (5.4), the language, $L(G)$ represents all the directed paths that can be followed along the state transitions that start from the initial state in the model. Therefore, a series of user actions, e , is in $L(G)$ if and only if it corresponds to an admissible path in the state transition diagram, equivalently, if and only if δ is defined at (s_0, e) . A user behaviour corresponding to a path is the concatenation of the action labels of the transitions composing the path.

Among the user activities in $L(G)$, this research defines another type of the user behaviour using marked language [126] as Equation (5.5):

$$L_m(G) := \{e \in L(G) : \delta(s_0, e) \in F\} \quad (5.5)$$

As seen in Eq. (5), $L_m(G)$ is a subset of $L(G)$ consisting only of the user activities for which $\delta(s_0, e) \in F$. These user activities correspond to paths that finish at a marked state, F , which is the set of final goals in the state transition diagram. Therefore, $L_m(G)$ defines all possible user experiences that start from the initial states and achieve the final goals in the artifact use. In terms of designing user experiences that achieve the final goals and related design specifications, the marked language $L_m(G)$ can be a significant concern.

Finally, an artifact that can afford $L_m(G)$ needs to be designed to contain corresponding affordances. In the AEP-based FSA, the affordance's relational property links the user behaviour and the affordances can be considered design requirements that match to user actions, therefore, user behaviours consisting of the actions. However, the affordances do not exist in isolation. The affordances should be interpreted as design requirements that in isolation identify bounds and targets for each property represented in the affordance attributes. In seat design, for example, this interpretation will integrate the target height and the width of the seat back, the elasticity of the seat components, etc. After the design requirements are specified, in terms of Design for AM (DFAM) the design specifications incorporate AM's process parameters such as the orientation, slicing, supports, and tool path planning to consider AM manufacturability that affects the level of personalization.

5.5 Summary and Preview

This AM-enabled design freedom offers the new opportunities for personalisation. However, conventional design methods are not qualified to embrace these new opportunities and consequently, it is required that new design principles and methods for AM to achieve a

personalised design. This research proposed a formal framework of a design process for AM-facilitated personalisation and relevant design knowledge representations. The proposed process structure showed a way to systemically integrate the concepts of affordance, effectivity, preference, and user behaviours into the Design for Customization (DfC) and Design for Manufacturability (DfM) frameworks for the advantage of the design freedom improved by AM. This research also proposed Affordance-, Effectivity-, and Preference-based Finite State Automata (AEP-based FSA) as a formal representation of an artifact-user interaction. Then formal representations for user behaviours in the artifact use were introduced as sets of user actions and formal language sets.

Although this chapter provides a formal design process and design knowledge representations for the AM-enabled personalisation, it is noted that shortcomings exist in the limited current scope of the conceptual design. In this point of view, this study can be extended to the related future work as follows. The future work will be conducted in terms of the embodiment and detail design, and production processes using AM technologies. Also, a design method needs to be developed to deal with the design and process selections and decision-making to identify optimal design solutions using the proposed preference indicator. The proposed design representations will be extended to match the affordances to geometrical design parameters. They will embed AM's process parameters to incorporate AM's manufacturability aspects. Therefore, the next chapter provides a method for representing design rules to incorporate AM's manufacturability into AM part designs.

Chapter 6. Knowledge Representation of Customizable Modular Design Rules for AM

This chapter as Step 3 of developing the Customized Design for Additive Manufacturing (CDfAM) in Figure 3.1 proposes a formal method for representing customizable modular design rules for AM (DRfAM). Section 6.1 introduces an overview of the chapter. Chapter 6.2 presents a framework of the proposed method for the development of DRfAM ontology, a design rule-oriented ontology as a sub-ontology of the CDfAM, and knowledge retrieval. Chapter 6.3 explains a knowledge modeling phase of the method for formalizing design fundamentals (DFs) and design principles (DPs) and developing the DRfAM ontology. Chapter 6.4 presents a knowledge reasoning phase of the method with design rule-based design recommendations in given contexts. Chapter 6.5. provides a summary of this chapter and a preview of the next chapter.

6.1 Overview

AM is a set of manufacturing processes that produce 3D objects from 3D model data layer-upon-layer, as opposed to subtractive manufacturing processes [1]. Therefore, AM restricts design spaces based on its manufacturability constraints that are distinct from the others generated by the subtractive or formative manufacturing processes. To integrate AM's restrictions through the product's lifecycle from the early design phase, Restrictive DfAM

has been proposed with its concentration on AM's manufacturability constraints as a type of Design for Manufacturability (DfM).

To incorporate manufacturability into design, DfAM studies have had their focuses on process-property-structure-function correlations in AM [27-29]. Then, the correlation studies are related to design rules (DRs) that can provide rules for manufacturable AM feature designs in relation to part design, process, and material [30]. To provide fundamental principles that are usable in different AM applications and process types, studies on DRs have provided DFs and DPs as modular knowledge blocks that designers can modify, extend, reconfigure for customizing them [30].

Ontologies have provided a source of shared design rule knowledge in AM by representing process, material, and design classes and properties in DfAM knowledge [83]. The ontology-based approaches enable designers no longer merely to exchange specific geometric data, but rather more knowledge about DRs in AM including design and product development process, design specifications, constraints and rationale. A computational framework and a method are required in a DR representation for AM to enable mechanical product development by effectively supporting the formal representation, capture, retrieval, and reuse of DR knowledge.

Generating robust design rules for AM requires an understanding of AM feature geometry and the effects of process and materials of AM in design. However, current AM solid models and design software cannot be considered advantageous drivers of robust design rules for AM, because they provide incomplete product and feature definitions in AM and are not able to act according to semantic contents of AM's manufacturability constraints. Also, existing AM software know-how is still far from being mature enough to allow

designers to fully grasp AM's manufacturability requirements and limitations in developing AM parts. The reason is that they are developed only for geometric models or a limited set of few mechanical or material properties are in the center of design and product models for AM. Geometry is of great importance during design, however, morphological characteristics are consequences of the design rationales and of influences of AM's principle physical processes on designs.

To address such limitations, this research proposes a method for modeling and sharing the DRfAM knowledge. First, this research extends a structured modular hierarchy and associated formalisms in the representation to develop the principles of design rules (PDR) languages. Second, this research develops a DRfAM ontology that captures the ontology's classes, hierarchies, and properties and retrieves DRfAM knowledge with Semantic Query-Enhanced Web Rule Language (SQWRL) by enhancing the extended set of PDR languages as metamodels. The ontology-based knowledge modeling and sharing enables capturing the semantic content of the DRfAM generated from AM contexts. The proposed method explicitly represents definitions of design rule's fundamental elements in AM's domains of design, process, and material and their correlations. Based on the correlations, the formal method systematically shows how AM's manufacturability constraints are associated with additively manufacturable part structures and how the AM feature designs are recommended as consequences of the AM constraints. This research produces a DRfAM knowledge base that is constructed with reconfigurable design rule knowledge blocks which allow semantic queries of the DRfAM knowledge selectively.

6.2 Framework

This chapter proposes a formal method with two parallel phases: i) PDR language development and ii) the DRfAM ontology development, as shown in Figure 6.1. The proposed method takes text-based Design Guidelines (DGs) as inputs and process the knowledge transformation in the forms of formal languages. By the method, DFs, DPs, and DRs are identified and formulated in language sets and then matched to the DfAM ontology.

Figure 6.1. An overall framework of the proposed method

The method consists of two sequential phases: i) knowledge modeling (Chapter 6.3) and ii) knowledge retrieval (Chapter 6.4). First, the knowledge modeling phase establishes classes and properties by using and DFs and DPs (consisting of DP I, II, and III) as meta-

models. The knowledge modeling phase starts with taking text-based design guidelines as input and identifies DFs. This step defines DFs illustrated in input DGs and separates their types such as AM features and geometry, process, and material parameters specific to categories. Then, design principles are developed by analyzing the relations between the DFs. Based on the DFs and DPs sets, the DRfAM ontology is constructed by matching its classes and properties to the structured modular hierarchy and associated formalisms in design fundamentals and principles.

Second, the knowledge retrieval phase takes DGs, DFs, and DPs as inputs and interprets the DGs using IF-THEN statements for descriptive expressions using the DFs and DPs. The structured IF-THEN statements serve as meta-models for semantic queries in this research. Semantic queries retrieve design recommendations for improving manufacturability by reasoning with SQWRLs.

6.3 Design Rule Element Modeling

6.3.1 Identify Design Fundamentals and Formulate Design Principles

As reviewed in Chapter 2.3.2, DRs contain DFs and DPs that include, but are not limited to AM features, geometry, process, and material parameters. To provide an extended set of design rules for abstracting designs, constraints, and guidelines for AM in detail that is required for mechanical design, the DFs and DPs need to be thoroughly investigated for an extension. The key consideration in this chapter for extending existing design rule

representations is to provide a modular method for formally representing context-to-module-to-primitive knowledge transformations and vice versa by the PDR language sets. By doing so, this chapter presents the design, constraints, and their relationships as DFs and DPs.

6.3.1.1 Identify Design Fundamentals

To propose a new set of DFs, this research proposes form feature's design abstraction hierarchy as seen in Figure 6.2. Form feature's design abstraction hierarchy has three levels of design abstractions as follows.

Primitive form feature level (PFLv) is a design abstraction level where an AM feature is defined at the lowest form feature level. As form features are defined based on a design context, a primitive form feature is defined by a unit manufacturing constraint in AM. In the case of a thin wall, the only context considered is an AM process constraint that defines the thin wall feature. For example, a thin wall can be defined as a primitive feature in AM based on a wall thickness requirement generated by manufacturing constraints from a target AM process.

On the other hand, some AM features can be defined based on multiple AM process constraints and therefore represented as a combination of primitive features; this research defines them as compound features. In incorporating manufacturability in part designs, a part is defined using a set of features associated with specific manufacturing processes [142]. The compound feature level (CFLv) is a design abstraction level where a form feature is defined as a combination of primitive features at a lower level. Here, a compound feature cf_i in Figure 6.2 can be composed of a set of primitive features $\{pf_1, pf_2, pf_3, \dots, pf_i\}$. For example, a

honeycomb structure can be defined as a compound feature and represented as a set of relevant primitive features such as thin walls and porous parts.

Geometric Entity level (ELv) is a design abstraction level where topological and geometric entities and their relationships are defined and characterized. A form feature's shape constraints specify relationships between the geometric entities of edge, vertex, and face. Typically, a form feature is used to indicate form elements that are described at a higher level than the geometric entities of edges, vertexes and surfaces [76]. Therefore, at the PFLv, a primitive feature, pf_i , in Figure 6.2, can be composed of a finite set of shape entities $\{e_1, e_2, e_3, \dots, e_j\}$. Then, for example, a thin wall feature can be represented by relevant entities composing the feature. Therefore, the explicit representation of form feature is through reference to elements of the boundary representation of a solid model that defines the shape of the for feature presented with shape entities' relationships [143]. Also, in AM, manufacturability constraints are analyzed not only at the form feature levels but also at the ELv. Examples can be a sharp edge of a corn feature or an undercut surface of an overhang feature, and surface quality of a complex surface of a freeform structure.

Figure 6.2. Three levels of design abstractions in form feature representation

Then, the existing concepts of primitives G , P , and M are leveraged. The qualitative and quantitative aspects of the modules' geometric characteristics can be explicitly

represented by geometry primitive G with certain values or ranges. Such characteristics include shapes and constraints such as locations and adjacencies and geometric relationships. Also, Primitives of P and M are AM process and material parameters which distinguish AM techniques about AM parts' geometric boundary constraints with considering qualities and behaviors. P and M provide manufacturability constraints from AM processes and therefore are defined or selected depending on a domain AM process.

A new set of extended DFs is defined as a set in Equation (6.1).

$$DF = \{Mo, PR\} = \{\{CF, PF, E\}, \{G, P, M\}\} \quad (6.1)$$

where,

Mo : a set of modules, $Mo = \{CF, PF, E\}$,

PR : a set of primitives, $PR = \{G, P, M\}$,

CF : a set of compound features, $CF = \{cf_1, cf_2, cf_3, \dots, cf_i\}$,

PF : a set of primitive features, $PF = \{pf_1, pf_2, pf_3, \dots, pf_j\}$,

E : a set of geometric entities, $E = \{e_1, e_2, e_3, \dots, e_k\}$,

G : a set of geometry parameters, $G = \{g_1, g_2, g_3, \dots, g_l\}$,

P : a set of process parameters, $P = \{p_1, p_2, p_3, \dots, p_m\}$, and

M : a set of material parameters, $M = \{m_1, m_2, m_3, \dots, m_n\}$.

As shown in Equation (6.1), the DFs have two types: module (represented as Mo) and primitive (represented as PR) [30], while Mo includes CF , PF , and E and PR includes G , P , and M in this study. Equation (6.1) adds new AM feature-oriented modules CF , PF , and E

into the extended DF set as graphically compared in Figure 6.3. The DFs' properties are shown in Table 6.2. In Table 6.2, the modules are defined based on AM manufacturability contexts such as geometric tolerance evaluation [78] and grouped according to the design abstraction levels CFLv, PFLv, and ELv. AM process-independent examples of the primitives are shown in Table 6.3.

**Figure 6.3. Graphical comparison between (a) previous DF set [26, 30] and
(b) Extended DF set**

Table 6.1. Properties and characteristics of DFs

Terms	Notation	Type	Methods of generation	Semantic conno- tation
Compound Feature	<i>CF</i>	Module	Derived or developed	Implicit
Primitive Feature	<i>PF</i>			
Geometric Entity	<i>E</i>			
Geometry Parameter	<i>G</i>	Primitive	Measured or defined	Explicit
Process Parameter	<i>P</i>			
Material Parameter	<i>F</i>			

Table 6.2. Examples of modules at CFLv, PFLv, and ELv

Design Abstraction Level	Module
CFLv	Lattice structure Topology-optimized structure ⋮
PFLv	Overhang feature (angular, circular, hole) Wall (normal, thin) Radii Beam (cylinder, square) Cubes Slots Rectangular bosses Base surface of the test part Circular holes Solid and hollow cylinders Spheres, Half-Spheres ⋮
ELv	Downskin surface Base surface Inclined surfaces Sharp edge ⋮

Table 6.3. Examples of primitives common to different AM processes

Index No.	<i>G</i>	<i>P</i>	<i>M</i>
1	Part dimension (set)	Energy source type for bonding material (set)	Material type
2	Part location (set)	Bonding sheets (set)	Material thermal property (set)
3	Part tessellation tolerance	Material feeding (set)	Material mechanical property (set)
4	Feature dimension (set)	Scanning (set)	Material electrical property (set)
5	Feature location (set)	Part orientation (set)	Feedstock size (set)
6	Feature orientation (set)	Layer thickness	
7	Feature shape (set)	Build chamber (set)	
8	Feature topology (set)	Build temperature	
9	Feature property (set)	Platform orientation (set)	
10	Feature undercut angle (set)	Platform dimension (set)	
11	Surface type		
12	Surface position		
13	Surface orientation (set)		
14	Surface dimension (set)		
15	Surface shape		
16	Edge type		
17	Edge position		
18	Edge shape		
19	Vertex type		
20	Vertex position		

Figure 6.4 shows an example representing an overhang feature that requires support structures when it is additively manufactured. Figure 6.4 is adapted from [85] and interpreted using the DFs proposed in this research. Descriptions for notations are in Table 6.4.

(a)

(b)

Figure 6.4 Overhang feature (o) based on downskin angle (θ) and normal vector ($\vec{n}$) of downskin surface (e) and (b) with support structures ($s_1, s_2, \dots$, and s_6)

Table 6.4. Notation of modules for overhang and support structures in Figure 6.4

Notation	Description
cf	A compound feature composed of an overhang feature pf and support structures $s_1, s_2, \dots$, and s_6
pf	An overhang feature as a primitive feature of cf . pf contains e as an entity
$s_1, s_2, \dots$, and s_6	Support structures as primitive features of cf
e	A downskin surface of pf as an entity

6.3.1.2 Formulate Design Principles

DPs are foundational and logical correlations between the DFs. As the DFs are extended, DPs need to be formulated to explain the relationships between the extended DFs. Figure 6.5 outlines a DP formulation approach in this chapter. DPs can be formulized as three types as follows: i) *DP I*. Module decomposition and interaction design principle and ii) *DP II*. Module-primitive relationship design principle, and iii) *DP III*. Composite design principle. The relationships in the DPs are focused on i) module relationships and ii) module-primitive relationships, and iii) primitive relationships.

Figure 6.5. Outline of DP formulation approach from (a) design and AM domains (b) DP I. Module decomposition design principle (c) DP II. Module-primitive relationship design principle (d) (iii) DP III. Composite design principle.

DP I. Module Decomposition and Interaction Design Principle

$$f:mo_i \rightarrow \{SubMo, InterSubMo\} \quad (6.2)$$

where,

mo_i : a module; $mo_i \in Mo$,

$SubMo$: a set of submodules: $\{smo_1, smo_2, \dots, smo_{j-1}, smo_i\}$,

$$SubMo \subset \begin{cases} PF & \text{if } mo_i \in CF \\ E & \text{if } mo_i \in PF, \\ \emptyset & \text{if } mo_i \in E \end{cases}$$

InterSubMo: a set of interacting submodules,

$$ad(SubMo) = InterSubMo = \{ \{\emptyset\}, \dots, \{smo_k, \dots, smo_l\} \} \in \mathcal{P}(SubMo),$$

$\mathcal{P}(SubMo)$: the power set of *SubMo*, the set of all subsets of *Submo*,

f: a module decomposition function,

ad: a module interaction function.

By Equation (6.2), *DP I* captures an AM feature representation with form feature and geometric entity relationships based on decomposition and interaction relationships between modules *CF*, *PF*, and *E*. In design, decomposition methods have been useful for form feature representations, while using both design and manufacturing features. Note that the goal of decomposition representations in this research not only AM feature representations but also manufacturability analysis and modular representation of feature-based design rule elements at the CFLv, PFLv, and ELv. Module decompositions are addressed in *DP I*, while primitives are not yet involved in order to mainly focus on the module relationships for presenting modular representations.

In *DP I*, a module at a higher design abstraction level is represented as a combined set of submodules *SubMo* that exists at a lower design abstraction level and a set of adjacent submodules as ordered pairs in *InterSubMo* (Equation (6.2)). There are two relationships represented in Equation (6.2): i) a module decomposition relationship and ii) a module interaction relationship. An example of such module relationships in *DP I* is shown in Figure 6.6. First, the module decomposition relationships are formulated using a module decomposition function *f*. A decomposition approach with *f* enables discretization of geometry regions and volumes depending on manufacturability evaluations strategies. A

geometry region decomposition method for a manufacturability evaluation can use f as a guideline for manufacturability analysis, to explore the decomposition of AM features from the compound feature to primitive features, then to entities. An AM feature with complex topology geometries can be decomposed into sub-modules of primitive features such as thin wall, overhang, and slim cylinder features in such modular approach using f . For example, if an AM part is defined as a compound feature such as a complex overhang feature with multiple overhang surfaces, the compound feature can be decomposed into overhang feature submodules of primitive features and then to overhang surface modules of geometric entities.

Second, the module interaction relationships are formulated using a module interaction function ad . Once a module is decomposed into submodules, submodule interactions are considered for identifying geometric and manufacturing constraints generated from the submodule interactions. For example, form feature interactions identify how a feature is attached to a global model by coupling some of the feature faces with the pre-existing faces [144]. In this case, feature interaction constraints can be geometric constraints that specify geometric relations between submodules such as parallelism of two faces or a location of interactions between two faces. Even when an AM part is represented by using manufacturable submodules, the part design cannot be manufacturable due to the submodule intersections' geometric and relevant manufacturing constraints. Note that this is because the interacting submodules create a new set of module geometric characteristics in their relationships by relatively locating and orienting the adjusting modules according to their spatial relationships. An example is a concave edge generated in two thin wall feature interactions that can generate additional manufacturability considerations such as overhang and sharp edge depending on their relationships. Therefore, additional manufacturing and

material constraints are applied to interacting geometric regions. In *DP I*, only module relationships are identified. Relevant geometry, process, and material parameters are explicitly represented in *DP III* with associated primitive relationships.

Figure 6.6. Module relationships in DP I

Based on the module decomposition and interaction relationships in *DP I*, this research develops relationships R1-R4 in Table 6.5. that categorizes the types of the module relationships, which will be utilized in the property establishment in the DRfAM ontology development phase in Chapter 7.

The module decomposition and interaction relationships connect AM process contexts as design rationales to the solid design modules of AM features and geometric entities and their hierarchical relationships, which enables an AM process context-to-module knowledge transformation and vice versa by linking manufacturability-part structure-form feature-geometry entity. Especially, when a functionality-oriented AM parts and products such as a lattice structure or a bracket is linked to manufacturability-oriented modules such as a thin

wall or an overhang feature in the hierarchical decomposition, *DP I* enables exploring design synthesis of different AM knowledge domains in a context-to-module knowledge transformation and vice versa, which link functionality and manufacturability requirements in form feature designs. Once identifying the modular relationships, explicit representations of manufacturability constraints are conducted in *DP II* and *DP III* by involving associated primitives.

Table 6.5. Relationship types established in DP I

Relation	Description
R1	A higher-level module (mo_i) <u>is composed of</u> a set of lower-level modules.
R2	A higher-level module (mo_i) <u>contains</u> a set of the interacting lower-level module.
R3	Lower-level modules composing a higher-level module (mo_i) <u>interact with</u> each other.
R4	A subset of submodules composing a higher-level module <u>is involved in</u> interacting submodule sets.

DP II. Module-Primitive Design Principle

$$g: mo_i \rightarrow h(X_{mo_i}) \quad (6.3)$$

where,

g : a module-to-primitive function,

h : a primitive correlation function,

mo_i : a module,

X_{mo_i} : a set of primitives of mo_i , $X_{mo_i} \subset PR$,

PR : a set of primitives, $PR = G \cup P \cup M$,

G_S : a set of design specification geometry parameters, $G_S \subset G$,

G_R : a set of AM-constrained geometry parameters, $G_R \subset G$,

G_j : a set of geometry primitives at j level, $G_j \subset G$

P_j : a set of process parameters at j level, $P_j \subset P$,

M_j : a set of material parameters at j level, $M_j \subset M$,

j : design abstraction level,

$$j = \begin{cases} CFLv & \text{if } mo_i \in CF \\ PFLv & \text{if } mo_i \in PF \\ ELv & \text{if } mo_i \in E \end{cases}$$

By Equation (6.3), *DP II* presents i) formalisms of primitives associated with modules by a module-to-primitive function g , and ii) correlations between the primitives by a primitive correlation function h . By presenting formalisms that involve primitives, *DPS* identify explicit design constraints for modules with measurable entities. With primitives'

parameterized representations of the constraints, the constraints can be further classified into details such as dimension constraints, algebraic constraints, boundary constraints, and feature interaction constraints to link explicitly represented design guidelines.

In *DP II*, note that G , P , and M are defined at each level of design abstraction as G_j , P_j , and M_j , respectively, in which j represents the design abstraction levels CFLv, PFLv, and ELv, depending on the corresponding module's design level of abstractions. If a module is defined as a compound feature, geometry primitives for the compound module can be the associated parameters that capture the geometry of the module at the CFLv. For example, a compound feature as an AM part can be characterized by a geometry primitive set G_{CFLv} with part dimension, part location, and part orientation, etc. In a case of a primitive feature, the primitive feature needs to be characterized using another subset of G , G_{PFLv} , consisting of geometry primitives such as feature location and feature shape. A geometric entity can be characterized using geometry primitives at the ELv; for example, an overhang feature's downskin surface can be characterized using G_{ELv} that can be a set of the surface dimension and undercut angle.

Such G explicitly represents geometry characteristics of modules with their parametric relationships that capture the modules' i) design specifications of geometry surface regions and ii) critical geometric elements where manufacturability is considered. Therefore, G consists of two types: i) a design specification geometry parameter set G_S and an AM-constrained geometry parameter set G_R . G_S is design requirement-oriented and an example can be dimensions of a customized lattice structure and its functional volumes and surfaces (i.e. volumes and surfaces of a feature fulfilling specific functional requirements). G_R is AM

process-constrained and examples are additive manufacturable part size, feature orientation, undercut angle without or with support structures, etc.

On the other hand, primitives of P and M consist of process and material parameters defined or selected based on manufacturability such as surface roughness that P and M impose at each design abstraction level where the target modules exist. Then, the ranges of values for each parameter to the AM process are imposed depending on AM process contexts. The identification of P and M can be done by using a tool such as the cause-and-effect relationship diagram between process control parameters and process signatures [31] or design and analysis of experiments [81], which identify the restrictive relationships between the G , P , and M primitives. A general framework of module-primitive and primitive relationships in $DP II$ is in Figure 6.7.

Figure 6.7. Module-primitive and primitive relationships in $DP II$

Based on the module-primitive and primitive relationships in *DP II*, relationships R5-R7 in Table 6.6 are developed to categorize the types of module-primitive and primitive relationships. Such relationships are leveraged in the property establishment in the DRfAM ontology in Chapter 7.

Table 6.6. Relationship types established in *DP II*

Relation	Description
R5	A module <u>has a geometric characteristic of</u> geometry primitives.
R6	Design space of a module (mo_k) <u>is restricted by</u> geometry, process, and material primitives.
R7	The types and value ranges of primitives for a module <u>are restricted by</u> one another.

DP III. Composite Design Principle

Once *DP I* and *DP II* are established, *DP III* can be developed as a composite design principle that is a composition of *DP I* and *DP II* that combines f , ad , g , and h functions as shown in Equation (6.4).

$$g \circ f: mo_i \rightarrow \{\cup_{j=0}^n h(X_{submo_i}), \cup_{k=1}^m h(X_{intersubmo_i})\} \quad (6.4)$$

Equation (6.4) can be explained as follows. Equation (6.4) consists of two phases. First, the module decomposition function f conducts a decomposition of a module mo_i into

a set of sub-modules $SubMo$ and a set of interacting sub-modules $InterSubMo$ as seen in Equation (6.5). Relations from $DP I$ are applied in this process.

$$g \circ f: mo_i \rightarrow g:\{SubMo, InterSubMo\} \quad (6.5)$$

Second, the module-to-primitive function g is applied to $SubMo$ and $InterSubMo$, respectively, to relate them to relevant primitives and primitive correlations as shown in Equation (6.6).

$$g:\{SubMo, InterSubMo\} \rightarrow \{g:SubMo, g:InterSubMo\} \quad (6.6)$$

where,

$$g:SubMo \rightarrow \bigcup_{j=0}^n h(X_{submo_i}) \quad (6.7)$$

$$g:InterSubMo \rightarrow \bigcup_{k=1}^m h(X_{intersubmo_i}) \quad (6.8)$$

By Equations (6.7) and (6.8), the g function relates $SubMo$ and $InterSubMo$ to the associated primitive sets and primitive correlations, $\bigcup_{j=0}^n h(X_{submo_i})$ and $\bigcup_{k=1}^m h(X_{intersubmo_i})$.

In a form feature decomposition approach on manufacturability analysis, incorporating manufacturability into geometries is conducted not only on a part's global geometry with imposed manufacturability constraints but also on local geometric regions with imposed manufacturability constraints in order selectively. Therefore, an AM part is manufacturable only when manufacturability constraints are incorporated into both the part's global and local geometric regions. For incorporating manufacturability into local geometric regions, a module's whole geometry needs to be identified with its submodules and submodule

interactions and associated with manufacturability constraints arising from the surface geometries of the submodules and submodule interaction regions for detailed manufacturability analysis. Such tasks require both module relationships for identifying module decompositions and submodule interactions from *DP I* and module-primitive and primitive relationships from *DP II* for explicitly representing design constraints. However, *DP I* can only represent module relationships without primitives G , P , and M , while *DP II* can only relate primitives to unit modules. *DP III* enables a module to be linked to primitive relationships associated with the module's i) submodules and ii) interactions between the submodules at a lower level. The identified submodule interactions in *DP I* are finally explicitly represented with G , P , and M in this phase. A generic framework for such relationships is shown in Figure 6.8.

Figure 6.8. Submodule interaction-primitive relationships

The submodule-primitive Relationships can be explained by R5-R7, since submodules are unit modules. However, the submodule interaction-primitive relationships and associated primitive relationships in *DP III* (shown in Figure 6.8) establish additional relationships R8-

R10 in Table 6.7. The relationships R8-R10 are leveraged in constructing the DRfAM ontology in the following chapter.

Table 6.7. Relationship types established in *DP III*

Relation	Description
R8	Geometry regions where modules interact <u>have geometric characteristic of</u> associated geometry primitives.
R9	Geometry regions where modules interact <u>are restricted by</u> associated geometry, process, and material primitives.
R10	The types and value ranges of primitives associated with module interactions <u>are restricted by</u> one another.

By the extended DFs and DPs, the PDR enables abstracting design rule knowledge for AM in detail that is required for a traditional mechanical design; the extended language set represent AM feature representations including

- form features (AM features),
- form feature relationships,
- geometric and topological entities,
- geometric and topological entity relationships,
- geometry parameters, and
- geometry parameter relationships.

Also, the extended DFs and DPs include AM process and material context knowledge represented with

- AM process and material parameters and
- AM process and material parameter relationships.

Then, AM feature representations and AM process and material constraints are associated with one another, which explains how geometric characteristics of AM features are related to AM's physical processes.

6.4 Design Rule Representation

Once DF and DP knowledge is modeled in the DRfAM ontology, various designers in AM domains can access the DRfAM knowledge base by using a semantic query to incorporate manufacturability to their designs. In this phase, DRs are constructed as formal conditional statements while using the DFs and DPs from Chapter 6.3 as knowledge blocks. The structured DRs serve as meta-models for semantic queries in this research.

6.4.1 Structure Design Rules as IF-THEN Statements

Syntax refers to the set of abstract grammar rules in a language, governing the order of words in a correct sentence [145]. DRs are built by selecting DFs and DPs as syntactical units and grammars and then appending them into a sentence according to the input DGs in IF-THEN conditional statements. Such process structures text-based DGs into a conditional statement

$$p \text{ (design and manufacturing specifications)} \Rightarrow q \text{ (design recommendations)},$$

where p is the dependent clause or the antecedents expressing the conditions and q is the main clause or the consequents expressing the consequences while p and q consist of DFs and DPs. A DR is an IF-THEN statement expression that represents a restrictive relationship between design and manufacturing specifications and design representations based on manufacturability-oriented design criteria in AM implementation contexts.

In the IF-THEN statements, p expresses design and manufacturing specifications of modules considered in a DR by specifying the types of the modules and their geometries. p also expresses manufacturing and material specifications that restrict the physical design space of the modules as AM constraints. On the other hand, q is a sentence that specifies design recommendations in the given context in p and q consists of i) recommended feature geometries and ii) support structures. This is due to that, typically, DfAM constraints are either accommodated i) by modifications of intended geometries, or ii) by the use of support material to enable acute inclination angles and to transfer heat as required [34, 67]. As support structures extend the design spaces of feasible geometries [146], q includes support structure specifications in design recommendations, if the modules in p are identified non-self-supporting designs.

6.4.2 Formulate Design Rule

6.4.2.1 Design Rules for Feature Geometry Recommendations

This chapter presents formal expressions of DRs and corresponding SQWRLs. First, *DRI* expresses a DR model that highlights recommended feature geometry elements of modules with implied constraints *CI* as below. A corresponding SQWRL set, *SQWRLI*, is presented based on *DRI* and *CI*.

IF-THEN statement

DRI: $Mo \cup G_S \cup P_{Mo} \cup M_{Mo} \Rightarrow G_R$

Implied constraints

CI: $G_S, G_R \subset G_{Mo}$ and $G_{Mo}, P_{Mo}, M_{Mo} \subset X_{mo}$, where $g: Mo \rightarrow h(X_{mo})$

SQWRL in DL

SQWRLI:

$\text{Module} (?Mo) \wedge \text{GeometryParameter} (?G) \wedge \text{ProcessParameter} (?P) \wedge$
 $\text{MaterialParameter} (?M) \wedge \text{hasGeometricCharacteristicOf} (?Mo, ?G) \wedge$
 $\text{isRestrictedBy} (?G, ?P) \wedge \text{isRestrictedBy} (?G, ?M) \rightarrow \text{sqwrl:select} (?G)$

The dependent antecedents of *DR1* as design and manufacturing specifications are expressed as $Mo \cup G_S \cup P_{Mo} \cup M_{Mo}$. *Mo* is a set of modules considered in *DR1*. As presented in the previous Chapter 6.3, the modules in *Mo* define the module types, however, contains implicit target geometry information. To add explicit geometry specifications of *Mo*, G_S is included as a set of geometry primitives associated with *Mo* in a given condition for *DR1*. The combination of *Mo* and G_S becomes the design specification. Then, $P_{Mo} \cup M_{Mo}$ is presented as manufacturing specifications, since $P_{Mo} \cup M_{Mo}$ is a union set of a process primitive set P_{Mo} and a material primitive set M_{Mo} associated with *Mo*.

The consequents recommend geometry specifications of critical AM-restrictive geometric regions and volumes of *Mo* as design recommendations and represent them as G_R . While $Mo \cup G_S \cup P_{Mo} \cup M_{Mo}$ specifying design and manufacturing requirements, G_R is provided by design criteria that are the restrictive relationships between the design and manufacturing specifications (for example, the minimum height of an AM feature should be larger than the layer thickness of an AM process). Therefore, *DR1* is applicable when such restrictive relationships are defined in the constraint *CI*. Here, *CI* leverages *DP II* that defines the restrictive relationship between modules and primitives using the functions g and h , respectively.

Then, SWRL expressions are developed by matching them to the formulated design rules and relevant constraints; SWRL expressions are matched to i) the DFs in p and q and ii) the DPs in the implied constraints. In this phase, *SWRL1* matches *DR1* and *CI* to its expressions consisting of associated classes, individuals, and properties in the DRfAM ontology. In *SWRL1*, first, the classes and individuals are matched to the DFs in *DR1*. Second, the DPs in *CI*, the restrictive relationships between the DFs in *DR1* are expressed. The first

four clauses of *SWRL1* above are to query the DFs (modules and the primitives) represented in *DR1*. Then, the last three clauses are to query their restrictive relations in *CI* by adding relevant properties such as *hasGeometricCharacteristicOf* and *isRestrictedBy* in the expression. An SWRL operator *sqwrl:select* is used to retrieve design recommendation variable ?G that meets the query conditions in the antecedent.

6.4.2.2 Design Rules for Support Structure Recommendations

The second design rule *DR2* focuses on support structure-oriented design and manufacturing specifications and relevant restrictive relationships between modules and primitives. While having the same dependent antecedents to *DR1*'s, *DR2* expresses a design rule with support structures and support structures' geometry specifications as recommendations.

IF-THEN statement expression

$DR2: Mo \cup G_S \cup P_{Mo} \cup M_{Mo} \Rightarrow S \cup G_{Sup}$

Implied constraints

C2-1: $G_S \subset G_{Mo}$ and $G_{Mo}, P_{Mo}, M_{Mo} \subset X_{mo}$, where $g: Mo \rightarrow h(X_{Mo})$

C2-2: $G_{Sup} \subset X_{Sup}$, where $g: S \rightarrow h(X_{Sup})$

C2-3: $Mo, S \subset SubMo$ and $\{Mo, S\} \in InterSubMo$, where $f: mo_j \rightarrow \{SubMo, InterSubMo\}$

SQWRL

SQWRL2:

```
Module(?Mo) ^ GeometryParameter (?G) ^ ProcessParameter (?P)
^
MaterialParameter (?M) ^
hasGeometricCharacteristicOf(?Mo, ?G) ^ isRestrictedBy
(?G, ?P) ^ isRestrictedBy (?G, ?M) ^ Module(?S) ^
interactWith(?Mo, ?S) ^

GeometryParameter(?G_sup) ^
hasGeometricCharacteristicOf(?S, ?G_sup)

isRestrictedBy (?G_sup, ?P) ^ isRestrictedBy (?G_sup, ?M) ^
isRestrictedBy (?G_sup, ?G)

→ sqwrl:select(?S, ?G_sup)
```

As *DRI*'s dependent antecedents, $Mo \cup G_S \cup P_{Mo} \cup M_{Mo}$ becomes the design and manufacturing specification that represents the design and manufacturing context, however, the context indicates a support structure necessity this time. Then, the consequents of *DR2* as design recommendations are presented to express a support structure specification SUG_{Sup} . SUG_{Sup} is a union set of a support structure module set S and the support structure geometry specification G_{Sup} .

SUG_{Sup} specifies types of support structures and their geometric parameters and parameter values in a condition that Mo is not self-supporting. If the dependent antecedents present a design context in that Mo is self-supporting, SUG_{Sup} becomes a null set, since no support structure is recommended. $DR2$ is applicable only when such restrictive relationships between the design and manufacturing specifications and support structure specifications are defined in $C2-1$, $C2-2$, and $C2-3$. Here, $C2-1\sim3$ leverage $DP I$ and $DP II$ that define the restrictive relationships between modules and primitives using the functions f , g , and h . For example, $C2-3$ defines a module interaction relationship constraint between Mo and S using f of $DP I$ where Mo and S are defined to interact each other as interacting submodules of a compound feature module mo_j . Support structures are designed to support overhang structures by physically interacting with the overhang structures' overhang surfaces. Therefore, overhang features and support structures adjust each other as shown in Figure 6.4. $C2-3$ constrains the module interaction relationships between Mo and S . Then, $SWRL2$ matches the design fundamentals and principles in $DR 2$ and $C2-1\sim3$ to the classes, individuals, and properties and retrieve design recommendation variables $?S$ and $?G_{sup}$ for a support structure type and its geometry specification, respectively.

6.5 Summary and Preview

As a Restrictive DfAM approach to incorporate AM manufacturability into product's functional geometries, this research proposed a formal method for representing customizable modular design rules for AM. First, this chapter introduced a novel modular hierarchy and associated language sets for design rule elements by extending existing design rule languages.

Second, this chapter introduced structured design rule representations utilizing the knowledge modules.

Although this chapter provides a novel Restrictive DfAM method, it is noted that shortcomings exist in the limited current scope of 1) formal representations and 2) Restrictive DfAM. In this point of view, this study can be extended to the related future work as follows: 1) extension of the method to merge it with existing functionality-oriented DfAM methodologies, 2) identification of fundamental design-process-material correlations based on data analytics and data-driven decision makings, and 3) ontology development. The next chapter is a chapter that addresses such limitations with case studies

Chapter 7. Case Study

This chapter presents Step 4 of validating models, collecting case study knowledge, and constructing the CDfAM ontology in Figure 3.1. Chapter 7.1 demonstrates the proposed FSA-based affordance structure with a case study of AM-enabled seat design for validation. Chapter 7.2 builds a CDfAM ontology that is the main body of this study's DfAM knowledge base that contains AM application knowledge for prosthesis leg design in addition to AM process and additive manufacturability knowledge. Chapter 7.2 also presents a prescriptive design rule knowledge retrieval for design recommendations. Chapter 7.3 presents a case study of data-driven CDfAM knowledge construction that evolves knowledge in the proposed ontology. Following this, the research is concluded, and future work is discussed in Chapter 7.4.

7.1 Case Study I: Validation of FSA-based Affordance Structure

To validate and demonstrate the effectiveness of the proposed FSA-based formal affordance structure method, this chapter uses a case study in which interactive product behaviors are apparent, and the product use and individual customer interactions are perceptually available.

7.1.1 Background

For the case study, this research considers personalized seat designs. Figure 7.1 shows examples of AM-enabled customized seat designs.

Figure 7.1. (a) Toyota car seat (Courtesy of Materialise) and (b) Navy Aircrew Common Ejection seat designed for AM [14].

The purpose of the case study is to demonstrate the usability of the FSA-based affordance structure in automated DfAM environment and to validate the proposed FSA model. For validating the proposed affordance structure, cases that a user interacts with two different seats are considered in this section. There are two interactions assumed: seat A-user interaction and seat B-user interaction. Suppose that the two different interactions intentionally possess the same general affordance and effectivities, but different preference levels towards the user actions due to their embodiment designs are not customized. The starting point of the user behaviors is user's action of sitting on the seat in both interactions. Table 7.1 describes artifacts, users, and the possible user actions involved in the seat-user interactions.

Table 7.1. Descriptions of artifacts, users, and user actions involved in the seat-user interaction

Artifact	User	User action
Seat A, Seat B	User	Sit on
Seat A, Seat B	User	Lean back
Seat A, Seat B	User	Put arms on armrest
Seat A, Seat B	User	Propel back

7.1.2 Representation of Affordance Structure

The two seat-user interactions are represented in the state transition diagrams in Figure 7.2.

Figure 7.2. Transition diagram of the seat A-user interaction

According to Equation (5.1), the formal model of the seat A-user interaction corresponding to the diagram is Equation (7.1).

$$G^A = \langle S^A, \Sigma^A, \delta_{exp}^A, s_0^A, F^A, G_{atom}^A, \{X^A, Z, W^A\}, \{P^A, Q^A, PR^A, PA^A\}, Pr, j, \pi \rangle, \quad (7.1)$$

S^A : $\{s_0^A = \text{initial},$
 $s_1^A = \text{user_sitting_on_seat_A},$
 $s_2^A = \text{user_leaning_back},$
 $s_3^A = \text{user_put_arms_on_armrest},$
 $s_4^A = \text{user_moved_back_by_propeling_back_seat_A}\};$

F^A : $\{s_4^A = \text{user_propelled_back_seat_A}\};$

X^A : Seat A;

Z : User;

W^A : Seat A-user;

P^A : $\{p_0^A = \varphi,$
 $p_1^A = \text{seat_A_sit_on_able},$
 $p_2^A = \text{seat_A_lean_back_able},$
 $p_3^A = \text{seat_A_put_arms_on_armrest_able},$
 $p_4^A = \text{seat_A_propel_back_able}\};$

Q^A : $\{q_0^A = \varphi,$
 $q_1^A = \text{user_capability_to_sit_on_seat_A},$

$$\begin{aligned}
q_2^A &= \text{user_capability_to_lean_back}, \\
q_3^A &= \text{user_capability_to_put_arms_on_armrest}, \\
q_4^A &= \text{user_capability_to_propel_back_seat_A}; \\
PR^A: \quad &\{pr_0^A = \varphi, pr_1^A = 0.8, pr_2^A = 0.7, pr_3^A = 0.5, pr_4^A = 0.5\}; \\
C^A: \quad &\{c_1^A: \text{reachable height for the user} \geq \text{height of seat A}, \\
&c_2^A: \text{force to lean back from user} \geq \text{drag from seat A's}, \\
&c_3^A: \text{backrest reachable distance for the user} \geq \text{height of armrest}, \\
&c_4^A: \text{length of the lower leg of the user} \geq \text{height of seat A}\}; \text{ and} \\
PPA^A: \quad &\{ppa_1^A = 0.8 \cdot \text{user_sit_on_seat_A}, \\
&ppa_2^A = 0.5 \cdot \text{user_lean_back}, \\
&ppa_3^A = 0.7 \cdot \text{user_put_arms_on_armrest}, \\
&ppa_4^A = 0.5 \cdot \text{user_propel_back_seat_A}\}.
\end{aligned}$$

Note that user' interactions with both seats A and B have the same transition diagrams and AEP-based FSAs except for the preferences values, since they generate the same user behaviors with different preferences. For illustrative purposes, this research randomly define the preferences between 0 to 1 for the seat B-user interaction, G^B as $PR^B: \{pr_0^B = \varphi, pr_1^B = 0.9, pr_2^B = 0.8, pr_3^B = 0.3, pr_4^B = 0.7\}$.

7.1.3 Representation of Behaviors

In this case study, according to Equation (5.4), the sets of user behaviors that start from the

initial state are defined as follows:

$$\begin{aligned}
L(G^A) := & \{ ppa_1^A, ppa_1^A \cdot ppa_2^A, ppa_1^A \cdot ppa_3^A, ppa_1^A \cdot ppa_4^A, ppa_1^A \cdot ppa_2^A \cdot ppa_3^A, ppa_1^A \cdot \\
& ppa_2^A \cdot ppa_4^A, ppa_1^A \cdot ppa_3^A \cdot ppa_4^A, ppa_1^A \cdot ppa_2^A \cdot ppa_3^A \cdot ppa_4^A \}, \text{ and} \\
L(G^B) := & \{ ppa_1^B, ppa_1^B \cdot ppa_2^B, ppa_1^B \cdot ppa_3^B, ppa_1^B \cdot ppa_4^B, ppa_1^B \cdot ppa_2^B \cdot ppa_3^B, ppa_1^B \cdot \\
& ppa_2^B \cdot ppa_4^B, ppa_1^B \cdot ppa_3^B \cdot ppa_4^B, ppa_1^B \cdot ppa_2^B \cdot ppa_3^B \cdot ppa_4^B \}.
\end{aligned}$$

In terms of designing user experiences that achieve the final goals and related design specifications, the marked language $L_m(G)$ can be a significant concern. According to Equation (5.5), the marked languages are defined as follows:

$$\begin{aligned}
L_m(G^A) := & \{ ppa_1^A \cdot ppa_4^A, ppa_1^A \cdot pap_2^A \cdot ppa_4^A, ppa_1^A \cdot ppa_3^A \cdot ppa_4^A, ppa_1^A \cdot \\
& ppa_2^A \cdot ppa_3^A \cdot ppa_4^A \}, \text{ and} \\
L_m(G^B) := & \{ ppa_1^B \cdot ppa_4^B, ppa_1^B \cdot ppa_2^B \cdot ppa_4^B, ppa_1^B \cdot ppa_3^B \cdot ppa_4^B, ppa_1^B \cdot \\
& ppa_2^B \cdot ppa_3^B \cdot ppa_4^B \}.
\end{aligned}$$

Here, $L_m(G^A)$ and $L_m(G^B)$ have the same user behaviors, because both interactions have the same properties of affordance and effectivity. However, they still have different preference levels toward the user activities, since PR^A and PR^B from the automa representations have difference preference values. For example, when comparing $pa_1^A \cdot pa_4^A$ and $pa_1^B \cdot pa_4^B$, they are defined as follows:

$ppa_1^A \cdot ppa_4^A = (0.8 \cdot \text{user_sit_on_seat_A})(0.5 \cdot \text{user_propel_back_seat_A})$, and

$ppa_1^B \cdot ppa_4^B = (0.9 \cdot \text{user_sit_on_seat_B})(0.7 \cdot \text{user_propel_back_seat_B})$.

Figure 7.3 shows the simulation of user activity in $L_m(G^A)$: $ppa_1^A \cdot ppa_2^A \cdot ppa_3^A \cdot ppa_4^A$ using FSM Simulator (FSM Simulator 2012). In Figure 7.3, a , b , c , and d represent ppa_1^A , ppa_2^A , ppa_3^A , and ppa_4^A respectively. The simulation demonstrates that how the user activities in $L_m(G^A)$ lead the artifact-user interaction model to the marked state. Table 7.2 displays the results of the simulation for the user activities in $L_m(G^A)$ and $L_m(G^B)$.

Figure 7.3. Simulation of user-product behaviors and transition diagrams

Table 7.2. Simulation results of $L_m(G^A)$ and $L_m(G^B)$ related affordances and preferences

$L_m(G_{comp}^A)$		
User Activity	Matching Affordances	Matching Preferences
$ppa_1^A \cdot ppa_4^A$	$p_1^A \cdot p_4^A$	$pr_1^A \cdot pr_4^A$
$ppa_1^A \cdot ppa_2^A \cdot ppa_4^A$	$p_1^A \cdot p_2^A \cdot p_4^A$	$pr_1^A \cdot pr_2^A \cdot pr_4^A$
$ppa_1^A \cdot ppa_3^A \cdot ppa_4^A$	$p_1^A \cdot p_3^A \cdot p_4^A$	$pr_1^A \cdot pr_3^A \cdot pr_4^A$
$ppa_1^A \cdot ppa_2^A \cdot ppa_3^A \cdot ppa_4^A$	$p_1^A \cdot p_2^A \cdot p_3^A \cdot p_4^A$	$pr_1^A \cdot pr_2^A \cdot pr_3^A \cdot pr_4^A$
$L_m(G_{comp}^B)$		
User Activity	Matching Affordances	Matching Preferences
$ppa_1^B \cdot ppa_4^B$	$p_1^B \cdot p_4^B$	$pr_1^B \cdot pr_4^B$
$ppa_1^B \cdot ppa_2^B \cdot ppa_4^B$	$p_1^B \cdot p_2^B \cdot p_4^B$	$pr_1^B \cdot pr_2^B \cdot pr_4^B$
$ppa_1^B \cdot ppa_3^B \cdot ppa_4^B$	$p_1^B \cdot p_3^B \cdot p_4^B$	$pr_1^B \cdot pr_3^B \cdot pr_4^B$
$ppa_1^B \cdot ppa_2^B \cdot ppa_3^B \cdot ppa_4^B$	$p_1^B \cdot p_2^B \cdot p_3^B \cdot p_4^B$	$pr_1^B \cdot pr_2^B \cdot pr_3^B \cdot pr_4^B$

Finally, artifacts that can afford $L_m(G^A)$ and $L_m(G^B)$ need to be designed for containing the corresponding affordances. The case study showed that when the artifacts have the same affordance properties, the preferences can differ. The preference level showed that it can act as indicators for the design requirements while represented in AEP-FSA. During the design process, the formal representations showed that it can specify design requirements by linking the individual's preferable user behaviors to designs.

Through the case study, with the examples of an individual user's interactions with two different seats, this research demonstrated that the proposed formal affordance structure representation method can provide designers with parameterized and measurable indicators for customized product behaviors in an AM-enable market-of-one market segment. Even when the different artifacts provide the same affordances to a user, the proposed model systemically categorized preferable affordances and corresponding user behaviors based on

preference values in a numerical way. The customized product behaviors are specified for personalized behaviors, *PB*, in terms of affordances, effectivities, and preferences to be incorporated into a 3LCM-based DfAM method. Once validated through simulations, validated FSA models enable parameterizing AM-enabled customized product behaviors and therefore systematic knowledge documentation. Figure 7.4 shows *AffordanceToSeat* class, its subclasses, and the object property *changeStateTo* that were captured using the FSA model. The resulted language sets and state-transition policies in the FSA model were directly mapped to the classes and object properties in a CDfAM ontology developed using Web Ontology Language (OWL)/Resource Description Framework (RDF). Figure 7.4 then can serve as a knowledge block that can be reused in the downstream CDfAM processes.

Figure 7.4. Hierarchy of the subclasses of the class *AffordanceToSeat*

Such validated formal knowledge models provide logic for knowledge reasoning as being machine-processible embodiment design/redesign requirement. However, the developed knowledge representation in the FSA model or the corresponding knowledge block in the ontology presents affordances in common descriptions, even though the proposed method addresses AM-enabled product behaviors at a market-of-one market segment. Individuals can have different characteristics and accordingly the characteristics product embodiment designs vary. Individualization of the knowledge concepts is required further. Then, the mapping between the individualized knowledge is necessary. Such process will be demonstrated in the following Section 7.2.

7.2 Case Study II: CDfAM Ontology Development

In Chapter 7.2, the CDfAM ontology is developed as the main body of a knowledge base in this study by applying the proposed CDfAM methodology. This study pursues the development of an advanced CDfAM system and the CDfAM ontology is the first major step towards developing such system. The proposed CDfAM methodology supports associated semantic model representations not only of product geometry concepts but also of AM-enabled product behaviors and additive manufacturability concepts. A priori knowledge is captured and embedded into the CDfAM ontology using the proposed methodology. Then, instantial prescriptive design recommendations are generated utilizing the knowledge in the ontology, which demonstrates the effectiveness of the proposed ontology.

7.2.1 Product

This chapter presents a case study for customized design of a transtibial (TT) prosthesis leg for AM that consists of socket, pylon, and foot [147] as shown in Figure 7.5. With emerging AM and 3D-scanning techniques, attentions have been put on custom-fit products (e.g., implants or prosthesis) characterized by a full interaction with the human body or its anatomical districts. Previous semi-automated/automated tools for product development were usually for a specific task such as geometric modelling, structural analysis, or gait analysis [148] rather than for integrated design and AM knowledge necessary in the full design process.

Figure 7.5. Example of transtibial (left) and transfemoral (right) prosthesis [148]

The study from the Project I4BIO (Innovation for Bioengineering) addressed knowledge-based custom-fit prosthesis designs [148]. The main goal of I4BIO was to develop a new design framework targeted for lower limb prosthesis. The framework centered on knowledge management and patient's digital models to improve the product quality as

well as the amputee's quality of life. However, the I4BIO project result falls short of developing an ontology that enables machine-based knowledge reasoning and reuse of knowledge. In addition, their design system does not focus on capturing amputee-product behaviors, additive manufacturable morphology, and AM process knowledge. Also, they do not have a logical formalism that will enable rigorous semantic representations. To address such limitations, this case study demonstrates formalizations and representations of product's customized characteristics and additive manufacturable morphology knowledge.

A team of prosthetics designers and automated CDfAM applications from various segments of the AM-enabled product lifecycle is assumed to be the users of the proposed CDfAM ontology. Therefore, it is assumed that the formal modeling of the functional requirements and the collective capturing of the relationships between the different DfAM domains introduced in Chapter 4.4 will be conducted based on the domain experts' best knowledge and experiences. The data and knowledge in this section were collected from validated literature and experimental AM data.

7.2.2 Affordance-based CDfAM Ontology

The CDfAM ontology has four main domains at the highest-level where DfAM knowledge domains for AM: *U*, *A*, *S*, and *AM* from Chapter 4.4. *U*, *A*, *S*, and *AM* define the highest-level classes. The domains are defined as classes of *User*, *Affordance*, *Product*, *DesignFundamental*, respectively, as seen in Figure 7.6.

Figure 7.6. Classes `User`, `Affordance`, `Product`, `DesignFundamental` that represent four CDfAM Knowledge Domains

This chapter describes the structure of CDfAM ontology and then its applications in knowledge mapping and knowledge reasoning. Since the definitions of axioms in the CDfAM ontology is given in DL language, brief explanations of the notations used in this section are introduced as follows.

- The subsumption relation shown as “ $A \sqsubseteq B$ ” means class `A` is a subclass (a specialization) of class `B` [149].

The classes of `User`, `Affordance`, `ProductStructure`, `DesignFundamental` are mapped as shown in Figure 7.7 based on knowledge domain framework in Chapter 4. The characterization of the class `Affordance` is based on the composition of `Product` and `User` due to the affordance’s complementarity property, which the `compose object` property captures. At the same time, the `Product`’s manufacturable design space is restricted and explicitly defined by AM design rules embedded in the relationships in `DesignFundamental` subclasses. AM’s layer-upon-layer nature provides extended design space of AM products and therefore customize individual users of

the products and AM machines. Additive manufacturability of layer-up-layer processes are captured in design fundamentals. The scope of the CDfAM is highlighted in a rectangle while the rest of the relationships out of the rectangle were analyzed in Chapter 1 and Chapter 2.

Figure 7.7. Mapping between CDfAM Domainss

For the TT prosthetic leg case study, instead of building this study’s own ontology from scratch, this study reuses publicly available TT prosthetic leg product knowledge [148] in order to link the CDfAM ontology to a priori knowledge and to present how this study addresses the limitations of the previous studies. Figure 7.8 shows the hierarchy of the subclasses of the class `ProductStructure`. The product structure knowledge of a TT prosthesis is a subclass of `ProductStructure` as Expression (7.2).

$$\text{TT_ProstheticLowerLimb} \sqsubseteq \text{ProductStructure} \sqsubseteq \text{Product} \quad (7.2)$$

If other types of product structures are of interests for CDfAM, their knowledge can exist in parallel as subclasses of `ProductStructure`.

Figure 7.8. Hierarchy of the subclasses of the class `ProductStructure`

The categorization of the subclasses of `TT_ProstheticLowerLimb` is formed based on a standardized assembly hierarchy. The subclasses are matched to the assembly modules shown in Figure A.1. For example, the main submodules of a TT prosthetic leg are

defined as Adopter, Foot, Liner, Lock, and Socket as seen in expressions (7.3)

$$\begin{array}{lcl}
 \text{Adopter} & & \\
 \text{Foot} & & \\
 \text{Liner} & \sqsubseteq \text{TT_ProstheticLowerLimb} & (7.3) \\
 \text{Lock} & & \\
 \text{Socket} & &
 \end{array}$$

The development of the TT prosthesis leg knowledge hierarchy in Figure 7.8 was based on commercial catalogues. Therefore, the ontology cannot capture knowledge of TT prosthesis leg's customized design knowledge yet. Among the modules, the socket module designed based on a patient's anatomy is the only module that is totally custom-fit in general [148]. Sockets had been completely hand-made before AM's influence on the design and manufacturing processes was identified.

7.2.2.1 Representing amputee-TT socket interactive behaviors in A and mapping U and S through A

As seen in Figure 7.9, a prosthetic socket is the primary interface between amputee's residual limb and the prosthesis. Therefore, the sockets are individually customized to avoid pains and difficulties in prosthesis uses caused by differences between individuals. While typically the CAD software and finite element simulations are often used in prosthetics studies [147],

a knowledge base for AM has been required for knowledge-based automated DfAM systems and applications.

Figure 7.9. (a) Amputee limb-socket interaction (b) Socket CAD in interior, anterior, and posterior views

A representative lower-limb amputee forms AM-enabled market-of-one market segments. This section targets to capture the amputee's customer needs for customized functional behaviors with a prosthesis: normal gait, normal walking patterns [150]. Remind that when considering the FbD approach, the first step is to construct a function structure based on the flow of energy, material, and signals as a block diagram. Then, the design process proceeds to break it into subfunctions [32]. However, the socket is a static structure with a single component which contains no internal flows of energy, material, and signals between part components. Therefore, the function structure is not able to represent the design requirements, since there is no flow to present. In fact, the normal gait for an amputee is a behavior that is achievable only in the amputee-prosthetic interactions and not possible in isolation. Therefore, an AbD approach is suitable in the conceptual design phase rather than a FbD approach.

Figure 7.10. A graphical representation of normal gait enabled in amputee-TT prosthetic leg interaction [151]

The affordance structure for a socket design is as Equation (7.4) and its graphical representation is in Figure 7.11. The definitions of affordance states are shown in Table 7.3. A new knowledge bock in the ontology enabled by Equation (7.4) is shown in Figure 7.12.

$$A = \langle S_a, \Sigma, \delta, s_0, F \rangle \quad (7.4)$$

$$S_a: \{s_0, a_1, a_2, F\},$$

$$\Sigma: \{b_1, b_2\},$$

$$\delta: \text{State transition function, } S_a \times \Sigma \rightarrow S_a,$$

$$s_0: \text{Initial (starting) state, and}$$

$$F: \{f = \text{goal state (a situation after 'standing' and 'forward progression' are achieved)}\}.$$

Figure 7.11. Graphical representation of amputee-socket interactive behaviors

Table 7.3. Descriptions of affordances in Equation (7.4)

A	Descriptions
a_1	afford the user an ability to stand on the ground
a_2	afford the user an ability to move forward

Figure 7.12. (a) Hierarchy of the subclasses of the class **Affordance** (2) **Affordance**

Structure-enabled relationships

Once the affordance structure enables parameterizing the desired AM-enabled TT prosthesis leg behavior knowledge and guides a knowledge representation in the ontology, the affordances can be mapped to U and S to find physical form features within a TT socket

designed based on the user variations. The normal gaits have a common description of such as stance (b_1) and forward progression (b_2) as well as corresponding affordances a_1 and a_2 . Therefore, individual instances are needed to be defined to capture varying characteristics of user and accordingly varying socket characteristics. In the CDfAM ontology, an individual's measurement characteristics and his/her characteristics of normal gaits are captured in the individuals of subclasses of `User_Characteristic` in Figure 7.13 and Affordance in Figure 7.12, respectively.

The general descriptions of elements in `User_Characteristic` are shown in Figure 7.13 with the hierarchy and subclasses. An individual patient's characteristics are used as the source of design requirements for CDfAM processes. A patient's characteristics are represented under `TT_Amputee_Characteristic` in the ontology that is a subclass of `User_Characteristic` as shown in Expression (7.5)

$$\text{TT_Amputee_Characteristic} \sqsubseteq \text{User_Characteristic} \quad (7.5)$$

The individual patient's characteristics, which are fundamental in designing a customized TT socket, are acquired by evaluations and anthropometric measurements of the patient and his/her residual limb. Knowledge is usually acquired by the evaluations and measurements captured as subclasses of `TT_Amputee_Characteristic` as in Expression (7.6). `AthropometricMeasure_Characteristic`, `PatientEvaludation_Characteristic`, and `Residual-Limb_Characteristic` provide the measurable types for defining patient characteristics in the CDfAM ontology. Among the `User_Characteristic`'s

subclasses, Figure 7.14 shows LoadZone and Off-LoadZone of a patient's residual limb and shown in Expression (7.7). Figure 7.15 defines a socket module's form feature surfaces interacting with a patient's residual limb. Detailed procedures of measuring a patient and parameter definitions can be found in [148].

$$\begin{array}{lcl}
 \text{AthropometricMeasure_Characteristic,} & & \\
 \text{PatientEvaludation_Characteristic,} & \sqsubseteq \text{TT_Amputee_} & (7.6) \\
 \text{Residual-Limb_Characteristic} & \text{characteristic} &
 \end{array}$$

$$\begin{array}{lcl}
 \text{LoadZone,} & & \\
 \text{Off-LoadZone} & \sqsubseteq \text{ResidualLimbEvaludation} & (7.7)
 \end{array}$$

Figure 7.13. Hierarchy of the subclasses of the class User_Characteristic

Figure 7.14. Knowledge on residual limb's surface that interacts with a socket

Figure 7.15. Hierarchy of the subclasses of the class Socket

Once the knowledge structures are defined as *User_Characteristic* and *Socket*, U^* and S^* are defined as individuals of *User_Characteristic* and *Socket* to characterize a target TT amputee and a socket that needs to be customized. In customizing a TT socket design, a key is to match the amputee limb's load and off-load zones to a socket surface. To support the task, the CDfAM ontology maps U^* and S^* as shown in Figure 7.16. Figure 7.16 (a) shows that a customized *AffordToStandOnGround* product behavior, a_1^* , through which U^* and S^* are mapped. The affordance is a customized desired product behavior in a TT amputee-socket interaction in the interaction state s_I in Figure 7.11. The customized *AffordToStandOnGround* provides the customized design context in the state s_I in mapping U^* and S^* , so their correlations can be interpreted properly according to the desired product behavior context. Figure 7.16 shows $a_1^*-U^*-S^*$ correlation model in the state s_I . The correlation model explicitly captures all the measurable knowledge elements necessary for designing S^* . It shows 40 measurable individuals are correlated through a_1^* .

(a)

to seek optimal solutions in a structured way. This advantage can be found for both intra-domain and inter-domain.

In terms of the intra-domain data and knowledge, U^* captures user measurement data that need to be obtained by different types of data acquisition methods in an integrated way. To be specific, an amputee limb's geometry surface information may require a user body scanning method to be obtained, while patient force data requires a gait analysis technique such as a human motion simulation. In terms of inter-domain data and knowledge, the mapping is advantageous. To be specific, the knowledge elements in U^* can be mapped to the form feature knowledge elements of S^* using individual affordances as U^* and S^* composite the affordances at each state of state transitions. The affordances present varying desired TT prosthetic leg behaviors, even though the elements in U^* are linked to the same elements in S^* . Therefore, the elements in U^* will affect the different design parameters of the socket form features when they are related to the different affordances. For example, when a user weight in U^* is related to S^* through a_1^* , the relationship can be explained with an assumption that the force from the body to the socket is equal to half the weight of the user when the user is a 'standing' state. Such loading conditions are useful for the topology optimizations of the socket structure which cannot be captures using the FbD approaches.

When the mapping is considered through other affordances such as `AffordToMoveForward`, the same loading conditions or other a_1^* -related design requirements and parameters cannot be applied due to the differences between the affordances. Integrating of such design requirements and parameters into form feature designs is a challenging work, however, it is very clear that the explicit correlations between A^* - U^* - S^* captured in the ontology can support knowledge reasoning for such design tasks.

This case study shows that the proposed affordance-based CDfAM approach enables modeling customizable product behaviors, organizing affordances with the affordance structure, and mapping of the elements in different CDfAM domains in the knowledge base. These advantages are enabled by the adoption of the affordances. The design process can go case-dependent and inefficient without the adoption. Therefore, other parts of the TT prosthesis leg can be also be customized following the same manners shown in this chapter. Also, correlated knowledge blocks can be reused once captured in the ontology in automated CDfAM iterations.

The knowledge in the ontology can be also leveraged in the downstream design process of the embodiment and detailed design phases of obtaining the additive manufacturable design parameter types and values of the socket design. Especially, to transform a customized functionality-enhanced product structure into additive manufacturable product structure, a product is decomposed into AM features. Figure 7.17 shows an example of a prosthesis leg socket with lattice and thin wall inner-structures. The purpose of utilizing lattice structures and thin wall features is to improve a socket performance and a customer satisfaction level while reducing weight using AM. At the same time, the lattice and thin wall infill features should be additive manufacturable form features. Such lattice and thin wall features have difference additive manufacturability constraints and they are explicitly captured by design fundamentals and design principles introduced in Chapter 6. The CDfAM ontology provides AM feature and associated parameter knowledge blocks leveraging Chapter 6. The CDfAM ontology also presents additive manufacturability knowledge utilizable downstream embodiment and detailed CDfAM phases.

Figure 7.17. Prosthesis leg sockets with different lattice and thin wall infills [152]

7.2.3 Design Rule-based CDfAM Ontology

This chapter presents a design rule-based ontology framework and establishes the ontology's classes, properties, and individuals. The DRfAM ontology has been established based on the extended DF and DP sets in Chapter 6.

7.2.3.1 Representing AM-restrictive Product Characteristics and mapping between *S* and *P*

In terms of design rule knowledge of the proposed ontology, a class defines a module or primitive type. Figure 7.18 graphically illustrates the hierarchy of the ontology classes. The

developed ontology contains Module and Primitive classes at the highest level as shown in Expressions (7.8).

$$\begin{array}{l} \text{Module} \\ \text{Primitives} \end{array} \sqsubseteq \text{DesignFundamental} \quad (7.8)$$

Module consists of SingleModule and InteractingModule classes at a lower level. SingleModule has subclasses of CompoundFeature, PrimitiveFeature, and Entity matching to *DF*, *PF*, and *E* from the module definitions in Equation (6.1), respectively, as shown in Expressions (7.9).

$$\begin{array}{l} \text{CompoundFeature} \\ \text{PrimitiveFeature} \\ \text{Entity} \end{array} \sqsubseteq \text{SingleModule} \sqsubseteq \text{Module} \quad (7.9)$$

InteractingModule is based on *InterSubMo* in Equation (6.2). Primitive class consists of GeometryParameter, ProcessParameter, and MaterialParameter classes as in Expressions (7.10) matching to the three types or primitives *G*, *P*, and *M*, respectively, in Equations (6.1). GeometryParameter, ProcessParameter, and MaterialParameter contain subclasses based on the modules and primitives in Table 6.2 and Table 6.3.

GeometryParameter

ProcessParameter $\sqsubseteq$ Primitive (7.10)

MaterialParameter

Figure 7.18. Hierarchy of the subclasses of the class **DesignFundamental**

Properties can be used to state relationships between individuals, or between individuals and data in an ontology. Table 7.4 shows object properties with domains and ranges that represent class relationships in the DRfAM ontology. The object properties are built based on the relationships R1-10 from *DP I*, *II*, and *III*. *DP I* is leveraged in establishing the objective properties that describe hierarchical and interactive relationships between module-oriented classes. *DP II* and *DP III* establish the objective properties between the

module and primitive individuals, as *DP II* and *DP III* define the design fundamental relationships between modules and primitives or between primitives. The descriptions of the objective properties are shown in Table 7.4.

Table 7.4. Domain and range of object properties and leveraged relationships

Object Property	Domain	Range	Leveraged DP
isComposed-Of	CompoundFeature	CompoundFeature, PrimitiveFeature	DP I
	PrimitiveFeature	Entity	
contains	CompoundFeature	InteractingCompoundFeatureSet, InteractingPrimitiveFeatureSet	
	PrimitiveFeature	InteractingEntitySet	
Interacts-With	CompoundFeature	CompoundFeature	
	PrimitiveFeature	PrimitiveFeature	
	Entity	Entity	
isInvolved-In	CompoundFeature	InteractingCompoundFeatureSet	
	PrimitiveFeature	InteractingPrimitiveFeatureSet	
	Entity	InteractingEntitySet	
hasGeometricCharacteristicOf	Module	GeometryParameter	DP II, III
isRestrictedBy	Module GeometryParameter	GeometryParameter, ProcessParameter, MaterialParameter	

Data properties describe relationships between individuals and data values in an ontology. Examples of the ontology's data properties are shown in Table 7.5. The data properties are defined by matching them to the primitives of *G*, *P*, and *M* types and value ranges. The domain and range of the data properties are established based on *DP II* and *DP III* where parameter value ranges are represented based on primitive-involved relations. The data properties are based both on quantitative and qualitative primitives. The quantitative data properties are matched to quantitative primitives. The qualitative data properties are matched to qualitative data properties, while their range is set as Boolean type and their values can be 1 or 0.

This research then formulates DRs used in knowledge retrievals for AM design recommendations. In this phase, SQWRL formulated based on the SWRLs introduced in Chapter 6.2 is used for developing semantic queries.

Table 7.5. Examples of data properties

Data Property	Domain	Range	Unit	Primitive Type	Leveraged DP
hasMax-OverhangLength	Dimension	Double	mm	Quantitative	DP II, III
hasMin-OverhangLength	Dimension	Double	mm		
hasMax-UndercutAngle	Dimension	Double	deg		
hasMin-UndercutAngle	Dimension	Double	deg		
hasMax-Thickness	Dimension	Double	mm		
hasMin-Thickness	Dimension	Double	mm		
hasLayer-Thickness	BuildLayer-Thickness	Double			
hasEnergy-SourcePower	Scanning	Double	W		
hasCore-ScanVelocity	Scanning	Double	mm/s		
hasSkin-ScanVelocity	Scanning	Double	mm/s		
isThin	ShapeModifier	Boolean	True or False	Qualitative	
isSupported	ShapeModifier	Boolean	True or False		
isPorous	ShapeModifier	Boolean	True or False		
has-OctetTrussCell	ShapeModifier	Boolean	True or False		

DFs and DPs of Thin Wall Feature

For demonstrated purposes, a DG, DG_{TW} , was developed for EOS 270xt, a Laser Powder Bed Fusion (LPBF) process with the process and material parameter settings in Table 7.6 [81]. Table 7.7 presents the DG with specific ranges of design criteria for a thin wall feature that incorporates EOS manufacturability into the thin wall's design parameters.

Table 7.6. EOS equipment parameter setting

Parameter	Value
Material Type	TiAl6V4
Layer thickness (μm)	30
Laser power (W)	Core: 170; skin: 120
Scan velocity (mm/s)	Core: 1250; skin: 1000
Hatch distance (mm)	0.1

Table 7.7. Descriptions of DG_TW

Structure	Explanation	Restrictions and recommendations
Thin wall	<ul style="list-style-type: none"> Consider minimum wall thickness for part design 	<ul style="list-style-type: none"> Minimum wall thickness: <ul style="list-style-type: none"> $90^\circ \geq \beta > 30^\circ$: min. wall thickness 0.4 mm $\beta = 30^\circ$: min. wall thickness 0.3mm
	<ul style="list-style-type: none"> Use additional ribs for wall stabilization if necessary 	<ul style="list-style-type: none"> 10 mm wide and high

First, DFs are identified from the acquired DG_TW . The identified design fundamental set DF_T is in Equation (7.11), where elements belonging to DF_T are defined as a set of modules Mo and primitives PR . The definitions and descriptions of each symbol used in DF_T are shown in Table 7.8.

$$DF_T = \{Mo, PR\} \quad (7.11)$$

where,

$$Mo = \{CF, PF, E\}$$

$$PR = \{G, P, M\}$$

$$CF = \{\emptyset\}$$

$$PF = \{pf_i\}$$

$$E = \{\emptyset\}$$

$$G = \{g_1, g_2, g_3\}$$

$$P = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}$$

$$M = \{m_i\}$$

Table 7.8. DFs of thin wall feature for LPBF

Symbol	Value	Abbreviation	Definition/Description
pf_1	n/a	TW	Thin wall feature
g_1	10	l	Length, l (mm)
g_2	10	h	Height, h (mm)
g_3	0.4 or 0.3	t	Minimum wall thickness, t (mm)
m_1	TiAl6V4	m	Material type
p_1	30	lt	Layer thickness (μm)
p_2	170	clp	Core laser power (W)
p_3	120	slp	Skin laser power (W)
p_4	1250	csv	Core scan velocity (mm/s)
p_5	1000	ssv	Skin scan velocity (mm/s)
p_6	0.1	hd	Hatch distance (mm)
p_7	$90 \geq \beta > 30$ or 30	β	Angle between the feature and the building platform ($^\circ$)

In this case study, the only module identified is the thin wall feature which is defined as a primitive feature pf_1 . As there is no compound feature or geometric/topological entity identifies in the DG_TW , CF and E become null sets. The primitive set PR contains G , P , and R as shown Equation (7.11). Then, the thin wall for the LPBF process is formally defined with DPs as shown in Table 7.9.

Table 7.9. DPs of thin wall feature for LPBF

DP	Expression
$DP\ I\ (TW)$	$f:pf_1 \rightarrow \{SubMo, InterSubMo\} = \{\{\emptyset\}, \{\emptyset\}\}$
$DP\ II\ (TW)$	$g:pf_1 \rightarrow h(X_{pf_1}) = h(\{\{g_1, g_2, g_3\}, \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}, \{m_1\}\})$
$DP\ III\ (TW)$	$g \circ f:pf_1 \rightarrow \{\{\emptyset\}, \{\emptyset\}\}$

$DP\ I\ (TW)$ defines the thin wall feature based on the module interaction and decomposition relationships. As pf_1 is the only module, its submodules and their relationships are not concerns in the design guideline, $DP\ I\ (TW)$ results in a null set. For the same reason, $DP\ III\ (TW)$ becomes a null set. On the other hand, $DP\ II\ (TW)$ presents a formal definition of pf_1 with explicit and measurable design specifications and constraints in X_{pf_1} and their relationships. Here, X_{pf_1} consists of the form feature's geometry specification and AM-restrictive parameters: g_1 , g_2 , and g_3 . Then, P and R are presented to define the AM context with relevant parameters p_1 , p_2 , p_3 , p_4 , p_5 , p_6 , p_7 , and m_1 as shown in the Figure 7.19.

Figure 7.19. *DP II* applied to thin wall feature for LPBF

7.2.3.2 Knowledge Reasoning: Prescriptive Design Rule

Generation

This chapter introduces a more complicated case study on a honeycomb structure for the LPBF process to demonstrate the proposed ontology-based prescriptive design rule generation. In this example, a relatively complex AM feature of a hexagonal honeycomb structure, a honeycomb consisting of regular hexagonal cells, is investigated. The design specification of the honeycomb structure is as follows [153]:

- A honeycomb is typically a homogeneous plate due to their cyclic cell structure.
- A hexagonal cell consists of cell walls and the walls are usually considered as a unit element for analysis in design phases (shown in Figure 7.20 adapted from [153]).

Based on the design specification, regular hexagonal cells and cell walls are identified as submodules of honeycomb structures. This case study demonstrates a hexagonal cell consisting of thin cell walls designed for the same LPBF process context in this chapter.

Figure 7.20. Regular hexagon cell feature consisting of cell walls

Based on the design specifications of the honeycomb structure, the process parameter setting in Table 7.6, and DG_TW in Table 7.7, DFs for a regular hexagonal cell is defined as Equation (7.12). The definitions and descriptions of each symbol used in Equation (7.12) are shown in Table 7.10. In this case study, design rule representations focus on the hexagonal cell's geometric region where the two thin wall features interact as highlighted in Figure 7.20.

$$DF_H = \{Mo, PR\} \quad (7.12)$$

where,

$$\begin{aligned} Mo &= \{CF, PF, E\} \\ PR &= \{G, P, M\} \\ CF &= \{cf_1\} \\ PF &= \{pf_2, pf_3\} \\ E &= \{\emptyset\} \\ G &= \{g_1, g_2, g_3, g_4, g_5, g_6\} \\ P &= \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\} \\ M &= \{m_1\} \end{aligned}$$

Table 7.10. DFs of regular hexagon cell feature for LPBF

Symbol	Value	Abbreviation	Definition/Description
cf_1	n/a	RHC	Regular hexagon cell feature
pf_2	n/a	$TW1$	Thin cell wall feature
pf_3	n/a	$TW2$	Thin cell wall feature
g_1	10	l	Cell wall feature length, l (mm)
g_2	10	h	Cell wall feature height, h (mm)
g_3	0.4	t	Minimum cell wall feature thickness, t (mm)
g_4	20	w	Regular hexagon cell feature width (mm)
g_5	(11, 11)	il	Location of interaction between TW1 and TW2
g_6	120	a	Interaction angle between TW1 and TW2 (°)
m_1	TiAl6V4	m	Material type
p_1	30	lt	Layer thickness (μm)
p_2	170	clp	Core laser power (W)
p_3	120	slp	Skin laser power (W)
p_4	1250	csv	Core scan velocity (mm/s)
p_5	1000	ssv	Skin scan velocity (mm/s)
p_6	0.1	hd	Hatch distance (mm)
p_7	90	β	Angle between the feature and the building platform (°)

In this case study, the modules identified in M_O are two the thin wall features and a regular hexagon cell feature that are defined pf_2 , pf_3 , and cf_1 , respectively. The primitive set PR contains G , P , and R as shown in Equation (7.12). Then, the thin wall for the LPBF process is formally defined with DPs as shown in Table 7.11.

Table 7.11. DPs of regular hexagon cell feature for LPBF

DP	Expressions
<i>DP I (RHC)</i>	$f:cf_1 \rightarrow \{SubMo, InterSubMo\} = \{\{pf_2, pf_3\}\}, \{(pf_2, pf_3)\}\}$
<i>DP II (RHC)</i>	$g:cf_1 \rightarrow h(X_{cf_1}) = h(\{g_4\}, \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}, \{m_1\})$
<i>DP III (RHC)</i>	$g \circ f: cf_1 \rightarrow \left\{ \begin{array}{l} h(\{\{g_1, g_2, g_3\}, \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}, \{m_1\}\}) \\ h(\{\{g_1, g_2, g_3\}, \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}, \{m_1\}\}) \\ h(\{\{g_5, g_6\}, \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}, \{m_1\}\}) \end{array} \right\}$

DP I (RHC) defines the cell feature's DP based on the module interaction and decomposition relationships. cf_1 is a compound feature module and is redefined as a set of submodules and their interactions: $\{\{pf_2, pf_3\}\}, \{(pf_2, pf_3)\}\}$. *DP II (RHC)* presents a formal definition of cf_1 with explicit design specifications and constraints for cf_1 with measurable entities in X_{cf_1} and their relationships at the CFLv. Here, X_{cf_1} has a geometry parameter g_3 as a primitive for the cell feature's width. g_3 , the parameter for the cell feature's width, is not associated with the geometry specifications of the other modules of pf_2 and pf_3 at the PFLv, but only with the geometry specifications of cf_1 at the CFLv.

Then, *DP III (RHC)* defines cf_1 with its relations with primitives associated with its submodules and their interactions, $\{\{pf_2, pf_3\}\}, \{(pf_2, pf_3)\}\}$. With the definition, *DP III*

(*RHC*) links cf_1 to $\{\{pf_2, pf_3\}\}$, $\{(pf_2, pf_3)\}$, then to primitives associated to $\{\{pf_2, pf_3\}\}$, $\{(pf_2, pf_3)\}$ at the PFLv as shown in Table 7.11. Then, P and R are presented again to define the LPBF context with the process and material parameters $p_1, p_2, p_3, p_4, p_5, p_6, p_7$, and m_1 . Figure 7.21 shows the cf_1 labeled with its submodules and some of the primitive introduced in this chapter (figure adopted and modified from [153]). Note that the thin wall feature's primitive correlations defined in *DP II (TW)* in the previous chapter are reused in *DP III* (*RHC*) for defining the primitive correlations associated with the submodules pf_2 and pf_3 in this chapter. The primitive correlations associated with (pf_2, pf_3) , the interaction between pf_2 and pf_3 , reuse the same process and material parameters in *DP III (RHC)*, since the manufacturing contexts are the same. However, they present different geometry parameters g_5 and g_6 that show the geometry specification of the local geometry regions of the hexagonal cell feature where pf_2 and pf_3 are interacting.

Figure 7.21. cf_1 module labeled with submodules and primitives

Once the DFs and DPs are formulated, the DRfAM ontology captures the structured design rule knowledge. Figure 7.22 (a) shows an individual capturing the pf_2 and pf_3

interaction in the DRfAM ontology. Figure 7.22 (a) demonstrates that it is composed of ThinWall_A_Honeycomb (shown in Figure 7.22 (b)) and ThinWall_B_Honeycomb (shown in Figure 7.22 (c)) that represent pf_2 and pf_3 , respectively. The individuals of ThinWall_A_Honeycomb and ThinWall_B_Honeycomb have geometric characteristics captured in Thinwall_Honeycomb_Dimension (Figure 7.22 (d)) and process and material constraints captured in EOS_Scanning_Parameter (Figure 7.22 (e)) and EOS_Material_Parameter (Figure 7.22 (f)), respectively. The individuals of Thinwall_Honeycomb_Dimension, EOS_Scanning_Parameter, and EOS_Material_Parameter are defined based on the thin wall feature pf_i 's primitive correlations defined in *DP II (TW)* and reused for ThinWall_A_Honeycomb and ThinWall_B_Honeycomb according to *DP III (RHC)*.

(a)

(b)

(c)

(d)

(e)

(g)

Figure 7.22 (a) Individual for pf_1 and pf_2 interaction (b) Individual for ph_1 (c) Individual for ph_2 (d) Individual for thin wall feature's design primitives (e) Individual for thin wall feature's process primitives (f) Individual for thin wall feature's material primitives

Based on the knowledge captured in the ontology, knowledge retrievals are conducted for design recommendations. DRs' conditional IT-THEN statements are directly reflected to the SQWRL expressions as shown in Figure 7.23. The structured DRs provide a basis for mathematical and computational interpretations of DGs for an AM process. Also, structured DRs based on the proposed formal representations provide computational modular approaches for customized design rules. As DfAM becomes progressively knowledge-intensive and collaborative in AM ecosystems, the proposed ontology as collaborative AM development platforms provides a shared knowledge base to improve AM part qualities and shorten the AM product development lifecycle.

So far, the proposed knowledge representations provided advanced logic for semantic and ontological relationship definitions needed in constructing machine-processable semantic design knowledge for AM. Utilizing the knowledge representation methods, extracted knowledge systematically updated the CDfAM ontology. Also, knowledge reasoning for knowledge retrievals was demonstrated based on the formal representations. The knowledge was parameterized based on assumptions on functionality requirements or using a priori knowledge in text-based experimental or AM benchmark reports. As AM systems become more data intensive, predictable AM parameters need to be selected or measured for AM analysis to extract knowledge from AM data. The following section demonstrates an opportunity that the proposed methodology can be extended to AM data analytics to discuss a possible future work direction of the study.'

Name		
Thin Wall - Design Recommendation (EOS, TiAl6V4)		
Comment		
SFF 2018 Case Study		
Status		
Ok		
Design Rule-oriented SQWRL Module(ThinWall_A_HoneyComb) ^ GeometryParameter(?G) ^ ProcessParameter(EOS_Scanning_Parameter) ^ MaterialParameter(EOS_Material_Parameter) ^ hasGeometricCharacteristicOf(ThinWall_A_HoneyComb, ?G) ^ isRestrictedBy(?G, EOS_Scanning_Parameter) ^ isRestrictedBy(?G, EOS_Material_Parameter) -> sqwrl:select(?G)		

SQWRL Queries	OWL 2 RL	Thin Wall - Design Recommendation (EOS, TiAl6V4)
G		
:ThinWall_Honeycomb_Dimension		

SQWRL Queries	OWL 2 RL	Thin Wall - Design Recommendation (EOS, TiAl6V4)
A	B	C
"10.0"^^xsd:double	"10.0"^^xsd:double	"0.4"^^xsd:double
Height	Length	Min. Thickness

Figure 7.23. Design Recommendations for Thin Cell Walls

7.3 Case Study III: Machine Learning-enabled CDfAM Knowledge

Construction

Chapter 7.3 demonstrates a case study on how Machine Learning (ML) on AM data can extract design rule knowledge from AM data and update the knowledge in the CDfAM ontology. So far, in this thesis, the knowledge construction has depended upon a priori knowledge. This case study shows that the thesis's knowledge-based approach can be further extended to data-driven approaches. This case study is developed to discuss how the current research can be linked to data- and knowledge-driven CDfAM study.

7.3.1 Data-driven Knowledge Extraction for AM

Knowledge constructions generally require i) known facts and ii) facts newly discovered from the data [154]. Currently, the existing AM design rule constructions are heavily depending on known facts written in text-based design guidelines reported from experimental results [81]. However, knowledge documented from text-based formats cannot be easily utilized or widely shared [155] and complicate manners of constructing AM design rules [30]. Machine-based data analytics is required for AM design rule knowledge constructions; it is worthy to investigate the impacts of ML algorithms in AM design rule studies.

Selection of ML algorithms considers i) natures of the AM data constrained by data sources (physical or simulated AM processes) and data obtainment techniques (sensors or in-situ monitoring and ex-situ measurement methods) and ii) natures of ML algorithms.

Considering them, suitable ML algorithms are selected, and then the AM data are curated to be inputs for the ML algorithms, while not losing their original meanings. The data can be split into multiple chunks for training, validating, and testing. The data types such as AM part structure model data, process planning and control data, in-situ monitoring data, ex-situ measurements data, etc. depend on the corresponding AM life cycle phases. Examples are shown in Table 7.12.

Table 7.12. Data generated through am life cycle

Life-cycle phases	Data type examples	Ref.
Design	CAD images, STL, AMF, and STEP formats	[156]
In-situ monitoring	Melting pool optical and thermal images, Acoustic emission signals	[157, 158]
Ex-situ measurement	Optical 3D surface images, X-Ray Computed Tomography (XCT) images	[159, 160]

The ML algorithm types depend on the types of data mining tasks: classification, clustering, association, and feature selections [161]. Among them, this section uses classification ML algorithms that can predict target classes for each test case of datasets. Predictive additive manufacturability models are necessary for generating prescriptive AM design rules. In our study, ML is conducted to generate predictive models of AM capability, additive manufacturability, based on PSP (Process-Structure-Property) relationship analysis. This is because prescriptive AM design rules are developed based upon the predictive models.

The prescriptive rules prescriptively guide what design decisions AM practitioners have to make for a predictive AM condition where an AM process provides certain additive manufacturability. The additive manufacturability varies depending on AM's predictive conditions set by a restricted set of properties in structure, material, and process domains that restrict the design options in those conditions. It can be summarized that ML algorithms for the AM design rule construction need an ability to classify correlated AM parameters and accordingly predict additive manufacturability. Examples of classification algorithms can be Decision Tree, C4.5, C5, ID3, KNN, Neural Networks, SVM, etc. [161].

Among the prediction algorithms, Decision Tree (DT) algorithms are suitable for extracting predictive rules; the algorithm creates conditional tree structures of which inherent patterns that can be directly interpreted as rules in the form IF-THEN statements [155], which is required in AM's design rule representations. Indeed, Classification and Regression Tree (CART) algorithm was successfully employed in the manufacturing sector of Resistance Spot Welding (RSW) to extract rules from datasets [155]. However, so far, such algorithms failed to utilize AM data in extracting predictive knowledge for AM design rule yet. Also, no level of design abstractions has been defined for the AM design rule extraction and predictable AM parameters have not been systematically selected or measured for CART analysis. In addition, the results of the CART algorithm have not been captured in the fundamental formalisms of logic and rules using principles of design rule languages that guarantee synthetical and semantical constructions of design rule knowledge blocks. Also, as AM data comprise heterogeneous formats and meanings generated from different domains, it is necessary to have a systematic and methodological adoption of AM data.

7.3.2 ML on Ex-situ AM data

This section presents a case study of constructing an AM design rule for an overhang feature and a support structure (shown in Figure 7.24). In AM studies, overhang structures are investigated with support structures.

Figure 7.24. An overhang feature with 45° orientation angle

The identification of a self-support or non-self-supporting overhang feature are based on the overhang's downskin orientation angles, surface roughness, and AM process parameters [30]. Therefore, this study used AM data on measuring such AM parameters. The datasets are collected to provide a variation of surface texture in Laser Power Bed Fusion (LPBF) AM process from NIST's AM database [162] where a NIST's measurement study on EOS M290 LPBF system provided surface height data that varies depending on part positions and surface orientations [163].

This study uses AM data obtained from a LPBF build with 9 identical parts. Each of which has 72 surfaces oriented differently in either XY direction or Z direction as shown in Figure 7.25. [163]. The 9 parts were built on 3 by 3 grids at the same z level 50mm from each other in both x and y directions. Each part has 8 ribs at increments of 45 degrees in XY plane. Each rib includes 9 surfaces oriented from 45 degrees to 165 degrees against Z axis at 15 degrees of increments. Measurements were conducted to evaluate the surface roughness for all the 648 full factorial designed surfaces. The surface height is measured based on ISO 4287 standards. Table 7.13 summarizes the datasets used for this study [163].

Figure 7.25. Build for surface roughness study [163]

Table 7.13. Parameters in the AM dataset

Feature Type	Feature Name	Unit	Value
Input variable	Part Location X	mm	{-50, 0, 50}
	Part Location Y	mm	{-50, 0, 50}
	X-Y Orientation	°	{0, 45, 90, 135, 190, 225, 270, 315}
	Z Orientation	°	{45, 60, 75, ..., 135, 150, 165}
Response variable	Surface Height	μm	{7.3, ..., 64}

Figure 7.26. LPBF part surface measurement results in scatter

Technically, the CART algorithm generates CART models as binary trees hierarchical in nature as shown in Figure 7.27. Each root or intermediate node in Figure 7.27 represents an input feature (x_1 or x_2 in Figure 7.27) and a split point on that feature ($x_1 > a$ or $x_2 > b$ in Figure 7.27). The leaf nodes of a CART have a response feature (y_1 or y_2 in Figure 7.27) and predictions are made at the leaf nodes. More specifically, first, the algorithm learns the most significant feature among input features to assign it as a root node a CART. Then, the algorithm recursively partitions the data space and builds the rest of the CART based on the hierarchy of the significance of the input features on the response features values or types. The mathematical representation of a CART model is given in Equation (7.13). The newly

identified relationships in Equation (7.13) update domain-specific AM data feature dependences.

$$Y_p = \bar{r}(X_t) = [r(X_t, \lambda, D)] \quad (7.13)$$

where,

Y_p : Final predictive value

$\bar{r}$: Average regression function

X_t : Observation from the dataset

λ : Random parameter of partition

D : Data from AMDB

Figure 7.27. A CART graph

The CART models are interpreted as predictive additive manufacturability rules. In Figure 7.27, an input feature in the root or the intermediate nodes depict part's or AM's physical conditions. The response feature in the leaf nodes represents a predicted additive manufacturability as the consequence. The values at each feature in the CART models

signify the states of the feature at each split that are the conditions for the CART's direct rule interpretation. For example, if the value of x_i is larger than a in Figure 7.27, take the left branch from the root, else consider the right branch. Interpretations are followed in the same way for the other nodes until the final leaf nodes.

Interpretations are followed in the same way for the other nodes from the top to the final leaf nodes. Such steps start with taking each individual CART $cart_1, \dots, cart_n \in CART$ as inputs in n -th iterations. Based on principles of design rule representations defined earlier in Section 6, a set of design fundamentals, design principles, and additive manufacturability rules associated with the i -th CART $cart_i \in CART$ can be defined as $\langle DF^{cart_i}, DP^{cart_i}, R^{cart_i} \rangle$, where DF^{cart_i} is a set of design fundamentals: terms representing AM parameters in $cart_i$; DP^{cart_i} is a set of design principles: relationship types between functionally restricted design fundamentals in $cart_i$; R^{cart_i} is a set of additive manufacturability rules from $cart_i$ in IF-THEN statements.

In Figure 7.28 this study extracted 17 conditions ($C1 \sim C17$) and 18 rules ($R1 \sim R18$) directly from the resulted CART. Orientation_Z is the root node followed by the predictive variables of Location_X and Location_Y. The values at each variable in the CART signifies the state of the variable at each split that are the conditions for the direct rule interpretation. For example, if the value of Orientation_Z is larger than 68, consider the left branch from the root, else right. Interpretations are correspondingly followed for the other nodes till the leaf nodes in this way the CART model can be interpreted as 18 IF-THEN rules. For example, $R18$ in Figure 7.28 is an IF-THEN statement in Table 7.15. Table 7.14 is showing design fundamentals used for representing extracted AM knowledge in this case study.

Figure 7.28. CART extracted from the LPBF part surface measurement datasets

Table 7.14. Design fundamental types and definitions.

Type	Unit	Definition/Description
cf_1	n/a	An overhang feature with support structure
pf_1	n/a	An overhang feature
pf_2	n/a	A support structure
e_1	n/a	A downskin surface
g_1	mm	Down-skin surface geometry dimension (set)
g_2	mm	Overhang feature dimension parameter (set)
g_3	mm	Support structure dimension parameter (set)
g_4	mm	Location of interaction between overhang feature and support structure (x, y, z)
m_1	n/a	Material type
p_1	μm	Layer thickness
p_2	W	Core laser power
p_3	W	Skin laser power
p_4	mm/s	Core scan velocity
p_5	mm/s	Skin scan velocity
p_6	mm	Hatch distance
p_7	$\angle$ ($^\circ$)	Orientation (X-Y orientation (α), Z orientation (β))
p_8	mm	Location (X, Y, Z)
p_9	μm	Surface height

Table 7.15. Representations of R18 in CART

Type of repr.	Representation
Interpretation in text-based repr.	If a surface's z orientation is less than 53 ($\neg C1 \& \neg C3$) and the surface's X location is less than 25 ($\neg C7$), surface height is 48.
IF-THEN statement	IF $p_7 \wedge p_8$ THEN p_9
Param. value range	$p_{7=}$ ($0 \leq \alpha \leq 360, 45 \leq \beta < 53$), $p_{8=}$ ($-50 \leq X < 25, -50 \leq Y \leq 50, Z=0$), $p_{9=48}$

The CART results provide predictive additive manufacturability rules on additive manufacturability based on PSP analysis. However, the extracted CART rules cannot be prescriptive design rules yet. The predictive surface height parameters show rather the LPBF's surface finish capability than AM part design parameters controllable in decision-making in AM design lifecycle phases. This means that the consequences of the CART rules do not present a design guideline for designers required in design rules. Therefore, the extracted CART rules need to be transformed into design rules consisting of constraints and guidelines through knowledge reasoning.

To do so, first, associated design and AM process contexts are fused with the CART predictive models in knowledge logic models. Then, they were syntactically represented and stored in the CDfAM ontology. Figure 7.29 shows a representation of a PSP relationship in *R18* fused with its design and AM contexts. In Figure 7.29, g_1 represents the geometry of the

downskin surface in *R18*'s context acquired from the surface's CAD data. m_1 and $p_1 \sim p_6$ represent material and AM process specifications, respectively, acquired from process planning data. Also, The CART results are captured in primitives p_7 , p_8 , and p_9 . The value ranges of p_7 , p_8 , and p_9 were observed at the CART's C1, C3, and C7 conditions and the corresponding leaf node. These knowledge elements are represented as individuals under associated class types in the ontology. Their relationships are captured in object and data properties.

Then, the fused knowledge becomes a knowledge block that includes correlations extracted from the CART along with the fused design and AM contexts. Based on the knowledge representation and knowledge fusion, a semantic rule *D18'* can be constructed as shown in Table 7.16. *D18'* is an extended *D18* that expresses the LPBF's downskin surface finish capability in the design and AM contexts of *D18*.

Table 7.16. Representation of *D18'*

Type of repr.	Representation
IF-THEN statement	IF $e_1 \wedge g_1 \wedge p_1 \wedge p_2 \wedge p_3 \wedge p_4 \wedge p \wedge p_7 \wedge p_8 \wedge m_1$ THEN p_9
Param. value range	$g_1 = (w=5)$, $p_1 = 30$, $p_2 = 170$, $p_3 = 120$, $p_4 = 1250$, $p_5 = 1000$, $p_6 = 0.1$, $p_7 = (0 \leq \alpha \leq 360, 45 \leq \beta < 53)$, $p_8 = (-50 \leq X < 25, -50 \leq Y \leq 50, Z=0)$, $p_9 = 48$, $m_1 = \text{Nickel Super Alloy 625}$

Figure 7.29. A PSP knowledge model fused with design and AM contexts

Second, this case study acquires a priori knowledge that can be considered in the design and AM contexts of *R18* for further knowledge reasoning demonstrations. Once it becomes a knowledge block, the knowledge block can be used for defining other knowledge; a support structure rule is developed from two other pre-developed knowledge on overhang feature and downskin surface [30].

In this case study, a design rule DR'_{oh} will be constructed for a given overhang feature that has a downskin surface with an undercut 45 degrees (shown in Figure 7.24). The overhang feature is designed to be manufactured in the same LPBF context. In this case study, a prescriptive design rule for an angular overhang feature and a support structure [30, 164], DR_{oh} , is acquired as a priori knowledge. Then, $DI8'$ and DR_{oh} are used for knowledge reasoning. DR_{oh} is shown in Table 7.17.

Table 7.17. Representations of DR_{oh}

Type of repr.	Rule representation
Prescriptive text-based guidance	If given an overhang (pf_1) with an undercut 45 degrees ($\beta=45$) and the surface roughness is less than “1” ($r<1$), then support structures (pf_2) are needed
IF-THEN statement	IF $pf_1 \wedge \beta \wedge r$ THEN pf_2

Knowledge reasoning is conducted using forward chaining. Forward chaining is a data-driven method of deriving a goal from given data and knowledge bases and a set of inference rules [165]. For forward chaining, this study has three IF-THEN statements based the facts from AMR_{I8} and DR_{oh} (Rule 1 and Rule 3) and an assumption put in Rule 2 as follows.

Rule 1: $DI8'$

Rule 2: Overhang feature with downskin surface height equal to 48 $\Rightarrow$

Downskin surface roughness less than 1

Rule 3: DR_{oh}

The given overhang feature definition satisfies the condition of $DI8'$. Therefore, after a logical interpretation based on Rule 1, the overhang feature is defined with the surface height parameter and its value ' $p_9=48$ ' given in the consequents of $DI8'$. Then, Rule 2 and Rule 3 are applied. If the assumption in Rule 2 is true, the overhang feature's downskin surface roughness becomes less than 1. In this case, Rule 3 becomes true for the overhang feature. Then, the overhang feature requires support structure pf_2 defined in DR_{oh} . On the other hand, if the assumption in Rule 2 is not true, the overhang feature becomes self-supporting and ph_2 's support structure type becomes null. The result of the knowledge reasoning is a design rule DR'_{oh} in Table 7.18 and captured in SWRL in Figure 7.30 .

Table 7.18. Representation of DR'_{oh}

Rule representation	
IF-THEN	IF
statement	1: $pf_1 \wedge$ 2: $g_2 \wedge e_1 \wedge pf_1 \cap pf_2 \wedge g_1 \wedge g_4$ 3: $p_1 \wedge p_2 \wedge p_3 \wedge p_4 \wedge p_5 \wedge p_6 \wedge m_1 \wedge p_7 \wedge p_8 \wedge p_9$
	THEN
	4: $g_2 \wedge pf_2 \wedge g_3$
Param.	$g_1 = (w=5), g_2 = n/a, g_3 = n/a, g_4 = n/a, p_1 = 30, p_2 = 170, p_3 = 120, p_4 = 1250, p_5 =$
value	$1000, p_6 = 0.1, p_7 = (0 \leq \alpha \leq 360, 45 \leq \beta < 53), p_8 = (-50 \leq X < 25, -50 \leq Y \leq 50,$
range	$Z=0), p_9=48, m_1 = \text{Nickel Super Alloy 625}$

Name
Overhang_SupportStructure_LPBF
Comment
Status
Ok
CompoundFeature(OverhangFeature_with_SupportStructure) ^ PrimitiveFeature(OverhangFeature_with_SurfaceR18) ^ PrimitiveFeature(?S) ^ Entity(Surface_R18) ^ hasGeometricCharacteristicOf(OverhangFeature_with_SurfaceR18, ?G) ^ hasGeometricCharacteristicOf(?S, ?G1) ^ isRestrictedBy(OverhangFeature_with_SupportStructure, EOS_Scanning_Parameter) ^ isRestrictedBy(OverhangFeature_with_SupportStructure, EOS_Material_Parameter) ^ isRestrictedBy(Surface_R18, Surface_R18_Location) ^ isRestrictedBy(Surface_R18, Surface_R18_Orientation) ^ isRestrictedBy(Surface_R18, Surface_R18_SurfaceHeight) -> isRestrictedBy(?G, EOS_Material_Parameter) ^ isRestrictedBy(?G, EOS_Scanning_Parameter) ^ PrimitiveFeature(?S) ^ Dimension(?G1)

Figure 7.30. Representation of DR'_{oh} in SWRL

The condition statement of DR'_{oh} expresses the design and AM contexts and constraints as follows.

- Contexts (line 1)
 - Overhang feature type and level of design abstraction where the design rule is applied (pf_1)
- Constraints
 - AM-restrictive form feature representation (line 2)
 - Geometry of the overhang feature (g_2)
 - Geometry region where the overhang feature and the support structure interact ($e_1 \wedge pf_1 \cap pf_2$)
 - Geometry of the downskin surface (g_1)
 - Location where the overhang feature and the support structure interact (g_4)
 - AM context imposing additive manufacturability constraints (line 3)
 - LPBF process and material specifications ($p_1 \wedge p_2 \wedge p_3 \wedge p_4 \wedge p_5 \wedge p_6 \wedge m_1$)
 - LPBF's surface finish capability in given surface location and orientation ($p_7 \wedge p_8 \wedge p_9$)

Based on the condition, DR'_{oh} 's conclusion provides design guidelines as follows.

- Guidelines (line 4)
 - Overhang feature's AM-restrictive part geometry (g_2)
 - Support structure types and their specifications ($pf_2 \wedge g_3$)

An updated knowledge block is shown in Figure 7.31. It was developed by stacking newly identified knowledge elements in the knowledge reasoning process using the design fundamentals and principles on the previous blocks. This result demonstrates the AM knowledge's self-improvement and an automated data-knowledge-rule transformation.

Qualified design rule knowledge in the knowledge base is used for i) automated rule-based decision-making in DfAM lifecycle or ii) new knowledge constructions. For knowledge constructions, the formal rules in IF-THEN statements can be applied to knowledge reasoning to mathematically or computationally match facts to their antecedents of consequences relations. The knowledge reasoning based on formal principles of design rule language sets shows an opportunity to extract new rules based on the matching whenever new AM datasets are obtained in a database and new predictive models are extracted from ML accordingly. In this way, AM design rule knowledge can self-evolve continuously while reflecting dynamically generated AM data in an automated and autonomous manner.

Figure 7.31. A PSP knowledge model after knowledge reasoning

7.4 Summary and Preview

This chapter validated the proposed models and constructed the CDfAM ontology as the main body of the CDfAM knowledge base with prosthesis leg design, AM process, and additive manufacturability knowledge. This chapter also presents a prescriptive design rule knowledge retrieval for design recommendations. Then, this study presented AM data-driven CDfAM knowledge construction with the CART algorithm.

Although this chapter presents a novel CDfAM knowledge construction method with case studies, it is noted that shortcomings exist in the limited current scope of 1) knowledge construction, 2) ex-situ AM process data, and 3) CART algorithm. In this point of view, this study can be extended to the related future work: extension of the thesis to merge it with AM application and AM process data-driven decision-making automation.

The next chapter is the final chapter that presents a summary of this research's achievements, contributions, and limitations. Also, the final chapter provides recommendations and future research direction along with the discussion of the limitations.

Chapter 8. Conclusion

In this thesis, the Customized Design for AM (CDfAM) has been developed, presented, and validated to support customized product developments with considering AM-enabled product functionalities and manufacturability constraints, especially with formal design knowledge representation approaches. Chapter 8.1 reviews the research objectives and the proposed methods. The resulting contributions and limitations of this thesis are summarized in Chapter 8.2. Future work is discussed in Chapter 8.3.

8.1 Research Summary

The unique tool-less and layer-upon-layer capability of AM has significantly broadened design freedom enabled by AM's unique capability of shape complexity, material complexity, hierarchical complexity, and functional complexity. At the same time, AM is challenging designers to identify how to incorporate AM's manufacturability generated from AM technology differences into AM part's geometries. Consequently, new design theories, methods, and methodologies are required to embrace AM's design freedom-enabled product development opportunity and AM-restrictive manufacturability, which underlines the need for new AM-oriented fundamental design knowledge to achieve AM products.

This thesis proposed a methodology for constructing customized design for AM (CDfAM) knowledge. One of the most important considerations for achieving AM products is the development and implementation of computational and reconfigurable CDfAM knowledge. Accordingly, this research has mainly focused on formal methods that capture

AM design knowledge on AM-enabled product behaviors and AM-restrictive process constraints and develop a CDfAM knowledge base.

The primary objective embodied in the CDfAM methodology is to construct a knowledge structure which an AM product architecture is customized based upon. The CDfAM methodology followed selecting a design tool: affordance as a systematic engineering design (SED) tool for capturing customized product behaviors, developing an affordance-based method for representing customized functional behaviors of AM products, developing a method for representing customizable modular design rules for AM, and constructing an ontology.

To adopt SED to design for AM (DfAM), it is essential to select a SED tool for capturing product's customized functional behaviors as functional requirements of AM products, which is required in the conceptual phase of SED. To address the challenge, Chapter 4 presents theoretic discussions on contradicting the function-based design (FbD) methods with the affordance-based design (AbD) methods in DfAM. The device-centric, form independent, and input/output-based transformative properties of the FbD methods such as function structures have strengths in modeling product's internal behaviors. However, the FbD methods show limitations in the new area of AM-enabled customization which requires design approaches for representing user-centric AM product architecture (e. g., a trans-tibial prosthesis socket) and form feature design requirements acquired only by AM's design freedom. On the other hand, the AbD methods can address the limitations of FbD methods in DfAM due to their user-centric (artifact-user interactive), form dependent, and non-transformative properties. After the contradiction, Chapter 4 proposes an affordance-

based DfAM framework and an affordance structure as a formal modeling technique for AM-enabled customized product behaviors taking advantage of the AbD methods.

In Chapter 5, the proposed affordance structure in Chapter 4 is more thoroughly discussed and extended to develop an affordance-based method for representing customized functional behaviors. This chapter mainly aims to develop a set of new formal design representations that capture design requirements to improve the level of customization while taking advantage of the AM-enabled design freedom. First, Chapter 5 proposes a formal CDfAM process structure that integrates the concept of AbD into the Three Link Chain Model (3LCM) to merge Design for Customization (DfC) and Design for Manufacturability (DfM). Second, Chapter 5 presents formal representations for an artifact–user interaction using Finite State Automata (FSA), a Discrete Event Systems (DES) modeling technique, and goal-oriented product behaviors in AM artifact uses as language sets. By adopting the relational properties of affordance, the proposed formal representations systemically link user behavior-supporting artifact capabilities and user preferences to functional behaviors of additive manufactured artifacts.

After AM product’s customized functional behaviors are captured and represented, Chapter 6 represents design rule knowledge and constructs a design rule knowledge base. In DfAM, designers are challenged with incorporating manufacturability differences in AM technologies, processes, and materials into functional and geometrical properties of additively manufactured part. To address the challenge, first, this study proposes a new method for representing AM design rules by extending a structured modular hierarchy and formalisms of the existing design rule language representations. With the extended set of

design rule element formalisms, this study provides formal and computational definitions of novel design rule elements and their relationships.

Then, in Chapter 7, this study validates proposed methods and constructs a CDfAM ontology utilizing web ontology language (OWL)/resource description framework (RDF), semantic web rule language (SWRL), and semantic query-enhanced web rule language (SQWRL). The ontology-based knowledge modeling and sharing enables capturing the semantic contents of the CDfAM knowledge generated from given customization and AM contexts. The proposed formal methodology systematically shows how AM-enabled functionality and AM's manufacturability constraints are associated with part structures with user-functionality-design-process-material correlations and how the AM feature designs are recommended as consequences of the AM constraints. Also, the proposed formal representations and the CDfAM knowledge base allow reconfigurable AM rule knowledge blocks to be semantic-queried selectively. Then, to discuss about linking data-driven CDfAM knowledge construction to the proposed methodology, Classification And Regression Tree (CART) Machine Learning (ML) algorithm is employed to AM data in an AM design rule construction. This study performs a case study on a seat, a prosthetic leg socket, a thin wall feature, an overhang feature, a honeycomb structure, and analytics on ex-situ measurement AM data. Figure 8.1 shows a summary of the thesis.

Figure 8.1. Overall summary of the thesis

8.2 Contributions and Limitations of the Research

The main contribution of this thesis is to address a current DfAM problem and then provides the Customized Design for AM (CDfAM) methodology to resolve the problem. The main result from the methodology is design knowledge on AM product's customized functional

behaviors, AM features, and user-design-functionality-process-material correlations. The specific contributions of this thesis are summarized as follows:

- Compare the two most representative functional behavior representation tools in SED, function and affordance, for selecting a functionality representation tool in the early phase of DfAM for customized products, see Chapter 4
- Provide a new CDfAM framework to systemically link the heterogeneous domains of performance, design, material, and AM processes to incorporate them into DfAM processes, see Chapter 4 and Chapter 5
- Develop a new concept of product functional behavior representation for AM-enabled customization and a relevant formal design method in the conceptual design phase of DfAM, see Chapter 4 and Chapter 5
- Propose a formal method for representing AM design rules by extending an existing design rule element language set, see Chapter 6
- Construct a CDfAM ontology by matching the ontology's knowledge elements to the proposed formal methods' modular hierarchy and associated formalisms for supporting the formal representation, capture, retrieval, and reuse of modular design and AM knowledge in CDfAM applications, see Chapter 7

The contributions provide foundations for the link between product design and AM processes with considering AM capabilities and constraints. Accordingly, new customizable AM knowledge is constructed to support the new concepts of AM product designs, exploration of AM design freedom from the early phases, and development of customized and additive manufacturable product architectures. This study also constructs an CDfAM

ontology for DfAM systems integrations. The proposed methodology supports not only a DfAM approach for AM product functionality and manufacturability, but also a DfAM approach that extends the single form feature level studies to the product and system levels in terms of design knowledge abstraction levels. The research introduced in this thesis has been validated with various case studies and provided significances from both industrial and research perspectives. However, some improvement can be further considered as follow.

(1) *Multi-functionality approaches for designing functionality-driven AM features and product architectures:* In DfAM, in terms of realizing design optimizations of Functional Volumes (FVs) and Functional Surfaces (FSs), it is important to capture AM's capability of functional complexity in the functional domain and reflect the capability to shape complexity, material complexity, and hierarchical complexity in the physical domains. Accordingly, design methods are developed in this study as follows: Finite State Automata (FSA)-based affordance structures in Chapter 4 and Chapter 5. However, these methods have developed to mainly support AM products such as bio-inspired forms and product with custom geometry and behaviors. The advances in manufacturing capabilities of AM now enable complex operational mechanisms and embedded components to be fabricated directly to achieve mechanical multi-functionalities. Additional functions with embedded electronics, sensors, or integrated heat exchange and cooling systems are examples of such parts. Also, AM enables the manufacture of parts with complex material compositions and designed property gradients for functionally graded materials. A methodology is needed to support AM's capability on such types of functional complexity.

(2) *Acquisition and analysis of data and knowledge for defining customizability and manufacturability for AM products:* Collecting design and process data and knowledge are critical in identifying the correlations between the user, design, process, and material parameters: the fundamental elements defining customizability and manufacturability of AM products. Although AM design and process data are being generated, quality data on AM characteristics related to customizability and manufacturability such as surface qualities and geometric tolerances are difficult to collect from real-life product lifecycles, in-situ monitoring, and ex-situ measurements. The quality of the data can influence achieving goals of AM product design. Accordingly, a methodology is needed i) to gather data through AM product life cycle and value chains, ii) to extract design knowledge related to AM product quality measurements and process capabilities, and iii) to identify customizability and additive manufacturability-relevant correlations between the user, design, process, and material parameters from collected data. Chapter 7.3 demonstrate the link between such data-driven DfAM approach and this thesis in a limited scope.

Although the research has such limitations, the limitations create opportunities for future improvements. Recommendations and future work for DfAM are discussed in the next chapter.

8.3 Recommendations and Future Research Direction

Although the CDfAM has focused on product design mainly for AM's functionality and manufacturability, it should be extended to integrate other design and analysis approaches and as well as specific AM applications and processes. The future work should investigate

more holistic approaches to design and validate robust AM products for maximizing AM-enabled performances and minimizing manufacturing difficulties. In pursuing such goals, future work will focus on data- and knowledge-driven DfAM. The future work will keep pursuing advanced DfAM automation.

Recently, a digital solution framework for AM Ecosystem is proposed by combining data, models, knowledge, and engineering decision support software tools. Then, a collaboration data management system was built based on the framework [166, 167]. Synchronized with the real world in dual-directions, the digital solution framework turns into a digital replica of AM ecosystem, named AM Digital Twin. As shown in Figure 8.2, the AM digital twin can be updated to better mimic the real world through continuously ingesting and mining the data generated from the AM ecosystem, and consequently, it will provide advanced engineering decision support to various AM activities for improved product quality. In order to achieve utilize the AM Digital Twin capability, recommendations and future work are highlighted as follows.

Figure 8.2. Concept of AM digital twin

(1) *Machine Learning enabled Continuous learning for DfAM*: AM assisted by a digital twin is expected to revolutionize the realization of high-value and high-complexity functional parts on a global scale. With ML introduced in the AM digital twin, AM data are transformed into knowledge continuously and automatically; hence AM products will be designed and manufactured with improved quality. Conventional product development systems, however, fail to fully adopt ML algorithms on the increasingly available AM data, which could directly contribute to a stagnant AM knowledge acquisition. To address the limitation, an algorithmic framework is required for constructing AM knowledge automatically and continuously from data. An algorithm will develop predictive models to correlate part structures, process parameters, and properties using ML algorithms on data related to product and user behaviors, design, process control, in-situ monitoring, and ex-situ measurement. Based on the predictive models, the algorithm will construct prescriptive rules necessary for decision-making in AM product developments. The constructed rule

knowledge will be stored in a knowledge base by the algorithm for further AM knowledge query and constructions. Then, the algorithm will provide feedback to a knowledge query formulation phase, which forms the algorithm into a closed loop. Through the algorithm, AM knowledge can self-evolve continuously, while reflects dynamically generated AM application and process data in an automated and autonomous manner.

(2) *Data-driven design rule knowledge engineering*: This research on the design rules focuses on the formal design rule language for representing design fundamentals and their relationships as modular knowledge blocks. The current design rule work item will be expanded to focus on fundamental correlations between design, material, and process primitives. The current design rule efforts on Powder Bed Fusion (PFB) will be expanded for other processes such as Directed Energy Deposition (DED) and for specific applications. For such research direction, the future work on the design rules will focus on the identification of fundamental parameter correlations using data-driven approaches to support design rule knowledge discoveries. Data analytics and AI techniques will be adopted. Such efforts will include identifying design, process, and material fundamentals and identifying patterns in design, process, and material datasets. The data-driven approaches will leverage AM datasets and a priori design rule knowledge.

(3) *Data-driven customization knowledge engineering in sensor-embedded AM product applications*: Among lots of AM applications, an example is a functional part of a new product that consists of electronic and mechanical subsystems [101]. This future work seeks to apply the CDfAM to sensor-embedded parts. The layer-upon-layer characteristic of AM can access a complex part's external and internal points during the production of a part, which makes it possible to embed sensors and components inside the functional part [168].

Toward achieving an additive manufactured part that is not only personalized in shape but also in function, the future research will seek a suitable case study that sensor-embedding part can be applied. The example will be designed by taking full advantage of the proposed method. Personal and responsive smart products will adapt to users' demands, biometric information, body temperature, sweat, and internal pressures [169]. Personalized and responsive products will behave in response to user's product-related behavior. After receiving input from users or completing a task, it would make a state transition and become ready once again to support users in another context until they achieve their final goals. The outcome of such operations will be designed to be transparent to related resources and well projected by means of instruments such as sensory devices installed in the product system. Knowledge extraction will be conducted on cumulated data in the sensors. Advanced data analytics will be employed to extract AM-enabled customization knowledge.

(4) *AI-enabled design decision-making automation for AM:* Advances in AM combined with a newfound abundance of AM data and AI algorithms will transform what, where, and how to design products [170]. However, conventional design techniques for AM are not mature enough to fully utilize available AM data and lack collaborations with data- and knowledge-based systems in designing product. Decision-making algorithms are not fully developed for DfAM. ML algorithms suitable for DfAM decision-making are not fully identified. Also, it is not clear yet which DfAM decision-making activities require AI's supports with its advanced data analytics automation. To counteract this limitation, the future work will develop decision-making algorithms, review the types of ML and AI algorithms, and look more inclusively across available application and AM datasets. More advanced methods of knowledge representation and reasoning will be investigated, which is expected

to provide formal methods toward automated DfAM decision-making. Extracted knowledge in the CDfAM ontology will be utilized for an AI-based design decision-making automation for AM. Utilizing the ontology, a part will be resized or re-designed for different individuals and AM processes automatically with AI algorithms. The future work listed in (1), (2), (3), and (4) is all closely related. I will continue to pursue data- and knowledge-driven DfAM automation.

Publications

Ko, H., Moon, S. K., "Contradicting Functions with Affordances in Design for Additive Manufacturing," ASME 2017 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Cleveland, Ohio, USA, August 6-9, 2017, Paper No. DETC2017-68157, 2017.

Ko, H., Moon, S. K., Wood, K. L., Oh, H. S., "An Integration of Function- and Affordance-based Methods for Product-service System Utilizing Finite State Automata," 9th IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, December 4-7, 2016.

Ko, H., Sacco, E., Chua, Z. Y., Moon, S. K., and Otto, K., "User-centered Design for Additive Manufacturing as a Customization Strategy," 2nd International Conference on Progress in Additive Manufacturing (Pro-AM), Singapore, May 16-19, 2016.

Ko, H., Moon, S. K., and Otto, N. K., "Design Knowledge Representation to Support Personalised Additive Manufacturing," Virtual and Physical Prototyping, Vol.10, No.4, pp.217-226, 2015.

Ko, H., Moon, S. K., and Hwang, J., "Design for Additive Manufacturing in Customized Products," International Journal of Precision Engineering and Manufacturing, Vol. 16, No. 11, pp. 2369-2375, 2015.

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Appendix: Modular Lower Limb Prosthesis Components

Figure A.1. Modular lower limb prosthesis components [148]