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Doctoral Dissertation

MODELING OF TASK COMPLEXITY IN HUMAN-CENTERED SYSTEMS

Moise Busogi

Department of System Design and Control Engineering

Graduate School of UNIST

2017

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ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Modeling of Task Complexity in Human-Centered Systems

A dissertation
submitted to the Graduate School of UNIST
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Moise Busogi

06. 13. 2017

Approved by

Namhun Kim

Advisor
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ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Modeling of Task Complexity in Human-Centered Systems

Moise Busogi

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Abstract

Throughout the years, technological expansion has been coupled with complex work allocation in Human-Centered System (HCS). In spite of the recent advances in automation, role of humans in the HCS is still regarded a key factor for adaptability and flexibility. Meanwhile, due to advances in computing, computer simulations have been the indispensable tool in the study of complex systems. However, due to the inability to accurately represent human dynamic behavior, the majority of HCS simulations have often failed to meet expectations.

The failure of HCS simulations can be traced in poor or inaccurate representation of key aspect of system. Whereas the machine component of HCS is often accurately simulated, research claims that human component is often the cause of a large percentage of the disparity between simulation predictions and real-world performance. This dissertation introduces a novel human behavioral modeling framework that systematically simulates human action behavior in HCS.

The proposed modeling framework is demonstrated with a case study using simulation in which a set of feasible human actions are generated from the affordance-effectivity duals in a spatial-temporal dimension. The model employs Markov Decision Process (MDP) in which NASA-TLX (Task Load Index) is used as cost estimates. The action selection process of human agents, i.e., triggering of state transitions, is stochastically modeled in accordance with the action-state cost (load) values. A series of affordance-based numerical values are calculated for predicting prospective actions in the system. Finally, an evacuation simulation example based on the proposed model is illustrated to verify the proposed human behavioral modeling framework.

The incorporation of human modeling in HCS simulation offers a wide range of benefits in representing human's goal directed action. However due to the complexity and the cost of representing every aspect of human behavior in computable terms, the proposed framework is better fit in simplified and controllable environment. Thus, we then propose a human in the loop (HIL) approach to investigate the operator's performance in HCS; particularly, the mixed model assembly line (MMAL). In HCS such as MMAL, human operators are often required to carry out tasks according to instructions. In the proposed methodology, rather than a mathematical representation of human, a real human plays a core role in system operation for the simulation and consequently influences the outcome in such a way that is difficult if not impossible to reproduce via traditional methods. At the initial stage of the simulation, various features are extracted after which, a stepwise feature selection is used to identify the most relevant features affecting human performance. The selected features are in turn used to build a regression model used to generate

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human performance parameters in the HCS simulation.

Finally, we explore the analytical relationship between the flexibility (variation) and the complexity of human role in HCS. As the number of alternative choices (or actions) available to human increases, the choice process becomes complex, rending human modeling and predictability more difficult. The dissertation will particularly utilize the visual choice complexity to convey the proposed computation of task complexity as a function of flexibility. Thus, we propose a method to quantify task complexity for effective management of the semi-automated systems such a MMAL. Based on the concept of information entropy, our model considers both the variety in the system and the similarity among the varieties. The proposed computational model along with an illustrative case study not only serve as a tool to quantitatively assess the impact of the task complexity on the total system performance, but also provide an insight on how the complexity can be mitigated without worsening the flexibility and throughput of the system.

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Chapter 1

Introduction

This chapter presents an introduction and background of the task complexities in distinct aspect of human behavior modeling. The chapter also discusses the underlying factor behind the need for a clear human behavior modeling in various human-involved systems, and the means at which the solution can be achieved.

The reminder of this chapter is organized as follow: Section 1.1 presents the basic background of human behavior modeling; the decision (choice) making in particular. Section 1.2 and 1.3 discuss the motivation and the objective of this research respectively. Section 1.4 states in clear terms the problems being dealt with, while section 1.5 introduces the methodologies used in this dissertation. Finally, a brief overview of the rest of the dissertation is offered in the last section of this chapter.

1.1. Background

In the last several years, roles and duties of human operators in complex systems, have undergone tremendous changes [1]. Despite the recent advances in automation, human is still regarded as a key factor in maintaining higher adaptability and flexibility. As a result, the technological expansion has been coupled with a need for effective and dynamic resource allocation methodologies in semi-automated systems[1, 2]. In the management perspective, the prevalent engineering viewpoint across systems is to reduce disturbance and variability in complex systems through automation; thus, rending it more predictable. However, due to uncertainties involved in human decision process, human action becomes hard to predict, thus rending it difficult to create a human-machine system devoid of human error possibility.

Modeling human goal-directed actions is an essential building block for understanding Human Machine Complex System (HCS) [3]. The goal-directed actions consist of four basic steps: (1) identify a goal, (2) evaluate the options to achieve the goal, (3) select the appropriate option and (4) implement the option. Once the goal is identified, the path to reach the goal is not necessarily clear. In fact, the more the number of feasible goal-directed action choices human has, the less predictable the human component of the system becomes. That is, while the increased number of alternate choices available to human makes the system more flexible, it undoubtedly leads to a "*choice complexity*", often resulting in an increased

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likelihood of human error or inefficient human performance [4, 5]. From the perspective of feasible options, we consider two major questions in choice process: (i) How to incorporate human decision process in the simulation of HCS; and (ii) How human flexibility affects the complexity of the decision process. The nature of the two facets of the human action selection process are very distinct and their implication in HCS are distinctive; thus, treated as two separate yet relatable cases in this work.

Existing human decision models fall into three categories: an economics-based approach, a psychology-based approach, and a synthetic engineering-based approach [6]. Whereas each approach offers compelling arguments, researchers have noted several limitations that range from the failure to represent human cognitive natures to a simplistic and informal representation of the dynamic environment. One the harder challenges researchers face while modeling human decision process lie in the level and variety of uncertainties in human decision-making processes. However, often, the prospective actions are quite interpretable under some physical, psychological, and environmental conditions upon which a human agent is trying to act. That is, the complexity of action modeling is significantly reduced through a systematic acquisition of relevant information on human agent’s beliefs and desires, and his/ her perception of the environment [7].

From the perspective of prospective control theory, within a given space and time, an environment offers several constraints (or cues) that limit the size of goal-directed action alternatives. Hence, modeling human- environment interaction is a major component in building intelligent agent systems. In this regard, we propose an agent-based simulation model, in which we apply the theory of affordance which conceptualizes the representation of human- environment interaction, and explains the existence of action opportunity, including the necessary conditions for actualization[8].

In additional to “affordance-based action modeling”, this dissertation proceeds to examine how various factors affect the complexity of making a choice. Recall that the increased human flexibility lead to a “choice complexity”, with a wide range of implications. Here, the flexibility refers to number of alternate choices available to human. In the perspective of HCS, human operators are often required to carry out tasks according to instructions. In a flexible and dynamic system, such tasks often entail a level of choice complexities. According to Hick’s law, initially proposed in 1952, the time required to make a decision is a function of the number of options available [9]. That is, the more the number of alternatives, the longer it takes to make a choice.

Campbell [10] suggests that complexity is often treated as (a) psychological experience, (b) an interaction between task and person characteristics, and (c) a function of objective task characteristics. As a result, the scientific notion of complexity has been traditionally conveyed using particular examples [11]. In this dissertation, we will particularly utilize the visual choice complexity to convey the proposed computation of complexity. The visual "choice complexity" refers to the complexity involved in visually identifying and choosing a specific predefined target entity from a number of alternatives. This is equivalent to visual search where human goal is to identify a specific predetermined target item from a large number of often similar alternatives.

In manufacturing contexts, in order to satisfy complex customer needs, manufacturing practitioners have opted for mixed-model assembly system and modular supply chains due to their reputation as flexible enough to handle the increased variety. The question then becomes how to increase the flexibility while maintaining an acceptable level of choice complexity, and how to increase the production variability while maintaining operation efficiency.

1.2. Motivation

The high level of complexity associated to the physical or analytical implementation of several human-involved, safety-critical experimentations has led to a hike of interests in the development of intelligent entities that mimic human behavior. As a result, human behavior modeling has been increasingly adopted when simulating actions and interactions of autonomous agents that serve as virtual representatives of real world entities[3].

Despite the progress made in modeling human (agent) decision process, researchers have noted several limitations; particularly, the lack of clear and formal consideration of economics of human behavior in the overall decision making framework [12]. Thus, this research explores dynamic modeling of goal-directed action, while emphasizing the role of bio-cost in the decision-making process.

Furthermore, the improvement in system flexibility often worsen the choice complexity. While the existence of choice complexity and its challenges is widely acknowledged [4], a formal quantification of choice complexity is still a topic for discussion. That is, there is no proper method to compare several system setups based on their respective choice complexities. Thus, based on information this research proposes a formal quantification of choice complexity in human-centered system such as a mixed model assembly line.

1.3. Objectives

There are three main objectives of this research: (a) to develop a formal affordance-based action modeling that systematically represent agent's goal-directed action with respect to the dynamic interaction of agent and environment; (b) develop a formal quantification metric for choice complexity as a function of flexibility; and (c) to propose a human in the loop simulation framework to assess and predict the choice complexity and its implication to performance metrics

1.3.1. Affordance-based choice modeling

A successfully build human agent model ought to properly represent the agent-environment interaction [3]. In fact, agent's actions are often considered as the consequences of agent-environment interactions [8]. Hence, in our model, we use the concept of affordance, which is one of the well-established theories that conceptualize the environment in the context of the human-environment interaction.

According to the theory of affordance, the animal's ability to use the action opportunities depends on what Gibson refers to as "animal effectivity." Once goal-directed action opportunities are represented through the affordance concept, the action selection becomes a matter of weighting on conflicting alternatives based on the relevant considerations that represent what the agent desires and values[13]. Thus, the affordance based choice modeling consist of:

①. Establishing the goal

②. Representing the dynamic environmental states and the affordances they offer to agents within the environment.

③. Representing the agent effectiveness with regards to the affordance opportunities

④. Establishing a clear methodology for action selection (i.e., weighting on conflicting alternatives) that takes into account both physical and psychological cost of taking an action

1.3.2. Computation of choice complexity

As the number of alternative choices grow, the effectiveness of making a choice becomes a crucial parameter in designing and building HCS. Thus, we explore the analytical relationship between the flexibility (variation) and the complexity of human role in HCS. That is, we define measures of complexity that reflect the underlying physics of visual choice complexity. Recall that the complexity is better conveyed using particular examples [11]. Thus, the complexity metric is presented along with a case study that showcases its application in a mixed model assembly line (MMAL). The proposed measure is expected to answer the question about the mechanism through which choices or variety causes complexity. The measure ought to:

①. Reflect the underlying physics of visual choice complexity

②. Include the factors of choice complexity

③. Adopt the concept of information entropy

④. Have an explicit relationship with performance metric

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1.3.3. Human in the loop simulation incorporating choice complexity

In additional to proposing a complexity metric, this research proposes a human in loop simulation framework to serve as a tool that quantitatively assesses the impact of choice complexity on total HCS performance such as MMAL. The tool also provides an insight into how the choice complexity, as often showcased in the mixed-model assembly line, can be mitigated without affecting the overall system performance.

Smart factories boost sensing technologies capable of capturing a wide range of data necessary for advanced analysis of manufacturing operations. Thus, this research aims to give insights on how to effectively make use of technological advances, to connect two heterogeneous components in manufacturing systems: human and automation. We propose a human in the loop machine learning for prediction of the operator's response to dynamic change of complexity. Learning algorithms are built and trained using data collected from operator's performance logs. That is, using a human in the loop simulation machine learning, this dissertation shows how specific manual component of smart manufacturing can benefit from advanced manufacturing infrastructure.

1.4. Problem Statement

1.4.1. Assumptions and Research Scope

The following assumptions and constraints are considered:

i. The number of environmental affordances and agent's effectivities that are available in the system is finite. With this assumption, the research area is limited in well-defined systems

ii. The human (agents) commit to the goal at hand

The affordance-based choice modeling which is the basis of choice evaluation is demonstrated in multi-story building evacuation simulation, while the (visual) choice complexity is demonstrated through mixed model assembly line.

1.4.2. Research Questions

In light of the research objectives outlined in the previous section, we examine the following hypothesis:

Hypothesis 1. It is possible to represent human-environment interaction using the affordance concept while ensuring the following:

- The dynamic environmental states are effectively modeled
- The agent capabilities and preferences are taken into account
- The capabilities and preferences are systematically generated in accordance with both physical and psychological dimensions.

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Hypothesis 2. As the number of goal-directed actions grow, it becomes harder to make a choice, hence "choice complexity". Thus, there is a choice complexity measure such that:

- Fulfill the metric properties.
- Do not contradict with human perceived complexity.
- Can be translated into traditional performance metric.

The two hypotheses are validated through simulation of practical and relevant systems that illustrate the applicability of the proposed research.

1.5. Research Strategies

The results of this research have been refined through a complex analytical process. We mainly used the following methods in research problem and questions identified in this dissertation:

- *Literature reviews:* The purpose of the literature reviews was to assess existing research on choice modeling and its complexity in order to pinpoint their benefits and drawbacks, and to confirm the need for, and the novelty of the results presented in this dissertation.
- *Simulations:* We performed two major simulations to explain the applicability of affordance-based choice modeling, as well as the analysis of choice complexity.
- *Theoretical development:* We applied and refined several theoretical concepts for a wide range of purpose. For example, Markov decision process was used to model agent state transition, while the information entropy served as the measure of complexities

1.6. Dissertation Overview

The dissertation is presented in a multiple manuscript format. Part of the work in Chapters 2, 3, and 4 has appeared as individual research papers. The organization of the dissertation is as follows. This chapter discussed background, motivation, objective, problem statement, and strategy of the research. Chapter 2 proposes an affordance-based choice modeling framework that systematically represent agent's goal-directed action with respect to the dynamic interaction of human agent and environment. The proposed modeling is demonstrated through an agent-based simulation of emergency evacuation.

Chapter 3 develops a formal quantification metric for choice complexity as a function of flexibility. The entropic measure accurately represents the core physical aspect of choice complexity, especially in a mixed model assembly line.

Chapter 4 proposes a human in the loop simulation framework to assess and predict the choice complexity and its implication to performance metrics. We illustrate the proposed framework using a

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simulation of operator's choice complexity as encountered in modern mixed model assembly line. The simulation framework draws a clear and reasonable relationship linking the complexity metric to the manufacturing performance

Finally, the chapter 5 concludes the dissertation by summarizing the contributions and impacts of the research. The chapter, comprehensively discusses also possible extensions of this research.

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Chapter 2

Weighted Affordance Based Task Modeling in the Simulation of Human Centered System

2.1. Introduction

Modeling human actions remains a challenging task, mainly due to the uncertainties resulting from human decision-making processes. Meanwhile, agent-based modeling, has been increasingly adopted to effectively simulate actions and interactions of autonomous agents that serve as virtual representatives of real world entities [3]. Existing human agent decision models fall into three categories: an economics-based approach, a psychology-based approach, and a synthetic engineering-based approach [6]. Whereas each approach offers compelling arguments, researchers have noted several limitations that range from the failure to represent human cognitive natures to a simplistic and informal representation of the dynamic environment. When modeling human-involved systems, it is obvious that understanding of the nature of human actions may help to reduce the complexity and uncertainty of the problem. From the perspective of prospective control theory, within a given space and time, environment offers several constraints (or cues) that limit the size of goal-directed action alternatives [7]. Hence, modeling human-environment interaction is a major component in building intelligent agent systems. In this regard, the proposed simulation model applies the theory of affordance which conceptualizes the representation of human-environment interaction, and explains the existence of action opportunity, including the necessary conditions for actualization [8]. Once goal-directed action opportunities are represented through the affordance concept, the action selection becomes a matter of weighting on conflicting alternatives based on the relevant considerations that represent what the agent desires and values [13].

In the context of evacuation process, human agent has a clear goal, and subjectively perceives action opportunities that the environment offers. A rational agent expectedly follows a cost-efficient path to reach the goal, assuming an appropriate cost factor (e.g., cognitive loads or perceived dangers) is quantitatively assigned to each action choice available. The perception of the loads is, however, subjective and heavily depends on human agent's traits (e.g., strength of body, his passions, his experience, his reason, etc.) [14]. That is, individual differences, both physical and psychological, are some of the critical factors determining agent's behavior in hazardous environment [15-17].

Thus, this chapter proposes a simulation model in which a set of feasible human actions are generated from the affordance-effectivity duals in a spatial-temporal dimension. The model employs Markov Decision Process (MDP) in which NASA-TLX (Task Load Index) is used as cost and reward estimates. The action selection process of human agents, i.e., triggering of state transitions, is stochastically modeled in accordance with the action-state cost (load) values. This article aims to assist system designers of the safety-critical systems by providing a systematic understanding of the interaction between heterogeneous agents and dynamic environments, with the implication of the agent dependent decision characteristics.

The remainder of this chapter[1] is organized as follows. In Section 2, we discuss the background of this work. Section 3 introduces weighted affordance-based action while section 4 includes an evacuation simulation to verify the proposed framework. Finally, Section 5 concludes our chapter and suggests future research directions.

2.2. Background

2.2.1. Affordance theory and prospective control

An agent-based model ought to properly represent the agent-environment interactions. In fact, agent's actions are often considered as the consequences of agent-environment interactions [8]. Hence, in some models, agents encompass the environment representation within their internal data structure [13], whereas other models use two-layered model in order to consider both the intelligent agents and the surrounding environments separately [14]. One of the well-established theories that conceptualize the environment in the context of the agent-environment interaction is the concept of '*affordance*' which is often referred to as the environment property that embeds actions opportunities for the agent within the given environment[8]. Also, there exists the complementary property of '*effectivity*' which refers agent's capability of taking an action.

The theory of affordance has received a great deal of attention from researchers in various fields including artificial intelligence, psychology, design and human-machine interactions. For example, [18] and [19] showed how an affordance-based modeling approach can be implemented to design robot controls and sufficiently mimic human actions in specific situations. For defining the concept of affordance in a

[1] Part of work in this chapter has appeared on: M. Busogi, D. Shin, H. Ryu, Y. G. Oh, and N. Kim, "Weighted affordance-based agent modeling and simulation in emergency evacuation," Safety Science, vol. 96, pp. 209-227, 2017.

formal way, Turvey modeled the affordance as a juxtaposition function of human effectivities and environmental affordances within the same time and same space [20]. Turvey's model of the affordance is as follows:

Let $W_{pq} = j(X_p, Z_q)$ be a function that is composed of two different objects X and Z, and further, p and q be properties of X and Z, respectively. Then, p refers to an affordance of X and q is the effectivity of Z, if and only if there exists a third property r such that:

(1) $W_{pq} = j(X_p, Z_q)$ possesses r,

(2) $W_{pq} = j(X_p, Z_q)$ possesses neither p nor q, and

(3) Neither X nor Z possesses r, where r is a joining or juxtaposition function.

Based on Gibson's definition and Turvey's affordance model, Kim, et al. [21].developed an affordance-based Finite State Automata (FSA) model to propose a formal representation of a human-environment interaction in manufacturing systems. The affordance exists in the spatial-temporal domain and it is independent of animal's perception [8]. However, in many cases, the ability to perceive the affordance is associated with physical and psychological characteristics of an individual agent. Thus, based on affordances and the related available perceptual information, Gaver [22] used the following terminology to distinguish the type of affordance :false affordance, perceptible affordance, hidden affordance and correct rejection (see Figure 2-1). In this study, we add two more terminologies regarding the temporal-spatial availability of the affordance: "expected (or imaginary) affordance" and "perceived (or real) affordance. That is, at the action planning stage, agents may expect or assume the existence of affordance outside their perceivable boundary. This affordance is referred to as "expected affordance" since its existence is not validated by a direct agent perception. On the other hand, "perceived (real) affordance" refers to the affordance that is located within the perceivable boundary and directly perceived by an agent, at the execution level [23]. In the proposed model, we integrate the affordance theory into a human agent modeling to capture the dynamic agent- environment interaction.

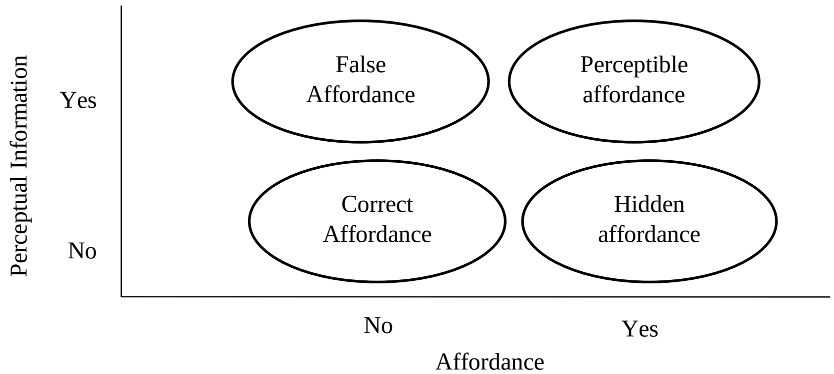

Figure 2-1. Affordance and perceptual information [14]

2.2.2. Human decision models

Decision modeling is a central construct of any intelligent system; thus, several researchers have proposed various decision models for various purposes[3, 24]. Several of the existing human agent decision models fall into three categories: an economics-based approach, a psychology-based approach, and a synthetic engineering-based approach. Economical approaches are based on the assumption that the decision-maker is rational, it is however limited in its capability to represent human cognitive nature. Psychology-based concepts goes further and considers the individual behaviors under a simple laboratory environment. The synthetic engineering-based approaches, complement the economical and psychological approaches. One of the well-known models using this approach is the belief-desire-intention, or BDI. BDI was developed as a way to explaining rational agent's future-directed intention. As shown in Figure 2, a BDI agent is assumed to be rational with certain beliefs, desires and intentions. Beliefs include the agent's knowledge, and they are stored in a type of a database (i.e., belief set). Desires represent the motivation or objectives of the agents. In other words, desires include the ultimate goals the agents wish to achieve. Intentions represent agents' plans to fulfill their desires or goals [9]. While the environment is considered in the BDI approach, its representation is yet to be formalized, thus represented under the user discretion [6, 25]. In this regard, especially within the scope of this article, i.e., a wayfinding task in an emergency situation, Joo, et al. [23] proposed the affordance-based FSA model of evacuation simulations, in which the simulation model can mimic both perception-based human actions that interact with various environmental changes. However, little consideration was given onto the agents' dynamic abilities and preferences.

The model presented in this chapter takes a similar approach to the BDI but exploits the affordance theory to formally and systematically represent agent-environment interactions [21, 22]. The model addresses human agent's action valuation that incorporates both physical and psychological demand prompted by action choice options (i.e., action opportunities). Note also that, while the BDI model assumes

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an absolute rational agent, our model allows a certain degree of irrationality, as consequence the probability-based action selection is considered. The overall framework is summarized in Figure 2-3.

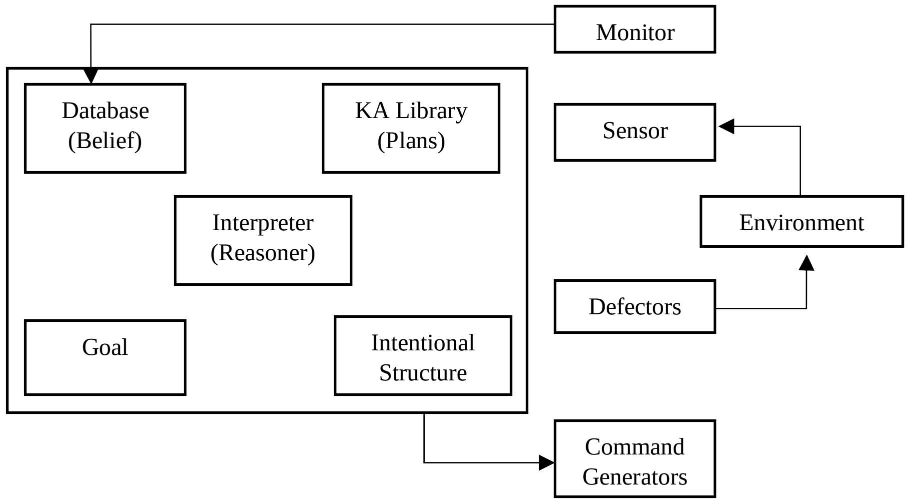

Figure 2-2. BDI Structure [3]

2.3. Weighted Affordance-based Action

In evacuation, a rational agent would be expected to follow a more cost-effective path when an appropriate cost factor (e.g., cognitive loads or perceived dangers) is quantitatively assigned to each action choice available. However, limited amount of information available and uncertainties included within an environment may hinder the agent from effectively choosing the optimal path to reach the desired goal. In practice, the agent makes decisions based on the information available and updates his/her choices when new information becomes available during the execution process [26, 27].

Suppose a situation where a human agent is attempting to exit a high-rise building. Once the agent’s goal (i.e., escaping from the building) is determined, a plan for achieving such goal needs to be established. The plan would be then set based on expected affordance-effectivity duals [20]. The realization of the plan is not fully guaranteed due to the limited amount of information available and environmental changes. In fact, when the agent starts executing the plan (i.e., wayfinding), the perceived affordance may not be the same with the affordance he or she expected. The plan would be then dynamically updated based on real-time perception of the environment. For example, an agent who has planned to take the elevator may have to change his or her plan after realizing that a large number of other human agents are waiting in front of the elevator. In this case, the agent would likely change his or her plan from taking the elevator to using the stairs depending on the cost-based dynamic decision criteria.

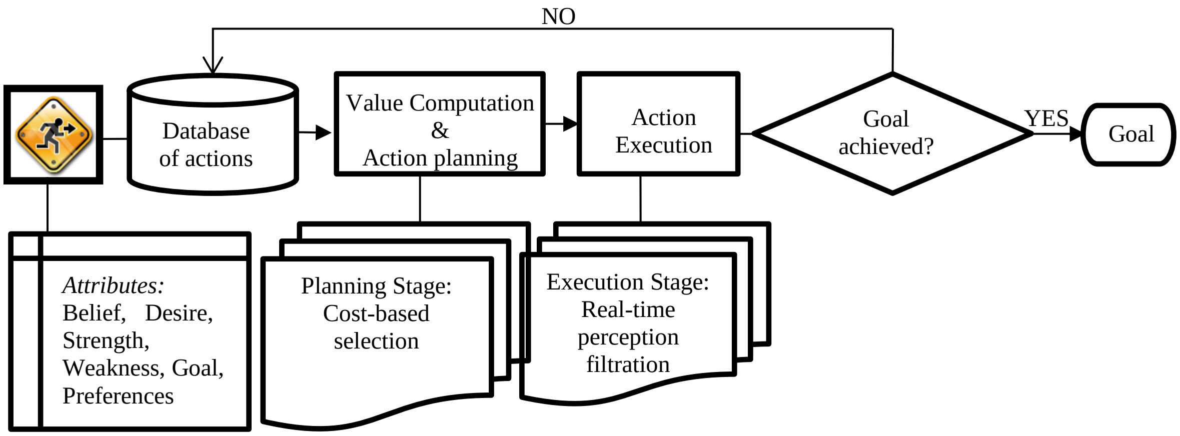

Figure 2-3. Action Selection Framework

2.3.1. Weighted affordance of agents

The modeling and simulation framework proposed in this study considers a combination of a functional set of entities, attributes, and relations, which consist of several autonomous human agents, surrounding environments, and interaction dynamics among them. Agents are entities that possess the causal propensity to bring about a spatial-temporal change within an environment. They are able to choose and perform actions in order to change the current state into being closer to the goal states (e.g., safely escaping from the building by taking cost efficient actions).

An environment is defined as anything except human agents within the system. Based on the theory of affordance, the relation between an agent and an environment is of a great importance in deciding the agent's actions. The agent is further classified depending on their respective inner resources, which are both physical and psychological. As such, action opportunities are perceived with different preferences. For example, a young and healthy agent may underestimate the physical load associated with taking a particular action which may be considered as much harder by the elderly.

Assuming the agents are rational to some extent, there would be a tendency to choose a cost-effective measure when choosing an action; that is, the lower the cost (or load) associated with an action, the higher the likelihood of that action being selected. In addition to the physical cost, mental cost would also heavily affect an agent's action selection process. For example, an agent may prefer a less stressful action to a more stressful one. Some researchers argue that people are satisfied more with a solution that enables them to obtain better results without overly taxing their cognitive system [28].

NASA-TLX (Task Load Index) is used to obtain the relative metrics for estimating both the physical and mental cost associated to taking a given action. NASA-TLX is a multi-dimensional rating scale in which information about the sources and the magnitude of workload factors are combined to derive a reliable estimate of both physical and psychological workload costs. It includes six factors: mental demand, physical demand, temporal demand, performance, effort, and frustration level [29]. See Table 2-.1 for further details on the six factors of NASA-TLX.

Table 2-1. NASA-TLX

Title	**Endpoints**	**Descriptions**
Mental demand (MD)	Low /High	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
Physical demand(PD)	Low /High	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal demand (TD)	Low/ High	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Performance (P)	Good/Poor	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?
Effort (E)	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration level(F)	Low/High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

In this work, an affordance is a crucial element in assessing NASA-TLX reflecting that the environment significantly affects agents to decide specific actions. Likewise, an effectivity also plays a key role in the action taking processes, since each agent has different capability levels of an action and different preferences on the action’s effectivity. An agent’s capabilities and preferences are rooted in the agent’s psychological and physical facets.

In reality, "Affordance" and "effectivity" have widely been used to explain the existence of action opportunity and the necessary conditions for actualization, respectively. However, not much attention has been paid to the differences in the level of difficulty in taking actions depending on affordance given by the environmental cues. For example, although the affordance of "walk-on-able" can be offered by both the dry and wet floor environments, the difficulty level in actualizing "walk" can be different. In this study, in order to cater for this aspect for effective modeling and simulation, *"weighted affordance"* is introduced as a numerical affordance that not only suggests the existence of action opportunity, but also takes into account the different difficulty levels in taking actions offered by an environment. Similarly, "*relative effectivity"* is also introduced to consider the relative difference in capabilities and preferences that agents possess in carrying out certain actions.

Let $X(a)$ be a multivariate random variable with values of $x_i^s(a); i = 1,2,3, \dots, N$ where N is the total number of agents in the system; s denotes the environment state in which action a ought to take place, if selected. The value x_i^s is the *"weighted affordance"*. x_i^s is a column vector ($x_i^s \in \mathbb{R}^6$) whose elements respectively correspond to the inverse values of load given that agent i is to take action a in state s. Under a dynamic environment such as an emergency situation, capturing each agent's perception of the environmental state requires considerable effort, especially when dealing with multiple agents in a complex environment. To address this difficulty, a "reference agent" is introduced. Let $x_r^s(a)$ represent weighted affordance of reference agent r. Rather than mapping the dynamic environment to each agent (See Figure 2-4a), $x_r^s(a)$ is a reference to which every other agent is compared (See Figure 2-4b) in terms of weighted affordance. Once the reference agent (r) is defined, $x_r^s(a)$ serves as an input when assessing $x_i^s(a)$ for each agent $i, i = 1,2, \dots, r-1, r+1, \dots N$.

Let $v_i(a)$ be a relative effectivity of agent i with regard to action a. That is, $v_i(a)$ is a column vector ($v_i(\text{a}) \in \mathbb{R}^6$) where each entry of the six elements denotes the relative difference in capabilities and preferences that agent i possesses (in comparison to the reference agent) when taking action a.

It should be again noted that NASA TLX is used as a metric for estimating both the physical and mental costs for actions from groups of human subjects and that, therefore, $x_i^s(a) \in \mathbb{R}^6$ and $v_i(\text{a}) \in \mathbb{R}^6$.

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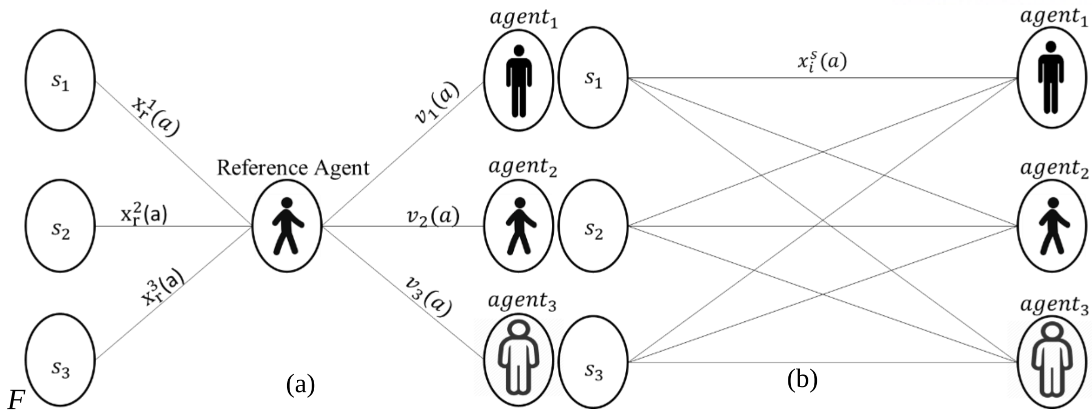

Figure 2-4. The value of $x_i^s(a)$ can be set using a reference agent (b); or set with a direct mapping of agent and environment (b)

Therefore, for a given action, $x_i^s$is obtained by Hadamard product as follows:

$$x_i^s = x_r^s \circ v_i = \left[x_{rMD}^s, x_{rPD}^s, x_{rTD}^s, x_{rP}^s, x_{rE,}^s x_{rF}^s\right] \circ [v_{iPD}, v_{iTD}, v_{iP}, v_{iE}, v_{iF}],\ where \tag{2-1}$$

x_r^s: weighted affordance of reference agent r in state s

v_i: relative effectivity of agent i.

Note that, $v_i(a)$ is an alignment that guarantees the agent's subjectivity by means of weighted affordance. Also, using $x_r^s(a) \circ v_i(a)$ as the estimate of $x_i^s(a)$ not only reduces the complexity (See Figure 2-4) of the model but also ensures a certain level of consistency in the model. Based on their profiles, distinct agents can be compared for their respective tendency in taking certain actions in a given environment. For example, relative effectivity for an action is dependent on the agent's attributes which include, in part, level of expertise, physical strength, skill, risk taking tendency, etc. In this study, an agent's attributes are represented in the form of "Agent = <Agent ID, Sex, Age, Skill level, Physical Strength Level, Risk taking tendency, Preference >." Table 2-2 shows an example of both $x_i^s(a)$ and $v_i(a)$ for two agents whose respective profile are "Agent1=<1, Male, 28, Null, 5, Null, Null>" and Agent2=<2, Male, 78, Null, 1, Null, Null>. In this example, Agent2 perceives the physical demand required for action "climbing stairs" to be two times more difficult than Agent1 perceives such action. Note that Agent 1 is the reference agent.

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Table 2-2. Weighted affordance and relative effectivity example

	$x_i^s(a)$ (climbing stairs)		v_i (climbing stairs)	
	Wet floor (From 0 to 20)	Dry floor (From 0 to 20)	Agent 1	Agent 2
Mental Demand	5	3	1	1
Physical Demand	6	4	1	2
Temporal	3	3	1	1
Performance	5	1	1	1.5
Effort	6	3	1	2
Frustration	5	2	1	2

2.3.2. Agent decision making process

To incorporate the cost in the agent decision-making, a Markov decision model is used in which agent i incurs cost $c_i(s,a,s')$ for performing action a and reaching state s' from state s. The Markov Decision Process (MDP) is known as a controlled stochastic process satisfying Markov process property and assigning cost to state transition. As a metric for estimating both the physical and mental costs of taking an action, NASA-TLX is used as the estimate of $c_i(s,a,s')$, in this study. Based on NASA TLX algorithm, $c_i(s,a,s')$ is a function of $x_i^s(a)$. That is $c_i(s,a,s') = f\ (x_i^s)$ where $f\colon \mathbb{R}^6 \to \mathbb{R}$ and can be obtained as follow:

$$c_i(s,a,s') = f\ (x_i^s) = \frac{\sum_j w_{ij} x_i^s}{\sum_j w_{ij}} \text{ where:} \tag{2-2}$$

$c_i(s,a,s')$: cost agent i incurs when taking action a in state s resulting in transition to state s', and

w_{ij}: respective weight of each of the 6 NASA-TLX scale where$j \in \{\mathrm{MD, PD, TD, P, E, F}\}$.

According to NASA TLX algorithm, w_{ij} is obtained through a series of pairwise comparison among all the load scales (see appendix)

Let $\pi^*(s)$ be the best policy to reach the goal with the minimum cost when starting from state s. Note that π is function that specifies the action $\pi(s)$ to be chosen when in state s. That's is $\pi : s \in S \to \pi(s) \in A_s$, where S denotes the set of states of the system, and A_s denotes the set of available actions in state s. As one of the most popular algorithm for solving MDP problem, the Dynamic Programming (DP) was used in this study to obtain the optimum policy[30, 31] . At the convergence after several iterations, the optimal policy for agent i (π_i^*) is as follow:

$\pi_i^*(s) = argmin_{a \in A_s}\{\sum_{s'} p(s'|s,a)[c_i(s,a,s') + V_i^*(s')]\}$ where: (2-3)

$\pi_i^*(s)$: the optimal policy of agent i when starting from state s

$p(s'|s,a)$: the transition probability from s to s′ given that action a was taken

$V_i^*(s')$: the optimal cost to reach the goal when starting from state s'

Once the policy is established, the resulting value can be expressed as follow:

$V_i^{\pi^*}(s) = \sum_{s'} E\ [c_i(s,a,s'|\pi_i^*(s) = a)$, where: (2-4)

$V_i^{\pi^*}(s)$: the expected optimal accumulated cost when agent i starts from state s, ($\forall s \in S$) and subsequently follows policy $\pi_i^*(s)$.

While in state s, an agent can choose any available action within the state. Since an action is the state transition trigger, it is necessary to pair the cost incurred while taking an action to reach a given state and the value offered by the destination state. Let $Q_i^{\pi^*}(s,a)$ denote the cost of taking action a to reach the new state and to subsequently follow policy $\pi_i^*(s')$. . In other words, $Q_i^{\pi^*}(s,a)$ is the expected cost when starting from state s executing action a and then following policy $\pi_i^*(s')$ afterwards. It is computed as follow:

$$Q_i^{\pi^*}(s,a) = c_i(s,a,s') + \sum_{s'} p(s'|s,a) V_i^{\pi^*}(s')\ . \tag{2-5}$$

Depending on the information available for the system in question, the transition probabilities can be estimated from historical data. On the other hand, if the probabilities are unknown, reinforcement learning can be utilized [32]. For every available action in the affordance perspective, $Q_i^{\pi^*}$ is computed. Note that π^* refers to the optimal policy obtained through policy iteration according to Bellman Equation as shown in Equation (2-3) [30, 31]. The probability of taking a given action is inversely proportional to their respective$Q_i^{\pi^*}$. According to several human decision models, a delayed value is often discounted. The most cited underlying reason to discount a delayed value is the risk associated with a delay [33]. Whereas most economists prefer the exponential discount, several experiments with animals and humans reveal that

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agents are better described as hyperbolic discounters [34]. In this study, we regard the delay as not necessarily extra time. Instead, any extra or avoidable load such as extra energy, stress and other extra cost can be interpreted as a source of delay in value. Thus, let δ_i^s be the minimum cost (incurred by agent i) to achieve the goal from state s.

$$\delta_i^s = min_{a \in A_s} \left(\mathrm{Q}_i^{\pi^*}(s, a) \right) \tag{2-6}$$

Hence, the probability of selecting a given action is given by:

$$P_i(a|s) = \frac{1/\left[1+k\left[\left(\mathrm{Q}_i^{\pi^*}(s,a)\right)-\delta_i^s\right]\right]}{\sum_{a \in A_s} 1/\left[1+k\left[\left(\mathrm{Q}_i^{\pi^*}(s,a)\right)-\delta_i^s\right]\right]}, \tag{2-7}$$

where:

δ_i^s: the minimum cost to achieve the goal from state s,

A_s: set of possible actions in state,

$P_i(a|s)$: the probability of selecting action a from state s, and

k: a constant denoting the sensitivity of agent to one extra unit of cost.

Since the total rationality implies that agents follow the optimal policies, k denotes the rationality level of the agents where $k \neq 0$. A higher value of k implies higher rationality level. We note that an agent does not necessarily follow the path that was conceived in the planning stage. Instead, he or she may adapt to the dynamic environment by either changing or maintaining the decision conceived at the planning stage. Agent's decision should be realigned with newly acquired information through direct perception of the environment. While some agents may demonstrate conservative behaviors, and stay committed to an earlier plan, the real environmental conditions are nevertheless considered as opposed to what was expected at the conception of the plan.

At the planning stage, human agents anticipate specific action opportunities that might help them to reach the goal in the imaginary spatial-temporal dimension. However, a real action opportunity of the affordance-effectivity dual is only available in the real space and time dimension. The expected environmental state can change and it inevitably makes the agent alter the plan to reach the goal.

To demonstrate the heterogeneous behavioral patterns with the agents' perceptions of the environmental discrepancies between the expected environment and the real environment, the NASA TLX values are reexamined by each agent in the simulation model. In order to improve the realism of the agent-environment interactions in the model, the overall expected cost for taking a given action is updated in real time manners.

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2.4. Building Evacuation Simulation

To demonstrate the applicability of the proposed weighted affordance-based modeling framework, an agent–based evacuation system is considered. The system consists of agents whose goal is to escape from a multi-story building. Two different agent groups are considered for the illustrative example: The first group, "Group 1", includes human agents who are physically strong and are more likely to take risks. A typical example of such environment would be a college dormitory. Most dormitory inhabitants, arguably, would be relatively physically strong, energetic, and inclined to take risks. The second group, "Group 2", assumes human agents who are considered as the opposite group of the first one. In this group, agents are physically weak and less likely to take risks. A typical example would be individuals in a nursing home who might be old, weak and conservative in their approach to risks.

For both groups, simulations are conducted with different number of agents in the building, their initial locations, and the emergency of an evacuation situation. As shown in Table 2-3, three situations are considered depending on the number of agents in the building and their initial locations.

Table 2-3. Factors and levels used in agent-based evacuation simulation

Factors	Levels		
Initial # of agents in Bldg.	100	300	500
Agent group	Group 1	-	Group 2
Emergency level	Low	-	High
Agent initial position	2F	2F	6F

Similarly, two different emergency levels (i.e., low and high) are considered in the simulation. The first level (i.e., low) is a non-emergency situation where there are no serious dangers present in the building. Agents are asked to exit the building and expected to comply with the guided egress. The second level (i.e., high) is an emergency situation, where the environment conditions change very quickly and life-threatening dangers (e.g., fire) are eminent. While the various resources in the building (e.g., elevators) are considered to be properly working in the simulation, taking an elevator in such an environment may be highly dangerous. However, since there is no safe action, agents are expected to take some levels of risks while selecting action.

In this illustrative example, both the environmental and agent states are discretized in order to capture different action opportunities in both the time and space dimensions. For example, the "take-ability" affordance that the elevator offers can be represented as depicted in Figure 2-5, where, for the sake of simplicity, the proximity is the only parameter that ensures the existence of agent effectivity; meaning, the agent has to be located in front of the elevator door for the affordance-effectivity juxtaposition to happen.

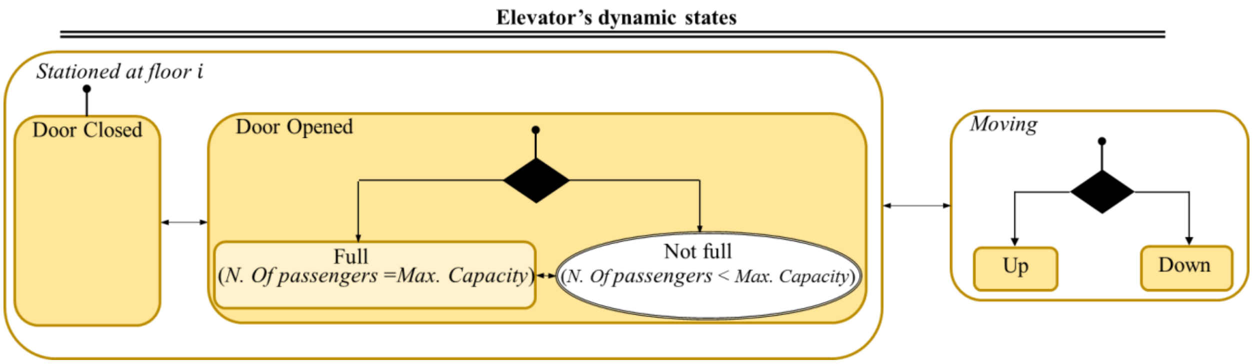

Figure 2-5. The "take-a-bility" affordance is only available when the elevator is in "Not full" state.

Agents are distinguished based on their profiles. Agent's profile has a high impact on the action selection. The subjective loads are generated from a normal distribution whose mean and standard deviation depend on the agent's profiles. NASA TLX survey has been carried out in order to determine the agents' subjective perception of the load, and 35 human subjects comprising of two distinct groups were asked to rate the expected workload associated with four different actions in various environmental states (see Appendix 1). In other words, the NASA-TLX data were collected from thirty-five real humans for eliciting psychological parameters of the two distinct groups. The first group consists of 20 human subjects between the age 18 and 34, while the second group includes 15 participants who are 65or older. To reduce the complexity of the questionnaire for older people, we only considered the sixth floor in the questionnaire. From the NASA-TLX data collected, a series of statistical distribution was extracted for both groups. For example, Figure 2-6 shows the NASA TLX distribution for Frustration (F) for four actions taken by agents in Group 1 located on the 4th floor.

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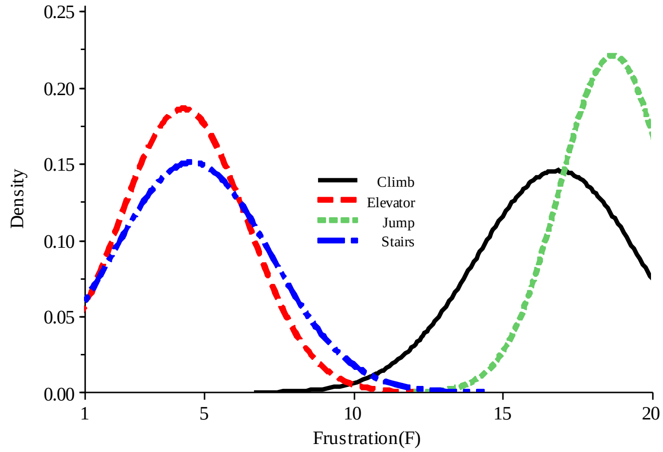

Figure 2-6. NASA TLX distribution for Frustration (F) for four actions when taken on the 4th floor by agents from Group 1.

To reflect a human subjects' perception on weighted affordance and relative effectivity, this simulation assumes that the agents' perception of the environment and the associated action opportunities are consistent to that of NASA TLX respondents. For example, in the simulation, the rating of the load by agents located on the sixth floor in a safe environment follows a truncated normal distribution with mean and standard deviation shown in Table 2-4. In this simulation, only limited environmental states were considered, allowing to directly map each agent to each environmental state; thus, the face values in Table 2-4 are equivalent to the distribution of $x_i^s(a)$.

Table 2-4. NASA-TLX rating for four actions when taken on the sixth floor in a safe environment.

	Elevator				**Stairs**				**Jump**				**Rope**			
	Junior		**Senior**		**Junior**		**Senior**		**Junior**		**Senior**		**Junior**		**Senior**	
	Me	StD	Me	StD	Me	StD	Me	StD	Me	StD	Me	StD	Me	StD	Mea	StD
M	3.0	1.9	2.6	0.6	4.0	1.6	8.0	1.1	16.	1.1	16.	1.0	18.	2.3	15.6	0.9
P	2.8	2.7	0.4	0.9	11.	0.9	14.	1.3	16.	0.6	18.	0.6	18.	2.4	14.0	0.5
T	6.0	3.2	2.9	1.7	12.	0.6	12.	1.1	12.	1.4	14.	0.8	2.8	4.1	4.53	0.7
P	1.3	1.4	0.5	0.4	2.1	0.4	16.	1.0	16.	0.4	19.	0.3	19.	1.9	19.8	0.3
E	1.8	2.8	1.3	0.6	8.5	1.0	13.	1.1	16.	0.9	17.	1.0	19.	1.1	16.9	1.7
F	3.5	2.2	2.4	0.7	4.6	0.9	8.5	1.3	16.	2.1	18.	1.5	19.	1.1	19.0	1.5

To successfully escape from the building, agents make a series of choices depending on the action opportunities available within the states to which they belong as shown in Figure 2-7. ANYLOGIC™ was

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used to build and run the simulation. The existing ANYLOGIC™ library has been used to simulate both the microscopic movement as well as the crowd behavior. As shown in the screenshot of the simulation run in Figure 2-9, ANYLOGIC™ contains a pedestrian library in which agents follow the basic rules of microscopic physical movement as well as crowd simulation. This includes the physical space occupation, or distance and speed adjustment based on the congestion of the crowds around them[2]. Table 2-5 summarizes the basic parameters used in the simulation [35].

Table 2-5. Basic parameters of simulation

Simulation Parameters	**Value**
Mean comfortable speed (m/s)	1.2
Mean initial speed (m/s)	0.7
Diameter (m)	Uniform(0.4, 0.5)

Based on the expected affordance, agents construct an initial plan for their actions. Once they perceive the real affordance, they update their plan based on newly acquired perception at the point of action execution. All choices are made following the framework as depicted in Figure 2-3. Prior to executing any action, the agent’s initial plan is revisited and updated in accordance with his or her perception of the surrounding environment.

[2] http://www.anylogic.com/consulting/pedestrian-traffic-flows

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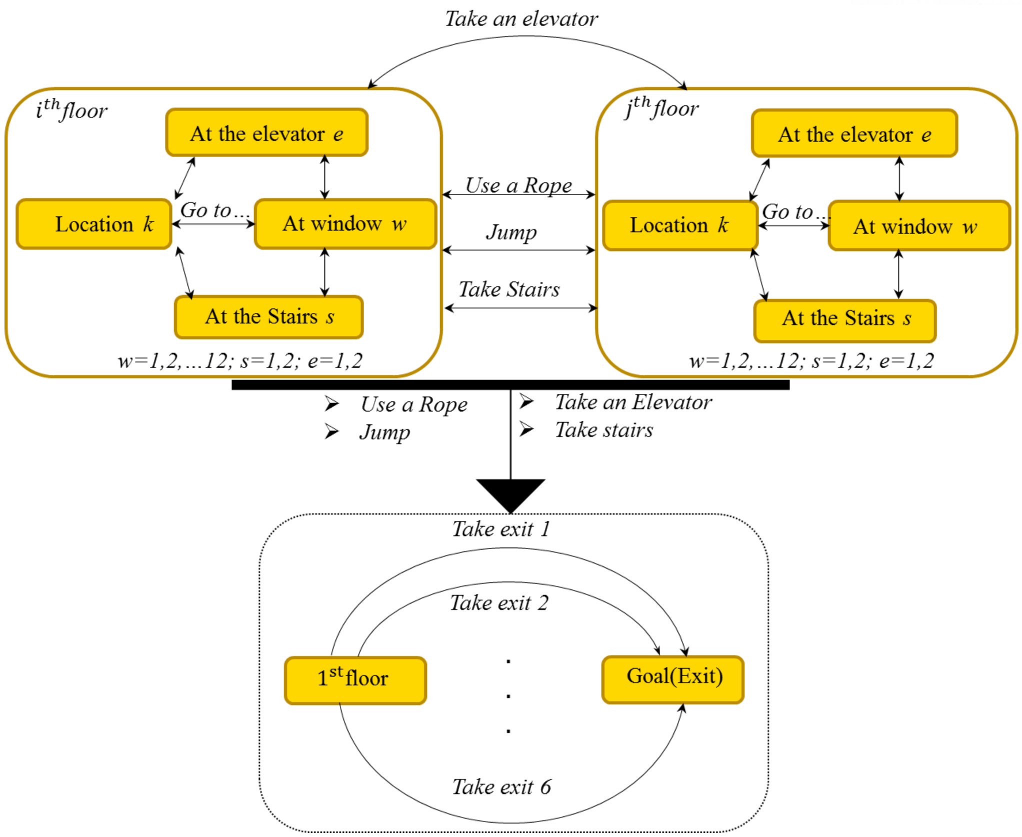

Figure 2-7. State chart for agent-based simulation of evaluation from multi-story building

2.4.1. Policy

In the simulation, we regard a policy as any combination of actions and states that results in reaching the goal state. For instance, for an agent *i* on the 6^{th} floor, taking an elevator to the 5^{th} floor and then jumping to the first floor to exit the building can be considered as one of the possible policies along with many other policies as illustrated in Figure 2-8.

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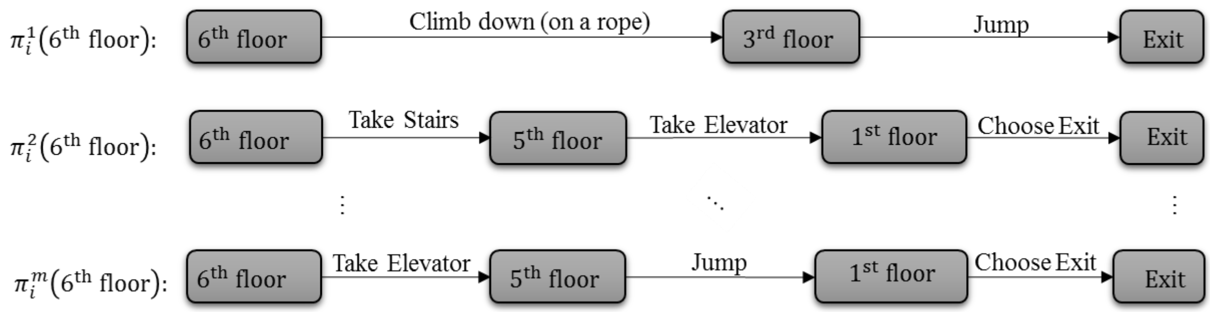
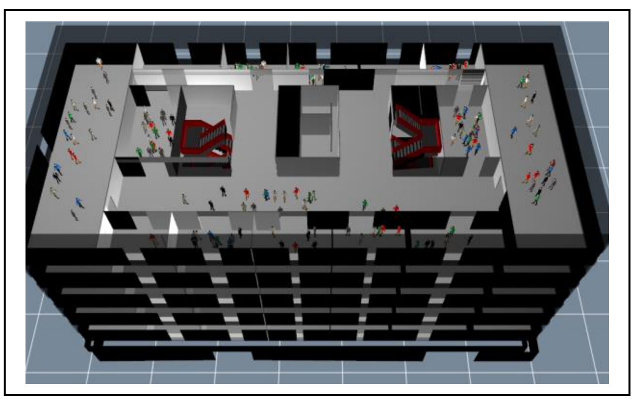
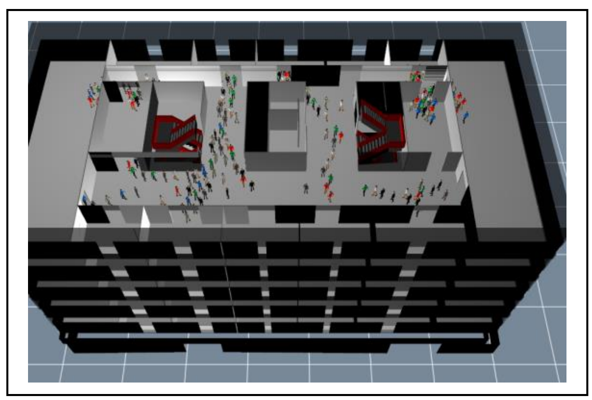


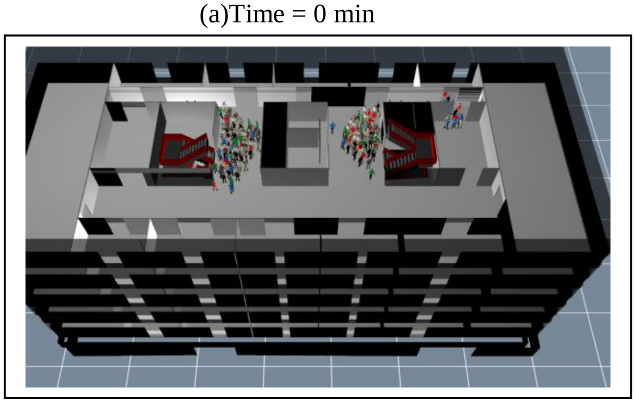
Figure 2-8. Example of evacuee's policies ($\boldsymbol{\pi_i^*} \in \{\boldsymbol{\pi_i^j} \mid \mathbf{j} = \mathbf{1}, \mathbf{2}, \ldots \mathbf{M}\}$)



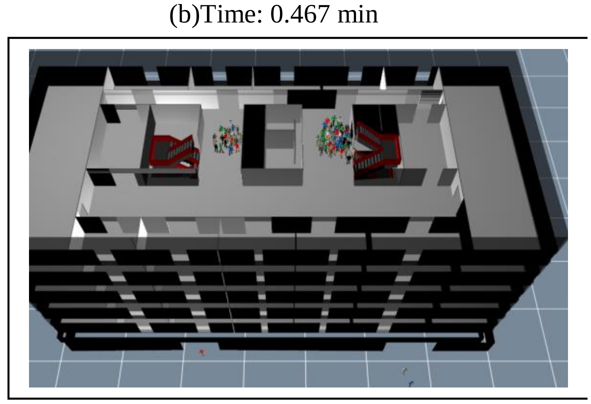
(a)Time = 0 min



(b)Time: 0.467 min



(c) Time: 1.423 min



(d)Time: 6.256 min

Figure 2-9. ANYLOGIC™ screenshots of agents' emergency evacuation, captured at various time of simulation.

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A policy is optimal if and only if it leads to the goal state while minimizing the total cost of reaching the goal state. For each policy $\pi_i(s)$, there is an associated value of $V_i{}^{\pi}(s)$, a function of costs incurred throughout the process to reach the goal.

Each action is rated subjectively by the agents, and the resulting NASA-TLX value is fed into an MDP model to generate the optimal policy. Once the policy is established, the execution begins. Each decision is preceded by a reevaluation of the plan based on an agent's real-time perception of the environment. Let V_i^j be the cost of reaching the goal state following the policy $\pi_i^j(s)$. Assuming agent i has M possible policies to follow, $\pi_i^j(\mathrm{s}) = \pi_i^*(s)$ if and only if $V_i^* = Min(V_i^j)$ for j=1,2,…,M. In this stage, a dynamic programming algorithm is used to assign the optimal policy to each state as well as the associated values [31].

Based on the optimal values of each state obtained following a given policy, the agent computes $Q^{\pi}(s,a)$ which is the expected value when starting from state s executing action a and then following policy $\pi_i(\mathrm{s}')$ afterwards. The action probability is computed based on the Q values of available actions.

2.4.2. Simulation Results

2.4.2.1. Parameter Overview

To investigate the factors that influence action selection, 20 replications were executed and statistical analysis was conducted on the simulation data collected from 48,000 agents. In the simulation, each agent was modeled to make his or her own decision based on the evaluated Q values from the dynamic environments. The agents were statistically grouped according to their action selection preferences. Although, there can be a number of actions to choose from at each of the states, attention is paid to the four main actions that move the agents from one floor to another, eventually leading to the ground floor: taking the elevator, taking the stairs, jumping out of the window, and using a rope. This would allow an interesting contrast, as our approach considers both the mental and the physical load associated with these actions.

To assess the statistical significance of each factor on agent's action choices, we conducted both the ANOVA tests and the multinomial logistic regression. Let A denotes the set of actions that agents ought to choose from (i.e., A= {“Elevator”, “Stairs”, “Rope”, “jump”}). Since the response variable for an ANOVA test must have numerical values, we run four ANOVA tests, where the response variable denotes the percentage of agents opting for respective action in A. Note that, in both the ANOVA tests and the multinomial logistic regression, we consider the entirety of the factors and levels shown in Table 2-3.

Meanwhile, in our multinomial logistic regression, Y is a set of response variables where y_i is an element of A (i.e., $y_i \in \{\text{“Elevator”}, \text{“Stairs”}, \text{“Rope”}, \text{“jump”}\}$). Thus, we model how multinomial response variable Y depends on a set of explanatory variables, X's, (i.e., Initial # of agents in Bldg., agent group, and emergency level, and agent initial position). Note that in case of categorical explanatory variables, we use dummy coding where the baseline level is equivalent to zero. Here, “group 2”, “high”, and “4F” are the baseline level of the explanatory variables “agent group”, and “emergency level”, and “agent initial position”, respectively. Notice how the agent initial position is represented with two dummy variables (e.g., $\mathrm{X_i}$ "2F vs 4F "and $\mathrm{X_j}$ "6F vs 4F") due to its three floor levels in the simulation (see Table 2-3). Since “4F” is considered as the baseline category, $\mathrm{X_i} = 1$ for “2F”, while $\mathrm{X_j} = 1$ for “6F”, while $\mathrm{X_i} = \mathrm{X_j} = 0$ for “4F”.

2.4.2.2. Results

First, ANOVA adequacy check results reveal that the model satisfies the ANOVA assumptions. Based on the means of reaching the ground floor, the mean averages (in percentage) and the standard deviation, are shown Table 2-6. According to the ANOVA tables summarized in Table 2-7, the majority of factors, significantly affect the agent's course of action. Furthermore, the analysis also confirmed the significance of the majority of factor interactions on agents' decision making. The interaction implies that the factor impact on agent's behavior depends also on the level of the other factor. For example, as the number of agents increases, an agent in the second floor is less likely to tolerate the extra waiting time for the elevator than an agent on the six floor. Due to the interactions, the main effect obtained through ANOVA test becomes non-interpretable. In this regard, we run a multinomial logistic regression analysis to get an insight on the effect of each individual factor on the agent's action selection behavior. Note that the logit equations in our multinomial logistic regression describe the log-odds that an agent select other actions instead of baseline category. Here, Table 2-8 shows the coefficient of logit equations where “Stairs” is the baseline category. Also, the data in Table 2-9 that shows the pairwise odds ratio of all possible categories, not only confirm the significance of most factors, but also shows how any change on the independent variable would affect the odds of a given agent's decision. For example, compared to the agents in the fourth floor, agents in the second floor are less likely to choose the elevator over the stairs (odds ratio: 0.07), while the agents on the sixth floor are more likely to take the elevator instead of stairs (odds ratio: 1.480), assuming all other factors are held constant.

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Table 2-6. Mean (in %) and standard deviation of evacuees by the means selected for evacuation (See Table 2-3. Factors' levels used in agent-based evacuation simulation for factors' combination)

Factor's (Level) combination				Action							
				Elevator		**Stairs**		**Rope**		**Jump**	
# of Agents	**Agent Group**	**Initial Position**	**Em. Level**	**Mean**	**St. Dev**	**Mean**	**St. Dev**	**Mean**	**St. Dev**	**Mean**	**St. Dev**
100	1	2F	Low	5.25	3.26	89.54	4.91	5.21	3.63	0.00	0.00
100	1	4F	Low	90.02	4.06	9.98	4.06	0.00	0.00	0.00	0.00
100	1	6F	Low	90.49	4.62	9.29	4.50	0.23	0.69	0.00	0.00
300	1	2F	Low	5.66	1.99	87.56	3.06	6.63	1.97	0.15	0.36
300	1	4F	Low	57.67	6.52	42.08	6.49	0.25	0.44	0.00	0.00
300	1	6F	Low	71.05	6.98	28.85	6.94	0.10	0.29	0.00	0.00
500	1	2F	Low	6.76	2.39	87.49	2.97	5.66	1.52	0.10	0.23
500	1	4F	Low	38.45	3.53	61.25	3.58	0.30	0.35	0.00	0.00
500	1	6F	Low	43.41	5.13	56.50	5.15	0.08	0.20	0.00	0.00
100	2	6F	Low	96.67	3.50	3.17	3.57	0.17	0.73	0.00	0.00
300	2	6F	Low	90.10	2.55	9.75	2.47	0.15	0.36	0.00	0.00
500	2	6F	Low	55.71	2.84	44.15	2.80	0.15	0.25	0.00	0.00
100	1	2F	High	1.18	1.72	69.24	7.28	29.58	6.94	0.00	0.00
100	1	4F	High	23.30	6.91	73.51	7.30	3.20	2.31	0.00	0.00
100	1	6F	High	44.37	9.07	54.20	9.03	1.43	1.89	0.00	0.00
300	1	2F	High	1.32	1.12	69.78	5.72	27.11	4.99	1.78	1.62
300	1	4F	High	19.67	3.00	78.03	3.62	2.25	1.60	0.05	0.21
300	1	6F	High	26.95	3.62	71.05	4.22	1.89	1.39	0.10	0.31
500	1	2F	High	1.51	0.83	68.20	2.67	27.22	2.38	3.06	1.16
500	1	4F	High	16.16	2.21	81.03	2.47	2.78	1.32	0.03	0.12
500	1	6F	High	23.30	2.45	74.71	2.68	1.91	0.96	0.09	0.29
100	2	6F	High	91.50	5.32	8.33	5.22	0.17	0.73	0.00	0.00
300	2	6F	High	47.50	3.37	52.25	3.21	0.20	0.51	0.05	0.22
500	2	6F	High	38.41	3.02	61.26	3.00	0.32	0.39	0.00	0.00

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Table 2-7. ANOVA tables evaluating the statistical significance of each simulation factor on the number agents choosing a given action.

Response Variable	**Source**	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
# of agent taking the elevator	Emergency Level	1.00	83242.00	83242.00	83242.00	486.31	<0.001
	Agent group	1.00	133451.00	24126.00	24126.00	140.95	<0.001
	Initial # of agents	2.00	60281.00	60281.00	30140.00	176.08	<0.001
	Agent initial	2.00	144630.00	144630.00	72315.00	422.47	<0.001
	Error	473.00	80964.00	80964.00	171.00		
	Total	479.00	502568.00				
# of agent taking the stairs	Emergency Level	1.00	44853.00	44853.00	44853.00	173.23	<0.001
	Agent group	1.00	92014.00	22305.00	22305.00	86.15	<0.001
	Initial # of agents	2.00	59351.00	59351.00	29675.00	114.61	<0.001
	Agent initial	2.00	55443.00	55443.00	27721.00	107.07	<0.001
	Error	473.00	122468.00	122468.00	259.00		
	Total	479.00	374129.00				
# of agent taking the rope	Emergency Level	1.00	5218.80	5218.80	5218.80	202.31	<0.001
	Agent group	1.00	3507.70	33.50	33.50	1.30	0.255
	Initial # of agents	2.00	3.70	3.70	1.80	0.07	0.931
	Agent initial	2.00	19737.70	19737.70	9868.80	382.57	<0.001
	Error	473.00	12201.60	12201.60	25.80		
	Total	479.00	40669.50				
# of agent jumping	Emergency Level	1.00	20.16	20.16	20.16	43.28	<0.001
	Agent group	1.00	7.54	0.03	0.03	0.07	0.786
	Initial # of agents	2.00	13.82	13.82	6.91	14.83	<0.001
	Agent initial	2.00	54.59	54.59	27.29	58.58	<0.001
	Error	473.00	220.37	220.37	0.47		
	Total	479.00	316.47				

Furthermore, agent's characteristics seem to play a principal role in the choice of action (see Figure 2-10). For instance, agents from Group 2 tend to favor "taking the elevator" more than the agents from the

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Group 1 (See Figure 2-10 (b)). The elderly's preference for "taking the elevator" can be partially explained by their overestimation of the load, especially the physical load, incurred when taking the stairs as reflected by NASA-TLX. Similarly, as shown in Figure 2-10 (d), when the initial number of agents in the building increases, the percentage of agents taking the elevator decreases, while the percentage of those taking the stairs increases. One important aspect of our model resides in the variations observed in the agent's decision. Note that other action selection models assume the total rationality of human agent, so they select the action with the highest reward or low cost. However, in our model, the selection allows to model bounded rationality, especially in the higher emergency level where the standard deviation tends to rise up. During the simulation, agents have an option to re-evaluate their decision. Congestion is one of the reasons triggering the re-evaluation of actions.

Table 2-8. Logistic regression Coefficient (Reference event: Stairs)

Event	**Predictor**	**Coef**	**SE Coef**	**Z**	**P**
Rope	Intercept	-4.517	0.245	-18.440	<0.001
	Emergency Level (Low vs	-1.766	0.059	-29.720	<0.001
	Agent group (Group1 vs	1.278	0.221	5.780	<0.001
	Initial # of agents in Bldg.	0.000	0.000	-2.040	0.041
	Agent initial location (2F vs	2.452	0.081	30.120	<0.001
	Agent initial location (6F vs	-0.301	0.121	-2.500	0.012
Jump	Intercept	-9.251	1.316	-7.030	<0.001
	Emergency Level (Low vs	-3.656	0.307	-11.900	<0.001
	Agent group (Group1 vs	1.362	1.096	1.240	0.214
	Initial # of agents in Bldg.	0.000	0.000	0.730	0.467
	Agent initial location (2F vs	5.258	0.710	7.410	<0.001
	Agent initial location (6F vs	1.000	0.837	1.190	0.232
Elevator	Intercept	0.926	0.049	18.890	<0.001
	Emergency Level (Low vs	1.340	0.023	57.020	<0.001
	Agent group (Group1 vs	-0.799	0.028	-28.050	<0.001
	Initial # of agents in Bldg.	-0.004	0.000	-45.970	<0.001
	Agent initial location (2F vs	-2.706	0.054	-50.240	<0.001
	Agent initial location (6F vs	0.390	0.029	13.500	<0.001

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Table 2-9 Pairwise odds ratio and 95 % Confidence interval

				95% CI	
Event	**Predictor**	**P**	**Odds**	**Lower**	**Upper**
Rope vs. Stairs	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	0.170	0.150	0.190
	Agent group (Group1 vs	<0.001	3.590	2.330	5.540
	Initial # of agents in Bldg.	0.041	1.000	1.000	1.000
	Agent initial location (2F vs	<0.001	11.610	9.900	13.620
	Agent initial location (6F vs	0.012	0.740	0.580	0.940
Jump vs. Stairs	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	0.030	0.010	0.050
	Agent group (Group1 vs	0.214	3.910	0.460	33.450
	Initial # of agents in Bldg.	0.467	1.000	1.000	1.000
	Agent initial location (2F vs	<0.001	192.020	47.790	771.500
	Agent initial location (6F vs	0.232	2.720	0.530	14.020
Elevator vs. Stairs	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	3.820	3.650	4.000
	Agent group (Group1 vs	<0.001	0.450	0.430	0.480
	Initial # of agents in Bldg.	<0.001	1.000	1.000	1.000
	Agent initial location (2F vs	<0.001	0.070	0.060	0.070
	Agent initial location (6F vs	<0.001	1.480	1.400	1.560
Rope vs. Elevator	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	0.040	0.040	0.050
	Agent group (Group1 vs	<0.001	7.980	5.170	12.320
	Initial # of agents in Bldg.	<0.001	1.000	1.000	1.000
	Agent initial location (2F vs	<0.001	173.790	143.960	209.790
	Agent initial location (6F vs	<0.001	0.500	0.390	0.640
Jump vs Elevator	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	0.010	0.000	0.010
	Agent group (Group1 vs	0.049	8.680	1.010	74.370
	Initial # of agents in Bldg.	<0.001	1.000	1.000	1.010
	Agent initial location (2F vs	<0.001	2874.760	712.890	11592.630
	Agent initial location (6F vs	0.466	1.840	0.360	9.500
Rope vs. Jump	Intercept	<0.001			
	Emergency Level (Low vs	<0.001	6.620	3.590	12.190
	Agent group (Group1 vs	0.940	0.920	0.100	8.210
	Initial # of agents in Bldg.	0.129	1.000	1.000	1.000
	Agent initial location (2F vs	<0.001	0.060	0.010	0.240
	Agent initial location (6F vs	0.124	0.270	0.050	1.430

For example, if the elevator is delayed, congestion increases around the elevator, prompting some agents to opt out for alternatives actions. This can be explained by the increased level of both physical and mental load associated with waiting. This reevaluation partially explains the increased percentage of agents taking the stairways when the initial number of agents in the building increases as showcased in Figure 2-10 (d), which is also theoretically supported by bounded rationality.

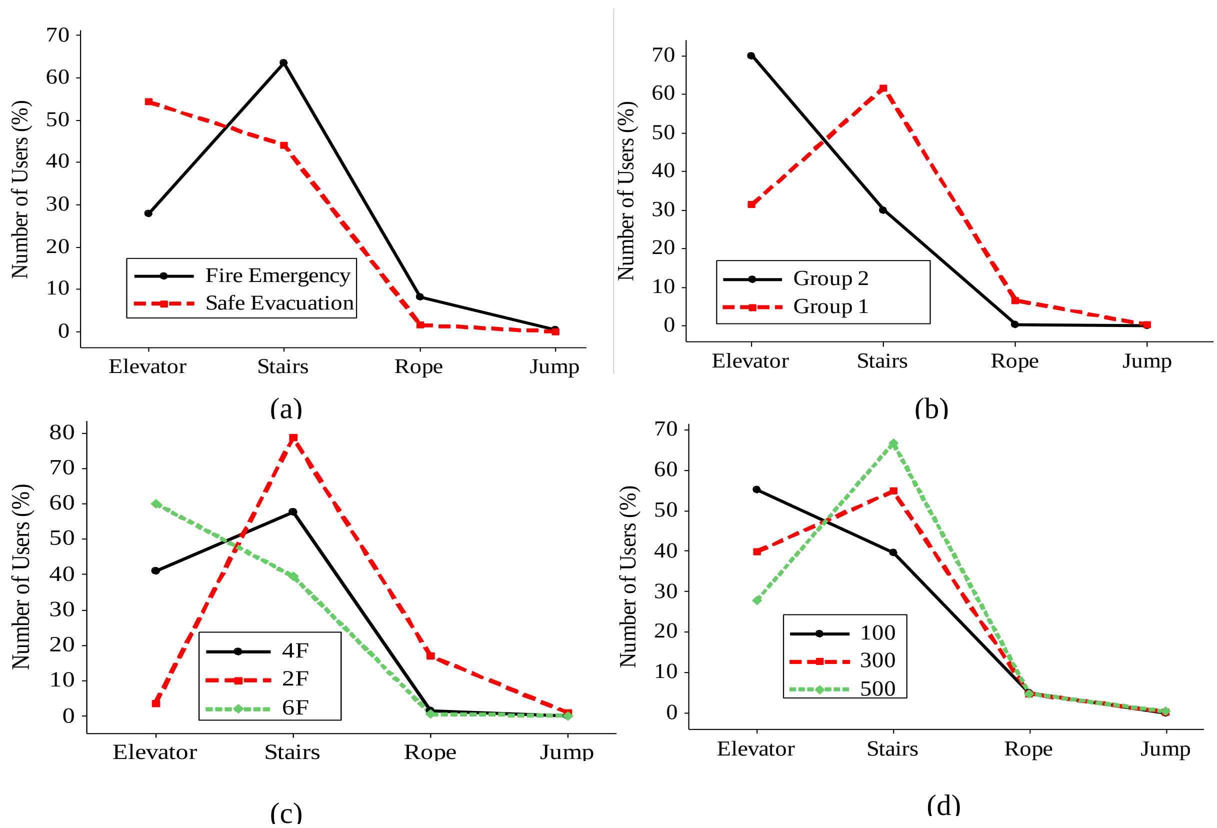

Figure 2-10. (a) Agent action selection in different emergency levels (b) Action selection by agent from both Group1 and 2 (c) Agent action selection according to their initial position in the building. (d) Agent action selection according to the initial number of agents in the building

2.5. Conclusion

Although affordance theory has explained the goal-directed and perception-based human actions within different environments, it has not been widely used to build computational models in human-involved systems. This study proposes a weighted affordance-based model for human agent decision-making behavior. The baseline assumption is a bounded rationality; an agent chooses a cost-effective measure when choosing an action; that is, the lower the cost (or load) associated with an action, the higher

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the likelihood of that action being selected. However, limited amount of information available and uncertainties included within an environment may hinder the agent from effectively choosing the optimal path to reach the desired goal. Under the MDP umbrella, the model quantitatively assigns agent' subjective load to each alternative choice that trigger state transition. Using dynamic programming, we assign an optimal value (i.e., minimum cost/load) to each state, corresponding to the optimal policy (optimum mapping of action to state) according the information available. The assignment of values to each state follows the theoretical principal of full rationality, hence the best policy is considered when setting the value. Here, the load is expressed in terms of NASA- TLX which serve a metric for estimating cost associated to taking a given action. NASA-TLX is a multi-dimensional rating scale in which information about the sources and the magnitude of workload factors are combined to derive a reliable estimate of both physical and psychological workload. NASA-TLX values are then generated in accordance with the theory of affordance. At the execution level, the actions are derived in a stochastic way from a formerly conceived plan followed by perception-directed adjustments.

The model proposed in this study is expected to be used for agent-based modeling of human-involved complex and dynamic systems. From the planning stage to the execution stage, this study proposes an affordance-embedded MDP framework that covers dynamic decision-making processes. We adopt the probability-based action selection model to present the uncertainty of human actions within dynamic environments. In addition to the general framework, an evacuation simulation study was conducted as an example to verify the feasibility of the proposed simulation framework. The evacuation example shows how the proposed framework can accommodate the MDP and the conception of affordance in the planning and execution levels. The illustrative example also offers various insights on human agent tendencies in dynamic environments. For example, results show that senior citizen overestimate the physical loads, hence prefer taking less physical action (e.g., elevator) over more physical one (e.g., stairs). Also, as the evacuation becomes more emergent, the agent decision becomes volatile thus, less predictable due to several reasons including the volatile state of the environment under the emergency (e.g., fire).

Although the primary research objective was attained, there still exist limitations. The challenges of validating of the proposed work in a real emergency, cannot be ignored. Also, due to the subjective nature of human agents and the small size of human subjects involved in estimating the NASA-TLX data, the simulation results cannot be generalized; instead, the example should serve as exemplary template of the proposed simulation framework. Despite the limitations, we envision that the proposed model can be used to examine the problems of human-involvement in system design. It can also be used to highlight the effect of interactions between human agents and the environment under dynamic and uncertain conditions.

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The proposed model makes it feasible to model and simulate human-involved system that cannot be tested with physical simulation, or whose physical simulation would be prohibitively expensive.

In the future, we are planning to integrate the proposed agent-based simulation model with a virtual reality environment to obtain more realistic results. This would be beneficial in implementing a human-in-the-loop simulation framework and adaptive agent-environment interaction which can enhance the ability to simulate and evaluate human-involved systems.

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Chapter 3

Computational modeling of task complexity in human-centered systems: A Case of a Mixed Model Assembly Line

3.1. Introduction

In manufacturing contexts, increasing production variability while maintaining operation efficiency is an important issue in many industries. In the past, manufacturers provided the market with a few models that had long life cycles and a small variety of attributes. However, industries have recently faced several challenges driven by various factors, including the accelerated pace of technology development, the global wage difference, and job skill shifts [36]. To remain competitive, manufacturing organizations must offer a high product variety due to the increasing customer expectations along with technological advancement. For example, Wiendahl and Scholtissek [37] have noted a 400% increase in the number of part variants from 1975 to 1990.

Meanwhile, to fulfill customer requirements, manufacturers have resorted to mass customization as the new manufacturing standard [38]. Mass customization has become a key factor in maintaining or increasing market share since it offers a flexible matching capability between customer preferences and offered products. It is widely thought that when a higher variety of models or options are offered, a competitive edge to companies can be guaranteed. On the other hand, manufacturing organizations are now facing an increase in manufacturing complexity due to the higher product variety. For example, around 64% of the respondents in a survey have identified the complexity resulting from managing variety as a significant cost driver in production by [39].

In order to satisfy complex customer needs, manufacturing practitioners have opted for mixed-model assembly system and modular supply chains due to their reputation as flexible enough to handle the increased variety. However, complexity inevitably arises in these systems. While the existence of complexity and its challenges are widely acknowledged, a formal quantification of manufacturing complexity is still a topic for discussion. In fact, complexity is often thought of as “the state of having many different parts connected or related to each other in a complicated way” [40] with no systematic way to quantify it. In addition, there is no proper analytical method to compare several manufacturing setups based on their respective complexities. Despite the clear lack of a common measure for manufacturing complexity, several studies have shown that a negative correlation between variety induced complexity and manufacturing performance exists [4, 41, 42]. That is, there is a tradeoff between additional advantages from a greater variety of options and the higher costs associated with complexity. Thus, from a decision-making standpoint, it is still a challenge to estimate the complexity tradeoff since it is not only subjectively defined but also very vague due to lack of a constitutional measurement of variety-induced manufacturing complexity.

In the automotive industry, analyzing manufacturing complexity is a reasonable way to ensure higher product variability, while maintaining production efficiency. Adding a model variant in a manufacturing system indeed increases the number of product components and the degree of their interaction. In addition, these conflicting aspects of complexity in the system incur additional direct and/or indirect costs for managing the manufacturing process and associated resources [4]. In other words, resource management and operations in the system are significantly affected by an increase in the system complexity, which should be properly managed and planned. For instance, adding to the variety in the assembly process may bring about changes in process plans, additional training for operators, different designs of tools (e.g., jigs and fixtures), and resource management. Thus, a cost-benefit scenario is typically studied to justify the variety introduced in the manufacturing line.

In spite of a recent advance in manufacturing automation, the role played by humans in the manufacturing system is still regarded a key factor in adaptable and flexible systems, such as in a mixed model assembly line. In this study, we define measures of complexity that reflect the underlying physics of the manual assembly process in the mixed-model system. Thus, the emphasis is placed on operator's choice complexity, which refers to the difficulties encountered by the operators when selecting the right component (e.g., tools, part, etc.,) from a number of options on the assembly line in manufacturing domains. The proposed measure integrates both the variety (i.e., option mix) and their respective similarities, which is expected to answer questions toward mechanisms between variety and complexity. Our proposed method also draws a clear and reasonable relationship linking the complexity metric to the manufacturing performance (e.g., cycle time). Once the complexity is measured in a representative quantifiable index that can be easily understood, a decision support system (DSS) for dynamic and effective manufacturing resource allocation will be suggested in our future work as a tool to mitigate overhead costs incurred by the complexities.

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The remainder of this chapter[3] is organized as follows. In Section 2, we provide an overview of the existing literature. Section 3 provides complexity computation in the automotive manufacturing system. Next, Section 4 introduces an illustrative example accompanied by a description of an experiment that showcases the relationship between the proposed complexity measure and the reaction time. Finally, Section 5 concludes our chapter and suggests future research directions.

3.2. Literature Review

The study of complex systems represents a relatively novel approach which examines the relationships between parts, and how they relate to the collective behaviors of a system [43]. Meanwhile, the prevalent engineering viewpoint across systems is to reduce disturbance and variability in complex systems through automation. However, despite the recent advances in automation, human is still regarded as a key factor in maintaining higher adaptability and flexibility. Thus, technological expansion has been coupled with a need for effective and dynamic resource allocation methodologies in semi-automated systems[1, 2].

The definition of complexity differs on a case by case basis and is considered to be subjective. Campbell [10] suggests that complexity is often treated as (a) psychological experience, (b) an interaction between task and person characteristics, and (c) a function of objective task characteristics. As a result, the notion of complexity is commonly conveyed using particular examples [11]. While decision makers agree upon the existence of complexity, the understanding of complexity and its characteristics is still limited[11].

The complexity in a manual assembly line is characterized by several factors, in which some of them are more impactful to the overall performance than others [44, 45]. However, the assessment of the impact of complexity is often constrained by the ability to measure the complexity itself. Thus, Falck, et al. [46] and Falck, et al. [47] categorize the complexity in a manual assembly line into different levels based on several defined complexity parameters. Similarly, [48] propose a Likert scale measure of workstation complexity based on number of key variables identified to be the primary drivers of complexity. These researchers show that the high complexity in a manual assembly line often corresponds to the high likelihood of error. A similar relationship is also noted between the complexity and the time and the cost [49]. In addition, Johansson, et al. [50] report a negative impact of high product on production quality. While the categorization of complexity is beneficial, it is limiting due to the range at which the complexity is defined. To this end, the information-based concepts (e.g., Shannon entropy) have been some of the most

[3] Part of work in this chapter has appeared on: M. Busogi, K. Ransikarbum, Y. Oh, and N. Kim. 2017. "Computational modeling of manufacturing choice complexity in a mixed-model assembly line." International Journal of Production Research:1-15. doi: 10.1080/00207543.2017.1319088.

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popular and commonly accepted theories used as a complexity measure. For instance, [51] demonstrate how axiomatic design principles can be used to control the effects of time-dependent complexity in manufacturing systems. Similarly, researchers have used the Shannon entropy to capture dynamic complexity of manufacturing systems, where all observable states of the manufacturing system are considered [52, 53]. In additional, Zeltzer, et al. [54] propose a complexity levelling method in which an entropic complexity measure is based on the variation of task cycle time. Also, using the entropy, Fujimoto and Ahmed [55] propose a complexity measure for different stages of process planning, while ElMaraghy, et al. [56] demonstrate how the entropy function can be used in the quantification of complexity in machining process. Deshmukh, et al. [57] define an entropic complexity measure for a part mix in job shop scheduling. While these efforts are worth lauding, the aforementioned studies of complexity measure pay little attention to the operator's choice complexity, its relation to variety, and how it impacts performance in a mixed model assembly line.

In this regard, recent researchers introduce models for the computation of operator choice complexity in a mixed model assembly line [58-60]. These models adopt Hick's law, or the Hick-Hyman law, to model the cycle time as a function of complexity measured by information entropy. Hick's law is popularly used to describe the time it takes for a person to make a decision as a result of the possible choice [9]. However, the proposed choice complexity modeling relies heavily on the part mix ratio and puts less focus on the relationship and interdependency among the options that have been shown to be a significant factor in choice complexity [61, 62]. Hick's law considers the option mix as the primary determinant of reaction time in human-factor perspectives; however, recent studies have shown that not only the number of options, but also the similarity of options can significantly affect the operator's reaction time [61, 63]. For example, several cases exist, in which parts have been mistakenly taken for one another due to their close similarities.

Although the similarity of options in a mixed model assembly line clearly impacts the choice complexity of the system operations and is detrimental to the total system performance, the formulation and analysis of the option similarity has received less attention from researchers and practitioners in the manufacturing industries. This is possibly due to its low perceived impact on the manufacturing performance in a mass-production environment. However, given the currently competitive manufacturing era, where the mass customization is essential and can significantly increase the number of options at an unprecedented rate, both the option counts and the similarity of options have become important factors to be considered as they can affect human errors and workloads. In particular, the similarity of options has been given a lot of attention in some specific industries where human error can have a tremendously negative effect, to illustrate its consequences on reaction time and human errors. For example, several

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studies have been done in the pharmaceutical industry on the similarity of both the name and the container of drugs in a pharmacy [61, 63]. Assuming a close proximity, it has been shown that the selection of a target medication within several similarly named medications increases the difficulty of the visual search for the target. Hellier, et al. [63] point out that the use of color to differentiate the drugs can not only improve the accuracy but also reduce the search time of the target medication. Similar conclusions have been noted on the shape differentiation of the drugs, to some extents. Thus, in this chapter we propose a novel choice complexity model that incorporates both the option mix and their respective similarity.

3.3. Choice Complexity Model

The choice complexity particularly in a mixed model assembly system is affected by several factors, some of which are more significant for operators than others. Recent studies show that increasing the number of options available for operators, including their respective similarities, can significantly affect the level of choice complexity [58-61, 63]. While quantifying the number of options is straightforward, measuring the similarity of options is both complex and subjective. Thus, in the next subsection, we propose a similarity measure in a mixed-model assembly line. Later, we develop a novel choice complexity model that integrates both the option mix and its respective similarity.

3.3.1. Similarity Measure in Semantics

While the definition of complexity can be customized to serve a given need, in the abstract sense, complexity is based on visual structures perception [64]. For example, before an assembly process, an operator will receive a command requesting him or her to select a specific part from a pool of available options. As in the abstract sense, the complexity of selection will increase based on perceptions of visual structures. Research has shown that, once the command is received, the operator's memory retrieval cue can become less effective when the command stimuli are associated with multiple items in the memory [65, 66]. That is, the more similar the options, the more ambiguous an operator will become when responding to the stimuli. The similarity effect on an operator's selection also depends on the brain activation, which is more or less category-based [67].

There is little to no existing research on the similarities of options in a mixed-model assembly, although psychologists have long attempted to formalize similarity measures [68]. The current formalization of similarity measures has relied heavily on knowledge representation, where the similarity between two objects is typically based on the semantic similarity. Here, objects are represented using the description of their properties[69] Thus, the commonalities and differences between two semantic representations of objects can be taken as one indicator for similarity [68]. That is, the more commonalities and the less differences, the higher the similarity. One of the well-known similarity measures built based on the commonalities and differences between two semantic representations is the feature-based similarity measure. In the feature-based similarity measure, the similarity between two particular objects A and B, s(A,B), can be formulated as a function between their common and distinct features as shown in Equation (3-1) [70].

$$s(A,B) = F(A \cap B, A - B, B - A) \tag{3-1}$$

Equation (3-1) shows the feature-based similarity measuring model based on a set-theoretic knowledge representation (Figure 3-1(a)). These features correspond to components with concrete or abstract properties of the object. Thus, objects can be represented as a linear combination of an unstructured set of features as shown in Figure 3-1(b).

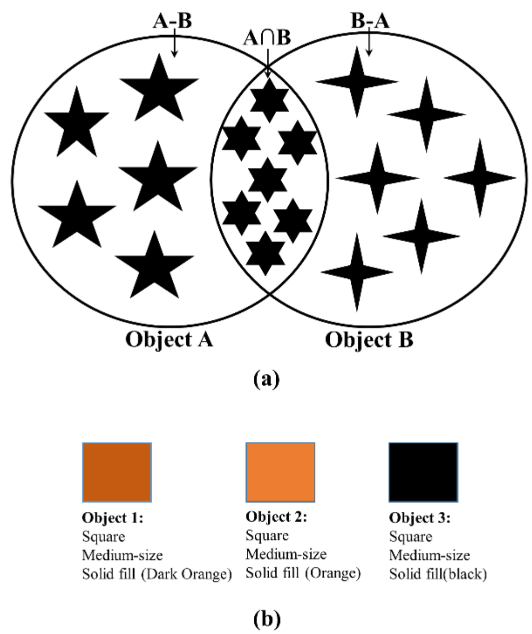

Figure 3-1. (a) Feature-based similarity measuring model in set-theoretic operations, (b) Object representation via an unstructured set of features

Although the feature-based similarity measuring model can, due to its simplicity, be easily adopted as the part mix similarity measure for the mixed-model assembly line, its inability to incorporate partial match in the model becomes a serious drawback. For example, based on the feature-based similarity measuring model, the similarity between objects 1 and 2 in Figure 3-1(b) can be said to be equal to the similarity between objects 1 and 3 despite the better color similarity in the former pair. Thus, to fill the

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loophole of a feature-based similarity measure, it is possible to express the similarity as a function of distance between an object's respective properties. In this case, object properties will be represented in the form of dimensions with ordered values. In this context, the geometric model can be used in analogy to spatial distance. Due to its superior performance, we utilize this approach in our study.

Geometric measure is based on the concept of multi-dimensional vector spaces, based on which objects or concepts are modeled and their spatial distance indicates the semantic similarity[71]. The geometric model uses what's called multi-dimensional scaling (MDS), which is a method that represents the measurement of similarities (or dissimilarities) as a distance between points of a low-dimensional multidimensional space among pairs of objects [71]. Once the dimensions are set and represented, the semantic distance between objects a and b denoted as $d(a,b)$ can be formulated as a function of total compound weighted distance of all their properties. We note that the distance obtained is spatial distance, which is also known as the Minkowski distance measure (Equation (3-2)).

$$d(a,b) = \left[\sum_{i=1}^{n} |\varepsilon_i (x_{ai} - x_{bi})|^r\right]^{1/r} \tag{3-2}$$

where x_{ai} is the value of dimension *i* for stimulus a,

x_{bi} is the value of dimension/feature *i* for stimulus b,

ε_i is the weight assigned to dimension/feature *i* as a functional reflection of the salience or prominence of the various dimensions, and

r determines the measured distance ($r = 1$ results in city-block distance and $r = 2$ results in Euclidian distance).

In this equation, it is important to acknowledge the difference in the object properties. For example, while some properties can be geometrically comparable (e.g., volume, etc.), other properties that are difficult to measure can present a bigger challenge (e.g., complex shapes, etc.) Thus, object properties with a measurement challenge can be presented as features with Boolean values (i.e., true or false). In this study, we represent objects using a combination of dimensions with ordered values as well as features that hold for that specific object, in which features can be considered as a special case of the dimension with only Boolean values. In particular, the distance between two objects based on a given feature can be obtained as shown in Equation (3-3).

$$|x_{ai} - x_{bi}| = \begin{cases} 0 & \text{if both a and b possess feature } \mathrm{x_i} \\ 1 & \text{otherwise} \end{cases} \tag{3-3}$$

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where x_{ai} and x_{bi} denote feature x_i of object a and b respectively.

Next, after the semantic distance between objects a and b, $d(a,b)$, is obtained, it is converted to the similarity measure by using Equation (3-4), where the similarity is an exponential decay function of distance [72].

$$s(a,b) = e^{-c.d(a,b)} \tag{3-4}$$

where $s(a,b)$ is the similarity between object a and b, and

c is the general sensitivity parameter.

Note that for N number of options, there exist a $N \times N$ distance matrix whose entry d_{ij}, $1 \le i,j \le N$, satisfies the following metric's properties:

- *d_{ij} = 0 for all $i = j$,*
- *All the off-diagonal entries are positive, such that $d_{ij} > 0$ if $i \neq j$,*
- *The matrix is a symmetric matrix, such that $d_{ij} = d_{ji}$ and*
- *For any i and j, $d_{ij} \le d_{ik} + d_{kj}$ for all k (the triangle inequality)*

Here, d_{ij} denotes the distance between option i and j, (See Equation (3-2)).

Recall that the representation often describes elementary characteristics such as the shape, the color, the texture, etc. While each visual properties of simple objects can be listed, the description of complex objects presents more challenges. Notice, however, how the similarity measure is heavily reliant on the representation of the discriminatory features, regardless of the part complexity. For example, a weighted color difference can be used for similarity measure of two very complex parts whose only difference reside in their color. Also, complex visual features can be automatically extracted and represented as feature vectors using several well-known algorithms often utilized in the field of computer vision [69]. In fact, recent research in neuroscience has shown that object recognition in primates is done in a manner similar to that used by feature descriptors algorithms used in machine learning such as Scale-Invariant Feature Transform (SIFT) [73, 74]. Thus, visual attributes are regarded as points in a multidimensional feature space, where the distance between extracted feature points (see Equation (4-2) for distance measure) reflects feature similarity.

3.3.2. Similarity in a Mixed-Model Assembly Line

In a mixed-model assembly line environment, before each task, an operator receives a stimulus requesting him or her to select a specific part from a pool of alternative options. Typically, the choice process involves two successive steps. First, the operator receives a stimulus, after which he/she proceeds to select the corresponding option. Note that often, at the station level, an assembly task may involve several sequential choices (i.e., part choice, fixture choice, tool choice, etc.). Let k=1, 2 ,…, K denotes a choice activity at a given station, where K is the maximum number of sequential choices on the station. It follows that for each station i, we can define two random variables X_i^k and Y_i^k describing the outcome of targeted variant (per stimulus) and the actual operator's choice, respectively. Note that both X_i^k and Y_i^k are defined on the same sample space $\Omega_i^k=\{v_{ij}^k | j = 1,2,..,\mathrm{N}\}$, where v_{ij}^k denotes the j^{th} variant and N is the total number of possible alternatives (parts/tool/fixture, etc.) that could be chosen in k^{th} choice activity at the station i. In this context $\mathrm{p}_{X_i^k}(v_{ij}^k)$ denotes the probability that $v_{ij}^k$is the target part/tool in a given task (i.e., $\mathrm{p}_{X_i^k}(v_{ij}^k) = \mathrm{P}(X_i^k{=}v_{ij}^k)$). On the other hand, $\mathrm{p}_{Y_i^k}(v_{ij}^k)$ denotes the probability that variant v_{ij}^k is the actual operator's choice in the given task. Once the targeted option is identified, the visual differentiation of options can be done based on their respective physical features, such as shape, color, size, etc. That is, the operator's effectiveness will depend on several factors including the available options and their similarities to the target variant. Thus, for each target variant v_{ij}^k, there is an associated perceived similarity level that differs from one target variant to another. Let $\Theta = \{\Theta_{v_{it}^k} | \mathrm{t} = 1,2,..,\mathrm{N}\}$, where $\Theta_{v_{it}^k}$ is the overall level of perceived similarity associated to target variant v_{it}^k. That is, Θ maps a given target variant to the sum of the pairwise similarities between the target variant and each alternative option as shown in Equation (3-5)

$$\Theta_{v_{it}^k} = \sum_{\mathrm{j}}^{\mathrm{N}} \left(\mathrm{s}\left(v_{it}^k, v_{ij}^k\right) \middle| X_i^k = v_{it}^k \right) \tag{3-5}$$

where N is the total number of variants,

$\mathrm{s}\left(v_{it}^k, v_{ij}^k\right)$ is the similarity between variant v_{it}^k, and v_{ij}^k

Based on Equation (3-4) the distance matrix can be transformed into a similarity matrix S as shown in Equation (3-6), where $s_{qp} = s\left(v_{iq}^k, v_{ip}^k\right)$; $s_{qp} \in [0,1]$; $1 \le q,p \le N$.

$$\mathrm{S} = \begin{bmatrix} s_{11} & \cdots & s_{N1} \\ \vdots & \ddots & \vdots \\ s_{N1} & \cdots & s_{NN} \end{bmatrix} \tag{3-6}$$

The level of the perceived similarity associated to the target variant $\Theta_{v_{it}^{k}}$, from Equation (3-5) can be extracted from the similarity matrix S as follows (Equation (3-7)).

$$\Theta_{v_{it}^{k}} = \sum_{\mathrm{j}}^{\mathrm{N}} (\mathrm{s}_{\mathrm{jt}} | X_i^k = v_{it}^k) \tag{3-7}$$

According to Equation (3-7), v_{it}^{k} is the target option, and the overall level of activated similarity is simply the sum of the pairwise similarities between v_{it}^{k} and every other available option, which is equivalent to the summation of t^{th} row of the similarity matrix *S*.

3.3.3. Incorporating Similarity Measure in a Complexity Model

Originally used as a measure of uncertainty, the information entropy, or so-called Shannon entropy, has been widely adopted as a measure of complexity in several manufacturing processes [75]. After a comprehensive justification on the use of entropy as a measure of choice complexity, [58] proposed the entropic measure of choice complexity as follow:

$$C = \alpha(a + bH), \alpha > 0 \tag{3-8}$$

where α is the weight of the choice, a and b are ergonomics constants, and H is the information entropy associated to the operator's choice.

The information entropy H quantifies the expected value of the information contained in a message and can be regarded as an average unpredictability of a random variable [76, 77]. In an uncertain environment, such as a mixed model assembly line, an operator shall make the right part selection from several options to be assembled within the limited allocated time to ensure the working flow for a specific task. Considering that an assembly task often involves several sequential choices at the station level (i.e., part choice, fixture choice, tool choice, etc.), based on the Equation (3-8), the total choice complexity at the station level can be expressed as follow:

$$C_i = \sum_{k=1}^{K} \alpha_i^k (a_i^k + b_i^k H_i^k), k = 1,2,..K \tag{3-9}$$

where *k* denotes the sequential choice activity comprised in the assembly operations at station *i*.

Since α, a, and b are constants, the choice complexity can be assessed by evaluating the information entropy H. Recall that, first the target option is revealed (per stimulus), then an actual choice is made

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accordingly. As stated earlier, the selection task. First, the operator receives a stimulus, after which he/she proceeds to select the right option. In terms of information entropy, the successive juxtaposition of information is equivalent to the overall information entropy contained in variables $X_i^k Y_i^k$ with joint distribution $p_{X_i^k Y_i^k}$ Thus, H_i^k from Equation (3-9) can obtained as follows (Equation (3-10)):

$$H_i^k = H\left(X_i^k Y_i^k\right) = H(X_i^k|Y_i^k) + \mathrm{H}(X_i^k) \tag{3-10}$$

Here, $\mathrm{H}(X_i^k)$ is the average information gained by acquiring the targeted variant (per stimulus), while $H(X_i^k|Y_i^k)$ denotes the average information required for selection of the part after the acquisition of the stimulus. Individually both $\mathrm{H}(X_i^k)$ and $H(X_i^k|Y_i^k)$ can be obtained using Equations (11) and (12), respectively.

$$\mathrm{H}(X_i^k) = -\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{p}_{X_i^k}(v_{ij}^k)\log_2 \mathrm{p}_{X_i^k}(v_{ij}^k) \tag{3-11}$$

$$\mathrm{H}\left(Y_i^k\middle|X_i^k\right) = -\sum_{\mathrm{j=1}}^{\mathrm{N}}\sum_{\mathrm{t=1}}^{\mathrm{N}} \mathrm{p}_{X_i^k}\left(v_{ij}^k\right)\mathrm{p}_{Y_i^k|X_i^k}\left(v_{ij}^k\middle|v_{it}^k\right)\log_2 \mathrm{p}_{Y_i^k|X_i^k}\left(v_{ij}^k\middle|v_{it}^k\right) \tag{3-12}$$

The term $\mathrm{p}_{Y_i^k|X_i^k}\left(v_{ij}^k\middle|v_{it}^k\right)$ in the above equations denotes the probability that the operator will select v_{ij}^k, after he or she receives the stimulus requesting to select v_{it}^k.Based on the fuzzy logical model of perception, Luce [78] suggests that the probability of selecting part “*a*” when “*b*” is requested, denoted by $\mathrm{P_{a|b}}$, can be calculated using Equation (3-13).

$$\mathrm{P_{a|b}} = \frac{\mathrm{s(a,b)}}{\sum_{\mathrm{l \in N}} \mathrm{s(l,b)}} \tag{3-13}$$

where $s(a,b)$ is the similarity between part “*a*” and “*b*” and *N* is the set of all available alternatives.

Thus, based on Equations (13) and (7), $p_{Y_i^k|X_i^k}\left(v_{ij}^k\middle|v_{it}^k\right)$ can be obtained using Equation (3-14)

$$\mathrm{p}_{Y_i^k|X_i^k}\left(v_{ij}^k\middle|v_{it}^k\right) = \frac{\mathrm{s}(v_{ij}^k, v_{it}^k)}{\sum_{\mathrm{l \in N}} \mathrm{s}(v_{il}^k, v_{it}^k)} = \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} \tag{3-14}$$

Next, Equation (3-10) can be extended as follows (Equation (3-15)).

$$\mathrm{H}(X_i^k Y_i^k) = -\sum_{\mathrm{j=1}}^{\mathrm{N}} \sum_{\mathrm{t=1}}^{\mathrm{N}} \mathrm{p}_{X_i^k}(v_{ij}^k) \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} \log_2 \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} - \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{p}_{X_i^k}(v_{ij}^k) \log_2 \mathrm{p}_{X_i^k}(v_{ij}^k) \quad (3\text{-}15)$$

The probability $p_{X_i^k}(v_{ij}^k)$ that a given variant is to be requested in a given product assembly is proportional to the ratio of the said variant and the total number of possible alternative variants. Thus, the probability $p_{X_i^k}(v_{ij}^k)$ is equivalent to the demand in percentage of the j^{th} variant (i.e., $\sum_j p_{X_i^k}(v_{ij}^k) = 1, \forall_k$) . We note that once the operator acquires the target (e.g., $X_i^k = v_{ij}^k$), the remaining complexity is equivalent to $\mathrm{H}(Y_i^k | X_i^k = v_{it}^k)$ and can be obtained as follows (Equation (3-16)).

$$\mathrm{H}(Y_i^k | X_i^k = v_{it}^k) = -\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{p}_{Y_i^k|X_i^k}(v_{ij}^k | v_{it}^k) \log_2 \mathrm{p}_{Y_i^k|X_i^k}(v_{ij}^k | v_{it}^k) = -\sum_{\mathrm{j=1}}^{\mathrm{N}} \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} \log_2 \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} \quad (3\text{-}16)$$

By using Jensen Inequality, it can be shown that the information entropy, $\mathrm{H}(Y_i^k | X_i^k = v_{it}^k)$will be maximized when all options are visually identical $(\text{i.e.}, \sum_{\mathrm{j=1}}^{\mathrm{N}} \frac{\mathrm{s_{jt}}}{\Theta_{v_{it}^k}} = \frac{1}{\mathrm{N}}, \forall_t)$. Thus, each part/tool has equal probability to be selected by an operator. Equation (3-17) thus follows.

$$H(Y_i^k | X_i^k = v_{it}^k) \leq -log_2 \frac{1}{N} \quad (3\text{-}17)$$

3.4. Illustrative Case Study

3.4.1. Screw Choice Complexity

We provide a case study for the screw choice complexity in this section. A sequence of assembly process typically involves a selection of proper screws. We note that the proposed complexity model presented earlier is not necessarily limited to the mixed model assembly line. In fact, the choice complexity does exist in many other manual assembly settings in which operator's task involves the "search" and the "selection" of an appropriate component Ma [79]. Also, several cases exist in which a company may choose a strategy to deliver product to be assembled by customer(s) at the destination to reduce inventory and transportation costs. However, although the package often includes an instruction and an assembly guideline, it can be challenging and time consuming for customer(s) to match each component to its right position. Similar to the mixed model assembly, one of the challenges is that the assembly involves a large

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number of parts, some of which are very similar and difficult to differentiate. Screws are especially some of the common parts causing an ambiguity to customer(s)/operators. In this illustrative example of screw choice complexity, we consider a set of screws to illustrate option similarity and variant as shown in Figure 3-2 (Screws A – K).

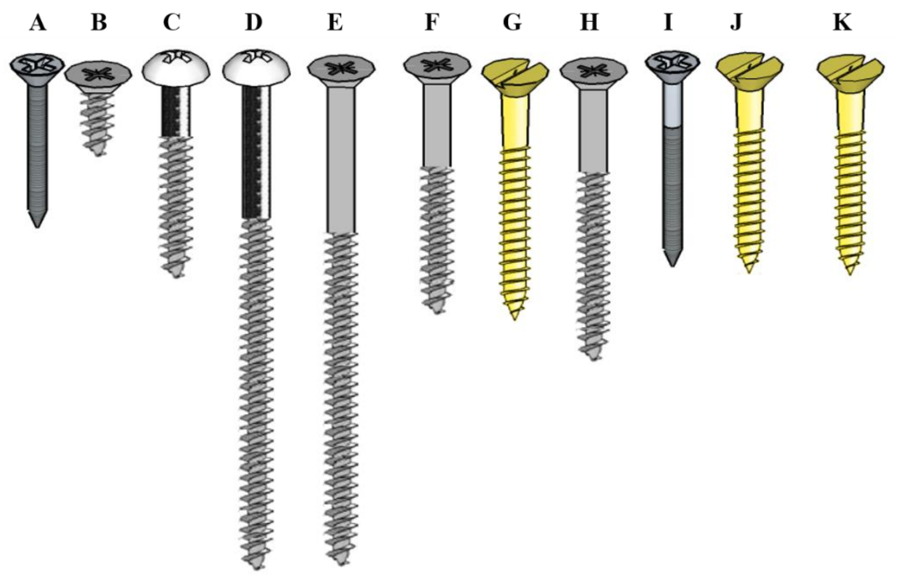

Figure 3-2 A set of screws and their variety

In this example, each screw can be represented using five dimensions: thickness, color, length, head shape, and screw drive type. We use the similarity measure explained in section 3 to generate the distance matrix and the resulting similarity matrix. We note that the overall dimension matrix is a weighted summation of all individual dimension-based similarity matrices (See Equation (3-2)). For example, the distance matrix that is based on color dimension is illustrated for all eleven screws (i.e., A… K) in Table 3-1. Each entry m_{ij} of Table 3-1 is a pairwise color distance between option i and j. We note that $m_{ij} = 0$ for all i=j implies that the colors are identical. The color distance is measured using the most recently updated color difference, known as CIEDE2000, proposed by the international Commission on Illumination (CIE). Compared to other color difference measure (e.g., CIE76, CIE94, etc.), CIEDE2000 is deemed to be perceptually uniform throughout the color space; thus, fits well as a color difference measure. Similar to any color difference measures, CIEDE2000 allows a quantified examination of color comparison that formerly could only be described with adjectives. For more details on CIEDE2000 and how it is computed, see Luo, et al. [80]. The matrix distance based on head shape as well as screw type was obtained using Equation (3-3). We note that other distance matrices based on other dimensions can be quantitatively calculated in a more-or-less similar way.

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Table 3-1 Distance matrix based on color dimension (CIEDE2000)

	A	B	C	D	E	F	G	H	I	J	K
A	0.00	21.94	30.97	30.97	21.94	21.94	42.08	21.94	25.77	42.08	42.08
B	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
C	30.97	9.50	0.00	0.00	9.50	9.50	25.59	9.50	7.66	25.59	25.59
D	30.97	9.50	0.00	0.00	9.50	9.50	25.59	9.50	7.66	25.59	25.59
E	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
F	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
G	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00
H	21.94	0.00	9.50	9.50	0.00	0.00	27.61	0.00	6.74	27.61	27.61
I	25.77	6.74	7.66	7.66	6.74	6.74	33.27	6.74	0.00	33.27	33.27
J	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00
K	42.08	27.61	25.59	25.59	27.61	27.61	0.00	27.61	33.27	0.00	0.00

Next, the overall distance matrix can be calculated using Equation (3-2) and the values are shown in Table 3-2. As stated earlier, the overall dimension matrix is a weighted summation of all individual dimension-based similarity matrices

Table 3-2 Overall distance matrix considering all dimensions

	A	B	C	D	E	F	G	H	I	J	K
A	0.00	0.63	0.66	0.82	0.54	0.40	0.74	0.42	0.17	0.72	0.72
B	0.63	0.00	0.59	0.75	0.46	0.32	0.94	0.35	0.57	0.92	0.92
C	0.66	0.59	0.00	0.16	0.45	0.31	0.86	0.33	0.51	0.84	0.84
D	0.82	0.75	0.16	0.00	0.28	0.42	0.98	0.40	0.67	1.00	1.00
E	0.54	0.46	0.45	0.28	0.00	0.14	0.76	0.12	0.43	0.78	0.78
F	0.40	0.32	0.31	0.42	0.14	0.00	0.62	0.02	0.29	0.64	0.64
G	0.74	0.94	0.86	0.98	0.76	0.62	0.00	0.64	0.67	0.02	0.02
H	0.42	0.35	0.33	0.40	0.12	0.02	0.64	0.00	0.32	0.66	0.66
I	0.17	0.57	0.51	0.67	0.43	0.29	0.67	0.32	0.00	0.65	0.65
J	0.72	0.92	0.84	1.00	0.78	0.64	0.02	0.66	0.65	0.00	0.00
K	0.72	0.92	0.84	1.00	0.78	0.64	0.02	0.66	0.65	0.00	0.00

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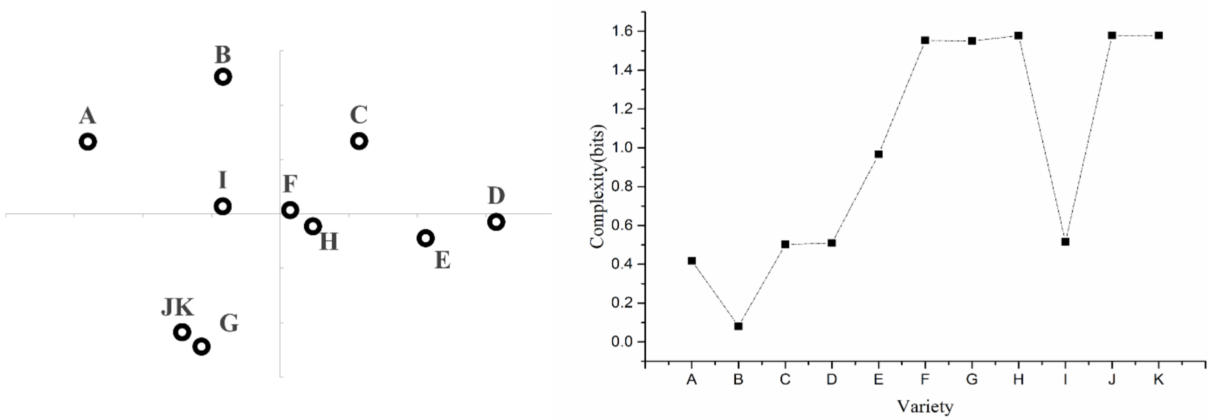
For a better visualization, we then used the multi-dimensional scaling (MDS) algorithm and the graphical result was obtained. As shown in Figure 3-3(a), options J and K are identical, while option G is closely similar to the pair J-K. On the other hand, options A and B are very dissimilar from all other options. By simply looking at the MDS plot, one can confidently argue that option F or H is more likely to cause a higher choice complexity than options A and B (all things being equal). In this example, each option is equally likely to be requested as the target option at any time. That is, $\mathrm{p}_{X_i^k}(v_{ij}^k) = \frac{1}{\mathrm{N}}$, where N is the total number of options. Figure 3-3(b) presents the contribution of each variety of screw to the overall complexity of the system. It can be observed how the options in the crowded area in Figure 3-3(a) are the major contributor to the complexity. This is because the similarity of options is one of the underlying factors of choice complexity.



(a) (b)

Figure 3-3(a) Option similarity plot based on MDS, (b) The expected complexity of each option

Next, Figure 3-4(a) presents the complexity when each variety of screw is sequentially added into the system. In the figure, the graphical cumulative complexity in bits is plotted against the screw variety as obtained using Equations (15). We note the different rates of increase of the cumulative complexity when each new screw variety is added. Thus, it is interesting to see how removing or adding some options can improve or worsen the choice complexity. However, in the proposed model, the similarity is by no means the sole major factor determining the level of choice complexity in a mixed-model assembly line in our study. In fact, the level of complexity is also affected by the demand share of every option in the system $p_{X_i^k}(v_{ij}^k)$. Considering an increase of the demand share of option A, for example, its contribution to the level of choice complexity varies as shown in Figure 3-4(b). It can be observed how its contribution starts from 0 bits when the demand share is 0. Then, it continuously increases and starts to fall once the demand gets very high. This is because, when the demand share of v_i is close to zero (i.e., $p_{X_i^k}(v_{ij}^k) \cong 0$), the operator is more likely to ignore part. v_i.Similarly, as the demand share approaches 100, the operator is more likely to ignore other options since he /she can correctly guess the next target option.

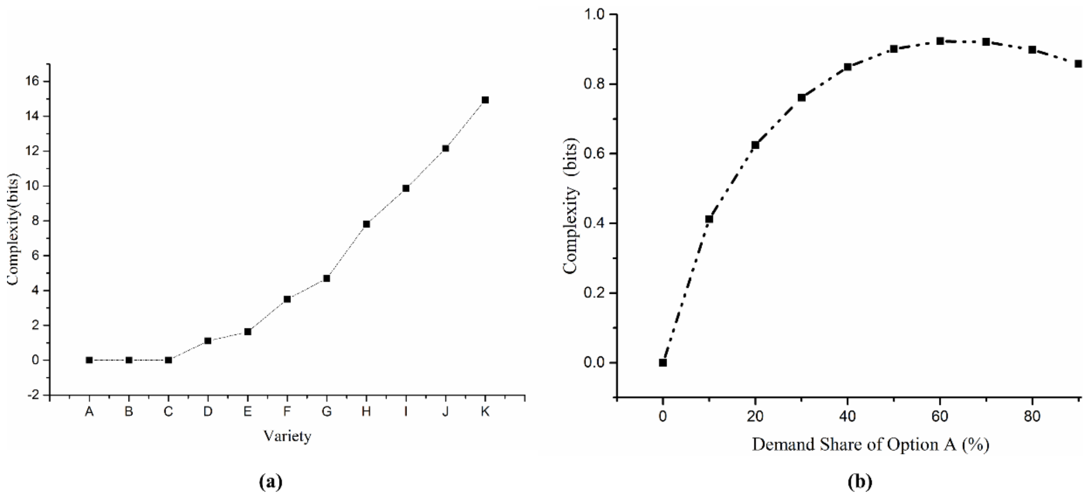


Figure 3-4(a) A graphical cumulative complexity against variety, (b) Option A's complexity contribution as its demand share varies

We further conducted a sensitivity analysis to see how adding or removing a particular option can affect the overall complexity. For example, by not introducing the F variety (option), the overall choice complexity ($H(Y_i^k X_i^k$) is found to reduce from 14.94 bits to 11.55 bits. A 22.65% drop is found despite holding 9.09% of the demand share ($\text{i.e.}, p_{X_i^k}(v_{ij}^k) = \frac{1}{N}$). On the other hand, option B is found to be the lowest contributor to the complexity at the station. Thus, removing option B only reduces the overall complexity from 14.94 bits to 14.17 bits, which is only 0.51% decrease in the overall complexity, despite equaling the market share of variety F.

It is clear that the complexity measure can offer an insight on how the complexity can be mitigated through various process such as modularization, etc. Once the major contributors of the complexity are identified, a detailed cost-benefit scenario can be used to decide the most appropriate solution for a decision maker. The solution may include moving some tasks to a different station, discontinuing or reducing the volume of products responsible for high complexity, introduction of an error-proofing system, designing optimal modules that ensure an acceptable level of complexity, etc. [81, 82]

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3.4.2. Choice Complexity and Reaction Time

This subsection aims to illustrates the validity of the proposed choice complexity, while assessing how the proposed metric fares compared to the existing choice complexity measure. We note that a detailed relationship linking the proposed complexity measure to a formal performance metric is in our future work. However, we briefly give a glimpse of what an entropic measure of manufacturing complexity implies in terms of traditional practical performance metrics (i.e., cycle time, etc.) in this subsection. Based on Hick's law [9, 83], the average reaction time (RT) can be approximately formulated as a linear function of the information entropy conveyed by the stimulus (Equation (3-16)).

$$RT = C_i \tag{3-18}$$

where C_i is station level complexity obtained using Equation (3-8).

According to Equation (3-18), as the complexity increases, the uncertainty also increases and the part selection generally takes additional time due to the slower reaction time of the operator. Thus, we intend to analyze a relationship between complexity and reaction time. The use of information entropy for modeling the manufacturing complexity in a mixed model assembly line is relatively novel; it can be seen that the few existing works use the option mix as the sole parameter in entropy computations. In the following toy example, we show that the proposed entropic measure can be used to predict the reaction time, which can provide an insight into the expected cycle time. We also illustrate that the proposed model that integrates both the option mix and similarity performs a better job compared to the existing entropic measure of choice complexity that simply relies on the part mix.

3.4.2.1. An Experimentation Overview

To verify the relationship between the proposed complexity measure and the reaction time, we conducted an experiment, in which an operator receives stimuli instructing him or her to perform a given task following certain guidelines. Practically, the form of these stimuli varies from one instance to another. For example, the operator may receive the instructions that include a coded name or an image of the part to be assembled with the mainframe. In this experiment, the stimulus is given in the form of an image. Once the operator receives the stimulus, he or she must click on the matching option according to the guidelines. An example of the stimulus and the pool of options in the form of Lego images are shown in Figure 3-5. We then pay more attention to the effectiveness of the stimulus-option matching process.

In this experiment, the operator (subject) is requested to select the matching image, after which the next matching command appears. The task begins when the stimulus is displayed on top of the options and finishes when the subject clicks on one of the options. Once the subject clicks on one of the options, the

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experiment proceeds by displaying the next stimulus. As stated in Equation (3-5), the target option at any time, *t*, is an element of the set of all options. Thus, a stimulus is uniformly selected from the set of all available options in this experiment. We vary the number of options with six levels (i.e., 2, 4, 8, 12, 16, and 20) as shown in Table 3-3. For each level, both the length in centimeters and color in Red-Green-Blue (RGB value) are randomly generated with three levels from a uniform distribution with specified minimum and maximum values. Thus, there are 18 experimental trials in the study in total. The experiment was run on a desktop with a 21-inch monitor and a total of 10 subjects participate in the experiment.

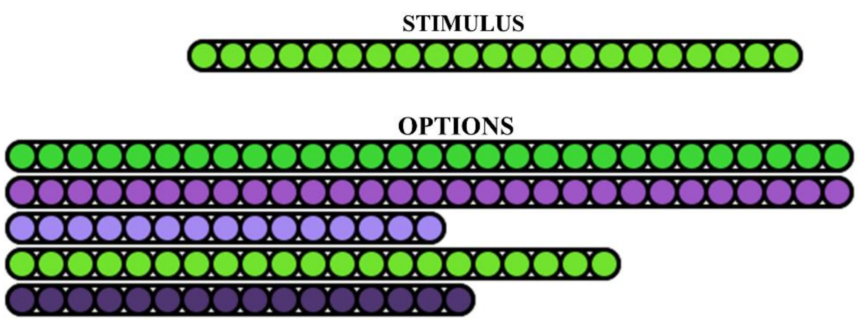

Figure 3-5 The reaction time experiment with stimulus and matching task

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Table 3-3 Experimental study based on length and color

Number of	Length(cm)		Colors (RGB)	
Options	**Min**	**Max**	**Min**	**Max**
2	4	16	0	250
2	8	12	50	150
2	8	10	50	100
4	4	16	0	250
4	8	12	50	150
4	8	10	50	100
8	4	16	0	250
8	8	12	50	150
8	8	10	50	100
12	4	16	0	250
12	8	12	50	150
12	10	12	50	100
16	4	16	0	250
16	8	12	50	150
16	8	10	50	100
20	4	16	0	250
20	8	12	50	150
20	8	10	50	100

3.4.2.2. Feature Selection and Complexity Measure

In order to properly measure the similarity of objects, discriminatory features should be selected based on the semantic representation of the objects. The representation of each feature should also be independent. That is, the degree that each feature or pair of features shares between two objects affecting the similarity should not be dependent on other shared features. In addition, the feature set should also be sufficiently rich and representative.

In the above experiment, the discriminatory features chosen in the study are the length and the color of the Lego images. The CIEDE2000 is used as a quantitative measure of difference between colors, whereas the length in centimeters is used to measure the size feature. As noted in an earlier section, the CIEDE2000 is popularly used to replace visual subjective judgments of color difference by instrumental

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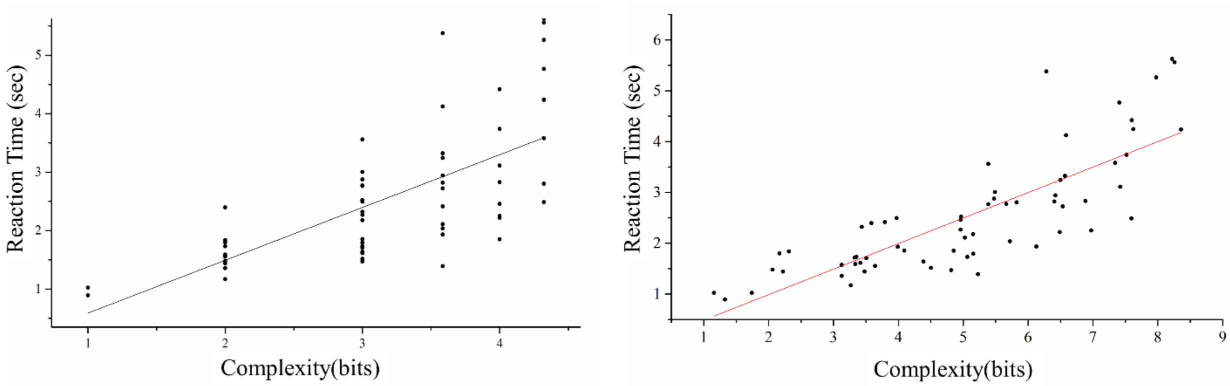
objective measurements. For each pair of objects, the similarity is obtained using Equation (3-4) and the resulting complexity is computed using Equation (3-8).

3.4.2.3. Result and Discussion

In this experiment, the average reaction time in seconds, *RT*, follows the Hyman-Hick's law, which can be shown to be linearly dependent on the information entropy representing the complexity (Figure 3-6). However, when we conducted a regression analysis to see how closely the data fits the regression line, the prediction power from using the traditional Hick-Hyman's law as the primary determinant of the reaction time (i.e., based on option counts and their respective demand share) is relatively low (R^2= 0.48) (Figure 3-6(a)). We next conducted a similar analysis using the proposed complexity measure based on the modified information entropy from Equation (3-13). The graphical analysis between the modified information entropy and the reaction time is shown in Figure 3-6(b). A regression analysis shows an improvement of the prediction power by over 34% ($R^2 = 0.64$), which is considered relatively high for human experimentation.



(a) (b)

Figure 3-6 (a) Reaction time as a function of the traditional complexity measure, (b) Reaction time as a function of the proposed complexity measure

We next compared the traditional method and the proposed complexity measure using the mean square error (MSE) as shown in Figure 3-7. The traditional method tends to become volatile when the number of options goes up. Thus, although the advantage of the proposed model over the traditional one may seem to be minimal for the cases with a low number of options, there is a clear tradeoff such that the gap grows larger when the number of options increases representing a higher complexity. In particular, when we increase the number of options from 4 to 14, the MSE increases more than seven times (7.2 times) when using the traditional method compared to less than two times (1.8 times) when using the proposed complexity model.

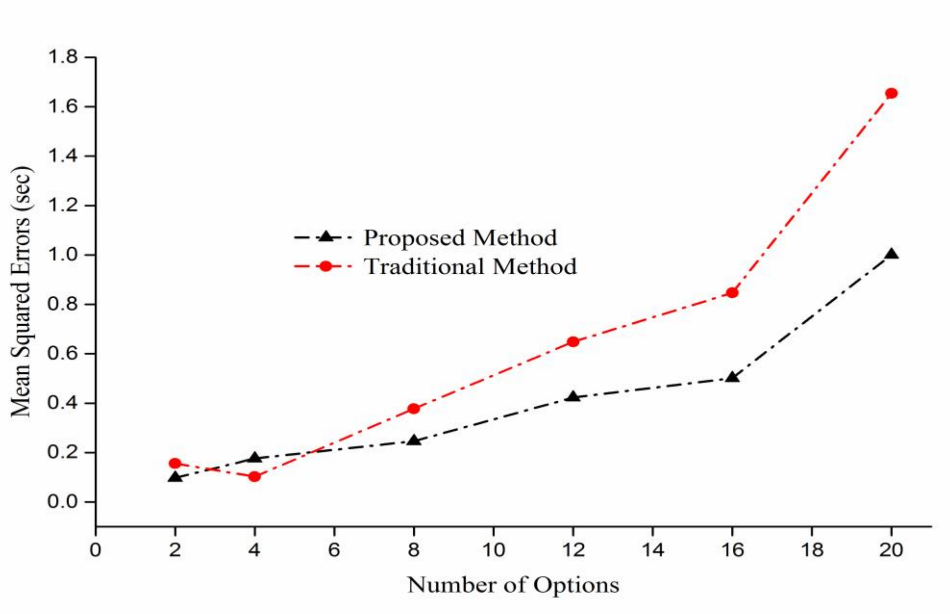


Figure 3-7 Comparison of MSE between the traditional and proposed complexity models

3.5. Conclusion

As mass customization is becoming a new norm in manufacturing systems, the number of distinct options in mixed model assembly line has been growing at an unprecedented rate, inducing complexity in the business. Additionally, due to flexible market demands, demand changes are also imminent in manufacturing systems. However, there is a lack of quantifiable methods to account for manufacturing complexity. In this chapter, we presented a novel method to compute manufacturing choice complexity, incorporating option counts and option similarity based on the well-known information entropy model. The proposed model not only has the ability to compute the overall complexity of the system, but can also track the contribution of each specific option or station to the overall system complexity. We conducted an experimental design to verify the impact of the similarity of options and reaction time to the overall complexity. Then, we further compared our proposed complexity measure with the traditional complexity that did not explicitly discuss the similarity of options and found that our model is more effective.

Our proposed complexity model can be used as a tool to investigate how the system performance will look if a given set of policies were to be implemented. For example, it offers a decision maker the ability to hypothetically add a number of options, after which an analytical result can be obtained. Thus, the model can be used to assess various scenarios and their respective effects on the overall complexity and

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reliability of the system. For example, to help an operator have less of a workload in terms of the decisions he/she must make, a company typically utilizes a system in which parts are delivered to the assembly line in a precise build sequence. Thus, parts associated with the highest level of complexity can be determined and included in the system using the proposed model. In addition to the computation of the system complexity, it can be shown that with a fixed option count, both the similarity and proximity level can be adjusted to mitigate the system complexity.

The proposed complexity model with an experimental study, while practical, could be further understood with more experimentations accounting for operator experience, stimulus sequence, etc. In addition, cost and time impacts on a decision maker should be further explored. Thus, future research directions include a justification study of how the addition of a new variation has impacts on the overall company performance in terms of the cost-benefit analysis. On one hand, if customers base their purchasing decisions on specific features, the increased complexity can be compensated by the increased sales. On the other hand, additional costs associated with the increased complexity may be unwarranted with lower demand. In addition, as the cost associated with system reconfiguration can depend on system flexibility, a study on the flexibility of a mixed-model assembly line and its relationship to overall system complexity, as well as to mitigation approaches, will be central to our future work. Last but not least, although the screw part is illustrated in our study, more complex parts could be further investigated in the future to see the impact and trend of complexity measure.

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Chapter 4

Modeling framework for Human in the Loop Simulation of Task Complexity: A Case of Mixed Model Assembly line

4.1. Introduction

In the past, manufacturers had provided the market with a few models that had few attributes and long life-cycles. Today the increasing customer sophistication and expectations along with the accelerated pace of technology development have led to a much more complex market [36]. Manufacturing organizations are now expected to offer a high product variety to remain competitive. As a result, the number of part variants registered a 400% increase between the year 1975 and 1990[37].

Meanwhile, the mixed-model assembly system and modular supply chains have been adopted in order to handle the increased variation [84]. By offering a range of models, companies have gained a competitive edge. However, as the variety increased, manufacturing performance worsened due to the complexity from creating and handling multiple product models [41]-[42]

This means that there exists a tradeoff between additional advantages from a greater variety of options and higher costs associated with manufacturing complexity. However, from a decision-making standpoint, it is still a challenge to estimate the tradeoff since it is not only subjectively defined but also very vague due to lack of constitutional measurement of manufacturing complexity.

Thus, analyzing the complexity of manufacturing is a promising way of ensuring higher product variability, while simultaneously maintaining the production efficiency. This study proposes a machine learning methodology in which various features of choice complexity are not only identified, but also used in assessing and predicting the dynamics of operator's performance. The study focuses on operator's choice complexity; since, in spite of advances made in manufacturing automation, human is still regarded as a key factor in adaptable and flexible manufacturing systems such as MMAL. Here, the operator's choice complexity (OCC) refers to the difficulties encountered by the operators when selecting the right component (e.g., tools, part, etc.,) from a number of options on the assembly line. The operator's performance is expressed as function of the time it takes to select the right component; which, according to research, diminishes as the number of options increases[58], [59].

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As in most complex systems in which closed-form analytical solution is nonexistent, simulation has become a powerful tool in the analysis of complex manufacturing systems. Thanks to the technological advances in the new "smart manufacturing" era, simulations analysis has hit its strides. However, the existing progress and research on smart manufacturing put little emphasis on human, the essential component of a smart factory, while focusing, instead, on the higher level artificial intelligence in factory environments[85],[86].

Furthermore, due to the dynamics of human behaviors, modeling or simulating human performance via traditional methods is often hard. In fact, the statistical estimations of the human role fall short in several human-involved systems [87]. This chapter aims to simulate and analyze the OCC and its underlying effects, by incorporating a real human (human-in-the-loop) in the overall assembly simulation in a manner that accurately represents the core physical aspect of choice complexity. Furthermore, using the human in loop simulation (HIL) platform, we build and train a machine learning model, to not only assess possible features affecting the operator's performance in an MMAL, but also through prediction, to potentially be used for allocating accurate dynamic cycle time in accordance with the task complexity. The proposed methodology provides an in-depth analysis of OCC, and gives a hint on how to effectively encapsulate human component in smart manufacturing settings.

The remainder of this chapter[4] is organized as follows. In Section 2, we provide an overview of the existing literature. Section 3 briefly introduce the concept of human in the loop machine learning in human-centered systems. Next, section 4 gives an in-depths discussion on the features and characteristics of choice complexity and its impact in MMAL. Finally, Section 5 concludes our chapter and suggests future research directions.

4.2. Literature review

4.2.1. Manufacturing Complexity

The study of complex systems represents a new approach to the engineering and science that investigates how relationships between parts give rise to the collective behaviors of a system and how the system interacts and forms relationships with its environment[43, 88]. Recent progress in the study of complexity has made it possible to systematically characterize a wide range of complex systems [88, 89].

[4] Part of work in this chapter has appeared on: M. Busogi and N. Kim, "Analytical Modeling of Human Choice Complexity in A Mixed Model Assembly Line Using Machine learning-based Human in The Loop Simulation," IEEE Access, 2017.

Due to heterogenous characteristics of different complex systems, the scientific notion of complexity has been traditionally conveyed using particular examples [11].

In this regard, recent researchers introduced models for the computation of operator choice complexity in a mixed model assembly[58], [59]. These models adopt Hick's law, later known as the Hick-Hyman law, to model the cycle time as a function of complexity measured by information entropy. Hick's law has been popularly used to describe the time it takes for a person to make a decision as a result of the number of possible choices [9]. However, Hick's choice complexity modeling relies heavily on the part mix ratio and pay little attention on other factors such as the relationship and interdependency among the options that have been shown to be an important factor in choice complexity [61].

From MMAL perspective, before an assembly process, an operator receives a command requesting him or her to select a specific part from a pool of available options. Research has shown that, once the command is received, the operator's memory retrieval cue can become less effective when the command stimuli are associated with multiple items in the memory[66],[65]. For example, the more similar the options, the more ambiguous it becomes to the operator when responding to the stimuli. The similarity effect on an operator's selection also depends on the brain activation, which is more or less category-based [67]. Thus, Busogi, et al. [90] proposed an entropic choice complexity model that considers both part mixes and their respective similarity. The model, however, ignores the effect of task sequence on the operators' effectiveness[91]. Despite these research attempts, there is still no validated model that explicitly explains the nature of choice complexity in MMAL and its underlying effects on system performance.

4.2.2. Modeling and Simulation of Human-involvement in Manufacturing Systems

Simulation, specifically the discrete event simulation (DES), plays a major role in analyzing the manufacturing complexity. Simulation allows the testing and analysis of a new resource policy before actual implementation, deployment, or gathering information and knowledge without disturbing the actual system[92]. Thanks to advances in computing, the simulation in manufacturing has had several progresses in recent history.

The success of the simulation is based upon the advances in the representation of several aspects of the manufacturing in computable terms (i.e., conceptual model)[93]. For example, computer simulations have represented different technological aspects of manufacturing systems (e.g., machines, conveyors) with deterministic and stochastic data. However, the traditional approach, which is based on simple discrete event-based specifications, often fails to represent the details of the relationship between the performance of a person and his or her working environments, which is regarded a key modeling attribute in human-machine co-working environments [87]. In fact, human variation is the cause of a large percentage of the disparity between simulation predictions and real-world performance. This presents a problem when modeling systems that involve highly manual work contents such as a MMAL.

Figure 4-1 Screw Selection task. The subject clicks on a specific screw according to the stimulus

While several aspects of manufacturing complexity can be modeled, and analyzed, the choice complexity presents a greater challenge due to several human factors involved. This is why few researchers opted to incorporate human models in DES for simulating various aspects of manufacturing processes[87]. Because of the complexity of human actions, the existing human models are often oversimplified and only built for specific purposes (e.g., military, etc.). For example, Baines, et al. [87] included a human performance model that only considers both the age and experience to simulate the manufacturing assembly production. Similarly, due to technological advances in 3D representation, several researchers have successfully opted for digital human models (DHM) to increase the accuracy of various simulation of manufacturing assembly process, particularly with regards to human factors[94]. However, the study also points out the need for several needed improvements to bridge the gap that still exists between DHM and real human operators [94] [95]

Although human models, including DHM do a better job compared to most other discrete event simulations, there is no ideal human performance model yet that encloses all the relevant human factors

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from a manufacturing point of view. In this regard, studies have noted a surge in number of researchers and practitioners embracing the virtual simulation as the new norm of simulation of human-centered systems[96]. Virtual simulation has many advantages, including the ability to provide adaptable virtual replication of physical systems that would otherwise be overly expensive, sometimes even impossible to explore[97]. Whereas the majority of virtual simulation focus on practice and testing user's knowledge using interactive scenarios and environments to reflect real-life situations[98]; in this study, we propose machine-learning-based HIL simulation in which a non-immersive virtual choice simulation is used to accurately represent and analyze the OCC and predicts its impact on manufacturing performance.

4.3. Human in the loop machine learning

4.3.1. Machine learning in manufacturing systems

Through the advancement of technology, manufacturing industry has become capable of collecting a wide range of data in different format and quality [99]. As the available data grow, practitioners have relied on machine learning to create new ways to support decision-making or to improve the system automatically. The goal of certain machine learning techniques is to detect patterns or regularities that describe vital relations, necessary to understand or improve the system [100], [101]. As a field that originated from the study of pattern recognition and computational learning theory in artificial intelligence and expert system, machine learning explores construction of algorithms that can learn from historical relationships and trends in the data to make data-driven predictions or uncover hidden critical insights needed to produce reliable, repeatable decision [102] , [103].

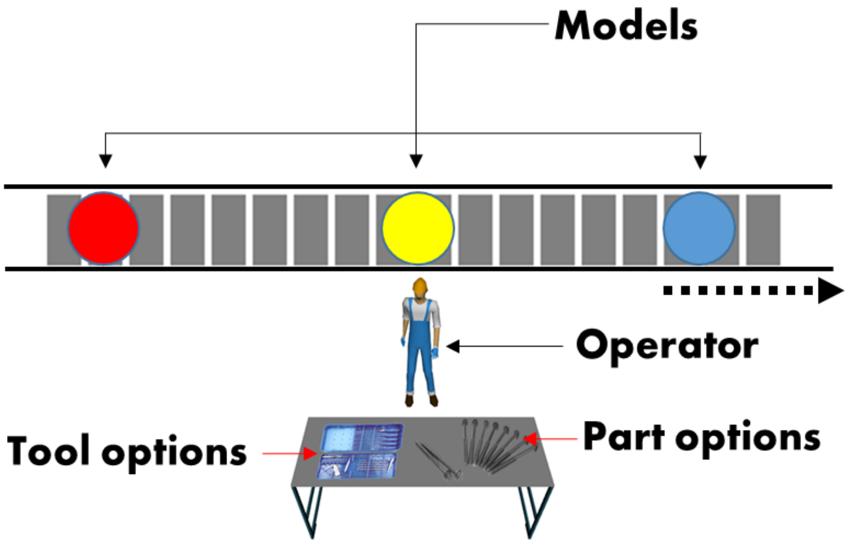

Figure 4-2 Choice Complexity in a mixed-model assembly line. Once an operator receives the stimulus, he/she proceed on selecting the right part from several options available

Machine learning has been successfully utilized in process optimization, monitoring, control applications, and predictive maintenance in different manufacturing industries[104], [105], [106]. Whereas the majority application of machine learning concept has often been limited to optimization of sequencing or line balancing problems, machine learning has, sometimes, been applied to predict the task duration of a wide range of manufacturing processes. For example, Benkedjouh, et al. [107] used support vector regression to predict the life of cutting tools. Similarly, in [108] various regressions models have been proposed to predict the factory cycle time based on historical data. However, little has been researched in quantified modeling and analysis of OCC under flexible manufacturing environments. In fact, the role of human involvement in the aforementioned research is either minimal, or considered as a physical resource expressed in statistical terms, which may not hold in reality, given the dynamism of human operators, especially in a complex MMAL.

4.3.2. HIL machine learning in MMAL

Planning and training assembly operations during the early stages of product design can ensure that a product is manufactured in the most efficient way. Thus, manufacturers rely on simulation results for insights necessary for adequate planning before further expenditure is made.

However, due to the dynamics of human behavior, it is often impossible to accurately simulate the choice complexity in a mixed model assembly via the traditional simulation methods. Thus, we use the HIL

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to reproduce the assembly problem by embedding a real human in the system to accurately reproduce the physical facet of choice complexity. As opposed to simply considering human as a physical resource represented in statistical terms, in this type of simulation, a human is always part of the simulation, thus, affects the outcome of the simulation in such a way that it would be almost impossible to reproduce without him/her[109]. In other words, HIL readily identifies the problems and requirements that may not be easily identified by other means of simulation.

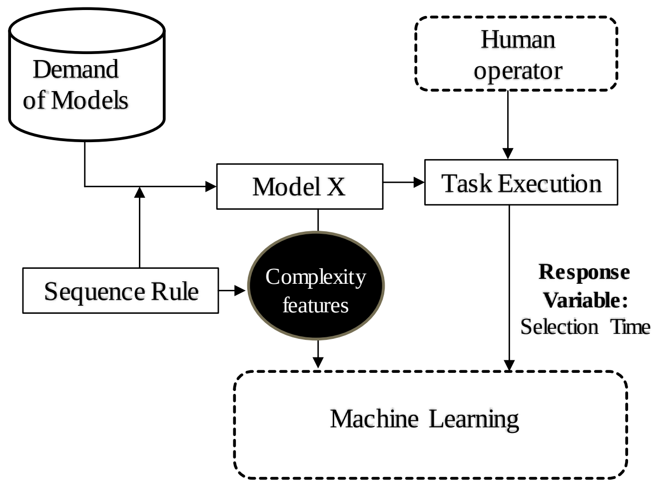

Figure 4-3 Human in the loop machine learning in a MMAL.

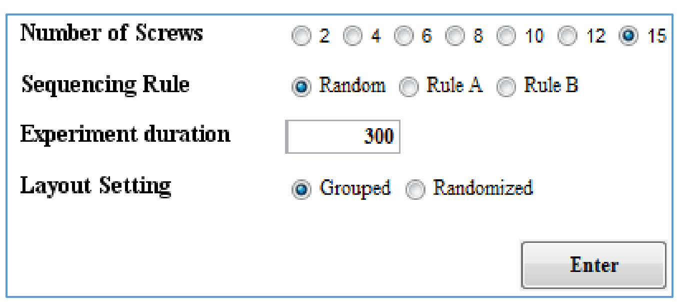

Figure 4-4 User interface of the experiment

As shown in Figure 4- 1 and Figure 4-2, in a MMAL environment, the operator receives, before each task, the stimuli instructing him or her to perform a given task following certain guidelines. Practically, the form of the stimuli varies from one instance to another. For example, the operator may receive instructions that include a coded name or an image of the part to be assembled with the mainframe. Once the command is received, the operator starts by selecting the right part from a pool of available options, after which he/she

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proceeds with the assembly. In this chapter, the proposed approach is accompanied by an illustrative example, in which a human subject is requested to identify the right part in similar fashion as in the real physical assembly line.

The proposed method mirrors the actual physical setups that characterizes the choice complexity in a MMAL. After selecting the features of choice complexity, we build and train a machine learning model based on the operator's selection time as depicted in Figure 4-3, which will be discussed further in the next sections.

4.4. Features and characteristics of choice complexity in MMAL

4.4.1. Simulation of choice complexity in MMAL

The mixed model assembly lines often consist of multiple stations arranged along some kind of a transportation system, e.g., a conveyor belt, which is carrying workpieces from one station to another. Operators move along the workpiece carrying out distinct tasks, most of which require the "selection of the right part" according to the model at hand. Recall that "operator's choice complexity" refers to the difficulty that operators face when selecting the right component from a number of options. That is, a more complex choice is more likely to take longer time to make, or results in an erroneous part selection. The selection process involves a visual search, which, according to [110], is "a type of perceptual task requiring attention that typically involves an active scan of the visual environment for a particular object or feature (the target) among other objects or features (the distractors)".Therefore, options can be visually differentiated on the basis of their respective physical features, such as shape, color, size, and position. The effectiveness of the visual search depends on several factors, some of which are more significant than others. The major factors include the number of alternatives or distractors and their similarities to the target object, the sequence and frequency of target and proximity, grouping and orientation[111] [110],[112],[113].

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Table 4-1 List of collected data in MMAL

Attributes	Attributes ID(s)
Number of options (screws)	1
Sequence rule	2
Physical arrangement (Layout)	3
Position data*	4, 22-36
Similarity data**	5, 7-21
Entropy	6
Variation in Similarity matrix	38
Reaction time	39

For further understanding, let us take an example, in which an operator is required to pick up the right screw to be used according to the stimulus. Each available screw has a distinctive corresponding model variety, in which it is to be used. As in most visual search experiments, subjects are asked to detect a target object upon receiving a command. That is, once the stimulus is received, the subject goes on to select the right screw according to the instructions. The selection is done by clicking on the corresponding part, after which a feedback is given to signal that the choice has been recorded (See Figure 4-1).

Subjects were asked to detect a particular target screw presented among the irrelevant non-targets. Here, six human subjects were involved in this illustrative example. Three major simulation parameters were considered: namely, the number of screws, the sequence rule and the layout settings. As shown in Figure 4-4, seven distinct numbers of screws, three sequencing rules and two layout settings were used in the simulation for a total of 41 distinct experimental setups. The experiment was run at a randomized order; that is, before each subject began the selection task, levels were set according to a predefined random order. The experiment lasted approximately 40 minutes consisting of at least 10 distinct factors' combination for each subject. The duration of each individual trial varied for each combination of factors' levels depending on the number of screws involved, ranging from 60 seconds for two screws to 300 seconds in the case of 15 screws.

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4.4.2. Features of operator's choice complexity.

Several factors deemed to be affecting the operator's choice complexity are considered in this simulation. As shown in Table 4-1, on each selection task, we collected a total of 39 raw variables, ranging from the number of options to operator's reaction time. The position data include distance between the two consecutively requested target screws (i.e., attribute 4) and the row of position matrix corresponding to the requested option (i.e., how far apart any given option is to the targeted option).

The similarity data include the similarity level as obtained in equation (4-3) (i.e., attribute 5), and the row of the similarity matrix corresponding to the requested option (how similar any given option is to the targeted option). The entropy refers to a complexity measure as proposed in [58], while the variation in similarity matrix refers to the standard deviation of the row of the similarity matrix corresponding to the requested option. Note that the collected data may contain variables that are either redundant or irrelevant, thus can be ignored without losing much information. Hence, it is important to select a subset of relevant features (predictors) to be used in model construction. A successful feature selection not only makes it easier to interpret, but also to reduce the training time and the variation[114].

For selection of features, researchers have shown the importance of selecting subsets of variables that together have good predictive power, as opposed to simply ranking variables according to their individual predictive power[115]. Thus, we use the wrapper method which evaluates selected subsets of variables in terms of their overall prediction power. Using greedy forward algorithm we select subsets of features to be evaluated under a specific criterion (i.e., root-mean-square error (RMSE)) [115]. Five algorithms representing an array of popular machine learning (i.e., Linear Regression, Regression Trees, Regression Rules, Instance-Based Learning Algorithms, and Support Vector Machines) were used for the evaluation. Figure 4-5 shows how frequently a given feature was deemed necessary in the prediction of time of selection. In the next section, we will discuss three of the more complex selected features of choice complexity in a mixed model assembly line and the form in which they were collected in this illustrative example.

4.4.2.1. Similarity of variants

Researchers have argued that an increase in the similarity of choice alternatives leads to longer decision time, due to inefficient memory retrieval [66],[65].

The current formalization of similarity measures has relied heavily on knowledge representation, where the similarity between two objects is typically based on the semantic similarity. Knowledge representation allows a better understanding of the complexity or the ambiguity caused by stimuli, since some semantic memory data structures store and use lexical information in a way similar to how humans store and use lexical information [116]. Semantically, objects can be represented using the description of their properties. That is, it is possible to express the similarity as a function of distance between an object's respective properties. In this case, object properties will be represented in the form of dimensions with ordered values [117]. In this context, the semantic distance can be used as an analogy to spatial distance.

Geometric based semantic distance measure is based on the notion of multi-dimensional vector spaces. Objects or concepts are modeled within a multi-dimensional space and their spatial distance indicates the semantic similarity. The geometric model uses multi-dimensional scaling (MDS), which is a method of representing the measurement of similarities (or dissimilarities) as a distance between points of a low-dimensional multidimensional space among pairs of objects [117]. Once the dimensions are set and represented, the semantic distance between objects a and b denoted as $d(a,b)$ can be formulated as a function of total compound weighted distance of all their properties. We note that the distance obtained is the Euclidian spatial distance as shown in (4-1).

$$d(a,b) = \left[\sum_{i=1}^{n} |\varepsilon_i (x_{ai} - x_{bi})|^2\right]^{1/2} \tag{4-1}$$

where x_{ai} is the value of dimension *i* for stimulus a x_{bi} is the value of dimension *i* for stimulus b, ε_i is the weight assigned to dimension *i* as a functional reflection of the salience or prominence of the various dimensions. By default, we set ε_i to 1, that is, each dimension is equally important.

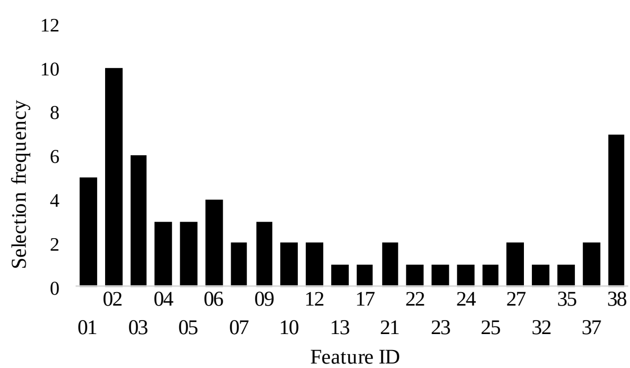

Figure 4-5 Selected features

In this equation, it is important to acknowledge the difference in the object properties. For example, while some properties can be geometrically comparable (e.g., volume, etc.), other properties that are difficult to measure can present a bigger challenge (e.g., complex shapes, etc.) Thus, object properties with a measurement challenge can .be presented as features with Boolean values (i.e., true or false). In this chapter, we represent objects by using a combination of dimensions with ordered values and Boolean values. Here Boolean values represent features that hold or not for that specific object. In this particular case, the distance between two objects based on a given feature can be obtained as shown in (4-2).

$$|x_{ai} - x_{bi}| = \begin{cases} 0 \; if\ both\ a\ and\ b\ possess\ feature\ x_i \\ 1 \qquad\qquad otherwise \end{cases} \tag{4-2}$$

where x_{ai} and x_{bi} denote feature x_i of object *a* and *b*, respectively.

Next, after the semantic distance between objects a and b, $d(a,b)$ is obtained, it is converted to the similarity measure by using (4-4), where the similarity is an exponential decay function of distance expressed as follow [72]:

$$s(a,b) = e^{-c.d(a,b)} \tag{4-3}$$

where $s(a,b)$ is the similarity between object *a* and *b*; c is the general sensitivity parameter. Note that for N number of options, there exist a $N \times N$ distance matrix whose entry d_{ij}, $1 \le i, j \le N$, satisfies the following metric's properties:

- d_{ij} *= 0 for all* $i = j$,
- *All the off-diagonal entries are positive, such that* $d_{ij} > 0 \; if \; i \neq j$,
- *The matrix is a symmetric matrix, such that* $d_{ij} = d_{ji}$ *and*
- *For any i and j,* $d_{ij} \leq d_{ik} + d_{kj}$ *for all k (the triangle inequality)*

Here, d_{ij} denotes the distance between option i and j, as seen in (1).

It follows that the level of similarity corresponding to a given target variant (v_t) can be obtained as follow:

$$S(v_t) = \sum_i^N s(v_t, v_i) = \sum_i^N \left(s\left(v_j, v_i\right) \middle| v_j = v_t\right) \tag{4-4}$$

where *N* is the total number of variants, t is the target variant, $s\left(v_j, v_i\right)$ is the similarity between variant i and j computed as shown in Equation (4-3).

In our illustrative example, we represent each screw using three dimensions: thickness, length, and head shape. The overall similarity matrix is shown in Table 4-2.

Table 4-2 Similarity matrix of screws

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15
s1	1.0000	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.0498	0.0183	0.0067	0.0025	0.0041	0.0015	0.0002	0.0025
s2	0.1353	1.0000	0.1353	0.0498	0.0067	0.0009	0.0302	0.0498	0.1353	0.0498	0.0183	0.0302	0.0111	0.0015	0.0183
s3	0.0183	0.1353	1.0000	0.3679	0.0498	0.0067	0.2231	0.0067	0.0183	0.0498	0.1353	0.0041	0.0111	0.0111	0.0025
s4	0.0067	0.0498	0.3679	1.0000	0.1353	0.0183	0.0821	0.0025	0.0067	0.0183	0.0498	0.0015	0.0041	0.0302	0.0009
s5	0.0009	0.0067	0.0498	0.1353	1.0000	0.1353	0.0111	0.0003	0.0009	0.0025	0.0067	0.0002	0.0006	0.0041	0.0001
s6	0.0001	0.0009	0.0067	0.0183	0.1353	1.0000	0.0015	0.0000	0.0001	0.0003	0.0009	0.0000	0.0001	0.0006	0.0000
s7	0.0041	0.0302	0.2231	0.0821	0.0111	0.0015	1.0000	0.0015	0.0041	0.0111	0.0302	0.0183	0.0498	0.0498	0.0006
s8	0.0498	0.0498	0.0067	0.0025	0.0003	0.0000	0.0015	1.0000	0.3679	0.1353	0.0498	0.0821	0.0302	0.0041	0.0015
s9	0.0183	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.3679	1.0000	0.3679	0.1353	0.2231	0.0821	0.0111	0.0183
s10	0.0067	0.0498	0.0498	0.0183	0.0025	0.0003	0.0111	0.1353	0.3679	1.0000	0.3679	0.0821	0.2231	0.0302	0.0067
s11	0.0025	0.0183	0.1353	0.0498	0.0067	0.0009	0.0302	0.0498	0.1353	0.3679	1.0000	0.0302	0.0821	0.0821	0.0025
s12	0.0041	0.0302	0.0041	0.0015	0.0002	0.0000	0.0183	0.0821	0.2231	0.0821	0.0302	1.0000	0.3679	0.0498	0.0183
s13	0.0015	0.0111	0.0111	0.0041	0.0006	0.0001	0.0498	0.0302	0.0821	0.2231	0.0821	0.3679	1.0000	0.1353	0.0015
s14	0.0002	0.0015	0.0111	0.0302	0.0041	0.0006	0.0498	0.0041	0.0111	0.0302	0.0821	0.0498	0.1353	1.0000	0.0002
s15	0.0183	0.1353	0.0183	0.0067	0.0009	0.0001	0.0041	0.0498	0.1353	0.0498	0.0183	0.0302	0.0111	0.0015	1.0000

4.4.2.2. Sequence Rule

The MMAL is an assembly line system, in which various models of a common base product are manufactured in intermixed sequences. In a mixed-model assembly line, assembly sequence planning plays a crucial role in a successful assembly procedure, and a good sequence often saves time and cost[118]. In fact, other than line balancing problems, the mixed-model assembly lines give rise to a short-term sequencing problem. Therefore, within a planning horizon, the production sequence ought to ensure an efficient workflow. Sequencing is central to effectiveness of the assembly process because different sequencing rules or constraints are set to ensure that the line do not present a work overload, or the works are well balanced throughout the stations. The sequencing rules often specify how many models should contain a specific option out of a given successive models. Thus, based on the predefined rules, the sequencing problem can be formulated as a constraint satisfaction problem.

Assembly sequencing in this illustration can be defined as a three-tuple, (V, S, r) where

- $V = \{v_1, .., v_{15}\}$ is the set of different variants (screw);
- $S = \{S_1, .., S_n\}$ is the set of different subsequences; $S_k = \{p_{k1}, .., p_{km}\}$ where p_{kj} denotes a position j in subsequence k, and m is the number of variants in the subsequence
- $r : V \times S_k \rightarrow \{0, 1\}$; that is, if variant v_i is to be part of assembly at p_{kj} then $r_{v_i p_{kj}} = 1$; $r_{v_i p_{kj}} =$ 0, otherwise.

Assuming that the objective is to minimize the choice complexity, a good sequence not only fulfils the constraint but also minimizes the uncertainties in the choice process by promoting a correct anticipation. Since there are three different classes, all variants are partitioned into 3 subsets (i.e., per head shape) where V = $\bigcup_{i=1}^{3} V_i$. The subsets are as follows:

- $V_1 = \{v_1, v_4, v_6, v_8, v_{12}, v_{14}, v_{15}\}$

- $V_2 = \{v_2, v_5, v_7, v_9, v_{10}, v_{11}, v_{13}\}$
- $V_3 = \{v_3\}$

We consider three types of sequence in this illustrative example. The first sequence rule (i.e., Rule A) can be described using the following constraint

$$\sum_{j}^{2} r_{v_i p_{kj}} < 2\,, v_i \in V \tag{4-5}$$

Constraints in Equation (4-5) mean that the same variant shall not be requested successively in any sequence. In other words, the constraint imposes that, for any subsequence of two consecutive models on the line, at most one of them may require v_i, for any $v_i \in V$. The constraints of the second sequence rule (i.e., Rule B) are as follows:

$$\sum_{v_i \in V_t} \sum_{j}^{5} r_{v_i p_{kj}} \leq 2, \mathrm{t} = 1,2,3 \tag{4-6}$$

$$\sum_{v_i \in V_t} \sum_{j}^{2} r_{v_i p_{kj}} < 2, \mathrm{t} = 1,2,3 \tag{4-7}$$

Constraints in Equation (4-6) mean that in any sequence of 5, at most two screws from any partition shall be included. That is, for any subsequence of 5 consecutive products on the line, at most 2 of them may require screw v_i from the same group V_k for all k. The constraints in Equation (4-7) imply that two variants from the same group or partition shall not be requested successively in any sequence. The final sequence rule is simply a random sequence in which the stimuli are randomly generated from a uniform distribution to ensure an equal probability for all the screws. That is, each variant is equally likely to be requested at any position of any given sequence.

The objective function in the sequencing problem is often minimizing the labor utilization or the spreading of material demand [119]. For example, the solution to a sequencing problem can ensure that models responsible for high station times alternate with less work-intensive ones. In this illustrative example, the objective is to minimize the time it takes to respond to the stimulus requesting to select a given screw. Here, the goal is to minimize the operator's visual search space. Let $x_{p_{kj}}$ be the position of screw requested at p_{kj}, thus our objective function is as follows:

$$min \sum \left| x_{p_{kj}} - x_{p_{kj+1}} \right| \tag{4-8}$$

Note that we assume that the positions of screws are fixed.

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4.4.2.3. Physical arrangement

According to [120], location information is one of the most important factors in ubiquitous computing. Methods like triangulation, scene analysis and proximity are mainly used to determine a position of an object. In this example, the positions of screws are fixed before each experimental run. Two setups are used: first; the screws are arranged according to their visual features. That is, we place screws from each subset (i.e., V1, V2& V3) closely together. In the second setup, screws are randomly positioned regardless of their features because the theory of grouping states that humans naturally perceive objects as organized patterns and objects. For example, parts that are similar and close to each other tend to be grouped since their attributes are perceived as related[113]. Note that the distance between any two closely positioned screws is equal for both setups.

4.4.3. Result and discussion

4.4.3.1. Machine learning and prediction of selection time

A perfect prediction of the operator's selection time is unattainable; however, the proposed method fairly mimics the actual physical setups that define the choice complexity in a mixed model. Hence, in accordance with the features of choice complexity, we built several machine learning algorithms and trained them by using the human in loop search time. As stated earlier, we select representative algorithms from some of the popular machine learning technique namely: linear regression, regression trees, regression rules, instance-based learning algorithms, and support vector machines.

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Table 4-3 Comparison of regression algorithms

Test options	Regression Algorithm	Correlation Coefficient	MAE	RMSE
10fold Cross-Validation	Linear Regression	-0.0461	16.4838	371.492
	Random Forest	0.9101	0.1832	0.2827
	Decision Table	0.8327	0.2406	0.3674
	K-NN	0.7917	0.2792	0.4119
	SVM	0.8405	0.2562	0.3625
70/30 split	Linear Regression	0.5597	0.3406	0.7369
	Random Forest	0.9172	0.1977	0.3236
	Decision Table	0.8358	0.2553	0.4138
	K-NN	0.784	0.3193	0.4743
	SVM	0.8434	0.2614	0.4114
Leave 1 out Cross-Validation	Linear Regression	-0.0474	16.7196	368.4111
	Random Forest	0.909	0.1846	0.2834
	Decision Table	0.8445	0.2369	0.3551
	K-NN	0.798	0.2757	0.4067
	SVM	0.8326	0.2637	0.3704

Linear regression: We fit the regression model using the least squares. Based on the result in Table 4-3, the performance of linear regression on our dataset is extremely poor.

Regression Trees: Regression trees are binary decision trees with numerical values at the leaf nodes: In this analysis, we use random forest to predict the operator's reaction time. The forests studied here consist of using randomly selected inputs or combinations of inputs at each node to grow each tree. The number of features the random forest is allowed to try in a given individual tree was set to the first integer less than log2M+1, where M is the number of features. We put no limitation on the maximum number of trees[121]

Regression Rules: Here we use the decision table with default mapping to the majority class, where a stepwise selection is used to find good attribute combinations for the decision table[122].

Instance-Based Learning Algorithms (IBL): IBL are learning algorithms that, instead of performing explicit generalization, compares new problem instances with instances seen in training, which have been stored in memory. That is, they construct hypotheses directly from the training instances themselves. Here we use k-nearest neighbor (K-NN) regression as exemplar IBL algorithm. K-NN is a non-parametric method that assigns weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. Using a cross validation, four nearest neighbors were obtained to be optimal. The Euclidian distance was used to compute the distance between neighbors[123].

Support vector machine: We used the sequential minimal optimization algorithm to implement the SVM with Gaussian kernels. After a thorough grid search, the SVM parameters, namely, C parameter, RBF Sigma and Epsilon were set to 0.7024, 0.9045, and 0.0702 respectively[124].

Three testing methods were used to assess the accuracy of each machine learning. First, seventy percent of the data were used for training while the remaining 30 was used for testing the regression models. Second, a 10fold and leave one out cross validation were also used for training and testing. The time to build each model varied from less than 0.1sec for KNN and decision table to approximately one second for random forest and SVM. We compared the regression models based on the three metrics; namely, the coefficient of correlation, the mean absolute error(MAE) and the root mean squared error (RMSE).

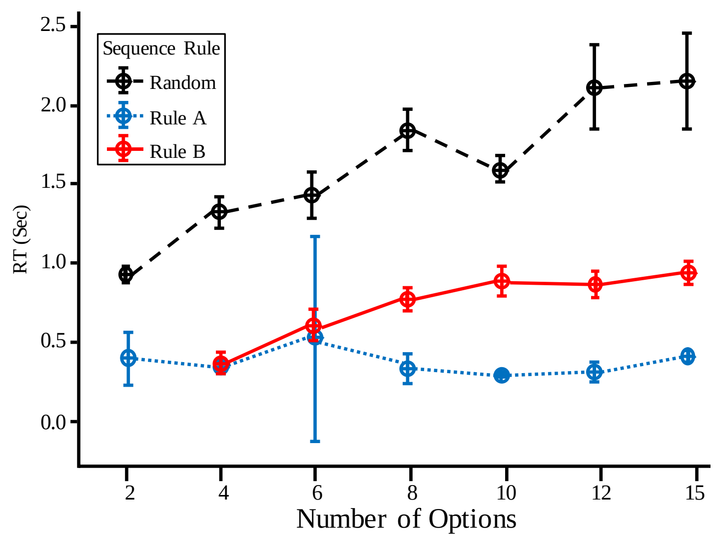

Figure 4-6. Changes in the mean of the actual reaction time(RT) caused by various parameter changes (per random forest algorithm). As the number of alternative choices grow, the changes in the selection time depend heavily on the sequencing rule

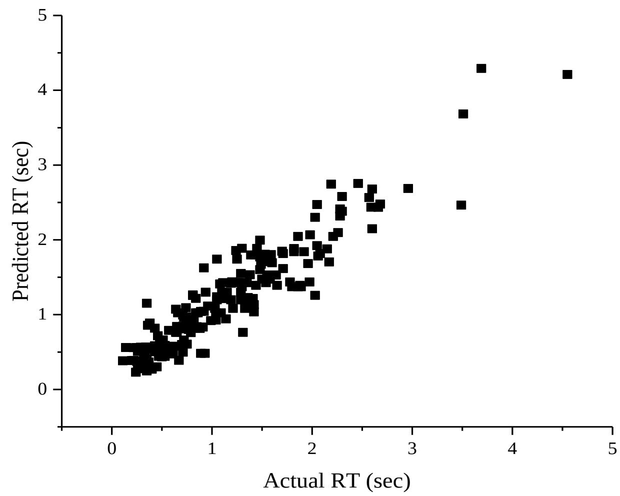

Figure 4-7 Comparison of Actual selection time(tested) vs Predicted selection time(simulated) obtained using random forest regression algorithm

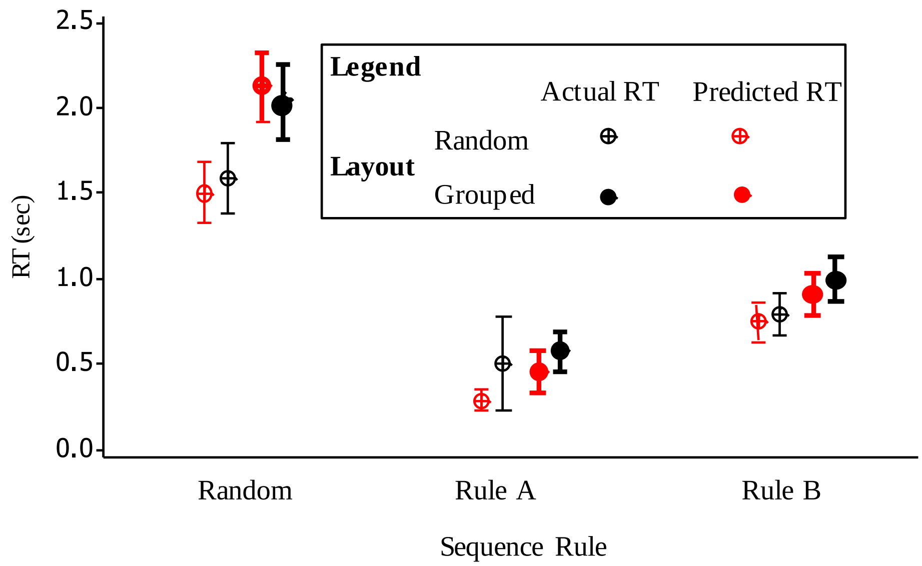

Figure 4-8. Combined effect of sequence rule and the layout setting on both the actual and predicted reaction time (selection time). We use random forest regression algorithm for the prediction selection time.

Table 4-3 shows the selected regression models and their respective performance according to the three metrics. The maximum coefficient of correlation reaches as high as 90% implying a high correlation between the actual and the predicted values. Decision tree appears to be the better fit for this particular problem where random forest outperforms other algorithms in all categories, regardless of the testing methods. That is, the Random forest presents both the highest coefficient of correlation, the lowest MAE and RMSE. Notice how all the three testing methods have very similar results. To some extent, the results shown in Table 4-3 corroborates the notion of human in the loop machine learning simulation. That is, while the standard for a good machine learning model varies depending on the prediction goal, one can argue that even the least accurate predication on the list still offer significant insights on the factors affecting the choice complexity and their implication on the service time. The results in Table 4-3 are confirmed in Figure 4-7 that shows the comparison between predicted selection times (per random forest) along with the real selection times.

4.4.3.2. Human-involved system control and simulation

Using the proposed method, the operator's task can be broken down into subtasks that include part selection whose service time can be obtained by following the steps in Figure 4- 6. Thus, the operator becomes a part of the simulation until the simulation parameters are accurately extracted. The training ends when the threshold RMSE or accuracy rate is consistently reached. This means that the model is reliable enough to be used independently in predicting the operator's performance to be included in simulating the overall assembly line.

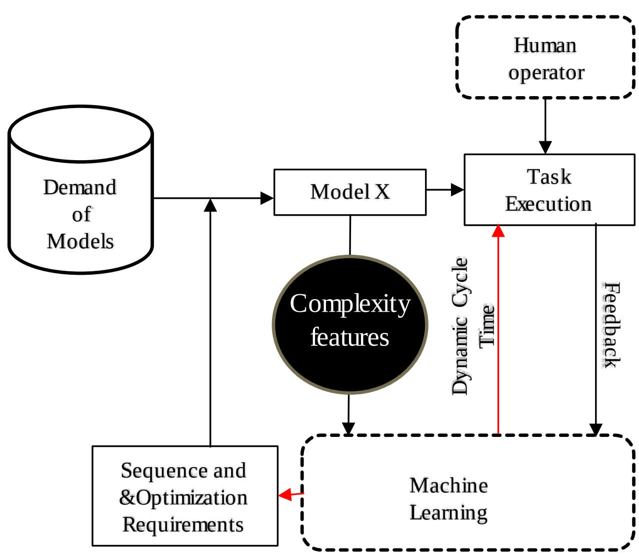

Figure 4-9 Incorporation of machine learning into a MMAL

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The inclusion of a real human in the simulation improves the accuracy and reliability of the simulation prediction, particularly regarding the operator's service time. Human involvement in the loop also provides more room for testing and optimizing the number of assembly line policies. As shown in Figure 4-8, changes in key factors improve the choice complexity in a mixed model assembly. Thus, it is possible to reduce the time required to make a choice by optimizing the sequence, the layout, or to reduce the number of options. Furthermore, Smart manufacturing boosts sensing technologies capable of capturing a wide range of data necessary for advanced analysis of manufacturing operations. (e.g., sequences, task data, etc.)[125]. That is, the imminent adoption of smart manufacturing in the future will give rise to several possible applications of machine learning in a wide range of human-involved manufacturing processes in which the proposed framework can be applied accordingly.

Each model commands a different level of complexity. Thus, in a flexible manufacturing environment, the proposed methodology can be of assistance in analyzing and optimizing the task sequence. Also, the predicted reaction time, can be used to allocate dynamic cycle time for tasks according to their complexities. For example, Fig 4-9 summarizes how machine learning algorithms can be incorporated into the overall assembly as follow:

- The human operator's performance logs serve as response variable (Feedback) used to train and continuously improve the machine learning algorithm
- The trained algorithm is used to predict the cycle time based on the complexity of the scheduled task.
- The scheduling and sequencing algorithm incorporates the machine learning data to ensure that the chosen sequence is associated with low complexity level.

4.5. Conclusion

One of the problems that emerges from increased varieties in a mixed assembly line is the choice complexity. Adding a model variant in a manufacturing system increases the number of product components, the resources needed to manage the interactions of these components. These aspects of complexity in the system incur additional direct and/or indirect costs for managing the manufacturing process and associated resources. As the number of options grow, operators inefficiently require more time to make accurate decisions. Different parameters have been shown to improve or worsen the choice complexity.

In this study, we propose a simulation framework in which various parameters of choice complexity are tested to assess the overall effect on operators' effectiveness. We select the features of choice

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complexity and build a regression model where human reaction time is the response variable used for training and testing the model. The model, along with an illustrative case study, serves as both a tool to evaluate the impact of choice complexity on operator's effectiveness, and provides insight on how to approach the choice complexity without necessarily affecting the overall manufacturing throughput.

Although the primary research objective was attained, there was some unavoidable limitations. For instance, while the screw selection experiment illustrates the overall proposed framework, it is arguable that the system is too simple to showcase every aspect of human in the loop machine learning simulation framework. Also, due to the subjective nature of human operators and the small sample size of human subjects involved in the experiment, the simulation results cannot be generalized; instead, the experiment should serve as exemplary template of the proposed simulation framework. Despite the limitations, the proposed model is valuable tool in the pursuit of an effective modeling and simulation of human-centered complex systems.

Although the proposed simulation framework is limited to the simulation of choice complexity in a mixed model assembly line, the same schematic may be applied in real-time simulation of most human involved systems, especially with the technological advances in data collection, e.g., sensors. Thus, the proposed model provides an example of how one can effectively incorporate human component in the smart manufacturing environments.

We admit that the illustrative example used in this study is not identical to the real manufacturing assembly line. However, it still captures the underlying source of complexity in the choice making. Thus, this method is further expected to be duplicated in a real assembly line with the right resources. In our future work, we plan to investigate the feasibility and scalability of the proposed model in real and complex manufacturing assembly lines, including an expansion of the model to include the overall assembly system simulation.

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Chapter 5

Conclusion

5.1. Research Summary

Although affordance theory has explained the goal-directed and perception-based human actions within dynamic environments, it has not been widely used to build computational models in human-involved systems. The first chapter of this dissertation proposes a weighted affordance-based model for human agent decision-making behavior. The baseline assumption is a bounded rationality; an agent chooses a cost-effective measure when choosing an action; that is, the lower the cost (or load) associated with an action, the higher the likelihood of that action being selected. However, limited amount of information available and uncertainties included within an environment may hinder the agent from effectively choosing the optimal path to reach the desired goal.

Under the MDP umbrella, the model quantitatively assigns agent' subjective load to each alternative choice that trigger state transition. Using dynamic programming, we assign optimal value (i.e., minimum cost/load) to each state, corresponding to the optimal policy (optimum mapping of action to state) according the information available. The assignment of values to each state follows the theoretical principal of full rationality, hence the best policy is considered when setting the value. Here, the load is expressed in terms of NASA- TLX which serve a metric for estimating cost associated to taking a given action. NASA-TLX is a multi-dimensional rating scale in which information about the sources and the magnitude of workload factors are combined to derive a reliable estimate of both physical and psychological workload. NASA-TLX values are then generated in accordance with the theory of affordance. At the execution level, the actions are derived in a stochastic way from a formerly conceived plan followed by perception-directed adjustments.

In flexible human-centered systems, operators are often offered multiple alternatives scenario to affect the system course of action. However, as the number of alternative choices grow, the effectiveness of making a choice becomes a crucial parameter in designing and building HCS. As showcased in manufacturing industry, the mass customization has become the new norm in manufacturing systems, and the number of distinct options in mixed model assembly line has been growing at an unprecedented rate,

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inducing complexity with potential impact on human performance. Thus, we explore the analytical relationship between the flexibility (variation) and the complexity of human role in HCS, specifically the MMAL. The third chapter, presents a novel method to compute manufacturing choice complexity, incorporating option counts and option similarity based on the well-known information entropy concept. The proposed model not only has the ability to compute the overall complexity of the system, but can also track the contribution of each specific option or station to the overall system complexity. We conducted a simple experimental design to verify the impact of the similarity of options and reaction time to the overall complexity. Then, we further compared our proposed complexity measure with the traditional complexity that did not explicitly discuss the similarity of options and found that our model is more effective.

In addition to complexity metric, the dissertation proposes a human in the loop (HIL) simulation approach to investigate human's performance in HCS. In HCS such as MMAL, human performance, a key factor in adaptability and flexibility, is of major interest due to its impact on the overall system. Thus, the fourth chapter proposes a HIL simulation framework in which various parameters of choice complexity are tested to assess the overall effect on operators' effectiveness. At the initial stage of the simulation, a stepwise feature selection was used to identify the significant features affecting the choice complexity. The selected features were in turn used to build a regression model in which human reaction time with regard to different degrees of choice complexity serves as a response variable used to train and test the model. The proposed model, along with an illustrative case study, not only serves as a tool to quantitatively assess the impact of choice complexity on operator's effectiveness, but also provides an insight into how complexity can be mitigated without affecting the overall manufacturing throughput.

5.2. Research Contributions

For the 4th industrial Revolution, the manufacturing system can be capable of managing highest level of complexity ever under the situation that multiple humans and robots are collaborating within same time and space.

The agent-based model in this chapter is expected to be used for modeling and simulation of human-involved complex and dynamic systems. We envision that the proposed model can be used to examine problems of human-involvement in system design. That is, the framework makes it feasible to model and simulate human-involved system that cannot be tested with physical simulation, or whose physical simulation would be prohibitively expensive. It can also be used to highlight the effect of interactions between human agents and the environment under dynamic and uncertain conditions.

Furthermore, the proposed complexity measure serves as a tool to investigate how the system complexity and the resulting performance will look if a given set of policies were to be implemented. For example, it offers a decision maker the ability to hypothetically add a number of options, after which an

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analytical result can be obtained. Thus, the model can be used to assess various scenarios and their respective effects on the overall complexity and reliability of the system. For example, parts associated with the highest level of complexity can be determined and managed appropriately.

Finally, the proposed HIL simulation framework offers the tool to investigate human's performance in HCS such as MMAL. Although the framework is limited to the simulation of choice complexity in a mixed model assembly line, the same schematic may be applied in real-time simulation of most human involved systems, especially with the technological advances in data collection, e.g., sensors. Thus, the proposed framework in chapter 4, provides a sense of understanding of how to encapsulate human component effectively in the smart manufacturing settings. The proposed HIL framework offers a capability to investigate the impact of human behaviors on the performance of the whole HCS, especially the manufacturing system.

5.3. Research Limitations and Future works

Although the primary research objectives were attained, there still exist limitations. The challenges of validating of goal-directed action modeling in a real emergency, cannot be ignored. Also, due to the subjective nature of human agents and the small size of human subjects involved in both the NASA-TLX data collection, and choice complexity experiments, the simulation results cannot be generalized; instead, the example should serve as exemplary template of the proposed simulation frameworks. In additional, the proposed complexity computation model with an experimental study, while practical, could be further understood with more experimentations accounting for operator experience, stimulus sequence, etc. In addition, cost and time impacts on a decision maker should be further explored.

Future research directions include:

- Integrate the proposed agent-based simulation model with a virtual reality environment to obtain more realistic results. This would be beneficial in implementing a human-in-the-loop simulation framework and adaptive agent-environment interaction which can enhance the ability to simulate and evaluate human-involved systems
- Investigate the feasibility and scalability for a full validation of the proposed model in real and complex manufacturing assembly lines, including an expansion of the model to include the overall assembly system simulation
- The proposed model of complexity computation, while practical, could be further understood with more experimentations accounting for operator experience, stimulus sequence, etc.
- A justification study of how variety impacts on the overall system performance in terms of the cost-benefit analysis. On one hand, if customers base their purchasing decisions on specific features,

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the increased complexity can be compensated by the increased sales. On the other hand, additional costs associated with the increased complexity may be unwarranted with lower demand.

- More complex parts could be further investigated in the future to see the impact and trend of complexity measure.

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Appendix

NASA TLX for Evacuation Simulation

Gender*

(Select your gender)

- ❑ *Female*
- ❑ *Male*

Age: ………………………………………...

(How old you)

BUILDING EVACUATION

Assume you are in a multi-story building and want to exit the building. There are 4 options to take: taking an elevator, taking the stairs, jumping all the way down, and climbing down (on a rope). Everything is operating normally (i.e., the environment is completely safe). Rate the workload you would expect from EACH action according to 6 scale titles, assuming the action is to be taken from the second floor (2F), the fourth floor (4F) or the sixth floor (6F).

Mental demand*

For EACH action (Taking an elevator, Taking the stairs, Jumping and Climbing down), on a scale of 1 (Low) to 20 (High), how much mental and perceptual activity would be required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Would the action be easy or demanding, simple or complex?

(Low ←→ High)

Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Climb down	*6F*	*Low*		*High*
	4F	*Low*		*High*

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	2F	*Low*		*High*

Physical Demand*

How much physical activity would be required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Would the task be easy or demanding, slow or brisk, relaxing or strenuous, restful or laborious?

(Low ←→ High)

Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Climb down	*6F*	*Low*		*High*
	4F	*Low*		*High*

	2F	*Low*		*High*

Temporal Demand*

How much time pressure would you feel due to the rate or pace at which the tasks or task elements occurred? Would the pace be slow and leisurely or rapid and frantic?

(Low ←→ High)

Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Climb down	*6F*	*Low*		*High*
	4F	*Low*		*High*

	2F	*Low*		*High*

Performance*

How successful do you think you would be in accomplishing the goals of the task/ action (i.e., to exit the building)?

(Good ←→ Poor)

Elevator	*6F*	*Good*		*Poor*
	4F	*Good*		*Poor*
	2F	*Good*		*Poor*
Stairs	*6F*	*Good*		*Poor*
	4F	*Good*		*Poor*
	2F	*Good*		*Poor*
Jump	*6F*	*Good*		*Poor*
	4F	*Good*		*Poor*
	2F	*Good*		*Poor*
	6F	*Good*		*Poor*

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Climb down	*4F*	*Good*		*Poor*
	2F	*Good*		*Poor*

Effort*

How hard would you have to work (mentally and physically) to accomplish your level of performance (your goal??? Optimal level of performance???)?

(Low ←→ High)

Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*

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Climb down	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*

Frustration Level *

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent would you feel while conducting the task?

(Low ←→ High)

Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
	6F	*Low*		*High*

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Climb down	*4F*	*Low*		*High*
	2F	*Low*		*High*

Part II

FIRE EMERGENCY

Similar to Part I, assume you are in multi-story building. However, this time, the building is ON FIRE and you want to exit the building in order to save your life. There are 4 options: Taking an elevator, taking the stairs, jumping all the way down, and climbing down (on a rope). Note that every action selection carries some risk, some more than others. After a careful consideration, rate the workload you would expect according to the 6 scale titles.

(Low ←→ High)

Workload Type: (e.g., Mental Load)				
Elevator	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Stairs	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*
Jump	*6F*	*Low*		*High*
	4F	*Low*		*High*

	2F	*Low*		*High*
Climb down	*6F*	*Low*		*High*
	4F	*Low*		*High*
	2F	*Low*		*High*

PAIRWISE COMPARISON

Select the scale title that represents the more important contributor to the workload for each action

	Mental Demand	Physical Demand
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Mental Demand	Temporal Demand
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Mental Demand	Performance
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Mental Demand	Effort
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Mental Demand	Frustration
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Physical Demand	Temporal Demand
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Physical Demand	Performance
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Physical Demand	Effort
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□

Climbing down (Rope)	☐	☐

	Physical Demand	Frustration
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Temporal Demand	Performance
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Temporal Demand	Effort
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Temporal Demand	Frustration
Taking the Elevator	☐	☐
Taking the Stairs	☐	☐
Jumping	☐	☐
Climbing down (Rope)	☐	☐

	Performance	Effort
Taking the Elevator	☐	☐

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Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Performance	Frustration
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

	Effort	Frustration
Taking the Elevator	□	□
Taking the Stairs	□	□
Jumping	□	□
Climbing down (Rope)	□	□

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Part III

(The third part of the questionnaire aims to capture how the load changes with the dynamic changes of the environment)

Assume you are planning to take an elevator, but due to congestion, you have to wait a little longer in order to take it. Rate each workload (6 scales) you would expect for each waiting time.

Waiting Time	*Workload Type: (e.g. Mental load)*	
30 sec	*Low*	*High*
1 min	*Low*	*High*
2 min	*Low*	*High*
3 min	*Low*	*High*