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Smart Manufacturing Nudging Design with Conjoint Prospect Theoretic Modeling of Nudging Behavior

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Abstract

With the development of advanced manufacturing technologies, the manufacturing environment becomes complex, dynamic, and filled with human-machine collaboration. To improve manufacturing performance, the efficiency of collaboration is critical. Nudging, a concept in behavioral economics, is employed to indirectly encourage individuals to act or believe in a certain way through subtle interventions. In the manufacturing context, nudging aims to alter or influence operators' behaviors to better work with technology during their interactions. Meanwhile, the research of manufacturing nudging design is to investigate the theoretical foundation of design for human behaviors. To solve this problem, this paper conducts system analysis for smart manufacturing nudging design and identifies four fundamental questions, including manufacturing nudge generation, nudging behavior modeling considering affective cognition, model parameter estimation, and nudging personalization optimization. The paper further proposes a conjoint prospect theory-based approach to nudging behavior modeling. Affective cognition modeling is also discussed for parameter shaping of the nudging behavior model. An example case of nudging for assembly inspection is presented to illustrate the proposed approach.

Keywords
Nudging Design, Behavioral Design, Prospect Theory, Manufacturing Nudging, Human-automation Interaction

1. Introduction
The development of advanced manufacturing technologies has greatly improved manufacturing system performance and changed the relationship between humans and automation agents. The manufacturing environment also becomes more complex and dynamic, requiring close collaboration between humans and machines. To facilitate the efficiency of such collaboration, the industry calls for the consideration of human factors in manufacturing operations with the concept of human-cyber-physical systems (Zhou et al., 2019). Nudging, as one approach to human-computer

interaction, aims to alter people's behaviors in a predictable way without forbidding any option or significantly changing their economic incentive (Thaler and Sunstein, 2009). In the context of manufacturing, nudging aims to improve manufacturing performance by indirectly or directly influencing human behaviors, such as using HoloLens's augmented reality to assist operators with machine maintenance, and Figure 1 shows some examples of manufacturing nudging. Apart from visual nudges, manufacturing nudging can also take other forms, such as auditory nudges and somatic nudges, with the objective of manufacturing performance improvement in the human-cyber-physical system context (Yang et al., 2022). These nudges can have direct or indirect effects on human operations and coupled with information from the cyber system.

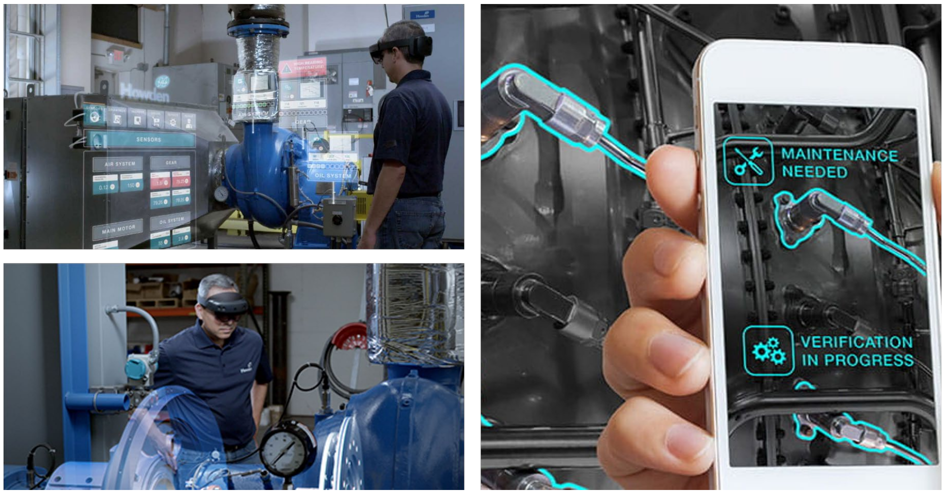


Figure 1. Examples of Manufacturing Nudging

With manufacturing operations becoming more complex, there are growing demands for manufacturing nudging to improve the efficiency of human-automation interaction. Although a lot of research has been conducted about nudging and its effects on human behaviors, few research studies how nudges should be designed. In this regard, the motivation of this paper is to study the framework of manufacturing nudging design and investigate its theoretical foundations. While nudging design is an interdisciplinary subject concerned with psychology, cognitive science, and behavioral economics, this paper addresses the nudging design problem from an engineering perspective with mathematical modeling.

Manufacturing nudging design is essentially to study how information should be presented to human operators and what information to present so that they can positively influence human behaviors for better performance. From this perspective, a nudge entails both the nudging form and the nudging content, and nudging design is to use different theories to identify the proper form and content that will guide operators for better behavior. In this regard, this paper identifies four key questions for manufacturing nudging design using behavioral economics, including nudge generation, nudging behavior modeling considering affective cognition, model parameter estimation, and nudging personalization optimization. Meanwhile, considering the conflicting goals inherent in behavioral economic concerns towards payoff and cost, such behavioral economic decisions in designing products and service systems should always be two-fold. Therefore, this paper proposes a conjoint prospect theory model based on the original prospect model for modeling a nudging behavior with customer-producer perceptions: production managers play the role of producers who think nudging helps improve manufacturing performance, while operators are customers who see nudging as a burden because of the extra work to interact with nudges. Apart from this, different affective states of decision-makers can influence their perceptions in certain patterns (Ahn, 2010). For instance, people tend to be more risk-seeking when they are in positive affective states. To model the influence of affective cognition, parameters of the conjoint prospect theory model in different prospect value curve shapes are studied.

The structure of this paper is as follows. Section 2 reviews the related work for this study, including nudging design and manufacturing nudging, and prospect theory for behavioral modeling. Section 3 presents the problem formulation of manufacturing nudging design, and system analysis for smart manufacturing nudging design is also discussed, which illustrates the four fundamental questions in nudging design through behavioral economics modeling. In Section

4, a conjoint prospect theory-based approach is introduced to model the nudge perception for nudging behavioral modeling. Section 5 further discusses operators' affective cognition modeling through model parameter shaping. Section 6 presents an example case of assembly inspection nudging to illustrate the proposed smart manufacturing nudging design. Finally, concluding remarks are made in Section 7.

2. Literature Review

2.1 Nudging Design and Manufacturing Nudging

Nudging design, as one type of behavioral design and persuasive design, has become an emergent and important domain of design research that aims to influence human behaviors by ethically motivating people in certain ways (Fogg, 2002; Khadilkar and Cash, 2020; Jiao et al., 2022). It also fits in the broader context of emerging human-cyber-physical systems design that is envisioned in Industry 5.0 (Leng et al., 2022). Considering its interdisciplinary perspective as the extension of user experience design research (Zhou et al., 2021), nudging design is still in an early stage, and its research foundations include psychology, behavior economics, sociological theory, and cognitive science. Some research focuses on conceptual works, such as guidelines on implementing nudges, to depict nudging design with multiple phases where the nudging goal and the nudging users are analyzed (Schneider et al., 2018; Meske and Potthoff, 2017). Meanwhile, with pervasive smart technologies applied in modern product and service systems, massive operational data and user information can be used, and digital nudging as well as data-driven nudging design become applicable (Mirsch et al., 2018; Wang et al., 2022). In the context of data-driven nudging design is particularly intrigued by personalization, which can be contributed by the utilization of personal, contextual, and social media data for smart, dynamic, and tailor-made nudges (Dalecke and Karlsen, 2020).

In the manufacturing context, nudging can be applied to focus the attention of operators or provide suggestions for certain tasks and activities for behavioral operations management (Borghans and Golsteyn, 2014). There exists much evidence that nudges can serve to steer operator behavior toward desired outcomes and increase performance and safety awareness (Dhanorkar and Siemsen, 2021). Nudges come from the signals from the manufacturing environment and take different forms that humans can sense (Yang et al., 2022). Normally, they act as interventions during operations, such as reminders, feedback, default options, and so on. For instance, operators working in an assembly line can wear augmented reality smart glasses to receive nudges for reducing assembly errors (Danielsson et al., 2020).

2.2 Prospect Theory for Behavioral Modeling

Prospect theory is a theory of behavioral economics and an important modeling approach to characterize the irrationality of human decision-making (Kahneman and Tversky 2013). It defers from the expected utility theory that the utility value is linear to the risk of a probabilistic alternative (Tversky, 1975). Instead, a more psychologically accurate modeling of the perceived value is related to the decision-maker's risk attitude. It also proposes that losses cause a greater emotional impact than an equivalent amount of gain. It includes several perspectives to utilize prospect theory for behavioral modeling, including reference dependence, loss aversion, affective impacts on decision-making (risk aversion), and probability weighting. Prospect theory is later extended by applying cumulative probability distribution to probability weighting as the cumulative prospect theory (Tversky and Kahneman 1992). Parameter estimation is a crucial aspect of prospect theory applications. Maximum likelihood estimation is a non-Bayesian approach that involves using individual data points directly or averaging them to group data before applying parameter estimation (Harrison and Rustrom, 2009). However, both approaches do not consider uncertainties in parameters, and hierarchical parameter estimation is proposed to first determine the probability distribution of a group and then decide the parameter for an individual through Bayesian approaches (Nilsson et al., 2011; Zhou et al., 2017).

3. Problem Formulation and System Analysis of Smart Manufacturing Nudging Design

This paper studies manufacturing nudging design from the conceptual design perspective, which aims to understand the potential of behavioral economics modeling for nudging design. In this regard, there are three stages for manufacturing nudging design: nudge generation, evaluation, and personalization. The nudge generation stage aims to use domain knowledge to identify potential nudges given the problem context. The evaluation stage involves utilizing behavioral economics to model the user perceptions toward different nudges. The personalization stage is to select one nudge that has potentially the best performance and apply it to the specific user. The left of this Section presents the problem formulation as well as the system analysis of smart manufacturing nudging design.

3.1 Problem Formulation

Manufacturing nudging design can be aligned with the processes of axiomatic design, which includes four design activities: customer needs, functional requirements, design parameters, and process variables (Suh, 1998). Based on this system design methodology, the elements of manufacturing nudges are identified, as shown in Figure 1. With such decomposition, a manufacturing nudge D is realized through two coupled aspects, which are nudging instruments D^I and nudging operations D^O, where $D = D^I \cup D^O$. A nudging instrument can be understood as the platform to implement and execute nudges. In the manufacturing context, based on the form of the nudge, such as visual or auditory nudges, there can be different options for the instrument, such as smart glasses, smart wristbands, or earphones. It is not necessarily a physical object but can also be virtual, such as a platform that alters user behaviors by advocating certain behaviors with rewards, which is normally seen in service systems. Meanwhile, nudging operations are the contents of a nudge. Nudging operations can be characterized by a set of nudging features that work at different nudging levels. Let D_i be a nudging feature, where $i = 1,2, \dots, N$ and N is the number of nudging features. A nudging feature can be understood as design parameters and can have various nudging levels D_{ik}, where $k = 1,2, \dots, K$. Nudging features can be related to process variables, and k corresponds to the k-th level of the nudging feature D_i. For instance, one nudging feature is the information provided to the user, and a highly nudged operation and a slightly nudged operation can differ in the information presented in that nudge.

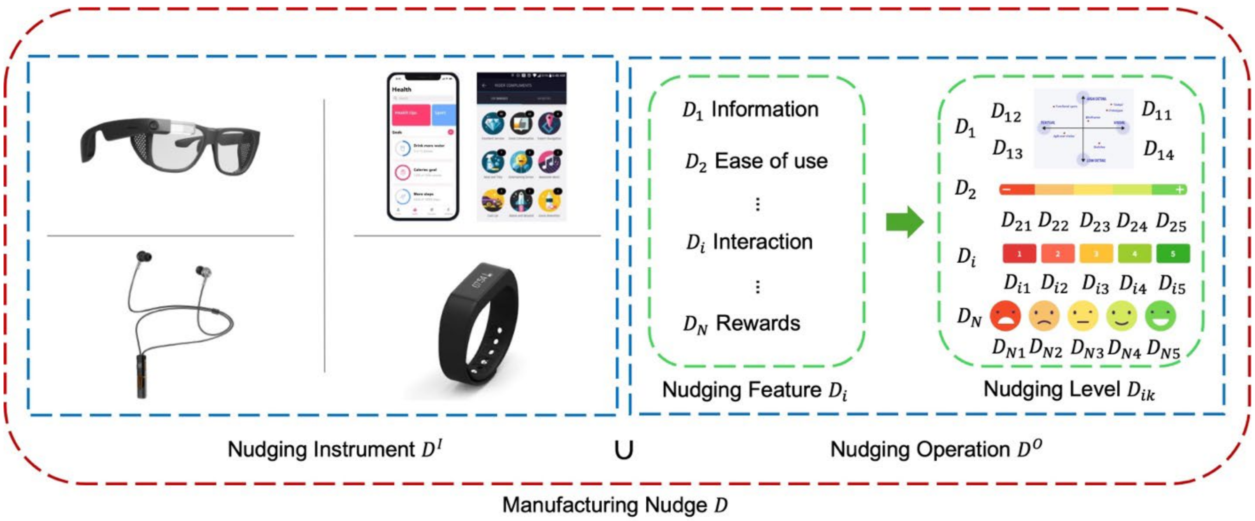


Figure 2. Modeling of a Manufacturing Nudge

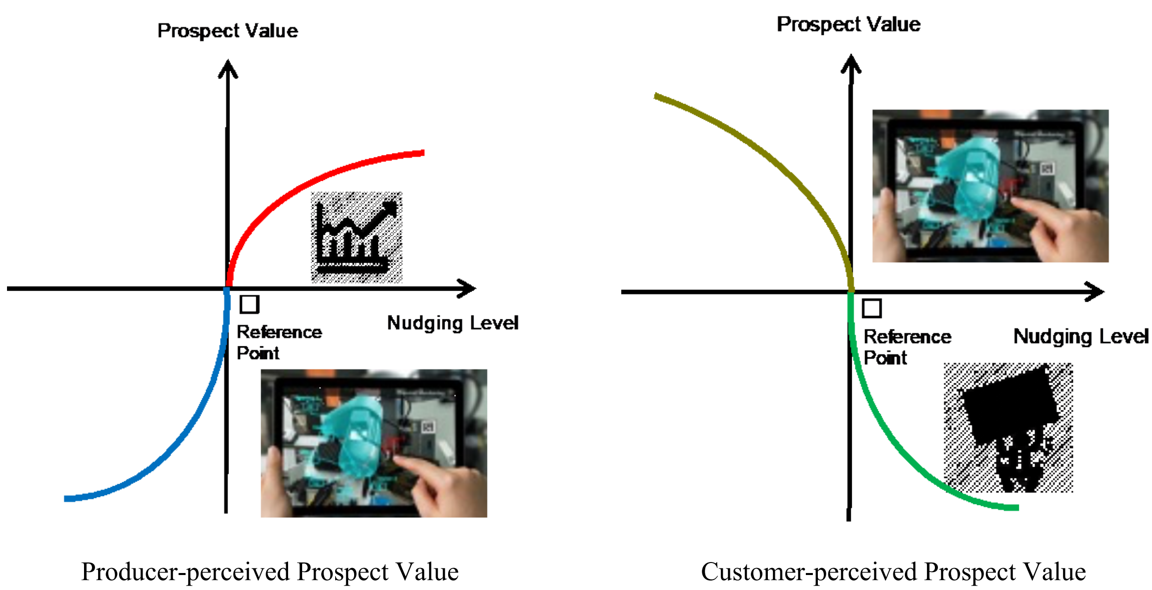


Figure 3. Conflicting Nudging Perceptions between Producers and Customers

Manufacturing nudging design can then be formulated as the process of identifying potential nudges consisting of nudging instruments and nudging operations at different levels of nudging and evaluating these nudges for execution. Different from conventional prospect theory-based behavioral economics modeling, this paper proposes to evaluate a nudging behavior through two-fold perceptions between the producer (the plant manager) and the customer (the user). This is based on the inherent conflicting perceptions in actual industrial operations between managers and operators. In this way, the evaluation does not only consider one type of stakeholder (the operators or the managers) but the overall benefits of a nudge. Such perception difference is illustrated in Figure 3, where manufacturing managers think applying nudges is beneficial to system performance, while operators see it as extra activities they need to operate.

3.2 Functional Analysis

To further illustrate the procedures of nudging design through behavioral economics modeling, system functional analysis is conducted using IDEF0 diagrams. In Figure 4, four fundamental procedures are listed, including nudge generation, nudging behavior modeling considering cognition, behavioral model parameter estimation, and nudging personalization optimization. From the axiomatic design perspective, nudge generation (A1) aims to formulate functional requirements, design parameters, and process variables for depicting the design space, which outputs potential nudging instruments and operations. After the nudges are formulated, nudging behaviors are to be modeled using the proposed conjoint prospect theory for nudge evaluation (A2). Considering human affective status plays an important role in decision-making, affective cognition modeling is implemented by changing certain model parameters to influence the prospect value curve shape that reflects the decision-makers' risk attitude. With the model developed, the next step is parameter estimation (A3). This step aims to group operators into different segments and identify proper parameter settings for the customization purpose. For instance, a junior-level operator and a senior-level operator can have different attitudes toward a nudge, and model parameters will be set differently. Finally, the nudging behavior model is used to evaluate different nudges and choose the most proper nudging operation for the operator, and the operator status is considered for the personalization purpose through context-aware reasoning. Details of the first three procedures are elaborated in the following.

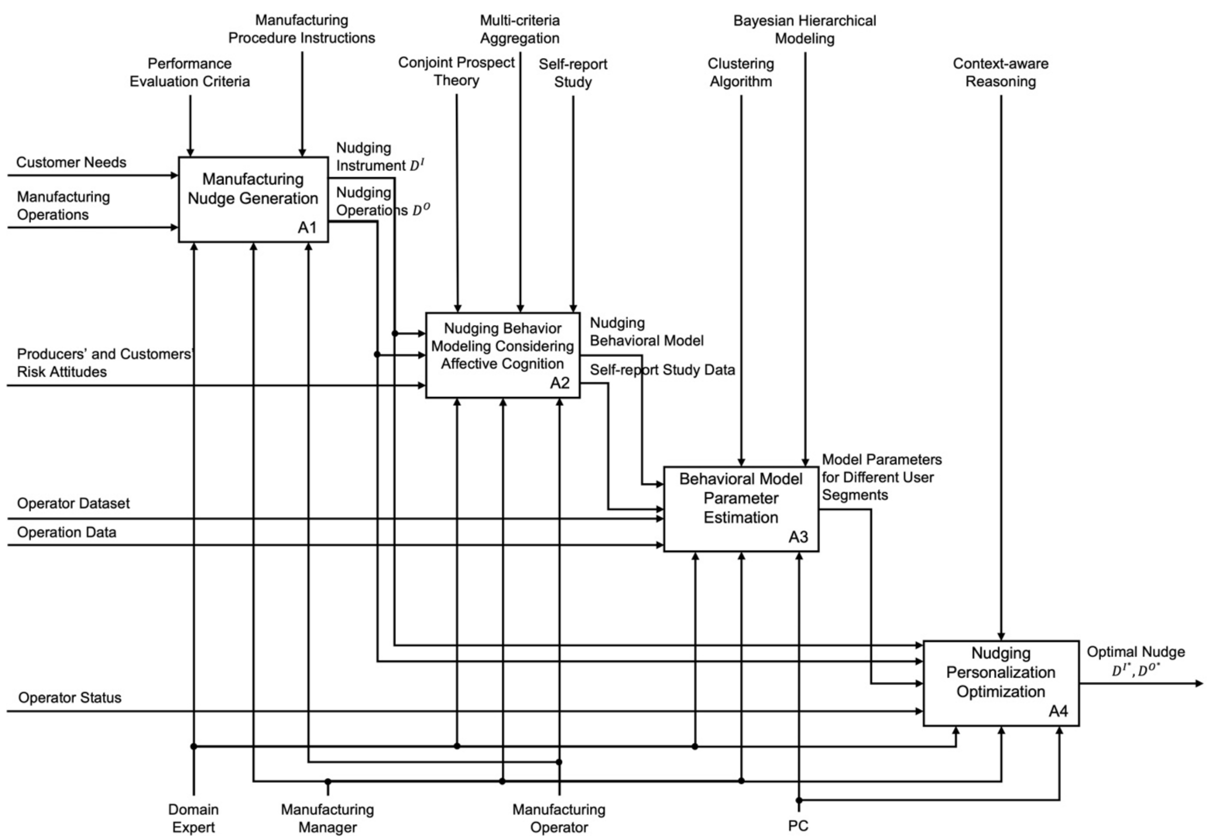


Figure 4. Workflow of Manufacturing Nudging Design

Figure 5 presents the workflow of nudge generation. Firstly, functional requirements are identified by analyzing the customer needs and manufacturing operations. Then, user-facing operations are analyzed to understand potential operator use cases for manufacturing nudging. Based on the use cases, feasible nudging instruments can be formulated. The next step is to design nudging features based on required functions and the instrument platform, which is essentially to formulate all nudging design parameters. After that, nudging operations can be depicted at different levels of nudging for each nudging feature.

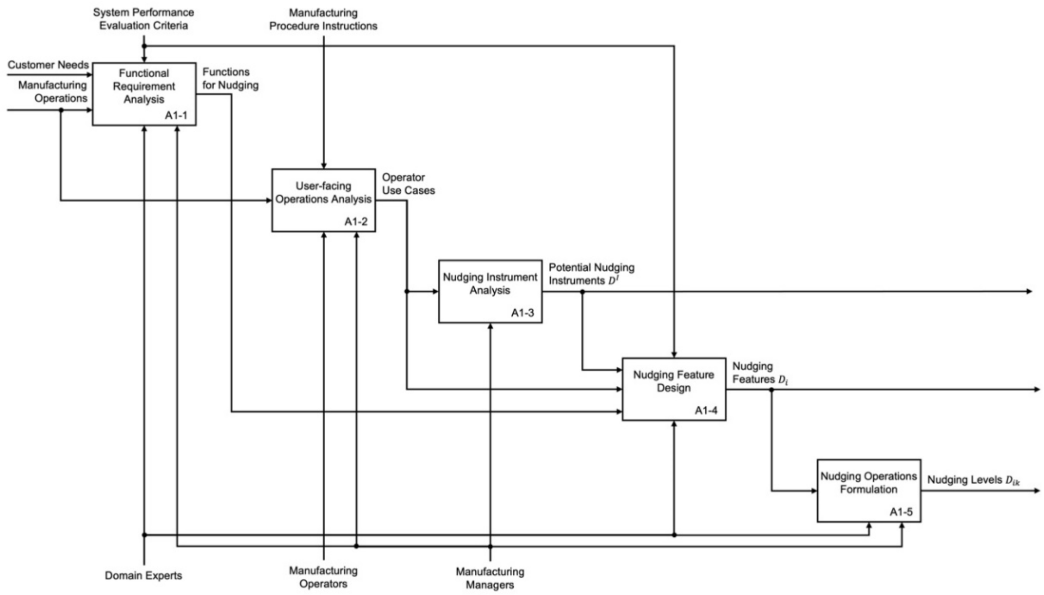


Figure 5. Nudge Generation Workflow

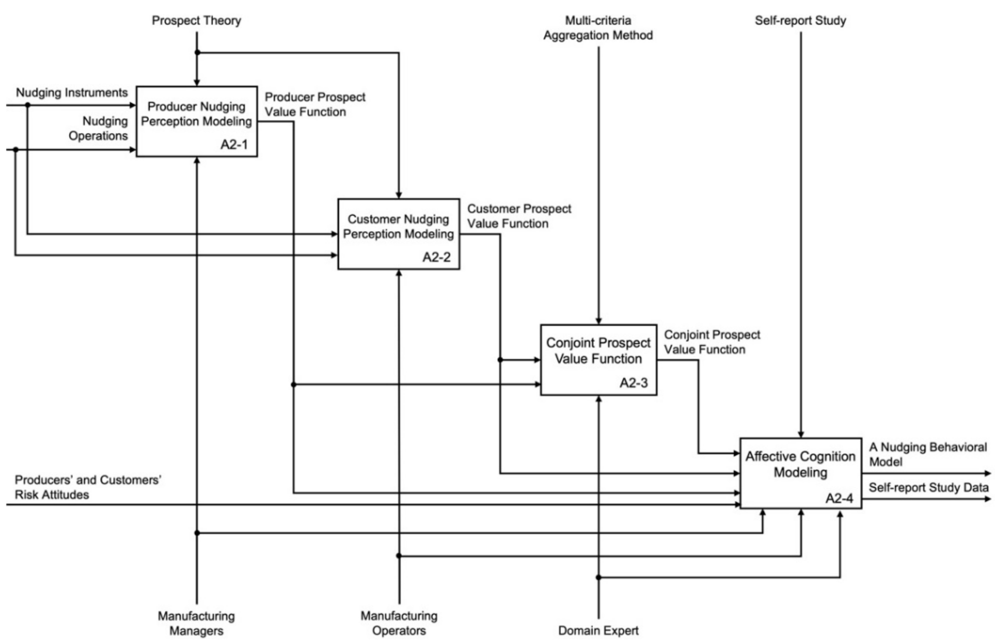


Figure 6. Nudging Behavior Modeling Workflow

Figure 6 shows the modeling process of nudging behaviors through the proposed conjoint prospect theory. Firstly, the producer-perceived prospect value function and the customer-perceived prospect value function are formulated based on nudging instruments and nudging features. Secondly, the two prospect value functions are aggregated to represent the prospect value for a certain nudge. Then, affective cognition modeling is implemented by setting different model parameters that influence the curve shape.

The parameter estimation workflow is shown in Figure 7. The objectives of this step are to implement customization for different scenarios and user groups and to estimate the model parameters for different user segments. Therefore, user segmentation and data aggregation are conducted first. Considering the uncertainties associated with these parameters, Bayesian hierarchical modeling is used to describe the parameter distribution for the estimation instead of using absolute values, while personalization that identifies the exact parameter value is conducted in the nudging personalization optimization stage.

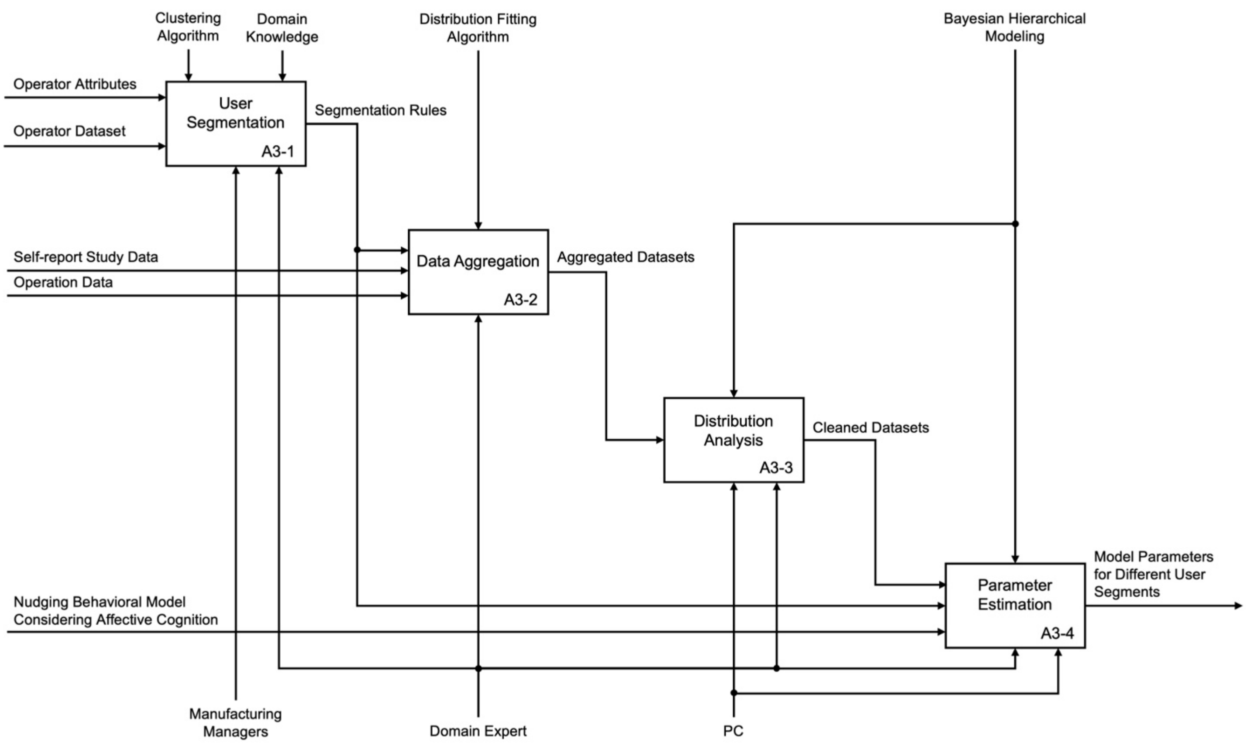


Figure 7. Parameter Estimation Workflow

4. Conjoint Prospect Theoretic Modeling of Nudging Behavior

As discussed in Section 3, this paper proposes conjoint prospect theoretic modeling for nudging behavior perceptions. Such formulation sees the perception of a nudge from both the producer and the customer aspects. Equation (1-10) below formulates the modeling of nudging behaviors.

$$v_i^J(D_i) = v_i^P(D_i) + v_i^C(D_i) \tag{1}$$

$$v_i^P(D_i) = \begin{cases} v_i^{Ref} + \left(D_i - D_i^{Ref}\right)^{\alpha'}, D_i \geq D_i^{Ref} \\ v_i^{Ref} - \lambda'\left(D_i^{Ref} - D_i\right)^{\beta'}, D_i < D_i^{Ref} \end{cases} \tag{2}$$

$$v_i^C(D_i) = \begin{cases} v_i^{Ref} + \left(D_i^{Ref} - D_i\right)^{\alpha}, D_i < D_i^{Ref} \\ v_i^{Ref} - \lambda\left(D_i - D_i^{Ref}\right)^{\beta}, D_i \geq D_i^{Ref} \end{cases} \tag{3}$$

$$u(D_i) = \begin{cases} v_i^J(D_i)\pi^+(p_i), v_i^J \geq v_i^{J,Ref} \\ v_i^J(D_i)\pi^-(p_i), v_i^J < v_i^{J,Ref} \end{cases} \tag{4}$$

$$w(p_i) = (p_i)^z/((p_i)^z + (1-p_i)^Z)^{1/z} \tag{5}$$

$$p_i = \exp(\eta[v_i^J(D_i)])/\sum_{i=1}^{N} \exp(\eta[v_i^J(D_i)]) \tag{6}$$

$$w \coloneqq w^+, z = \gamma \tag{7}$$

$$w \coloneqq w^-, z = \delta \tag{8}$$

$$\pi^+(p_{ix}) = w^+(\sum_{i=x}^{n} p_i) - w^+(\sum_{i=x+1}^{n} p_i), v_i^J \geq v_i^{J,Ref} \tag{9}$$

$$\pi^-(p_{ix}) = w^-(\sum_{i=-m}^{x} p_i) - w^-(\sum_{i=-m}^{x-1} p_i), v_i^J < v_i^{J,Ref} \tag{10}$$

$$V^J|D = \sum_{i=1}^{N} u(D_i) \tag{11}$$

In Equation (1), the conjoint prospect value function v_i^J is derived by additive representation of the producer-perceived prospect value v_i^P and the customer-perceived prospect value v_i^C. Equation (2) and Equation (3) are the producer-perceived value function and the customer-perceived value function based on the prospect theory, in which D_i^{Ref} is the reference level of nudging for the nudging feature D_i, $\alpha, \beta, \alpha', \beta'$ are parameters between 0 and 1 that influence the curve shape. λ and λ' represent the degree of loss aversion, and v_i^{Ref} is the neutral prospect value when the level of nudging is at the neutral point. When the performance of a nudge changes, the shape of v_i^J changes as well, making the highest prospect value change from the reference point to other points. The curve shape of the conjoint prospect value function under different conditions of $\alpha, \beta, \alpha', \beta'$ are shown in Figure 8.

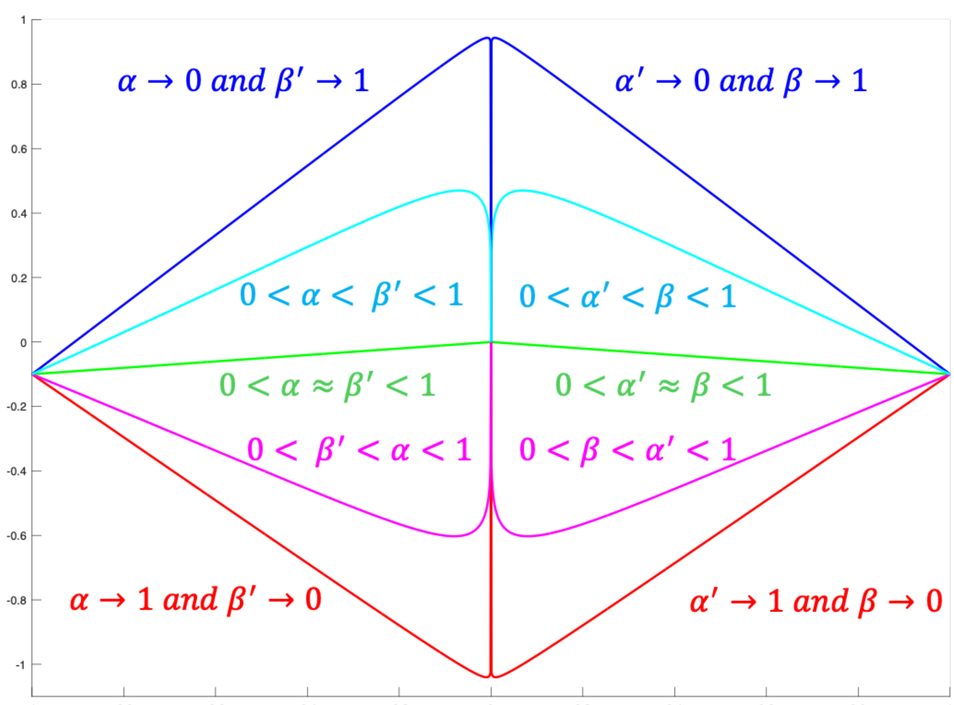
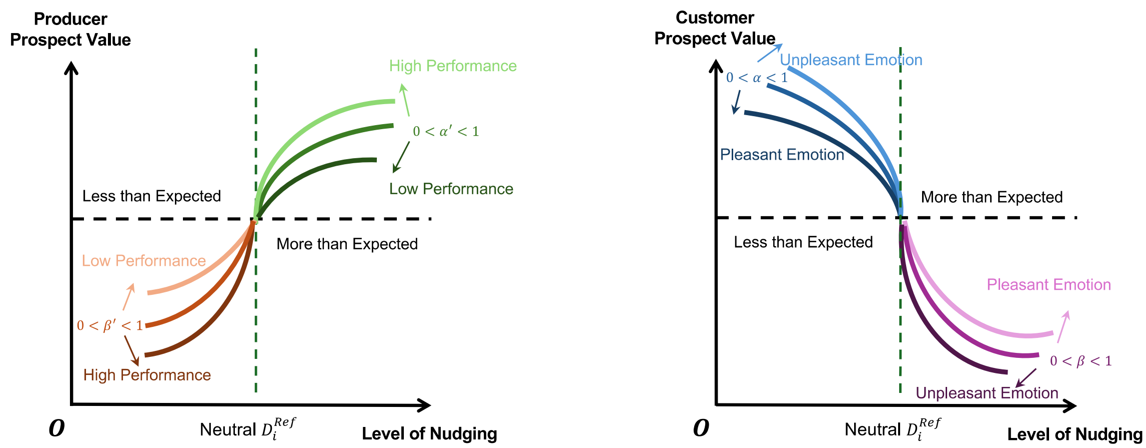


Figure 8. Conjoint Prospect Value Function Shape

Equation (4-11) represents the choice probability-based weighing functions for the conjoin prospect value function. These equations are extended from the cumulative prospect theory model for user experience design (Zhou et al., 2014). Equation (11) is the total conjoint prospect value function of all nudging features. $u(D_i)$ is the prospect value after probability distortion, $\pi(p_i)$ is the weight derived from the distorted probability, $v_i^{J,Ref}$ is the reference conjoint prospect value. The associated weighted cumulative choice probability p_i of a particular nudging design feature D_i is adapted from the popular logit model. $w(p_i)$ defines the weighting function, where z $(0 \leq z \leq 1)$ specifies the inverse s-shaped weighting function, such that $z = \gamma$ indicates positive experience with the nudge feature, and $z = \delta$ for negative experience.

5. Affective Cognition Modeling

The proposed conjoint prospect-theoretic model involves three types of parameters, including (a) affective-cognition shaping parameters, α and β $(0 \leq \alpha, \beta \leq 1)$ and α' and β' $(0 \leq \alpha', \beta' \leq 1)$, (b) negative experience aversion parameter λ and λ' $(\lambda, \lambda' > 0)$. Figure 8 presents the producer-perceived and customer-perceived prospect value functions under different affective states.



(a) Producer-perceived Prospect Value

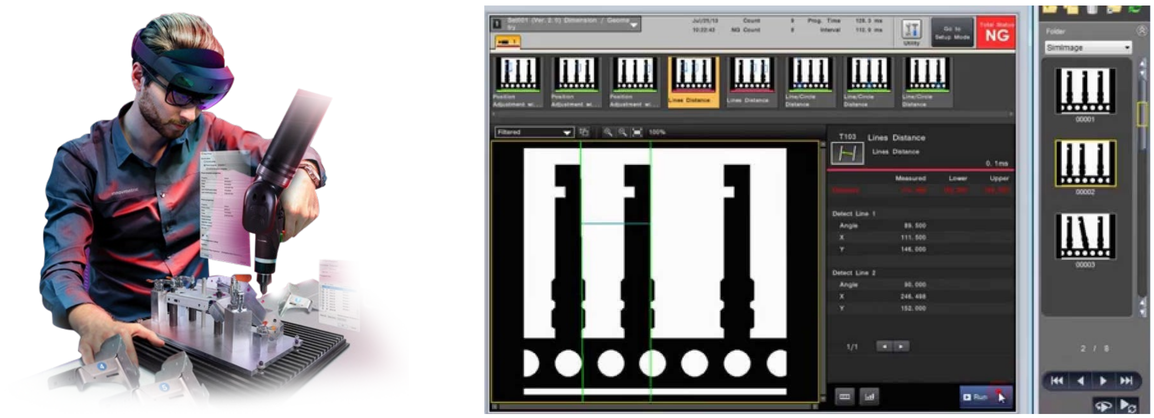
(b) Customer-perceived Prospect Value

Figure 9. Individual Prospect Value Functions under Different Affective States

In Figure 8 (a), the affective cognition factor that influences the prospect value is the performance of the nudge. When the nudge has better performance, the producer tends to be more sensitive to the outcome, indicating α' or β' become smaller, which makes the curve steeper. Similarly, if the nudge performance decreases, the producer tends to be less sensitive to the outcome, and α' or β' become larger, with the curve becoming flatter. Figure 8 (b) presents the influence of the operator emotion on the prospect value. With emotions more pleasant, operators tend to be less sensitive to the level of nudging, with α and β becoming larger. When operators feel unpleasant, they tend to be more sensitive to the nudging outcome, with α and β becoming smaller.

6. Example Case of Nudging for Assembly In-process Inspection

To illustrate the proposed smart manufacturing nudging design, an example case of nudging for assembly in-process inspection is briefed in this section. Figure 10 presents a basic nudge. Modern technologies enable fast and accurate visual inspection for very complex and precise parts, while the inspection criteria as well as the part-level judgement is difficult by its complex logic. Inspection is usually considered as a knowledge-intensive cognitive task. Considering machines' advantages in inspection speed and humans' strong cognitive capabilities, their collaboration in inspection tasks can greatly improve the inspection efficiency. This case is commonly seen in the assembly line, where inspection is conducted in situ and high inspection cycle time is needed to avoid the inspection to be the bottleneck of the production line. In this example case, Smart Glasses is chosen as the nudging instrument that informs the operator with the inspection results. The nudge interface shows the inspection information as well as suggestions the system proposes for defect disposition.



(a) Inspector with Smart Glasses

(b) Inspection Nudge Interface

Figure 10. Nudging for Assembly In-process Inspection

The objective of nudging is to influence and alter operators' behavior to reduce assembly errors. From this perspective, two nudging features are selected to design nudging operations, including the provided information and the ease of use. The provided information entails the inspection result details and suggestions for handling defective parts, including either scraping them or reworking them, as well as the specific rework operation. The ease of use indicates the user interaction. Based on the level of nudging, it can be a message displayed on the interface for certain time periods or a compulsory interaction that requires acknowledgment and confirmation from operators. Based on the two nudging features, different nudging operations can be designed. For instance, a nudge to a junior-level operator may entail very detailed inspection information and a comprehensive proposal for defect disposition, and the operator needs to interact with the interface by clicking certain interface controls to go into the next step. This nudge may bring more activities to the operator, but it tries to improve system performance with better product quality. On the other hand, a nudge to a senior-level operator may entail only key inspection information and proposal suggestions, and the nudging content displays on the screen without requiring operators' interactions. From this example, it can be known that nudging operations at different levels of nudging can be customized and personalized for different customers or operators.

7. Concluding Remarks

With continuous advancement in manufacturing technologies, human-technology interaction becomes more frequent than before, and the efficiency of human-machine collaboration becomes a critical factor for improving the overall system performance. Manufacturing nudging, which aims at altering or influencing human behaviors during collaboration, plays an important role in pursuing high-efficiency collaboration.

To implement smart manufacturing nudging design, this paper focuses on problem formulation of nudging design and conducts comprehensive functional analysis, covering nudge generation, evaluation, and personalization. Meanwhile, a novel conjoint prospect theoretic modeling approach is proposed for nudging behavior perception evaluation, which characterizes the inherent conflicting goals in behavioral economic concerns between producers and customers. Affective cognition modeling is also discussed in this paper, which utilizes the shaping parameters of prospect theory to represent the influence of affective states on perceived prospect values.

Several topics can be studied in future work. Firstly, in nudge generation, the analysis of nudging instruments and nudging features can be formulated as domain-specific context-aware symbolic reasoning problems. Using existing knowledge base with symbolic reasoning techniques, such as reasoning over knowledge graphs or generative artificial intelligence can better assist the decision-making process without domain experts. Secondly, nudging personalization optimization involves selecting a nudge toward a specific user. This requires analysis of the current operator status, and context awareness enables appropriate suggestions for model configuration, so that the selected nudge can help the user more efficiently. The reasoning and inference for such context awareness is therefore necessary to be studied.

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Biographies

Shu Wang is currently a Ph.D. student in Mechanical Engineering at Georgia Institute of Technology. His research topics include operations planning and optimization in manufacturing industries, industrial applications of artificial intelligence and data analysis, and decision science. He obtained M.S. in Mechanical Engineering and M.S. in Electrical and Computer Engineering at Georgia Institute of Technology from 2018 to 2020 and B.Eng. in Electrical Engineering at Wuhan University from 2014 to 2018.

Feng Zhou received the Ph.D. degree in human factors engineering from Nanyang Technological University, Singapore, in 2011, and the Ph.D. degree in mechanical engineering from Gatech Tech in 2014. He was a Research Scientist with MediaScience, Austin, TX, USA, from 2015 to 2017. He is currently an Assistant Professor with the Department of Industrial and Manufacturing Systems Engineering, University of Michigan-Dearborn. His current research interests include human factors, human–computer interaction, engineering design, and human-centered design.

Dr. Jiao joined the Woodruff School in December 2008. Prior, he was an Assistant Professor and then Associate Professor in the School of Mechanical and Aerospace Engineering at Nanyang Technological University, Singapore. Before his career in Singapore, he was a Visiting Scholar in the Department of Industrial Engineering and Engineering Management at Hong Kong University of Science and Technology from 1998 to 1999. From 1993 to 1994, he was a Lecturer of Industrial Engineering in the School of Management at Tianjin University, China, and from 1988 to 1990, he worked as an Associate Lecturer in the Department of Industrial Design at Tianjin University of Science and Technology, China.