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Research article

A process-tailoring method for digital manufacturing projects

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Abstract: Most digital manufacturing projects follow the software-development process. However, the application of all the characteristics and processes specific to a digital manufacturing project cannot be generalized to all other engineering projects. Therefore, digital manufacturing project teams typically design and apply process principles that can be customized to individual use cases by project members. Tailoring these principles, including developing and referencing them, is a knowledge-intensive activity that requires the gradual improvement of development processes. This paper proposes a knowledge-oriented digital manufacturing ontology model and a semantic rule-based tailoring system that can derive tailoring strategies from knowledge ontologies via an inference-rule design and engine. The proposed model and system can assist in concrete project implementations based on software-development experience. A practical example is demonstrated through the 3D-modeling digital manufacturing of a hospital kitchen.

Keywords: digital manufacturing; software development; semantic rule; tailoring system; project management

1. Introduction

Digital manufacturing and design are presently conducted primarily using project-based approaches [1,2]. Digital manufacturing projects involve knowledge-intensive processes [3], specifically, a series of complex processes and procedures [4]. For digital manufacturing and development to be successful, the experiences of information technology executives need to be considered and applied [5].

Digital manufacturing is generally referred to as the digitization of manufacturing processes, which involves the integration of the manufacturing technology, computer systems, and management aspects. Traditional manufacturing processes designed for mass production of identical products are labor-intensive, time-consuming, and incur high product development costs [6,7]. The digital manufacturing project model established through a best-practices approach can be used as the foundation for continuous learning in organizations.

Additionally, it can be employed as the baseline for information system management activities. Therefore, to achieve effective digital manufacturing and development, project teams often establish standards that are applied to all projects to standardize product quality control and optimize practice and experience by adjusting the standard. In practice, however, a single standard procedure may not be suitable for all digital manufacturing projects as each project is unique. Such generalizations of a single standard often lead to project failure due to extraneous increases in cost and time.

To address this issue, project teams often make adjustments to the standard based on specific project attributes. This process is called tailoring. At the project-execution level, each procedure can be tailored, simplified, replaced, and even eliminated. For example, in the case of a relatively small project with a short design lifecycle, the standard procedure can be simplified. Different formats with the same outcome can also be designed to meet consumer requirements. However, inappropriate tailoring can cause unnecessary workloads, leading to additional project costs. It can alternatively fail to achieve specific project management objectives and relinquish project knowledge on account of excessive omission of procedures. Therefore, one of the most important challenges in tailoring is determining an appropriate means of adjusting the standard procedure. For project teams composed of different levels and members with diverse experiences, the tailoring relies upon existing knowledge and experiences accumulated within the organization.

In knowledge engineering, ontology is used to integrate and process large amounts of information [8–10]. It is used to capture domain-specific knowledge, apply general explanations to this knowledge, and provide the user and the machine with shared definitions of the vocabulary and framework. It thereby enables users to obtain a common understanding of the domain knowledge concepts. It is thus worthwhile to explore the application of ontology in knowledge-oriented digital manufacturing and development project management [11,12].

With these considerations, this study applied a semantic rule-based language to build a proposed system and digital manufacturing project model for improved integration of past project experiences during a digital manufacturing project. Ontology was used to develop practical operation methods. The proposed system is referred to as the semantic rule-based tailoring system (SRTS). It primarily consists of a knowledge base (KB) and an inference engine. The KB of the SRTS is used to collect organizational tailoring experience based on a digital manufacturing project ontology model. The inference engine of SRTS, which includes the knowledge rule design, is used to make ontological inferences and yield tailored strategy recommendations. Furthermore, a real project using the system is demonstrated to confirm the proposed system's benefits.

The remainder of this paper is organized as follows. Section 2 discusses related work. Section 3 details the proposed method and system design of this paper. Section 4 describes the implementation of the proposed system. Section 5 analyzes the demonstration results. Section 6 discusses the system adoption. Section 7 presents the conclusions and limitations.

2. Related work

Every industrial manufacturing project is unique; the same digital manufacturing process is not necessarily applicable to other projects. However, redesigning processes for each project is inefficient and increases risks and costs. Digital manufacturing processes are tailored according to the project environment and features to enable specific project requirements to be fulfilled [13].

During process tailoring, a project team can create its own set of guidelines to be applied across projects while fulfilling the specific requirements of individual projects. The Capability Maturity Model Integration (CMMI) Product Team [14] defines tailoring guidelines in the CMMI-DEV V2.0 standard as those that provide a reference for the project team to adjust its standard procedures to suit different projects, work teams, and organizational guidelines. Therefore, there are no fixed criteria to determine which tailoring guidelines should be applied based on the size of the project. In general, in the traditional manufacturing industry, projects are typically large-size, complex, time-consuming (e.g., over one year), and incur huge costs (e.g., over two million Taiwan dollars). In contrast, a digital manufacturing project is similar to a software engineering project; it requires the use of tailoring guidelines that enable project teams to maintain a flexible structure while ensuring process consistency. Because each project has different characteristics, each project can be adapted based on certain principles to prevent problems due to the organization's bureaucracy. The guidelines of project tailoring in digital manufacturing thus enable flexibility and consistency, thereby preventing organizational disruption.

In a digital manufacturing project, it is necessary to understand the effects of different environmental factors on the tailoring process and to identify those factors based on project characteristics. Barcelona et al. [15] defined project characteristics as the key factors representing a project. Previous studies have proposed various factors and risks that affect the digital manufacturing project, such as consumers, work teams, technologies, project characteristics, and organizational works.

Xu and Ramesh [13] stated that tailored process objects generally include activities, documents, artifacts, roles, and phases. Some process objects are interdependent. For example, the requirements specification must be generated before performing digital manufacturing activities. Therefore, when a process area is removed, the work products associated with this process area are likewise removed. In a small project with a short development lifecycle, certain process areas and artifacts can be exempted or conducted in an informal manner (e.g., changing the original output proposal to a work list).

Furthermore, the roles of relevant personnel can be changed (e.g., the project manager can also be the tester in the case of insufficient personnel). In process-tailoring case studies, Xu and Ramesh [13] and Barcelona et al. [15] found that guidance from the standard procedure model or tailoring framework was inadequate to support process tailoring. Their studies showed that domain knowledge or experience played a very important role in process tailoring. Project specialists must have complete and varied knowledge or experience to smoothly execute tailoring. Furthermore, process tailoring is a knowledge-intensive activity [3,11,12]. Xu and Ramesh [13] concluded that effective use of updated knowledge or experience in digital manufacturing projects can significantly improve the effectiveness and efficiency of tailoring. Moreover, to improve knowledge sharing, project teams can build a comprehensive knowledge base with all relevant knowledge.

3. Methods and system design

3.1. System architecture

The proposed system is based on the architecture of general expert systems. It employs a knowledge-oriented digital manufacturing project ontology as the foundation of domain knowledge in the knowledge base. Through the design of inference rules, the system infers an ontology using the inference engine. Accordingly, it generates tailoring-strategy recommendations for reference by project specialists. The system architecture, shown in Figure 1, comprises four components: digital manufacturing project ontology, inference engine, digital manufacturing project tailoring knowledge structure, and web user interface (UI).

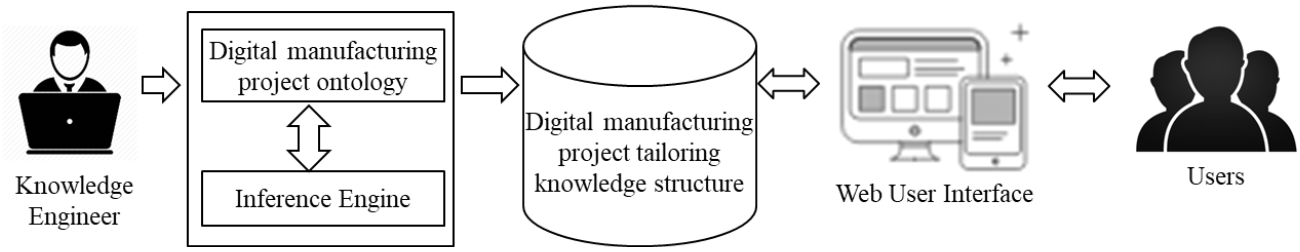

Figure 1. System architecture.

For the actual system operation, this paper employs the Web Ontology Language (OWL) [8]. It describes the digital manufacturing project ontology for establishing the ontology model. The inference rules were written in the Semantic Web Rule Language (SWRL) [10]. The inference engine, HermiT, was used to further infer the SWRL rules and generate the digital manufacturing project tailoring knowledge structure. Based on this structure, the system communicates with users through the UI and provides them with tailoring-strategy recommendations.

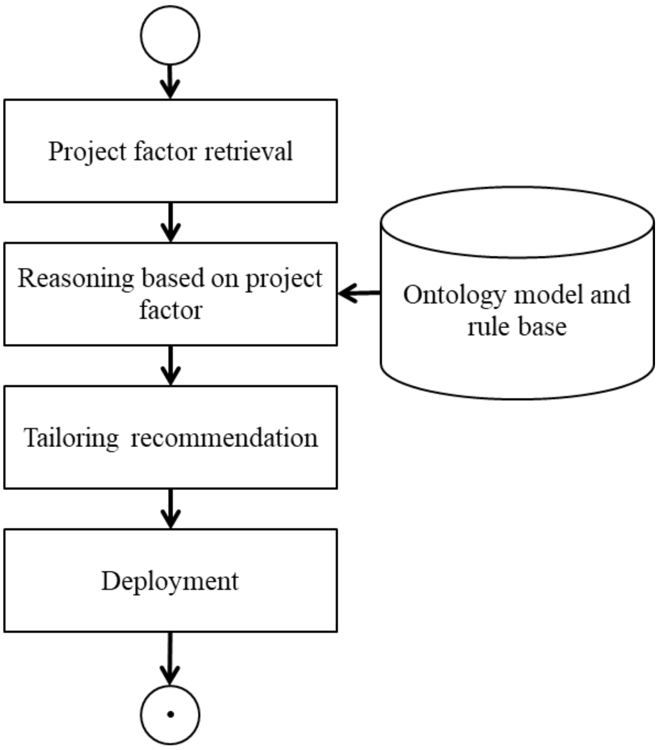

Figure 2. System flow.

The system must first retrieve the tailoring factors (TF) (i.e., project factors) in the initial stage of project tailoring, as shown in Figure 2. After the user enters the TF through the UI, the system generates tailoring-strategy recommendations for reference by project specialists. This is based on the tailoring-strategy knowledge structure produced by the inference engine. The project manager (PM) or project specialist makes assessments based on personal knowledge and experience and decides which process-tailoring recommendations to accept. After project completion, the tailoring experience is incorporated in the system to update the organizational knowledge. The updated knowledge thereby provides a tailoring reference for future project tailoring. Ontology and rule are updated by knowledge engineers.

3.2. Project tailoring process

In this study, the digital manufacturing project is the main knowledge framework; I focused on the inference of process tailoring and knowledge capturing practices. Specifically, I collected concepts and knowledge according to a predefined knowledge framework, on the basis of which the modeling and ontology building were conducted.

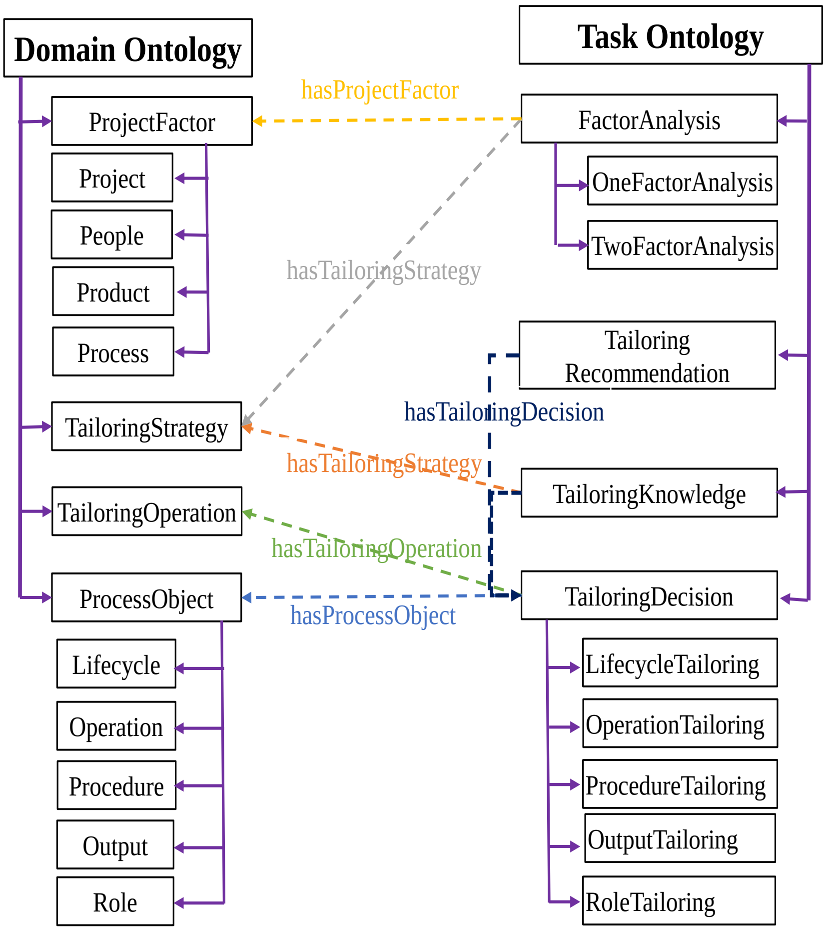

Figure 3. Digital manufacturing project ontology model.

This study follows the concept of knowledge modeling presented in my previous work [16], which was applied in the domain of medical information system. The method proposed in this study divides ontology into two main categories: domain and task ontology. The former is the background knowledge in a specific domain (i.e., digital manufacturing). It describes the concepts in the specific domain and the relationship among them. Moreover, it can be described as a tree structure, such as a class hierarchy diagram. Task ontology, on the other hand, describes the concepts of problems and solutions in a specific task and the relationship among these concepts. Accordingly, new concepts are derived from interactions among background knowledge items. By combining domain and task ontologies, the system can make inferences regarding the problem through logic and rules. The digital manufacturing project ontology model designed in this study is shown in Figure 3.

After digital manufacturing project ontology modeling and building, the inference rules can be designed. The established task ontology is applied to the inference mechanism. In task ontology, the attribute defined as the inferred property includes content of unknown tacit knowledge. The ontological tacit knowledge, which is concealed in predefined relationships, must be inferred through the design of inference rules. For example, “hasTailoringStrategy” and “hasLifecycleTailoringRec” are both attributes with unknown content. First, each individual project must derive “TailoringStrategy” from “ProjectFactor.’ Then, the recommended practices for LifecycleTailoring are inferred from the derived “TailoringStrategy.” The inference rules for “TailoringStrategy” and “TailoringRecommendation” are summarized in Table 1.

When establishing the problem-solving procedure, the problem and corresponding solution are first identified. The problem to be solved is determining the recommended tailoring practice, i.e., the inferred property. In the rule design, inferred property is the consequence of a rule. Rule building focuses on the rule antecedent design. This study follows the rule analysis form proposed in my previous work [16] to perform the solution analysis and construct the inference-rule design. The method was stated in natural language in a certain format to simulate the connecting process based on known relationships among the knowledge items, analyzing the problem-solving procedure and obtaining the conclusion. The goal of rule analysis is to obtain the rule consequence, i.e., the inferred property obtained through inference rules. Next, the project “TailoringStrategy” is used as an example to demonstrate the analysis steps.

Various rule languages have been developed to write inference rules, such as RuleML, SWRL, Metalog, and ISO Prolog. Among these languages, SWRL is customized for semantic web applications. It provides a simple syntax and easy connection with the ontology web language knowledge base. SWRL rules can be used to provide procedural knowledge [16], which is a knowledge type from indirect inferences through certain operations. It can be used to compensate for inference limitations in ontology, especially for the identification of semantic relationships between individuals [17].

SWRL adopts a representative logical expression “antecedent consequence” to present semantic rules. The antecedent is formed by a series of atoms. The rule can be written in a form in which the atom is equivalent to a step in the previous rule analysis form. According to SWRL rules, the inference rules of “TailoringStrategy” in the previous rule analysis form can be written as Rule 1 in Table 1, which is “OneFactorAnalysis” under “ProjectFactor.” Rule 2 is “TwoFactorAnalysis” under “ProjectFactor.” The inference procedures of the remaining rules are similarly developed using the rule analysis form. These procedures are used to further infer “LifecycleTailoring,” “OperationTailoring,” “ProcedureTailoring,” “OutputTailoring,” and “RoleTailoring,” respectively.

Table 1. Inference rules from SWRL.

Inference of Tailoring strategy	
Rule 1	TailoringRecommendation(?x), TailoringRecommendation_hasFactor(?x,?y), OneFactorAnalysis(?z), OneFactorAnalysis_hasFactor(?z,?y), OneFactorAnalysis_hasTailoringStrategy(?z,?a) → TailoringRecommendation_hasTailoringStrategy(?x,?a)
Rule 2	TailoringRecommendation(?x), TailoringRecommendation_hasFactor(?x,?y), TailoringRecommendation_hasFactor(?x,?z), TwoFactorAnalysis(?a), TwoFactorAnalysis_hasFactor(?a,?y), TwoFactorAnalysis_hasFactor(?a,?z), TwoFactorAnalysis_hasTailoringStrategy(?a,?b) → TailoringRecommendation_hasTailoringStrategy(?x,?b)
Inference of Tailoring Recommendation	
Rule 3	TailoringRecommendation(?x), TailoringRecommendation_hasTailoringStrategy(?x,?y), TailoringKnowledge(?z), TailoringKnowledge_hasTailoringStrategy(?z,?y), hasLifecycleTailoring(?z,?a) → hasLifecycleTailoringRec(?x,?a)
Rule 4	TailoringRecommendation(?x), TailoringRecommendation_hasTailoringStrategy(?x,?y), TailoringKnowledge(?z), TailoringKnowledge_hasTailoringStrategy(?z,?y), hasOperationTailoring(?z,?a) → hasOperationTailoringRec(?x,?a)
Rule 5	TailoringRecommendation(?x), TailoringRecommendation_hasTailoringStrategy(?x,?y), TailoringKnowledge(?z), TailoringKnowledge_hasTailoringStrategy(?z,?y), hasProcedureTailoring(?z,?a) → hasProcedureTailoringRec(?x,?a)
Rule 6	TailoringRecommendation(?x), TailoringRecommendation_hasTailoringStrategy(?x,?y), TailoringKnowledge(?z), TailoringKnowledge_hasTailoringStrategy(?z,?y), hasOutputTailoring(?z,?a) → hasOutputTailoringRec(?x,?a)
Rule 7	TailoringRecommendation(?x), TailoringRecommendation_hasTailoringStrategy(?x,?y), TailoringKnowledge(?z), TailoringKnowledge_hasTailoringStrategy(?z,?y), hasRoleTailoring(?z,?a) → hasRoleTailoringRec(?x,?a)

4. System implementation

After completing the system design, SRTS was built. To confirm the system usability in practical projects, SRTS was made available through a web UI. Project specialists could thus easily connect to it for project tailoring or searching the tailoring operations of previous projects. SRTS makes project tailoring more convenient for large project teams that are dispersed across locations.

In this study, the tailoring recommendation (TR) outputs were primarily determined by TF inputs. As shown in Figure 2, the TF had to be acquired before project tailoring. Different combinations of TF yielded different tailoring-strategy recommendations. The system implementation was based on the case of an academic unit.

4.1. Case description

3D modeling of a hospital kitchen (abbr. 3D-kitchen), including the kitchenware, which was manufactured by the Smart Living Lab at Oriental Institute of Technology (OIT) in January 2021, is presented as a digital manufacturing project case study. The 3D-kitchen is a typified digitization product design and manufacturing project. The design and manufacturing processes are similar to those of a software engineering project involving the use of a manufacturing technology, computer systems, and management aspects.

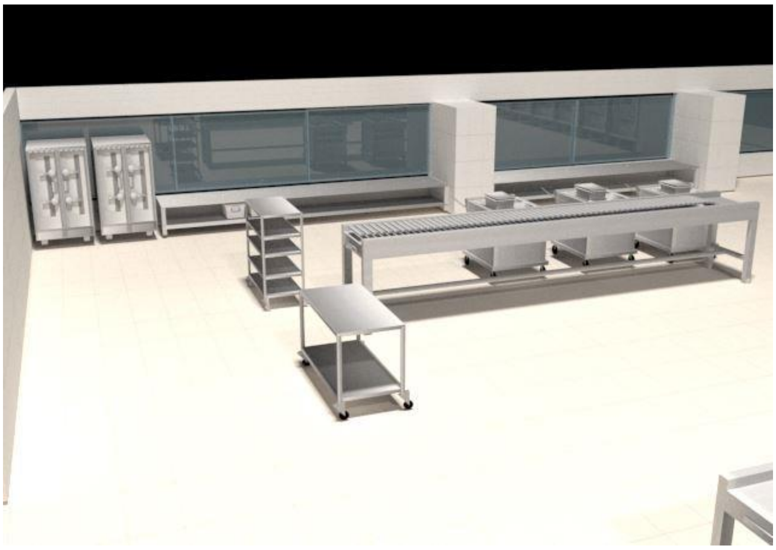

Figure 4. 3D scene of 3D-kitchen.

Figure 4 is one of the 3D scenes of the 3D-kitchen. Similar to other information integration companies, OIT has a set of standard procedures for regulating the digital manufacturing project. The 3D-kitchen is a medium-size project, whereas standard procedures are often designed for large-size and complex projects; thus, tailoring the process without compromising the ultimate manufacturing quality is critical.

To enable project specialists to conduct convenient TR searches during the project, an additional web UI was built. The project execution involved many relevant procedures. This paper describes and demonstrates only the system analysis and design activities of the software-development process.

4.2. Feature demonstration

This paper presents two use cases that demonstrate the efficacy of the proposed system. The first use case (Figure 5) shows the four TF input categories (namely, “Product,” “Project,” “Process,” and “People”) extended from the core function, “Tailor,” of SRTS. The other use case (Figure 6) shows the method of generating the tailoring results. The function “Tailor Decision” forms the core of the entire proposed system because it generates the tailoring decisions related to the digital manufacturing project. In SRTS, the inference procedures of the remaining rules are similarly developed using the rule analysis form. Five tailoring recommendations (TR)-“Lifecycle tailoring,” “Operation tailoring,” “Procedure tailoring,” “Output tailoring,” and “Role tailoring” are extended from “Tailor Decision” and then selected to confirm the tailoring decisions. The sequence diagram depicted in Figure 7 shows the detailed process of confirming a tailor decision.

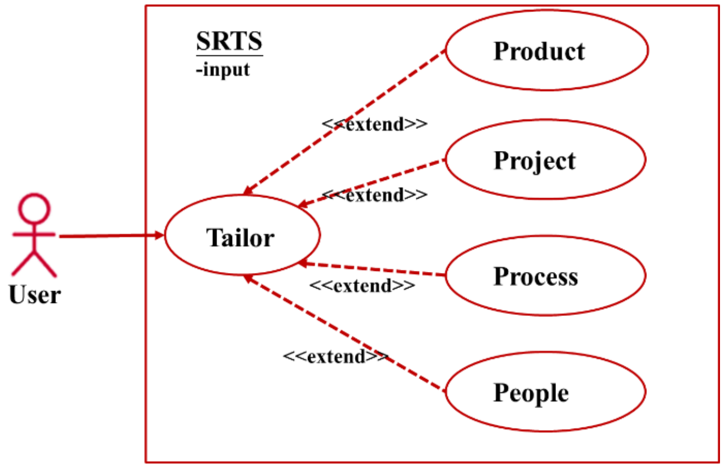

Figure 5. Use case of an input TF.

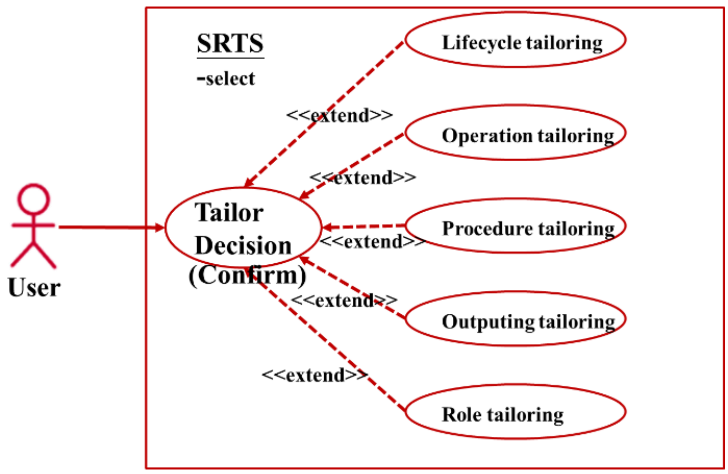

Figure 6. Use case of a selected TR.

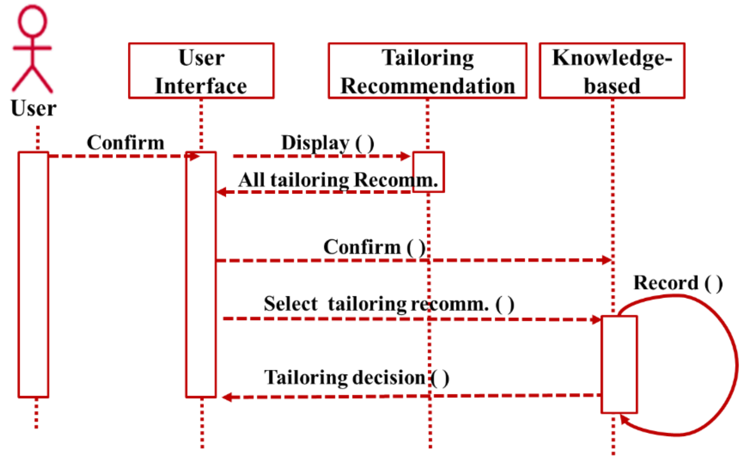

Figure 7. Sequence diagram of confirming tailor decision.

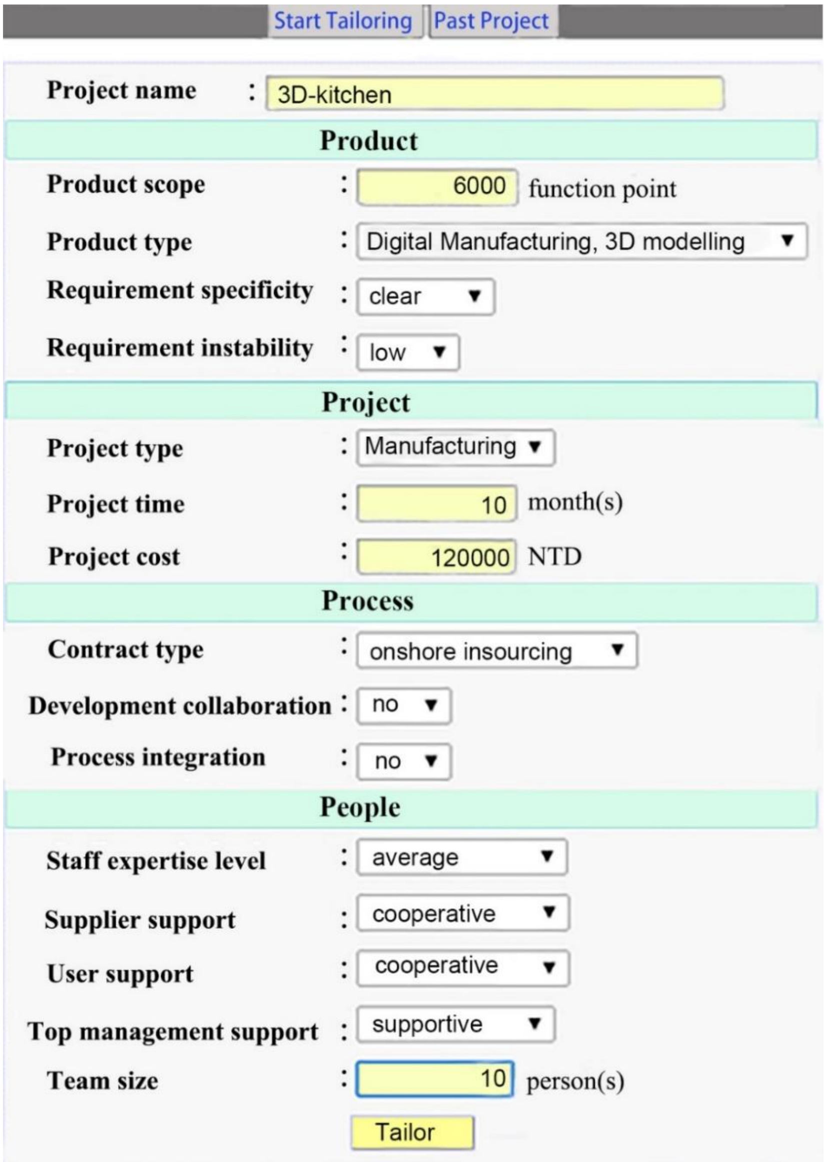

Figure 8. Screenshot of TF retrieval.

The following feature demonstration is based on 3D-kitchen. In Figure 2, the system started the project tailoring with the first stage of TF collection. Project specialists can input TF for the above situation using the TF collection interface shown in Figure 8. The TF collection of this paper is divided into four levels in a guided manner. The user first inputs the project name, followed by the TF input interface by successively selecting the titles of the TF categories. After completing the TF input, project specialists can click the "Tailor" button to start the TF analysis and generate a project TR.

Figure 8 also illustrates the advantages of a real project—3D modeling of a hospital kitchen. After entering the TF, the system generates a corresponding TR based on the tailoring-strategy knowledge structure previously inferred based on ontology. Specifically, the quantitative tailoring recommendations of SRTS (i.e., the proposed system) first trigger rules 1 and 2 presented in Table 1 to infer the tailoring strategy according to the TF. After the generation of the tailoring strategy, rules 3–7 are successively activated to infer the tailoring-strategy decision in the 3D-kitchen project. This study used Protégé (see Figure 9), as the core of the SRTS, to infer the SWRL rules. Protégé automatically identifies the tacit knowledge after starting the inference engine. The results of the tailoring decision thus obtained include the factors of the project, such as approximately 6,000 estimated function points, 10 months for execution, 120 thousand Taiwan dollars, and the requirement of 10 people. This can then be used as a reference by the lead managers to monitor the project. This will allow them to complete the digital manufacturing project on time, within budget, and with quality assurance.

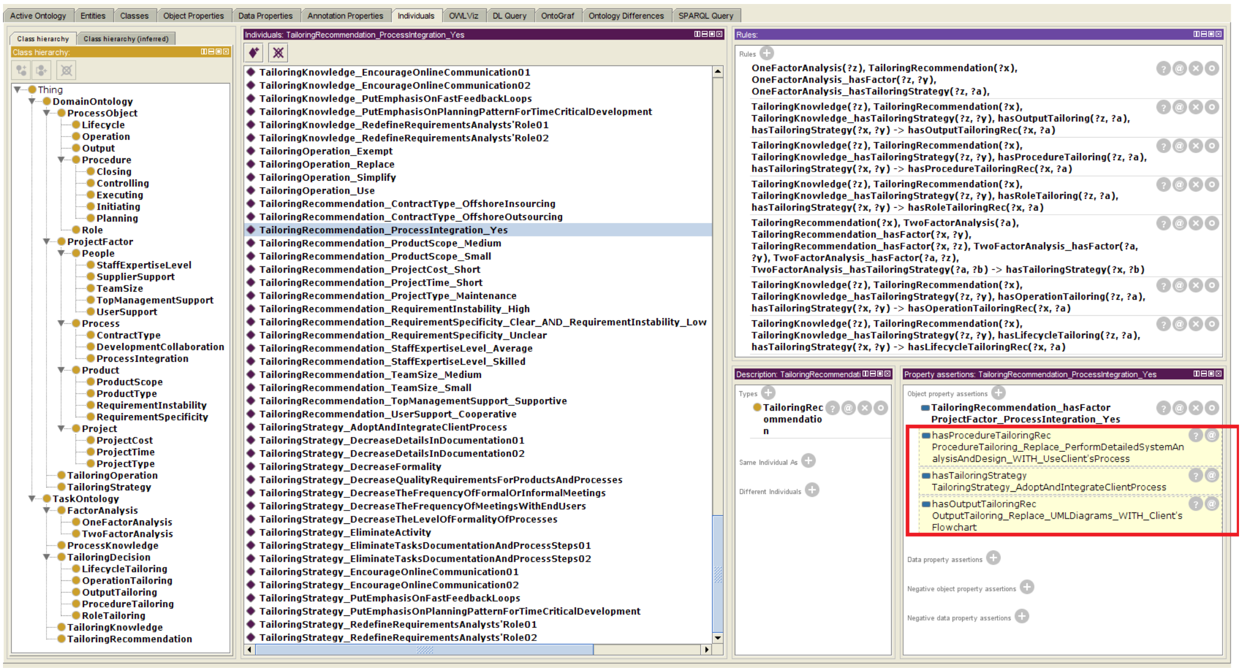

Figure 9. Screenshot of Protégé inferences.

5. Demonstration results

The main premise of this paper is the ontology of model building. Therefore, in this section, I analyze and discuss the developed ontology. In this context, it should be noted that Noy and

McGuinness [18] stated that there is no absolutely correct ontology model. Instead, the effectiveness of the ontology model depends on whether it fits applications in related fields. Studies by Noy and Hafner [19] and Dadkhah et al. [20] indicated that the main objective of ontology building is knowledge sharing and reuse. Many experts contend that the ontology structure superiority can be confirmed through the measurement of other factors or ontology diagnoses. These can be performed with ontology tools, such as the FaCT or RACER inference engine.

Furthermore, Lee and He [21] stated that the knowledge base of ontology is inherently incomplete. The knowledge in ontology is accumulated by successive and repeated processes, resulting in a more complete ontology with continuously modified and updated knowledge. Therefore, it was suggested that the quality of the ontology structure could be assessed through ontology completeness, consistency, and conciseness [22]. This paper analyzes the constructed ontology according to those three aspects in terms of reuse as explained in the next three subsections.

5.1. Completeness

To ensure sustained use of knowledge, ontology requires regular maintenance along with persistent expansion and revision. Therefore, "incompleteness" is an inherent limitation of ontology. It is impossible, by definition, to ensure the completeness of its content [21]. Nevertheless, we can still discuss whether the completeness of the target ontology is improved to meet the user's knowledge requirement. Furthermore, Quinn and McArthur [23] showed that ontology completeness can be assessed from a theoretical perspective.

With the above considerations, I conducted knowledge capturing through literature analysis, tailoring cases, and using personnel with relevant experience and applied the digital manufacturing project ontology model accordingly. In this model, the tailoring recommendation outputs are mainly determined by tailoring factor inputs, which are therefore considered the core model framework. Based on the literature analysis and discussion, this paper summarizes fifteen tailoring factors and five tailoring practices. The ontology instances are provided by the case unit. This model uses Protégé to revise the knowledge and integrate new concepts into the ontology. Therefore, in terms of structure, the model meets the requirement of completeness and expandability.

5.2. Consistency

Al-Sayed et al. [22] considered consistency as the state in which no conflicts exist between the designed ontology content and application outcomes. This paper followed the ontology building method proposed by Noy and McGuinness [18] to build the ontology model using the ontology instances provided by the case unit. The input instances were all validated. That is, the instance content was adopted in previous project development and approved by consumers to ensure consistency between the content and concepts of instances in the ontology. In addition, the inference engine in ontology tools can be used to assist in identifying ontology inconsistencies.

Rodler et al. [24] suggested that the consistency between ontology content and application outcomes can be investigated through the user experience of the completed system. This study used tailoring factors to generate tailoring-strategy recommendations. The proposed system also features a feedback mechanism. It enables the user to evaluate the system's suggested tailoring recommendations. This paper used this mechanism to understand the consistency between the model content and application outcomes. These are discussed in user interviews presented in the next section.

5.3. Conciseness

Conciseness means that the information gathered and produced in the target ontology is useful and precise [21]. However, conciseness does not exclude redundant ontology knowledge because, to some extent, controlled redundant knowledge still has value. Yang et al. [25] suggested that the system redundancy can be assessed by the user.

In this study, the case unit inspected the system conciseness through user feedback. The proposed system provides a feature for the user to rate the project TR produced by the system. This feedback mechanism affects the confidence level of the TR in future project tailoring. Based on the TR confidence level, the user can determine the acceptability and adoptability of the TR and decide whether to use it or not. The feedback mechanism of the proposed system can also improve the TR outputs and make the underlying tailoring-strategy knowledge structure more accurate. The system usefulness was discussed through case unit interviews in terms of a technology acceptance model (TAM).

6. System adoption

A key achievement in this study was the development of the proposed system. By means of the developed system, this study aimed to assist project specialists in information integration companies with project tailoring. As described in section 5, in the system implementation, this paper adapted the tailoring system to a case unit and introduced the actual situation of that case. Therefore, in addition to the assessment of ontology knowledge, the user in the case unit should be included as a validation subject. Storey et al. [26] proposed that qualitative methods can be used to validate such a highly customized and people-oriented non-quantitative model. Moreover, this study adopted a qualitative validation system application through the TAM.

TAM is one of the commonly used theoretical models for technology-user behavior research. TAM mainly investigates the user acceptance of the information system. The user's awareness, attitude, and use intention can be investigated through the perceived usefulness and perceived ease of use [27]. Perceived usefulness means that the user agrees that the job performance and personal knowledge are effectively improved by using a specific information system. In this system, perceived usefulness indicates that system use can effectively provide organizational knowledge and assist project specialists with process tailoring. Perceived ease of use indicates the ease of using the specific information system to complete the job. In this system, perceived ease of use means the ease with which the system can be used by project specialists.

When the user believes that information system use is beneficial to studying or working, and it is easy to learn and employ, the use intention will increase. Furthermore, perceived ease of use will positively affect perceived usefulness and thus affect the use intention. Because perceived ease of use enables the user to complete more tasks with the same effort, the user will be more willing to employ this system and will have more chances to experience its usefulness. The explanatory ability and theory conciseness of TAM have been proved in many studies. Therefore, this paper adopted TAM to investigate the practical value of the proposed system through perceived usefulness and perceived ease of use.

In information system related qualitative research, a semi-structured interview has been widely used as the research method [28]. This study conducted semi-structured interviews to investigate the system application with theoretical support from TAM. The interviewees in this study were potential users of the system, i.e., project specialists at OIT. The interviewed project specialists were from different OIT organizational levels, including the dean of college of healthcare and management (top management), lab manager (PM), and lab members. This interview was designed to inspect the system's usefulness and ease of use from different engineering perspectives.

The content, form, and interview structure were designed based on the perceived usefulness and perceived ease of use in TAM. The interview questions were designed according to the interview outline. Because a semi-structured interview is conducted in a relatively free and open manner, the interview content was not limited to the designed topics. The interviews began with predesigned questions, followed by more in-depth questions based on the responses. In this way, the interview was enhanced for further investigation. Lastly, the interview outputs were organized and discussed after the interview completion.

7. Conclusions

In the 3D-kitchen project, the project has specialized knowledge and skills in the field of digital manufacturing, which were acquired through experience and training. Project stakeholders are highly efficient and effective when solving problems in their specific domains. The digital manufacturing industry is a knowledge-intensive industry with high dependence on personal knowledge or experience, which also needs to be applied during the project-tailoring process. Specific knowledge and rules are stored in the knowledge base and used by the system to solve users' problems. This study used a semantic rule-based tailoring system to develop a process-tailoring knowledge structure for project tailoring in digital manufacturing and then built an expert system to assist project specialists with the project-tailoring process that complied with the required standards.

The tailoring system presented in this paper, however, suffers from some limitations. This study did not sufficiently investigate the interactions among the various tailoring factors. Ontology essentially implies that knowledge should be continuously expanded and accumulated. Therefore, the interactions among the various tailoring factors can be investigated in the future to expand the ontology of the digital manufacturing project. Furthermore, the system remains a research prototype. In the future, additional project factors can be introduced to increase the knowledge and number of instances in the given ontology. Because the proposed tailoring system was specifically configured to work with a given case unit, the instance of ontology used was built based on the previous data of this case unit. Therefore, the system was only required to meet the requirements of the 3D-kitchen. For other digital manufacturing industries, individual organizations should customize the tailoring knowledge based on the organization's characteristics and process standards.

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Conflict of interest

The author declares that there is no conflict of interest regarding the publication of this article.

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