International Journal of Innovative Computing, Information and Control
Volume **19**, Number **5**, October **2023**
ICIC International ©2023 ISSN 1349-4198
pp. 1439–1454

INTRODUCTION OF "TOY-CREATION CONTEST" IN CAD/CAM/CAE EDUCATION AND VERIFICATION OF EDUCATIONAL EFFECTIVENESS USING BAYESIAN NETWORKS

Takeshi Terazawa[1], Atushi Kondo[2] and Toshiya Arakawa[3,*]

[1]Advanced Medical Engineering Research Center
Asahikawa Medical University
Midorigaoka-higashi 2-1-1-1, Asahikawa, Hokkaido 078-8510, Japan
terazawa@asahikawa-med.ac.jp

[2]Department of Mechanical Engineering
Faculty of Fundamental Engineering
[3]Department of Data Science
Faculty of Advanced Engineering
Nippon Institute of Technology
4-1 Gakuendai, Miyashiro-machi, Minamisaitama-gun, Saitama 345-8501, Japan
kondo.atsushi@nit.ac.jp; *Corresponding author: arakawa.toshiya@nit.ac.jp

Received January 2023; revised May 2023

Abstract. *The project-based learning curriculum of the "Toy-Creation Contest" was introduced into practical training to improve comprehensive ability in engineering, and comprised planning, designing, drawing, and manufacturing. Its educational effects were verified by decision tree analysis and Bayesian networks using assignment and questionnaire grades after each session. The decision tree and Bayesian-network analysis showed that the "Toy-Creation Contest" not only improved the students' performance in the final examination and subsequent design classes, but also motivated them, indicating its educational effectiveness. The Bayesian networks can clarify that the "Toy-Creation Contest" related to mathematical ability; it was thought that it would be effective to establish, in advance, a grouping and follow-up system based on mathematical performance. In addition, the Bayesian networks also can clarify the causal relationship between the class design and educational effect of the teaching materials used in the class, as well as the relationship between the questionnaire comments and the task. Utilizing the method described in this study may be useful in restructuring class curricula and developing teaching materials, thus contributing to development.*

Keywords: Toy-Creation Contest, CAD/CAM/CAE education, Project-based learning, Decision tree analysis, Bayesian networks

1. **Introduction.** This study describes a project-based learning (PBL) curriculum of a computer-aided design/computer-aided manufacturing/computer-aided engineering (CAD/CAM/CAE) education class for third-year students of the Department of Mechanical Systems Engineering, Faculty of Engineering, Aichi University of Technology, where the authors were enrolled, and also clarified causal relationships such as class design, the educational effects of the teaching materials used in classes.

In recent years, many companies have been promoting digital transformation (DX), which utilizes CAD/CAM/CAE and other digital technologies in planning, design, and manufacturing to both improve product performance and quality and reduce costs.

DOI: 10.24507/ijicic.19.05.1439

Especially in the manufacturing industry, 80% of product quality and cost is said to be determined at the design stage. It is important to detect problems in the early development stage, improve quality, and reduce rework in later processes [1]. To shorten product-design lead time, 37.8% of the companies have introduced three-dimensional (3D) CAD/CAE, and 11.1% of the companies are emphasizing the use of 3D printers [2]. According to the 2021 edition of the Global Digital Competitiveness Ranking by the International Institute for Management Development in Switzerland, Japan ranks 28th out of 64 DX countries, while the Japanese government and Japanese companies are lagging behind in their proactive use of digital technology [3]. In the midst of this trend toward DX, there is a global need for human resources with a promising future in CAD/CAM/CAE technology, including among Japanese companies. The acquisition of CAD/CAM/CAE technology is nothing other than the acquisition of the basic skills of engineers who support today's "manufacturing". Therefore, efficient and effective CAD/CAM/CAE education at institutions of higher education is essential from the viewpoint of engineer development.

PBL is among the active learning educational methods on which the Ministry of Education, Culture, Sports, Science and Technology (MEXT) focuses. PBL is an instructional method in which students learn through facilitated problem solving, and student learning centers on a complex problem that does not have a single correct answer [4]. The aim of PBL is not to acquire knowledge and skills by working on tasks that have correct answers and solutions, but rather to develop knowledge and skills through tasks that do not have correct answers. PBL education is also used in CAD/CAM/CAE education [5]. In past cases, for example, educators would present students a product as a theme in advance, and the students would learn how to design and manufacture the product [6]; another example entails experimentally testing a bamboo dragonfly to promote an understanding of fluid dynamics, which is theoretically difficult to understand [7]. In recent years, there are some previous studies that XR (eXtended Reality) are introduced for PBL in CAD/CAM/CAE education [8]. As shown above, various innovations have been made for PBL in CAD/CAM/CAE. However, as far as the authors have been able to ascertain, there have been no examples of PBL education in which students themselves plan the product itself and consistently design and manufacture it using CAD/CAM/CAE technology. All of the authors of this paper are from manufacturing backgrounds, and from this perspective, we all understand that there are cases in which a single engineer performs planning, design, manufacturing, prototyping, and evaluation in the actual manufacturing process. Therefore, in higher education institutions, especially those that focus on manufacturing education, it is expected to be more effective than simply providing students with CAD/CAM/CAE experience in terms of acquiring engineers' basic knowledge, as mentioned above.

The aim of this study is to introduce the PBL curriculum for the "Toy-Creation Contest" for the purpose of improving the comprehensive engineering skills of planning, designing, drafting, manufacturing, prototyping, and evaluation, and to verify its educational effects.

The structure of this paper is as follows. Section 2 describes the details of the classes on CAD/CAM/CAE. Section 3 explains the results of the validation of the teaching effectiveness, while Section 4 discusses the results of the evaluation of the teaching effectiveness. Section 5 provides a summary.

2. **Educational Materials and Methods.**

2.1. **Curriculum for design classes and the position of CAD/CAM/CAE in curriculum at Aichi University of Technology.** An overview of the design curriculum

Table 1. Curriculum outline for design education

Year of course	Study contents concerning design
Late half of 1st years	Basic knowledge of mechanical drawing
First half of 2nd years	Hand-drawn drafting Basic class of CAM (G-code)
Late half of 2nd years	2D CAD training (AutoCAD) Control system analysis
First half of 3rd years	CAD/CAM/CAE1 3D CAD basic training (Inventor, CATIA)
Late half of 3rd years	CAD/CAM/CAE2 3D CAD advanced training (Inventor, CATIA) FEM (Finite Element Method) analysis

at Aichi University of Technology is shown in Table 1. The practical training discussed in this study was conducted in "CAD/CAM/CAE1" in the first semester of the third year, and it was conducted for third-year students (62 students) of the Department of Mechanical Systems Engineering in the Faculty of Engineering.

2.2. **Outline of the class.** In all 15 sessions, after reviewing CAM and two-dimensional CAD (2D-CAD), practical training in 3D-CAD was conducted. The 2D-CAD software used in the practical training was AutoCAD (Autodesk, Inc., USA) and the 3D-CAD software was Inventor (Autodesk, Inc., USA) and CATIA (Dassault Systèmes S.E., France). After each session, students were allocated an assignment related to the content of each session to measure their level of understanding. The full scores for the content of each session and grades for each assignment is shown in Table 2. Each assignment was corrected by the lecturers and graded by subtracting points based on the number of errors from the full score. In the following sections, each assignment is denoted by Ex (the number of each session), as shown in Table 2. For example, Ex56 refers to the assignments for the fifth and sixth sessions.

2.3. **How to conduct the Toy-Creation Contest.** The purpose of the "Toy-Creation Contest" was to improve students' overall ability as engineers.

The objectives of this project were to improve the planning ability to create ideas, designing ability to incorporate concepts into product parts, modeling of each part by 3D-CAD, confirmation of the motion of the mechanism by simulation, understanding and learning how to use 3D printers, and presentation ability; it was planned to be implemented in the 12th through the 15th sessions. Every student could choose the 3D-CAD software as they liked.

In the 12th session, the contents of the "Toy-Creation Contest" were explained, and the following three conditions were presented for the creation of the toys.

1) The toy must have some kind of mechanism and be "movable" by hand or other power.
2) The toy should be divided into multiple parts so that it can be assembled after being modeled by a 3D printer.
3) Do not reuse toys created by others or posted on the Web.

Considering the 3D printer's operating time, we set the restriction that "the total size of all parts must be within $150 \times 150 \times 20$ mm". In the 12th session, students were required to submit a plan and a concept of a toy that satisfied these conditions in the form of a punch drawing. In the 13th session, we aimed to design the parts to realize the concept and draw them by 3D-CAD, and we explained the method of modeling by 3D printer.

Table 2. Class objectives, assignments, and distribution of points

Session	Learning items	Pedagogical objective	Assignment	Assignment no.	Scoring
1	CAM (G-code)	Understand the coordinate instruction method (absolute command and incremental command method) in G-code for CAM.	Basic problem 1 Read the coordinates from the graph paper with the tool path drawn on it and then create the G-code using the absolute command method.	Ex12	10
			Basic problem 2 Read the coordinates from the graph paper with the tool path drawn on it and then create the G-code using the incremental method.		
2		Understand the difference between the unit system of processing instruction values in drafting and the unit system in G-code and set numerical values in G-code by appropriately converting units.	Application problem 1 Read the coordinates from the graph paper on which the tool path is drawn, and create the G-code using the absolute command method.		
			Application problem 2 Read the coordinates from the graph with the tool path drawn and then create the G-code using the incremental command method.		
			Application problem 3 Read the coordinates from the graph paper with the tool path drawn and then create the G-code using the absolute command method.		
			Application problem 4 Read the coordinates from the graph paper with the tool path drawn and then create the G-code using the incremental command method.		
			Developmental problems Read the drafting drawing and create a machining program. The coordinate system is the complete system. The end mill diameter is 6 mm, and the cutting depth is 2 mm. Straight lines are machined with a peripheral circumferential speed of 90 m/min and a feed rate of 0.2 mm/rev, while curved lines are machined with a peripheral circumferential speed of 50 m/min and a feed rate of 0.1 mm/rev.		
3·4	2D-CAD review	Review basic 2D-CAD drawing methods as an introduction to 3D-CAD sketching.	2D-CAD exercises Draw the 20 shapes illustrated in the textbook using AutoCAD.	Ex34	20
5	3D-CAD Inventor	Be able to draw rough sketches using Inventor and understand geometric and dimensional constraints.	Draw a rough sketch and geometric and dimensional constraints to make the shape identical to the specified drawing. Create a total of five figures.	Ex56	10
6		Understand how to create features that extrude sketches.	Model the illustrated 3D shapes using 3D-CAD. Create a total of six figures.		
7		Understand how to assemble parts in 3D-CAD with appropriate constraints on multiple parts.	· Model the three-dimensional figures in the textbook using 3D-CAD. Create a total of four works. · Create a cube by combining Tetris-like blocks that are the basis of the cube. Create a total of three works.	Ex7	5
8		Understand how to convert 3D models to parts and assembly drawings	Create two parts and assembly drawings from Inventor data.	Ex8	5

(continued)

Session	Learning items	Pedagogical objective	Assignment	Assignment no.	Scoring
9	3D-CAD CATIA	Understand how to assemble multiple parts by applying appropriate assembly constraints using CATIA.	· Create a cube by combining Tetris-like blocks that are the basis of the cube. Create a total of two works. · Assemble the pre-modeled engine parts using the assembly constraint and complete the two works of single-cylinder and two-cylinder engines.	Ex9	5
10	3D-CAD	Understand how to simulate mechanism operation using Inventor and CATIA.	Complete the 5-way cam with proper assembly constraints.	Ex10	5
11	3D-CAD CATIA	Understand how to create drawings of parts and assemblies from 3D models created in CATIA.	Create two parts and assembly drawings from CATIA data.	Ex11	5
12	Implove engineering capabilities	PBL learning (Toy-Creation Contest)	Conceptualization of toy creation, punch drawing, basic design, 3D-CAD drafting, simulation, and 3D printer modeling of parts.	ExToy	15
13					
14					
15		Toy-Creation concept presentation. Preliminary explanation of the final exam.	Cramming of exams.		

Two da Vinci 1.0 Pro and two da Vinci 2.0A Duo 3D printers (XYZprinting, Inc., Taiwan) were used for modeling. In the 14th session, the goal was to create parts by 3D printers, check whether they operated as designed by assembling them on the actual object, and redesign them if necessary. In the 15th session, a presentation of the work was held. Grading was conducted by all students who participated in the presentation, and students were instructed to score their works on a 15-point scale, with 5 points for each of the three items: "Interest of the toy", "Complexity of the mechanism", and "Design and completeness of the product".

2.4. **Evaluation of the effectiveness of the "Toy-Creation Contest".** The "Toy-Creation Contest" was designed to test overall manufacturing skills; therefore we thought that the scores for this contest would be affected by the performance of the tasks performed before the contest. If we can determine which of the tasks listed in Table 2 affects the score for the "Toy-Creation Contest", we can expect to obtain guidelines and knowledge for acquiring planning, design, and manufacturing skills. In addition, planning skills were considered to be influenced by courses taken in the first and second years, i.e., before taking CAD/CAM/CAE1, the subject of this study. Furthermore, Table 1 shows that CAD/CAM/CAE2, which is offered in the second semester of the third year, is a course to develop advanced design skills; the results of the "Toy-Creation Contest" may also affect the students' performance in CAD/CAM/CAE2. If we can understand the influence between the above-mentioned subjects, we can understand the position of the "Toy-Creation Contest" in the design education at Aichi University of Technology; additionally, we can verify that this contest is an important content for acquiring engineers' basic knowledge.

To verify this, we conducted a validity evaluation using decision tree analysis, Bayesian networks, and a questionnaire. The questionnaire was administered after the 15th session and comprised the following nine questions: Q1-1, Q2-1, and Q3-1 were on a 5-point Likert scale, and the remaining questions were open-ended.

Q1-1 Do you think the "Toy-Creation Contest" was useful in improving your engineering skills for the future? (1: not useful – 3: neither useful nor not useful – 5: useful)

Q1-2 Please tell us why you think so in Q1-1.

Q2-1 Was the level of difficulty of the "Toy-Creation Contest" appropriate for you? (1: extremely difficult – 3: adequate difficulty – 5: very easy)
Q2-2 Please tell us why you thought so in Q2-1.
Q3-1 Did the content of the "Toy-Creation Contest" arouse your interest in CAD/CAM/ CAE? (1: not at all interested – 3: neither interested nor not interested – 5: very interested)
Q3-2 Please tell us why you thought so in Q3-1.
Q4 Which 3D-CAD did you mainly use, Inventor or CATIA?
Q5 Did you end up using the 3D printer you mainly used? Please tell us the model.
Q6 Did you encounter any error problems such as modeling defects when using a 3D printer? If so, what was the cause and how did you solve it?

The statistical software R version 4.0.5 and the rpart and bnlearn functions of R were used for the analysis. The following process was used for the validity evaluation.

1) To determine which tasks significantly affect the performance of the "Toy-Creation Contest", a decision tree analysis is performed.
2) Based on the results of the decision tree analysis, a Bayesian-network analysis is performed to extract the causal relationship between the tasks that significantly affect the students' scores in the "Toy-Creation Contest" and other tasks.

This process allows us to identify the tasks that directly affect the students' scores. Furthermore, by extracting the causal relationship between each task and the questionnaire, it is possible to extract tasks that contribute to the improvement of students' design ability, and to evaluate whether they bring about the improvement in academic achievement that the class design aims to achieve. Decision tree analysis and Bayesian-network analysis is often used for data structural analysis. However, there are few previous studies that decision tree analysis and Bayesian-network analysis is used for analysis of educational effect. There are examples of decision tree analysis being used in terms of various industrial applications [9, 10], and it appears that it is often used in educational research [11, 12]. Similarly, as for Bayesian networks, there are examples being used in terms of various industrial applications [13, 14]; however, there are not many previous studies that are used in educational research [15]. Decision trees have a characteristic that the structure is analyzed based on rules, and Bayesian networks has a characteristic that the network explains causal relationship; therefore, educational effect is expected to be able to be analyzed in more if we combine these two analysis methods. This is one novelty point of this work. A decision tree analysis allows us to understand which assignments are affecting student scores, and Bayesian networks allow us to visualize what the relationship is between each assignment and the questionnaire indicating motivation to design, and to identify the impact.

In each analysis, the score for the CAD/CAM/CAE1 assignment was used as the explanatory variable, while the scores for the "Toy-Creation Contest" and final exam were used as the objective variables. The full score for the assignment and scoring method are described in Subsection 2.2; the final exam score was worth 50 points. The analysis was conducted on 48 students, excluding those who did not participate in the "Toy-Creation Contest" or the questionnaire survey and those who did not take the CAD/CAM/CAE2 class. For reference, Table 3 shows the lowest, highest, and mean scores, and standard deviation of the scores of the 48 students included in the analysis.

2.5. **Decision tree analysis.** Decision tree is a method developed from auto interaction detection (AID), a popular data mining technique [16]. Decision trees aim to discover explanatory variables that are strongly related to a target variable or subgroups of interest by selecting one appropriate explanatory variable from a set of explanatory variables and

Table 3. The minimum, maximum, average, and standard deviation of the students' scores for each assignment and total score.

Assignment no.	min.	max.	mean	SD
Ex12	5	10	9.19	1.39
Ex34	0	20	12.65	4.75
Ex56	7	13	9.65	0.95
Ex7	4	5	4.98	0.14
Ex8	0	5	4.60	1.09
Ex9	0	5	4.60	1.05
Ex10	0	7	4.15	1.76
Ex11	0	5	4.13	1.66
ExToy	3.92	13.23	10.60	1.42
Q1-1	3	5	4.17	0.72
Q2-1	1	5	2.33	0.97
Q3-1	1	5	3.67	0.88
Final exam.	10.2	50	34.56	11.99

repeatedly dividing the dataset into subsets with more homogeneous trends. Although there are various algorithms for decision tree analysis, this study used classification and regression trees (CART) [17], which are popular algorithms for decision tree analysis [18, 19]. The CART algorithm works via the following process [20].

Step 1 The best split point of each input is obtained.
Step 2 Based on the best split points of each input in Step 1, the new "best" split points are identified.
Step 3 Split the chosen input according to the "best" split point.
Step 4 Continue splitting until a stopping rule is satisfied or no further desirable splitting is available.

Considering the process, we thought the CART is easy to visualize and understand the relationship of issues that affect the grade; therefore, CART seems to be an adequate method for this study.

By conducting a decision tree analysis of the relationship between the scores using the "Toy-Creation Contest" score as the objective variable and each task score as the explanatory variable, we could understand the relationships between the tasks that affected the students' performance in the "Toy-Creation Contest" and identify the tasks that hindered the students' performance in the contest. It is thought that it is possible to grasp the students' characteristics by clarifying the tasks that hinder the execution of the "Toy-Creation Contest". Here, the G-code of CAM, review of 2D-CAD, and conversion of 3D-CAD data into plan drawings (the tasks in the first through the fourth, eighth, ninth, and eleventh sessions) were excluded from the explanatory variables because it is difficult to assume a direct causal relationship to the evaluation of the "Toy-Creation Contest" considering design of the class.

2.6. **Bayesian networks.** A Bayesian network is a graphical model which is a directed acyclic graph that encodes probabilistic relationships among variables of interest and facilitates data analysis when there are many variables [21, 22]. The validity of the class design was evaluated by analyzing the dependencies between the grades for all the assignments using Bayesian networks.

In this study, the following three steps were taken modeling a data-driven Bayesian network [23].

1) Pre-condition setting

The class design is designed to be a stage in which students understand the prerequisite knowledge and work on its application, and the corresponding directed graphs are visualized as directed graphs, as intended by the network design. In this study, as a pre-condition, we set a constraint so that arcs that reverse the time series of the exercises do not appear. As in the decision tree analysis, the CAM G-code, 2D-CAD review, and 3D-CAD drawing were excluded from the variables to be analyzed because it was difficult to assume a direct causal relationship to the evaluation of the "Toy-Creation Contest" in terms of the design of the class. Meanwhile, we examined the influence of the "Toy-Creation Contest" on the classes for fostering basic mathematical processing and logical thinking skills in the first and second years, and on "CAD/CAM/CAE2" in the latter half of the third year. For this purpose, when examining Bayesian networks, we used the scores for the "Mathematics Achievement Test" (given at the time of admission) and for the "Programming Exercises" (required in the second semester of the first year) and "Useless Manufacturing Contest" in "Study Build-up 2" (required in the second full year) to verify the relationship to basic mathematical processing skills and to logical thinking skills, respectively.

The "Useless Manufacturing Contest" in "Study Build-up 2" is a low-cost manufacturing experience that incorporates originality and ingenuity [24]. In terms of the "manufacturing" of originality and ingenuity, these contests mainly test planning ability, and are considered to have something in common with the "Toy-Creation Contest" addressed in this study. The details of these subjects are described in Subsection 3.2.

In applying Bayesian networks, the variables used must have discrete values. Therefore, the scores for the "Toy-Creation Contest" and main exam were transformed into classification results based on decision tree analysis, while the scores for the "Mathematics Achievement Test", "Programming Exercises", and "Study Build-up 2" were converted into classification results based on whether they corresponded to 0-60, 61-70, 71-80, 81-90, or 91-100 points. These scores correspond to the grades of "F", "D", "C", "B", and "A", which are commonly used as grades in higher-education institutions.

2) Structural learning

The first step in Bayesian networks is structural learning, which learns the probabilistic dependencies among nodes from the data. In this study the structural estimation of the Bayesian networks was performed using the hill-climbing method based on the Bayesian information criterion (BIC) score. To obtain robust Bayesian-network models, model averaging [25] was applied in this study. The model averaging generates samples by bootstrapping and performs structural learning on the samples.

3) Conditional probabilities computation

Conditional probabilities are computed using parameter estimation. In this study, we analyzed the dependencies between the scores for all the assignments using Bayesian networks. The root of acyclic graph is considered as cause, and the tip of acyclic graph is considered as effect. Thus, when two nodes are connected, the root of the node can be considered the cause and the tip of the node the effect. Arc strength was calculated as the frequency of an arc occurring between two nodes across the 200 bootstrapped network structure [26].

3. Results.

3.1. Result of decision tree analysis. The results of the decision tree analysis are shown in Figure 1. As shown in Figure 1, with the decision tree algorithm as CART, the structure of the model is bifurcated. The root, which is the first node without a parent,

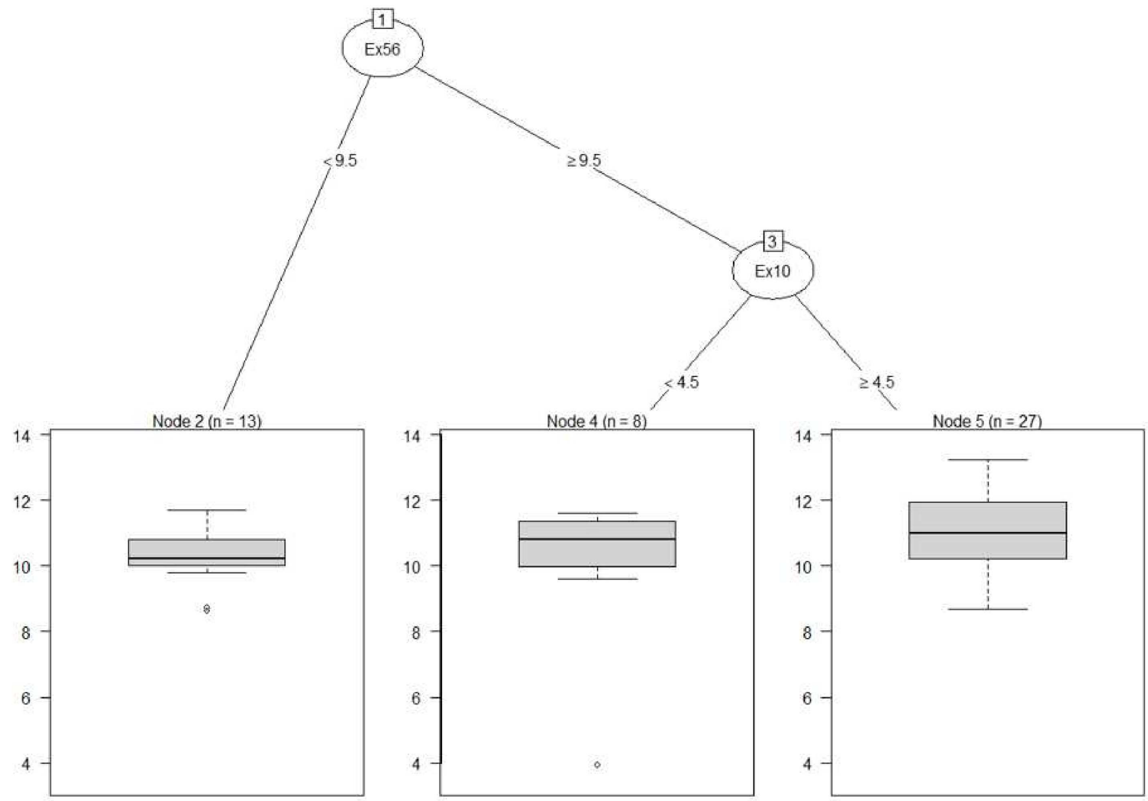

FIGURE 1. Decision tree of "Toy-Creation Contest" score

is Ex56, and the node is Ex10. The tasks most closely related to the grades in the "Toy-Creation Contest" were the fifth and sixth tasks, "Rough Sketch Exercise with Inventor", and the tenth task, "Assembly Constraint Exercise".

The Ex56 branch was categorized differently depending on whether the grade of Ex56 was 9.5, higher, or lower. Students who scored less than 9.5 (n = 13, 27% of the total) belonged to Node 2, with median, maximum, and minimum scores of 10.23, 11.69, and 8.64, respectively, for the "Toy-Creation Contest". Students who received an Ex56 grade of 9.5 or higher were significantly affected by their Ex10 grade, while those who received an Ex10 grade of less than 4.5 (n = 8, 16.7% of the total) belonged to Node 4, with median, maximum, and minimum scores of 10.82, 11.62, and 3.92, respectively, for the "Toy-Creation Contest". Students with an Ex56 grade of 9.5 or higher and an Ex10 grade of 4.5 or higher (n = 27, 56% of the total) belonged to Node 5, with median, maximum, and minimum scores of 11, 13.23, and 8.68, respectively, for the "Toy-Creation Contest".

3.2. **Result of Bayesian networks.** The estimated Bayesian network is shown in Figure 2. Figure 2 shows the relationship between each assignment (the "Toy-Creation Contest" is labeled "ExToy"), Questions Q1-1, Q2-1, and Q3-1 of the questionnaire, the grades for the "Programming Exercises", "Study Build-up 2", "Mathematics Achievement Test", and the final exam, which were taken before this training, and CAD/CAM/CAE2 in the second half of the third year.

Table 4 shows the arc strengths related to the "Toy-Creation Contest". In Figure 2, only variables with an arc strength of 0.505 or greater are indicated by arcs. Variables with an arc strength of 0.8 or greater are represented by thicker arcs. The task with the highest arc strength for causality with ExToy was Ex56, with an arc strength of 1.0. The

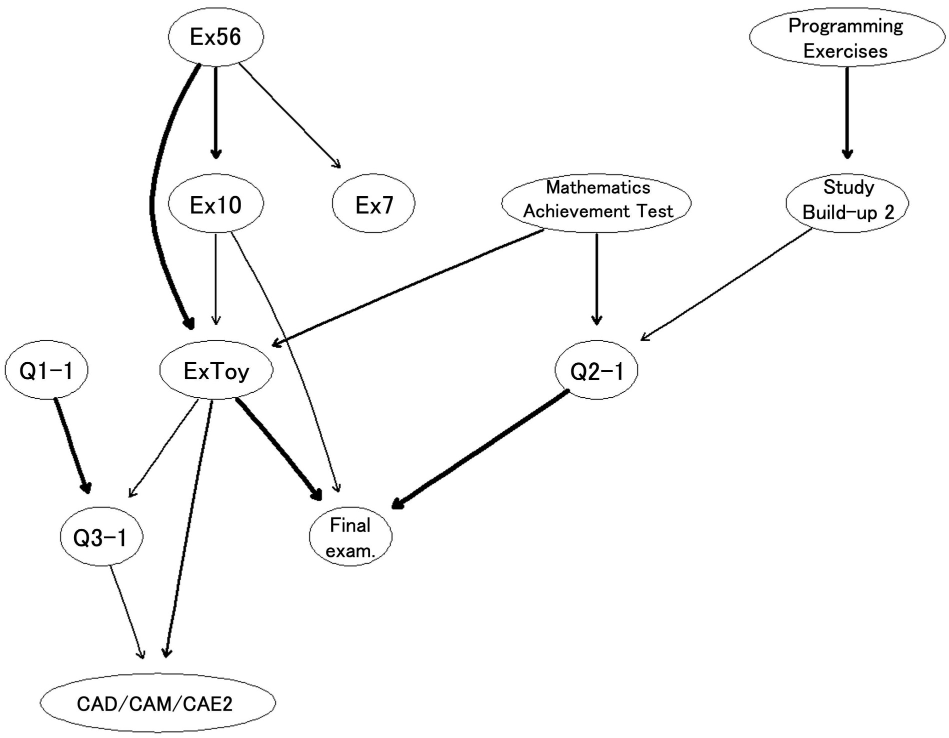

Figure 2. Estimated Bayesian network

Table 4. Arc strengths of Bayesian network

From	To	Arc strength
Programming Exercises	ExToy	0.210
Study Build-up 2		0.085
Mathematics Achievement Test		0.685
Ex56		1.000
Ex7		0.280
Ex10		0.655
ExToy	Q1-1	0.060
	Q2-1	0.276
	Q3-1	0.565
	Final exam.	0.995
	CAD/CAM/CAE2	0.665

causal relationship between ExToy and Ex56 also shows an arc through Ex10. In addition, there was an arc between the Math Achievement Test and ExToy, with an intensity of 0.685. An arc from ExToy to the subsequent session, CAD/CAM/CAE2, was observed, with an intensity of 0.665. The items that affected the final examinations were Ex10 and ExToy, and there was a causal relationship with Question Q3-1.

3.3. **Comments obtained from the questionnaire about the class.** For the questionnaire item, Q4, "Which 3D-CAD did you mainly use?", 51 (96%) of the 53 valid responses were for Inventor, and 1 (2%) for CATIA, and 1 (2%) could not get around to using 3D-CAD. In addition, 36 (67.9%) of the 53 valid responses to Q5, "What model of 3D printer did you mainly use?" This means that these students had completed the

Table 5. Student comments in the questionnaire

Question		Student comments
Q1-2	Positive	It was an opportunity for a considerable amount of trial and error, such as investigating the mechanism. Conceiving things and creating products helped me to improve my own abilities. I felt that it was very difficult to generate an idea on my own and to create a product through repeated trial and error. It was the first time for me to design a product from scratch; thus, it was a good experience.
Q2-2	Positive	There were times when the 3D printer did not work; thus, it took some time; however, creating the product itself was not that difficult. Product creation was neither too easy nor too difficult. It was a little difficult to work with the new functions; however, it was worthwhile. It was difficult to think about the meshing of the gears.
	Negative	Due to COVID-19, I could not work in the university and could not ask teachers or my friends questions. There are insufficient 3D printers. The printer frequently broke down and took a long time to recover. Moreover, the accuracy was low and none of the dowels would fit. There was insufficient time for production.
Q3-2	Positive	Although I was not good at CAD, I felt a sense of accomplishment when I could successfully produce the actual product that I had designed. It was fun to perform simulations and investigate why the 3D printer did not work. I have never used a 3D printer before and this was my first experience. I am now more interested in CAD/CAM/CAE and want to improve it. I realized how fun it was to use CAD. I learned the joy of creating products. The process of modeling with the 3D printer was difficult. However, I felt a sense of accomplishment when the parts perfectly fit together. If I had more time, I would like to try my hand at making other products.
	Negative	I was looking forward to it at first; however, when I tried it, it was a struggle and entailed a considerable amount of work. I could form the product; however, it did not work properly. I was no longer motivated to create.
Q6	Negative	The rest of the support material on the part after molding could not be removed. Nozzle was clogged, disassembled and cleaned. Tried to solve the problem of the filament not coming out. The dimensions of the actual product were slightly different from the design dimensions. The 3D printer stopped in the middle of molding. The raft peeled off. Zero-point alignment and sheet reattachment were performed. Material jammed and was pushed out with a thin metal needle.

modeling work. Other comments obtained from students in Q1-2, Q2-2, Q3-2, and Q6 are shown in Table 5.

3.4. **Example of students' works.** In the 15th section, all students were recommended a presentation using PowerPoint. Those who had completed modeling on the 3D printer (only approximately 20% of the students) were also asked to explain their work by operating the actual product. Examples of the presented works are shown in Figure 3.

4. **Consideration.** The results of the decision tree analysis showed that the influence on the grade for the "Toy-Creation Contest" was large for the 5th and 6th (Ex56) and 10th (Ex10) in-session exercises, and the Bayesian-network analysis showed that not only arcs leading directly from Ex56 to ExToy, but also those leading from Ex56 to ExToy via Ex10, and those between Ex56, Ex10, and ExToy were found. Both Ex56 and Ex10 were tasks to measure Inventor comprehension. From Q4, 96% of the students indicated that Inventor was the 3D-CAD tool used in toy construction; thus, it is not surprising that there was a relationship between the grades for these exercises, which indicate basic Inventor skills in realizing toy creations.

FIGURE 3. Examples of students' works presented in the 15th session. The upper left work is a pantjack, which took 72 hours of work outside of class time. The work on the left in the middle row is a magic hand, which took 15 hours to make. The work on the left in the lower row is a model of a rotary engine. The upper right work is a planetary schmid joint, which took approximately 40 hours of work outside of class time. The work on the right in the middle row is an automatic dice-rolling machine, which took approximately 30 hours to make. The work on the lower right is a 10-second pendulum clock, which took approximately 40 hours to make.

However, the seventh in-session exercise (Ex7) was also a task that tested Inventor comprehension; however, no arc was observed between Ex7 and ExToy. This suggests that there was insufficient understanding of concepts common to both Ex56 and Ex10 in Inventor operations. Ex56 is an exercise to test the understanding of the process of determining a unique 2D shape by drawing a rough sketch and correctly constraining the geometry and dimensions. Ex10 is a task to test the understanding of the process of constraining the degrees of freedom by applying appropriate assembly constraints between parts in order to correctly assemble the parts. In contrast, Ex7 differs from Ex56 and Ex10 in that it mainly focuses on understanding how to set up a plane in Inventor and how to add and subtract objects, and does not question the concept of constraints on degrees of freedom. This suggests that, although the commonality in terms of testing the comprehension of Inventor is evident, there was insufficient understanding of the concept of reducing the degrees of freedom by means of constraints and ultimately determining a unique shape and structure. The ratio of students who scored less than 9.5 on Ex56 to the total number of students in the decision tree was approximately 27%. The results suggest that there is a need to improve the curriculum for the 5th session so that these students can understand the concept of constraints on the degrees of freedom in modeling.

The Bayesian-network analysis showed no causal relationship between “Toy-Creation Contest” and, “Programming Exercises” and “Study Build-up 2”, which are the content of the first and second year classes; however, there was a causal relationship with the mathematics achievement test. This suggests that basic mathematical processing skills may have an influence on “Toy-Creation Contest”. In creating a toy, each student must consider “how to move the mechanism” and “how to avoid deviations in modeling”. In this consideration, it is necessary to go beyond abstract concepts and incorporate concrete numerical values into the process. Therefore, from the conceptual stage, it is necessary to imagine the mechanism with a view to modeling and design accuracy assurance. However, the study based on these images suggests that basic mathematical processing capability is the foundation. No causal relationship was found between Ex56, Ex7, and Ex10, which indicate the ability to understand CAD and the content of the classes in the first and second years. It seems that the ability to understand CAD tools is independent of basic mathematical processing and programming skills. Thus, it is suggested that at least basic mathematical processing skills and an understanding of CAD are important when working on the “Toy-Creation Contest”. Therefore, it is necessary to assume that all students do not have sufficient mathematical skills in order to effectively engage them in the learning process. It is suggested that it is important to predict in advance which students are likely to stumble in the “Toy-Creation Contest”, to increase the frequency of follow-up by teachers and teaching assistants for students with low grades in the most important exercise (Ex56), which shows the students’ understanding of CAD, and to group students who seem to be able to make toys and have them work on them while following each other’s leads.

The analysis in this study did not find a causal relationship between the “Programming Exercises” and the “Study Build-up 2”. The grade for mastery formation was analyzed with the grade for the “Useless Manufacturing Contest”. It is assumed that they were not connected to logical thinking in hardware design, as in the “Toy-Creation Contest”, because “Programming Exercises” are courses that assess logical thinking in software design [27]. Regarding the “Useless Manufacturing Contest”, the content of the contest was to assemble materials based on students’ own ideas without using knowledge of CAD/CAM/CAE, and it emphasized planning skills rather than designing and production. Therefore, it is suggested that this did not affect the “Toy-Creation Contest”, which also has a strong design and production component.

The grade (ExToy) for the “Toy-Creation Contest” was found to have an arc to the results of the final examinations, Questionnaire Q3-1, and the CAD/CAM/CAE2 class grades following the second semester of the third year. This suggests that the “Toy-Creation Contest” positively impacts the final exam and CAD/CAM/CAE2 class grades in the second semester, and we believe that this indicates the educational effects of PBL learning through toy creation. Furthermore, ExToy seems to affect Questionnaire Q3-1, “Did the content of the “Toy-Creation Contest” arouse your interest in CAD/CAM/CAE?” In Q3-2, there were also comments such as “It was interesting to investigate why it did not work”, “I became more interested in it and want to improve it further”, and “I learned the fun of creating things”, suggesting that the toy creation motivated the students to further their engineering learning.

During the practical training, problems such as molding stoppage and the filament not coming out of the 3D printer frequently occurred. Students could troubleshoot problems by adjusting the printer themselves. In addition, the accuracy of the printers themselves caused some works to be re-molded due to mismatch problems, and the time required for modeling and number of printers were also a bottleneck in this training. It is necessary to appropriately select the model and secure the number of 3D printers.

In this study, we use Bayesian networks to evaluate the usefulness of the “Toy-Creation Contest” and validity of the class design. Bayesian networks can be used to evaluate the validity of class design, basic knowledge required for the class, and effectiveness of the class through causal inference and is considered to be an effective method for objective class evaluation. Furthermore, by showing the dependence of the results on the questionnaire results, it is possible to visualize which classes led to which results and comments, which is important information that can be utilized to provide feedback for class design.

5. **Conclusions.** In this study, we introduced a PBL curriculum, “Toy-Creation Contest”, in CAD/CAM education, and clarified its educational effects by using decision tree analysis, Bayesian networks, and questionnaire surveys as follows.

- The “Toy-Creation Contest” not only improves the grades for the final examinations and subsequent design classes, but also motivates the students.
- The results showed that there was a relationship between mathematical ability and the implementation of the “Toy-Creation Contest”, and that it would be effective to establish a grouping and follow-up system based on mathematical achievement in advance of the contest.
- A Bayesian network can clarify causal relationships such as class design, the educational effects of the teaching materials used in classes, and relationship between questionnaire comments and issues.

The results in this study were analyzed for a single year, while it is desirable to analyze the results obtained over multiple years. In addition, the results obtained in this study are in themselves quite natural. However, the appeal of this study is that it is possible to visualize the causal relationship between students’ abilities and the effects of the class curriculum using Bayesian networks, and a verification by this method is suggested to have a certain validity based on the experience of the teachers in charge (the authors). The method described in this study may be useful in the restructuring of class curricula and development of teaching materials, and we appeal to its usefulness as a methodology that contributes to the development of such curricula. In summary, we think our research contributed to pedagogy area, and we think that an academic contribution to pedagogy in that it demonstrates a quantitative evaluation method for class curriculum design using data mining techniques, an engineering technology.

In the future, the results of these analyses will be fed back into the design of classes to make them more efficient and effective. We will also verify the generality of the evaluation method developed in this study by applying it to other subjects.

REFERENCES

[1] Ministry of Economy, Trade and Industry, *Ministry of Economy, Trade and Industry’s Manufacturing White Paper 2020*, https://www.meti.go.jp/press/2020/05/20200529001/20200529001-7.pdf, Accessed on 20 January, 2022 (in Japanese).

[2] Mitsubishi UFJ Research & Consulting Co., Ltd., *Survey on the Actual State of Manufacturing Base Technology: Report on Issues and Directions for Response in Japan’s Manufacturing Industry*, https://www.meti.go.jp/meti_lib/report/2019FY/000283.pdf, Accessed on 20 January, 2023 (in Japanese).

[3] International Institute for Management Development, *World Digital Competitiveness Ranking*, https://www.imd.org/globalassets/wcc/docs/release-2021/digital_2021.pdf, Accessed on 20 January, 2023.

[4] C. E. Hmelo-Silver, Problem-based learning: What and how do students learn?, *Educational Psychology Review*, vol.16, no.3, pp.235-266, 2004.

[5] F. A. Fernandes, N. Fuchter Júnior, A. Daleffe, D. Fritzen and R. J. Alves de Sousa, Integrating CAD/CAE/CAM in engineering curricula: A project-based learning approach, *Education Sciences*, vol.10, no.5, 125, 2020.

[6] H. Lorenzo-Yustos, P. Lafont, A. Diaz Lantada, A. F.-F. Navidad, J. L. Muñoz Sanz, J. M. Muñoz-Guijosa, J. Muñoz-Garcia and J. Echavarri Otero, Towards complete product development teaching employing combined CAD-CAM-CAE technologies, *Computer Applications in Engineering Education*, vol.18, no.4, pp.661-668, 2020.

[7] K. Takato and S. Shirayama, Flow visualization experiments around a flying toy "Taketombo" for PBL education, *Proceedings of Mechanical Engineering Congress, 2016 Japan (MECJ-16)*, G2000104, 2016 (in Japanese).

[8] X. N. Skosana, K. Mpofu, J. Trimble and E. A. van Wyk, An empirical framework for developing and evaluating a virtual assembly training system in learning factories, *Interactive Learning Environments*, pp.1-17, 2022.

[9] C. Zhang, S. Chai, L. Cui and B. Zhang, Road condition recognition in self-driving cars based on classification and regression tree, *ICIC Express Letters, Part B: Applications*, vol.10, no.12, pp.1115-1122, 2019.

[10] L. R. Abreu, I. S. Maciel, J. S. Alves, L. C. Braga and H. L. Pontes, A decision tree model for the prediction of the stay time of ships in Brazilian ports, *Engineering Applications of Artificial Intelligence*, vol.117, 105634, 2023.

[11] J. Wang and H. Yang, Research on online evaluation method of MOOC teaching quality based on decision tree-based big data classification, *International Journal of Continuing Engineering Education and Life-Long Learning*, vol.33, no.1, pp.10-22, 2022.

[12] S. Batool, J. Rashid, M. W. Nisar, J. Kim, H. Y. Kwon and A. Hussain, Educational data mining to predict students' academic performance: A survey study, *Education and Information Technologies*, vol.28, no.1, pp.905-971, 2023.

[13] O. Bayazit and M. Kaptan, Evaluation of the risk of pollution caused by ship operations through bow-tie-based fuzzy Bayesian network, *Journal of Cleaner Production*, vol.382, 135386, 2023.

[14] L. S. Chan, A. M. Chu and M. K. So, A moving-window Bayesian network model for assessing systemic risk in financial markets, *PloS One*, vol.18, no.1, e0279888, 2023.

[15] T. Arakawa, Analyzing the causal relationship for an effective remedial education based on Bayesian network: A case study, *International Journal of Innovative Computing, Information and Control*, vol.17, no.4, pp.1421-1433, 2021.

[16] D. Biggs, B. De Ville and E. Suen, A method of choosing multiway partitions for classification and decision trees, *Journal of Applied Statistics*, vol.18, no.1, pp.49-62, 1991.

[17] L. Rutkowski, M. Jaworski, L. Pietruczuk and P. Duda, The CART decision tree for mining data streams, *Information Sciences*, vol.266, pp.1-15, 2014.

[18] H. Liu, J. Jin, K. Liu, J. Zhang and Y. Niu, Research on UAV air combat maneuver decision based on decision tree CART algorithm, in *Proceedings of 2022 International Conference on Autonomous Unmanned Systems (ICAUS 2022). ICAUS 2022. Lecture Notes in Electrical Engineering*, W. Fu, M. Gu and Y. Niu (eds.), Singapore, Springer, 2023.

[19] X. Li, X. Wu, J. Qian, Y. Yuan, S. Wang, X. Ye, Y. Sha, R. Zhang and H. Ren, Differentiation of lacrimal gland tumors using the multi-model MRI: Classification and regression tree (CART)-based analysis, *Acta Radiologica*, vol.63, no.7, pp.923-932, 2022.

[20] GeeksforGeeks, *CART (Classification And Regression Tree) in Machine Learning*, https://www.geeksforgeeks.org/cart-classification-and-regression-tree-in-machine-learning/, Accessed on 7 April, 2023.

[21] D. Heckerman, A tutorial on learning with Bayesian networks, in *Innovations in Bayesian Networks. Studies in Computational Intelligence*, D. E. Holmes and L. C. Jain (eds.), Berlin, Springer, 2008.

[22] T. A. Stephenson, An introduction to Bayesian network theory and usage, in *IDIAP Research Report*, IDIAP-RR00-03, Switzerland, 2000.

[23] K. Sasaki and Y. Okada, Role expectations for Bayesian networks, *Journal of the Operations Research Society of Japan*, vol.65, no.6, pp.299-303, 2020 (in Japanese).

[24] T. Arakawa and Y. Ito, Practice of "Useless Manufacturing Contest" in "Study Build-up 2", *Journal of Japan Society for Engineering Education*, vol.65, no.5, pp.5_98-5_103, 2017 (in Japanese).
[25] P. Caillet, S. Klemm, M. Ducher, A. Aussem and A. M. Schott, Hip fracture in the elderly: A reanalysis of the EPIDOS study with causal Bayesian networks, *PLoS One*, vol.10, e0120125, 2015.
[26] S. Xu, W. Thompson, J. Kerr, S. Godbole, D. D. Sears, R. Patterson and L. Natarajan, Modeling interrelationships between health behaviors in overweight breast cancer survivors: Applying Bayesian networks, *PLoS One*, vol.13, e0202923, 2018.
[27] J. Voogt, P. Fisser, J. Good, P. Mishra and A. Yadav, Computational thinking in compulsory education: Towards an agenda for research and practice, *Education and Information Technology*, vol.20, pp.715-728, 2015.

Author Biography

Takeshi Terazawa received a B.Sc. degree from Iwate University, 2003; an M.Sc. degree from the Tohoku University, 2005; and a Ph.D. degree from Hokkaido University, 2019. He worked at Fuji Heavy Industries, LTD. from 2005 to 2016, National Cerebral and Cardiovascular Center from 2017 to 2018, and Aichi University of Technology, Japan, as an assistant professor from 2019 to 2020.

Dr. Terazawa is currently a full-time associate professor/lecturer at the Asahikawa Medical University, Japan. His main research interests include artificial heart valve and tissue engineering.

Atushi Kondo received his B.A. degree in Mechanical Engineering from Kogakuin University in 1997, and master's and Ph.D. degrees from Sophia University in 1999 and 2011, respectively.

Dr. Kondo is currently an associate professor in the Department of Mechanical Engineering at Nippon Institute of Technology. His main research interests are computational engineering and its application to the mechanics of composite materials.

Toshiya Arakawa received a B.Sc. degree from Waseda University, 2001; an M.Sc. degree from the University of Tokyo, 2003; and a Ph.D. degree from SOKENDAI, the Graduate University for Advanced Studies, 2012. He worked at Fuji Heavy Industries, LTD. from 2003 to 2013, and Aichi University of Technology, Japan, as a professor from 2013 to 2021.

Dr. Arakawa is currently a full-time professor at Nippon Institute of Technology, Japan. His main research interests include human factors in autonomous driving and the application of machine learning and statistics to social problems. He has published over 50 papers in well-known journals.