Structural Equation Modelling of Human Factors and Their Impact On Productivity of Cellular Manufacturing

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Abstract: Cellular manufacturing has become an integral part of lean manufacturing systems; more and more attentions have been paid to cellular manufacturing. Although the quality and productivity of cell production systems depends largely on operators' skill and other human factors, it is still insufficient to investigate how human factors affect manufacturing cells. Here, we apply structural equation modeling to analyze the impact of human factors on productivity of cellular manufacturing. We design a laboratory experiment of cellular manufacturing to measure the efficiency of the operators in manufacturing cells and meanwhile, conduct a questionnaire to grasp the operators' aptitude. A covariance structure model is constructed based on the experiment data and the questionnaire's answers, the potential causal dependencies between the productivity and human factors can be showed graphically and quantitatively through the path diagram. Our results have showed that operators' aptitude has significant effects on cell's efficiency and the impact of operators' aptitude is largely stronger than the learning effect.

Key Words: Cellular manufacturing, Human factor, Operation improvement, Structural Equation Model

1. Introduction

The Cellular Manufacturing (CM) has been recognized as an important ingredient of lean manufacturing, many organizations have applied cellular manufacturing concepts in manufacturing and service processes. Cellular manufacturing system is known an essential production system of world class manufacturing for small batch size requirements. The effects of cellular manufacturing are including reduction in setup time, cycle time, tooling requirements and material handling. Furthermore, implementation of cellular manufacturing has been shown to achieve significant improvements in product quality, scheduling, space utilization, control of operations and employee morale [1].

The numerous techniques and methods have been developed for solving the cell formation problem over the past 30 years. Archival literature has focused on technical aspects of cellular manufacturing, such as the best groupings for products, parts, or machine clusters. Some attention has been directed towards selecting tools, jigs, and fixtures, determining process flow, determining cell capacity and selection of equipment. Although technical problems of cellular manufacturing have been thoroughly researched and many mathematical and computer based approaches have been reported, there is a singular absence of articles that deal with the human element in cellular manufacturing because human related issues are typically difficult to quantify [2].

However, it has been found that for successful implementation of cells, people who will eventually operate, manage, support and maintain the manufacturing cells should actively participate in their design and development. It is essential to focus both on technical issues (cell formation and design) and human issues including worker assignment strategies, skill identification, training (workforce multi-functionality), communication, reward or compensation system, defining worker roles, team works and conflict management [3]. Olorunniwo, et al [4] showed that cellular manufacturing practices in industry depend also on judgment, experience, and familiarity with the part/machine spectrum. Wemmerlov, et al [5] surveyed 46 user plants with 126 cells and confirmed that dissemination is not broad and that many companies are struggling with issues related to implementation. They concluded that substantial benefits could be achieved from cellular manufacturing but that implementation is not simply a rearrangement of the factory layout; it is a complex reorganization that involves organizational and human aspects. They emphasized that most of the problems faced by companies implementing cells were related to people, not technical issues.

Bopaya, et al [3] presented an overview and evaluation of the diverse range of human issues involved in cellular manufacturing based on an extensive literature review, and further administered a survey to determine the importance of eight different human issues in cellular manufacturing. There are also some studies [6],[8] that use queuing theory or learning curve theory to investigate analytically the impact of learning on cellular shop performance, and use simulation method to validate the models.

We have collected literatures dealing with human factors in cellular manufacturing and made a review from three viewpoints: type of study, main factors considered, and methodolo-

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gies [9]. As described in our previous study, researches published to date can be classified into the following three types according to causal relation or whether human factors are dependent variables or independent variables:

- **Type A:** This type of studies is to investigate effects or impacts of cellular manufacturing on human factors such as employees' perceptions and attitudes, job satisfaction. Huber and Hyer [7] conducted a questionnaire to workers who had been working in cells for only six months, and concluded that attitudes were not affected by the adoption of cellular manufacturing. In contrast, Shafer, et al.[10] collected questionnaire answers from workers who had been working in cells over two years respectively, and showed that the cellular workers displayed both favorable and unfavorable attitudes compared to their functional counterpart.
- **Type B:** Studies of type B considered effects or impacts of human factors on the productivity of cellular manufacturing or its successful implementation. The considered human factors include labor issues (employees' skill, flexibility, teamwork, etc.), organizational culture, training and education, and management strategies.
- **Type C:** As reported by Fraser et al [11] who presented a comprehensive literature review and developed a sequential model of cellular manufacturing implementation, studies of type C is to deal with how to implement cellular manufacturing successfully and consider the role of both technical and human aspects in the implementing process of cellular manufacturing.

2. Aim and Contribution of This Study

As described above, although a number of researches have focused on human factors in cellular manufacturing, but major studies have put their emphasis on technical factors (machine order/layout, family part grouping, workflow sequence, etc.) and it is still insufficient to investigate how human factors affect manufacturing cells. This study aims to investigate the impact of human factors in cellular manufacturing from the following two viewpoints:

- (1) To evaluate the impact of human factors more precisely. As most of previous researches applied questionnaire survey or case study methods, it is only possible to evaluate human factors' impact comparatively and empirically. Because of this, evidence could change with who answered the questionnaire [10], and there are differences in the importance of various types of human issues among academics, managers, and workers [3]. In order to evaluate the impact of human factors more precisely, this paper will apply the experimental study method in which a cell production experiment is conducted and operation times are measured, and then the effect of human factors is to be assessed statistically based on the time measurement results.
- (2) To clarify the relationship between operators' aptitude and productivity of manufacturing cells. Several researches

have suggested that performance of cellular manufacturing depends largely on workers' abilities and experience, and therefore selection of cell workers is a very important factor in cellular manufacturing. However, to the authors' knowledge, no studies have been published in which the impact of workers' aptitude was quantitatively examined. In this paper, we design a questionnaire to grasp the operators' aptitude, and then build a structural equation model to investigate how the aptitude of operators affect the performance of cellular manufacturing.

This paper is organized as follows. At first, we introduce the experimental and questionnaire design. Then we give a brief description of basic statistics of assembly time, and main result of the questionnaire. Next, we give a detailed description of factor analysis to specify exogenous and endogenous variables affecting performance of cellular manufacturing. At last, we show pass diagram of the structural equation model constructed from observed data.

3. Experiment and Questionnaire Design

3.1 Cell production experiment

We design a laboratory experiment to examine the impact of human factors on the performance of the cell production. We use a toy robot that built up of LEGO Mindstorms (see Figure 1) as the virtual goods. It consists of 106 pieces of parts and the assembling process is divided into 17 tasks. This toy robot can be assembled and disassembled repeatedly and hence this experiment can be executed at a very low cost.

Fig. 1 The toy robot as good

The experimental is carried out along with the following steps:

- Step 1** The experimental is designed on the assumption that the operators have no any experience of assembling the toy robot. At first, we give the operators some assembly manuals and then, the instructor demonstrates the assembling tasks of the toy robot through assembling it practically in front of the operators. Following the instructor's demonstration, the operators learn the sequence and techniques to assemble the toy robot, and then assemble one toy robot by oneself.
- Step 2** After the instruction, the operators assemble the toy robot in the mode of one-person cell (see Figure 2). When doing the assembling tasks, the operators measured the operation

time to complete every task by themselves but the disassembling operation time is not included. Furthermore, the operators have not been given a standard time for the assembling.

Step 3] The assembly time to assemble a toy robot is calculated as the sum of operation times of all tasks. In order to investigate the learning effect, the assembling operation and time measurement are repeated 5 times.

Fig. 2 Assembling by One-Person Cell

3.2 Questionnaire design

As Olorunniwo and Udo [12] points out, in cellular manufacturing, employees are moved from segregated work groups into cells that combine jobs and workers from several specialized skill areas. Cell team members have to work together, though each may have originally been under different pay or reward system, or possess different levels of raining, skills, and experience. The adoption of cellular manufacturing certainly changes the social relationship and interactions among employees and their supervisors. Given the potential impact on employee attitudes, motivation, and retention, these social changes call for an effective management [13]. When employees are affected, the success of cellular manufacturing implementation is likely to be affected as well.

In assessing the human factor in cellular manufacturing, it is important first to determine how various job characteristics affect the behavior of individuals in organizations and oppositely how human aspects affect the performance of cellular manufacturing. While several theories have been proposed by behavioral scientists and human engineers [14], the Job Characteristics Model (JCM) proposed by Hackman & Oldham [15] is perhaps the most prominent.

The Job Characteristics Model argued that, essentially, enriched or complex jobs are associated with increased job satisfaction, motivation, and work performance. More specifically, Hackman & Oldham assumed that five core job characteristics (i.e., skill variety, task identity, task significance, autonomy, and feedback from job) influence three critical psychological states (i.e., experienced meaningfulness of the work, experienced responsibility for outcomes of the work, and knowledge of the actual results of the work activities), which in tum affect work outcomes (i.e., internal work motivation, growth satisfaction, overall job satisfaction, work effectiveness, and absenteeism). Additionally, they proposed three factors (i.e., knowledge and skill

Table 1 Questionnaire

No	Question Item
Q1	This experiment was as same as I expected.
Q2	The purpose of this experiment was achieved.
Q3	This experiment was difficult.
Q4	This experiment was meaningful.
Q5	The assembly tasks were repeated too many times.
Q6	This experiment was more enjoyable than other experiment.
Q7	I worked actively during this experiment.
Q8	The instructor performed very well in this experiment.
Q9	The instructor ' s instruction could be understood well.
Q10	The experiment manual was very comprehensible.
Q11	This experiment was interesting.
Q12	The experience of this experiment can be applied to other lessons or activities.

growth, need strength, and context satisfaction) as moderators of both the job characteristics-critical psychological states relationships and the critical psychological states-work outcomes relationships.

According to Hackman & Oldham ' s Job Characteristics Model (JCM) and our observations from the experiment, we designed a questionnaire to investigate how personnel-related aspects, such as self-interest, participation, skillfulness, etc., affect the performance of cellular manufacturing [16],[17]. As showed in Table 1, the questionnaire sheet consists of twelve questions. We require all operators to answer it when finishing the assembling operation. When answering questionnaire, a five-point Likert scale was employed: 1= strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

4. Results of the Experiment and Questionnaire

4.1 Basic statistics of assembly time

The participant of this experiment is the students in Fukushima University who take the experimental lesson entitled as Industrial System Laboratory. There are 73 students attended the experiment, they assembled the toy robot and measured assembly time. Basic statistics of the assembly times for all of one-person cell are shown in Table 2, where the experience represents the order of assembling and time measurement.

From Table 2, it is clear that:

- The average time to assemble the production at the first experience was 10.55min and it got shorter into 6.98min at the fifth experience. At the same time, the median of total assemble time decreased from 10.20 to 6.67. It is clear that the total assemble times decreased along with the increase in the operators ' experience. Learning effect could be confirmed statistically.
- Averagely the time to assemble one toy robot ranges from 13.49min to 4.67min and there is a difference of 2.89 times between the slowest operator and the fastest one. It is obvious that the total operation times changes widely by operators and therefore the operators ' aptitude gives a strong impact to performance of manufacturing cells.

4.2 Shortening rate of assemble time

Table 3 shows shortening rate of assemble time from first experience to fifth experience for the assembly task T1, T2, ...,

Table 3 Shortening rate of assemble time from first experience to fifth experience

Statistics	Tasks																
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17
Average	69	69	92	92	77	78	81	81	79	81	69	89	82	104	77	70	99
Median	67	63	72	75	71	73	73	76	60	65	66	66	74	66	62	61	77
Std. dev.	21	23	89	86	43	33	41	42	53	61	30	89	59	309	118	42	110
Min	3	21	25	13	19	27	18	15	6	27	12	12	15	30	11	8	7
Max	142	144	467	700	300	217	311	293	271	424	184	700	408	2700	1042	226	620
Range	139	124	442	687	281	190	293	278	266	397	173	689	394	2671	1030	219	613

Note: data represents percentage (%)

Table 2 Basic Statistics of assembly time(minute)

Statistics	Experience				
	1st	2nd	3rd	4th	5th
Average	10.55	8.77	8.00	7.50	6.98
Median	10.20	8.75	7.75	7.37	6.67
Std. deviation	2.23	1.66	1.49	1.59	1.53
Minimum	5.90	4.43	4.73	4.35	3.95
Maximum	16.47	13.85	12.33	12.37	12.43
Range	10.57	9.42	7.60	8.02	8.48

T17. From Table 3, it is obvious that operation times of every task were shortened at 69% -92% and averagely at 82% as the experience increased. For some task, the standard deviation and range are very large values and the maximum of range is 2671%, there was a wide variety in the improvements of operation time of some tasks. It is clear that some operators could learn quickly the assembly operations and shorten the operation time at a very large rate but others almost could not improve their operations.

4.3 Main result of questionnaire

Q7: I worked actively during this experiment

Fig. 3 Answers to the question Q7

Of the 73 students who answered the questionnaire, 71 of them returned valid answers. As we requested the students to write their name when conducting both the questionnaire and the time measurement, we can identify and investigate completely the relation between their answers to the questionnaire and assembly times.

Some distinctive answers were collected. The first one is the answers to the question Q7 (I worked actively during this experiment). As shown in figure 3, 69% of the students chose score of five or score of four. Since the question Q7 was designed to check the students' behavior or attitude how actively or positively they worked on the assembly tasks, the result of figure 3 showed that a major portion of the students actively worked on this experiment and so the time measurement can be judged to

be reliable.

figure 4 shows the students' answers to the question Q3, this question was designed to check if the students felt that experiment was difficult. 21% of the students chose score of five or score of four, and these students felt difficult to assemble the toy robot. Meanwhile, 34% of the students chose score of one or score of two and they felt easy to complete the assembly tasks. This result showed that the toy robot is a suitable good for investigating the productivity of cellular manufacturing.

Q3: This experiment was difficult

Fig. 4 Answers to the question Q3

5. Structural Equation Model

5.1 Variables specification

To investigate how the human factors, such as personal aptitude or behavior, affect performance of cellular manufacturing, Structural Equation Modeling (SEM) is used as a confirmatory technique and therefore two different kinds of variables, namely exogenous and endogenous variables must be specified correctly. Furthermore, because factor analysis is a statistical method used to examine how underlying constructs influence the responses on a number of measured variables, here we applied factor analysis to specify endogenous variables.

Concretely, the following three kind of factor analysis were conducted using SPSS10.1, where principal component analysis (PCA) was used for factor extraction, criteria for determining the number of factors was Kaiser Criterion and rotation method was promax rotation. In addition we used only the time measurement data of the 71 students who returned a valid answer to the questionnaire.

(1) Job characteristics and necessary aptitude

To identify the job characteristics and the personal aptitudes that are necessary to complete the assembly tasks, the first factor analysis was conducted, where the observed variables are the assembly times of the 71 students at the first experience. As the result, the rotated factor matrix was obtained and shown in

Table 4 Rotated factor matrix for assembly time at the first experience

Assembly time TF of Task T_i	Factor	
	1	2
TF6	0.996	-0.252
TF10	0.630	-0.073
TF2	0.507	0.195
TF14	0.489	-0.031
TF13	0.382	0.183
TF5	0.379	0.353
TF1	0.344	0.329
TF16	0.330	0.116
TF3	0.319	0.168
TF4	0.287	0.128
TF17	0.257	-0.167
TF12	-0.067	0.856
TF7	-0.075	0.583
TF9	-0.052	0.348
TF8	0.134	0.342
TF11	0.221	0.310
TF15	0.015	0.304

table 4.

Based on the result shown in table 4, we have made a thoroughly researching on the contents of every task. It is clear that task T6, T10, T2, T14 are very simple tasks, and so neither special skill nor inventiveness is necessary to complete these tasks. It can be considered that the operation times of task T6, T10, T2 and T14 represent how the operators are awkward at doing the assembly tasks. That is, the more the operators are awkward, the longer time will be taken to complete these tasks. Hence, an endogenous variable, named as "Awkwardness" is to be introduced into SEM.

Task T12 and T7 are comparatively simplex or difficult and it is necessary for the students to devise how to complete these tasks efficiently. The operation times of these two tasks can be considered as representing the ability of creation or devising of the students and in this paper, we do not consider this ability temporarily.

(2) Learning effect

Learning effect is very important to improve productivity, but it is rational that required learning effect changes with tasks. To identify learning effects appeared in every assembly tasks, the second factor analysis was conducted, where the observed variables are the shortening rate of operation time from the first experience to the fifth experience for the assembly task T1, T2, ..., T17. The rotated factor matrix was obtained and shown in table 5.

Based also on the result of a thoroughly researching on the contents of every tasks, it was clear that task T15, T8, T7 and T9 include some delicate assembly operations and the operators couldn't shorten the operation times through only reading manual or following the instructor's demonstration, and therefore the operators needed to devise an efficient way to assembly some simplex parts skilfully. Here, we give a name to the first component as "Delicate work". In contrast, task T17, T11 and T6 are not difficult, but these tasks use more parts than other tasks and thus the operators took long time to complete them. Here, we named the second component as "Monotonous work".

(3) Personal attitude

To investigate the impact of operators' personal attitude

Table 5 Rotated factor matrix for shortening rate

Shortening rate SR of Task T_i	Factor			
	1	2	3	4
SR15	0.795	-0.055	0.009	0.089
SR8	0.554	-0.004	-0.069	-0.097
SR9	0.549	0.186	-0.023	0.097
SR7	0.429	-0.233	0.026	-0.159
SR12	0.369	-0.215	0.238	-0.001
SR17	0.143	0.720	-0.015	-0.025
SR11	-0.032	0.506	0.180	-0.157
SR6	-0.101	0.383	-0.014	0.101
SR13	-0.056	0.283	0.004	-0.010
SR5	-0.047	-0.047	0.852	0.011
SR4	0.053	0.317	0.515	0.010
SR3	-0.040	0.001	0.174	0.834
SR2	-0.039	-0.173	0.250	-0.383
SR14	-0.008	-0.101	0.287	0.360
SR1	0.013	0.226	0.166	-0.350
SR16	0.256	0.037	-0.114	0.274

on production performance, the third factor analysis was conducted, where the observed variables are the 71 students' answers of the questionnaire. The rotated factor matrix was obtained and shown in table 6.

Because question Q7, Q11, Q1 and Q6 represent how interested or positively the operators worked on the experiment, we give a name to the first component as "Interest". Q8 and Q9 are questions about instructor's performance and so the second component is named "Impression of the instructor". Question Q3, Q4 and Q12 represent how difficultly the operators considered this experiment and at the same time, how meaningfully and hoe worthy they considered it, and therefore the last component can be named as "Worthwhileness". "Interest" and "Worthwhileness" will be considered in SEM as endogenous variables.

Table 6 Rotated factor matrix for questionnaire's answers

Question No	Factor		
	1	2	3
Q7	0.905	0.079	-0.182
Q11	0.796	0.102	0.040
Q1	0.716	-0.196	-0.027
Q6	0.681	0.002	0.041
Q2	0.345	0.053	-0.120
Q9	0.034	0.978	-0.009
Q8	-0.058	0.864	0.036
Q12	0.126	-0.041	0.699
Q4	0.254	0.031	0.638
INV_Q3	0.391	-0.051	-0.484

5.2 Path diagram

Based on the results of the factor analysis described above, we conducted an exploratory covariance structure analysis and constructed a structural equation model. The pass diagram is shown in figure 5.

All of calculation was executed by using the packaged software AMOS 17.0. The model adaptability was checked using RMR, GFI and AGFI. In order to improve the model compatibility into acceptable level, some observed data and endogenous variables have been removed. At finally, we could obtain the model of figure 5, and its values of RMR, GFI and AGFI are:

Fig. 5 Path diagram

RMR = 0.010

GFI = 0.806

AGFI = 0.729

As the GFI and AGFI range between 0 and 1, with a cut-off value of 0.9 generally indicating acceptable model fit, these two indexes of the model shown in figure 5 are 0.806 and 0.729, and therefore this model is not good enough. However, because the RMR is 0.010 and very close to 0, the model can be considered as being well suited to the observed data.

From figure 5, it is obvious that:

- The direct effects of “Awkwardness”, “Interest” and “Learning effect” on operation times are 1.00, -1.15 and -0.47 respectively, operators’ “Awkwardness” has a negative impact on productivity, and meanwhile, the operators’ “Interest” and “Learning effect” have positive impact on the productivity. Among these three factors, the operators’ “Interest” has a comparatively strong impact on performance of cellular manufacturing.
- There are three factors that have a significant relation to learning effect. Two of them were derived from the job characteristics and represent whether an assembly task is

“Monotonous work” or “Delicate work”. As path coefficient from “Monotonous work” to “Learning effect” is 1.00, the learning effect is easy to appear in monotonous tasks. In contrast, “Delicate work” has a negative impact (path coefficient=-1.56) on “Learning effect” and so the learning effect is difficult to appear in delicate tasks.

Furthermore, “Worthwhileness” has a positive impact on the learning effect. As the path coefficient is 0.75, the impact of the operators’ “Worthwhileness” is weaker than the job characteristics.

- The indirect effects of the job characteristics: “Monotonous work” and “Delicate work”, and the operators’ “Worthwhileness” can also be computed, the values are -0.47, 0.73 and -0.35. Therefore, “Monotonous work” and the operators’ “Worthwhileness” have negative impact on the operation time and so these two factors give positive effect to the productivity. In contrast, “Delicate work” gives the strongest impact to the operation time, it is very important to efficiently complete the delicate assembly tasks in order to improve the performance of cellular manufacturing.

6. Concluding Remarks

This paper has designed a laboratory experiment of cellular manufacturing to measure the efficiency of the operators in manufacturing cells. Meanwhile, a questionnaire was designed to grasp the operators' aptitude. Based on the measurement data of the experiment and the answers of the questionnaire, we conducted three kind of exploratory factor analysis to specify exogenous and endogenous variables that affect performance of cellular manufacturing, and then we constructed a structural equation model. As the result, we could obtained a pass diagram that shows graphically and quantitatively potential causal dependencies between productivity of cellular manufacturing and some human factors such as learning effect, awkwardness on assembly tasks, the impact of the operators' "Awkwardness", "Interest" and "Worthwhileness" on the productivity of cellular manufacturing has been verified statistically.

Through this research, the effectiveness and attractiveness of structural equation modelling as an important research tool have been confirmed. But there are many issues to be addressed further. Our future study includes refining our model to achieve higher adaptability level and giving more comprehensible and meaningful interpretation of the results.

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