

Intelligent Manufacturing Engineers' Knowledge Transfer and Innovation Capability: From the Perspective of Big Data Acceptance Attitude

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Abstract: In the face of intelligent manufacturing (or smart manufacturing) human resource shortage, the training of industrial engineers in the field of intelligent manufacturing is of great significance. In academia, the positive link between learning transfer and knowledge innovation is recognized by most scholars, while the learner's attitude toward big data decision-making, as a cognitive perception, affects learning transfer from the learner's experienced engineering paradigm to the intelligent manufacturing paradigm. Thus, learning transfer can be regarded as a result of the learner's attitude, and it becomes the intermediary state between their attitude and knowledge innovation. This paper reviews prior research on knowledge transfer and develops hypotheses on the relationships between learner acceptance attitude, knowledge transfer, and knowledge innovation.

Keywords: Big data decision making; Attitude; Learning transfer; Knowledge innovation

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1. Introduction

With information technology represented by the Internet of Things, big data, and artificial intelligence continuously integrating with various industries and becoming a new engine of economic growth, the world has entered an era dominated by intelligent manufacturing. China has formulated the "Made in China 2025" development strategy and implemented it in various industries. Intelligence is a fundamental feature of the Fourth Industrial Revolution.

The shortage of engineering human resources caused by intelligent transformation in traditional industry is very serious. Currently, this shortage is a global problem. In recent years, with the rise of intelligent manufacturing and digital production, the demand for "Intelligent + Skilled" engineering human resources in various industries has become increasingly strong. This type of engineer is a group of people who possess knowledge of intelligent engineering and industrial engineering. However, the number of such new skilled engineers is insufficient, and there are difficulties in such human resource supply. The "Guidelines for the

Development of Manufacturing Human Resources” points out that by 2025, the total number of intelligent manufacturing human resources in high-end Computer Numerical Control (CNC) machine tools, robots, and other fields in China is predicted to reach nine million, with a human resource shortage of up to 4.5 million [2]. In some fields and regions, the shortage of new skilled engineers is becoming a problem that restricts industrial upgrading. Especially, in traditional industries, with their digital and intelligence transformation, there is a serious shortage of such engineers.

This paper believes that the key to solving the shortage of intelligent manufacturing engineers still lies in the transformation training of industrial engineers. When it comes to intelligence, many people worry that it will replace manual labor. However, according to research by Corney and the Global Economic Forum, 60% of jobs may be affected by automation, and less than 5% of job opportunities can be fully automated [1]. Intelligence is people-oriented, not replacing manual labor with intelligence. In the process of intelligent transformation, the manufacturing industry, which used to make more use of the labor dividend, may now shift from the labor dividend to the engineer dividend. Many firms have started retraining their employees, to adapt to intelligent manufacturing, Artificial Intelligence (AI), and automation. Many factories have started to combine industrial engineering teams, intelligent teams, and automation teams together.

The above illustrates that it is a common situation that to solve the intelligent engineer shortage, industrial engineers are moving to intelligent work environments (called the new technological paradigm in management). Moreover, the importance of the knowledge accumulated (or learned) by industrial engineers in (old) engineering environments (such as experiential knowledge) for intelligent engineering cannot be ignored. In short, it is of great theoretical and practical significance to investigate how their engineering experience knowledge is transferred to the intelligent new technology paradigm.

2. Previous literature on learning transfer

The theory of transfer of learning or transfer of knowledge is widely applied in various fields such as psychology, management, and education. The definition of knowledge transfer in education is the impact of one learning on another. That is, to apply the knowledge, skills, thinking methods, principles, emotions, and values learned in one environment to another new environment, to analyze and solve problems in this new environment. The previous literature on learning transfer theory are shown in **Table 1**.

Table 1. Prior and current work

Subject	Period	Focus
Prior research	Early stage	Learner’s motivation and abilities
	1980s	Learner’s cognitive structure
	Recent years	Adaptive learning (transfer)
This paper		Learners’ acceptance of big data

The details are as follows. Earlier researchers on knowledge transfer theory explored the objects and motivations of knowledge transfer, attempting to find general patterns in the sensory, associative, and memory abilities of learners, including formal discipline, identical elements, experience generalization, transposition-relationship, and learning sets. However, in different learning contexts, different types of knowledge, and different experimental populations, the above studies present different results in learning transfer [3].

In the 1980s, related research began to focus on transferring content, and Ausubel proposed the classic

theory of cognitive structure transfer in the field of learning transfer theory^[4]. From the perspective of cognitive structure, Ausubel re-observes the learning transfer. The forward transfer in his viewpoint still refers to the influence of previous learning (original knowledge) on subsequent learning (new knowledge). However, what was the previous learning? How does it affect subsequent learning? The content of learning transfer is not the transfer of knowledge itself, but the organizational characteristics of the learner's cognitive structure. This theory suggests that in situations where there is a change in context, the already formed cognitive structure can be transferred to a new context. Specifically, when learning new knowledge in a new context, the new knowledge does not directly interact with the stimuli or response components learned in the original context but rather indirectly affects the relevant features of the original cognitive structure (clarity, stability, generalization, inclusiveness, etc. of knowledge in a certain field) due to the influence of new knowledge or new scenarios, thereby indirectly affecting new learning or transformation.

Later researchers continued to explore the influencing factors of transfer ability and transfer effect based on Ausubel's theory. Their research suggests that subjective factors that affect transfer effectiveness include learning interest and motivation, psychological state, cognitive level and structure, and thinking patterns. Objective factors include the teacher's ability, the structure and arrangement of textbooks, and the similarity of learning situations^[5].

In recent years, the constructivist school has focused on the role of "context" and "construction" in learning transfer (knowledge transfer) and believes that learning transfer is a reconstruction in new contexts, thus providing some new interpretations of the theory of learning transfer^[6]. Scholars of this school advocate that learners should adjust and reshape the transferred learning content in the new environment^[7]. This type of learning transfer is called adaptive transfer. Learners are not passive containers, but as participants in learning transfer, they adjust and reshape the learning content they accept in a dynamic environment. The environmental factors that promote such learning transfer include the right to other transfer behaviors that can also be observed or cooperated with, and factors such as a sense of responsibility and leadership ability when solving problems in a new environment^[7,8].

In today's world where machines have become indispensable members of organizations, factors that affect the effectiveness of knowledge transfer should be considered from machines. When industrial engineers move to the field of intelligent manufacturing, the new challenge they face is not the collaboration between people in their previous work, but rather the collaboration between people and machines.

Given the aforementioned limitations of previous literature, the field of human resource development, in digital and intelligent manufacturing ages, needs more studies to explore how individual engineers understand new technology paradigms (big data decision-making) and how the understanding affects their motivation to transfer what they have learned in old technology paradigm. What they have learned in the old technology paradigm is called experiential knowledge. Moreover, the old technology paradigm indicates industrial engineering work and the new technology paradigm indicates digital and intelligent manufacturing work.

Therefore, this paper takes the cognitive structure (i.e. experiential knowledge) proposed by Ausubel as the object (content) to be transferred, and analyzes the mechanism of engineer experiential knowledge transfer to the new paradigm of intelligent manufacturing, from the perspective of engineers' acceptance attitude towards big data generated by machines in human-machine cooperation as the influencing factor.

3. Acceptance attitude, knowledge transfer, and knowledge innovation

3.1. Attitude and learning transfer

Attitude is the core of human personality, and has always been the research center for explaining social

behavior^[9,10]. Attitude is considered as one of the most unique and indispensable concepts in social psychology, as it has aroused the interest of researchers due to its importance in guiding or influencing individual behavior in social, political, and organizational environments^[9,10].

Prior definitions of attitude, are defined from various perspectives. Prior works defined it mainly as effective attitude, cognitive attitude, and behavior attitude. Firstly, effective attitude factors include occupational satisfaction and learning satisfaction. Career satisfaction refers to the trainees' feelings towards their work and organization, while training satisfaction refers to their level of liking towards training and related factors^[11,12]. Secondly, cognitive attitude factors involve work perception, training perception, and individual perception. The job perception of learners includes their commitment to the organization, their participation in work, and their perception of the usefulness of the learning content for their work^[13]. Training perception refers to the cognitive perception of trainees towards the training environment and content. And, individual perception is the self-related attitude including factors of attitude toward transfer, career commitment, and so on^[14].

3.2. Acceptance attitude in this paper: attitude toward big data decision-making

Acceptance attitude in this paper refers to an engineer's work perception, whose definition will be based on the prior researcher's definition mentioned above^[13]. A specific illustration is followed. Some studies have found that although machines can help humans perform tasks in a more effective way (including providing big data for decision-making), simultaneously, humans also have some aversion or incomplete acceptance towards machines^[15,16]. For example, Fildes *et al.* pointed out that managers often discount machine-generated suggestion information^[17]. When they consider these suggestions, they often do not give them enough weight. It can be seen that in today's world where machines have become members of organizations, in the collaborative work mode between engineers and machines, the question of to what extent engineers recognize big data decision-making ability needs to be thoroughly studied. In short, we consider such a question as an engineer's work perception and call it as engineer's attitude towards the intelligent manufacturing paradigm.

Specifically, in order for machines (big data decision-making) to play a better role in human-machine cooperation, it is necessary to gain human recognition. This paper considers the weight that engineers are willing to give to big data parameters in decision-making as their acceptance attitude toward it.

3.3. Acceptance attitude and knowledge transfer

When we develop an accepting attitude towards new knowledge, it stimulates our desire to explore the unknown. In this process, we will naturally review and integrate existing foundational knowledge to better understand and accept new information. Knowledge heterogeneity represents the degree of deviation of potential knowledge differences among subjects^[18]. This difference is a necessary condition for individual curiosity, which allows individuals to exploit their existing knowledge and explore new knowledge, thus promoting the generation of knowledge transfer. The relative strength of acceptance of heterogeneous knowledge affects the level of communication and coordination between individuals' existing knowledge and new knowledge, which in turn affects an individual's creative ability and the firm's innovation capabilities.

3.4. Acceptance attitude and knowledge integration

When we introduce new knowledge into our brains, our acceptance attitude to it directly affects our willingness to integrate it with existing knowledge bases or models. A sense of acceptance helps to reduce cognitive conflicts between new and old knowledge, reduce learning costs, and make the integration process smoother. Learning cost affects knowledge innovation^[19]. The stronger the acceptance attitude is, the stronger the power of individual learning, the stronger the knowledge transfer, the stronger the power of knowledge integration.

Thus the first hypothesis is the acceptance attitude towards new knowledge that has a positive impact on knowledge transfer. The second hypothesis is the acceptance attitude towards new knowledge has a positive impact on knowledge innovation.

3.5. Learning transfer and knowledge innovation

Knowledge transfer (or learning transfer), as a state of knowledge flow at the individual level, inter-individual level, or inter-organizational level, is considered to be one of the key processes for improving innovation ability. Learning transfer is indeed an important way to enrich personal knowledge foundation and diversity. Transferring one's old knowledge to new work areas not only updates one's knowledge base but also greatly increases his knowledge diversity.

Enterprises need knowledge from different fields to supplement and enhance the process of technological innovation. The type of transferred knowledge required here is supplementary knowledge. At the same time, some knowledge in the professional field needs to be updated and upgraded, and this type of knowledge is called auxiliary knowledge ^[20]. Transferring one's old knowledge to a new work area not only upgrades one's auxiliary knowledge but also provides supplementary knowledge.

When auxiliary knowledge is transferred to a new job area, it is integrated with supplementary knowledge. Auxiliary knowledge absorbs and accepts new knowledge, enriches itself, and increases individual knowledge diversity. Knowledge diversity will have a positive effect on the quality of knowledge created ^[21]. Knowledge innovation is the inevitable result of diverse knowledge. Although the transaction cost theory suggests that knowledge diversity negatively impacts cost-saving performance ^[22]. However, knowledge transfer activities still positively promote knowledge innovation. The third hypothesis is knowledge transfer has a positive impact on knowledge innovation.

3.6. Intermediary effect of knowledge transfer between acceptance attitude and innovation performance

As mentioned above, the attitude towards accepting new knowledge not only promotes knowledge transfer but also knowledge innovation. Then, what needs to be considered is that an attitude toward accepting new knowledge promotes knowledge transfer, which in turn increases knowledge diversity and leads to knowledge innovation after transfer. After knowledge is transferred to a new area, new acceptance attitudes emerge, which in turn generate knowledge innovation. From the perspective of the background, the attitude towards accepting new knowledge is the existing state inside of organizational members. The potential knowledge curiosity formed by this state has a significant impact on knowledge transfer. Besides, knowledge transfer without the background of organizational members is difficult to explain. Therefore, from the perspective of the causal chain, the attitudes of members first have an impact, followed by knowledge transfer. Thus, the following assumption can be proposed. The final hypothesis is knowledge transfer plays an intermediary role between knowledge acceptance attitude and knowledge innovation.

4. Conclusion

The shortage of "Intelligent + Skilled" engineers in the intelligent manufacturing industry is becoming more severe. To explore the research question of how individual engineers understand the new technology paradigm (big data decision-making) and how the understanding affects their motivation to transfer what they have learned in the old technology paradigm to the intelligent manufacturing paradigm, this paper examines the relationship of learner's attitude towards big data decision-making, learning transfer, and knowledge

innovation. As a result, we develop theoretical positive assumptions which are the acceptance attitude towards new knowledge has a positive impact on knowledge transfer, the acceptance attitude towards new knowledge has a positive impact on knowledge innovation, and knowledge transfer has a positive impact on knowledge innovation. Furthermore, we investigate the intermediary effect of knowledge transfer between acceptance attitude and innovation performance.

This paper has the following limitations. Firstly, the results are theoretical hypotheses. Therefore, these hypotheses require further empirical testing, which is our future research. Secondly, the attitude referred to in this article only focuses on prior attitudes. However, attitude is a state of the attitude held in advance towards a certain event, and a new attitude formed afterwards. Therefore, further differentiation analysis is needed. Thirdly, the analysis of learning transfer and knowledge innovation in this article does not distinguish between individual and organizational levels.

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