The Human Factor in Industry 4.0: A Quantitative Study on the Impact of Learning Commitment and Interpersonal Adaptability on Human Capital Creation in Smart Manufacturing

[1]Manisha Negi, [2]Dr Geeta Rana
[1]Research scholar School of management studies, Swami Rama Himalayan University.
[2]Associate professor School of management studies, Swami Rama Himalayan University.

Abstract – Smart manufacturing (SM) as a paradigm under the industry 4.0 is essentially transforming the international industrial environment. Although the technological pillars of SM, namely the Cyber-Physical Systems (CPS), the Internet of Things (IoT), and Artificial Intelligence (AI) are sufficiently documented, the human behavioral antecedents needed to harness the given technological advantages are an essential area of research missing. The current research examines how two behavioral constructs are influenced i.e. the Learning Commitment (LC) and Interpersonal Adaptability (IA) in the employees concerning the creation of Human Capital (HCC) in the SM industries. Since the present study is based on resource-based view and adaptive performance theories, it uses a quantitative research approach of a cross-sectional one. The number of respondents sampled was 287 professionals who are working at the manufacturing firms in Indonesia which actively implement the use of SM technologies. LC, IA, and HCC measurement scales were modified based on the existing scales and were tested in this particular situation. The analysis of the data was carried out by use of the Partial Least Squares Structural Equation Modeling (PLS-SEM). The outcome is strongly suggesting that not only Learning Commitment (= -0.381, p = 0.001) but also Interpersonal Adaptability (= -0.422, p = 0.001) instruments have positive significant effect over Human Capital Creation and their effect is stronger with IA. There is a relationship on HCC that is explained by the model with 51.2%. The conclusions made can be summarized thus: to achieve the goals of the successful human capital development in the complex, socio-technical setup of the SM, companies should have two packages in their strategy: establishing the culture of lifelong learning and becoming proactive to instill interpersonal plasticity in order to ensure fruitful human-human and human-machines interaction. The study is an empirically correct strategic human resource development framework that managers and policymakers have acquired in the age of the Fourth Industrial Revolution.

Keywords - Smart Manufacturing, Human Capital, Learning Commitment, Interpersonal Adaptability, Industry 4.0, PLS-SEM, Workforce Development.

I. INTRODUCTION

The manufacturing industry of the world is experiencing a radical revolution commonly known as Industry 4.0 that is defined by the massive penetration of digital, biological, and physical technologies (Schwab, 2017). The core of this change is the concept of Smart Manufacturing (SM), which is based on using the newest technologies, including Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), analytical tools (Big Data), and Artificial Intelligence (AI) to create a self-optimizing and intelligent system of production (Zheng et al., 2021). The advantages of these incentives are enormous as mass customization, never-before-seen achievements of operations as well as the policies of new data-driven businesses arise (Kagermann et al., 2013). As a result, governments and corporate bodies across the globe are channelling huge investment on SM technologies with a hope of achieving high competitive advantages (Frank et al., 2019).

But the human dimension of the change is largely ignored by this techno-centric story, even though perhaps this is the more difficult side of the transformation. A nagging and vexing human capital gap is threatening to derail such huge technological spending (Hecklau et al., 2016; Liboni et al., 2019). The capabilities and competence needed in SM would as well go way beyond the conventional technical expertise. Now the business population should be digitally literate, can think in data and able to work and communicate with intelligent systems that are also complex and even autonomous (Tortorella et al., 2022; World Economic Forum, 2023). The generic knowledge that is reflected in the human being in the form of knowledge, skills, and abilities, which are used to bring out a personal, social, and economic well-being,

by definition, the Human Capital (HC) is, therefore, experiencing a radical redefinition. This new context can be thoroughly approached as a Human Capital Creation (HCC) process, which is dynamic, continuous, and that one that is heavily dependent on the capacity of an organization to provide an environment where swift learning and adaptation can occur (Kumar et al., 2023).

Although the role of upskilling cannot be underestimated, most available studies and practice tend to be limited on the actual technical training programs, overlooking the reasons behind success and behavioural motivation in the workers that allow successful and efficient involvement and functioning within the SM setup (Grosse et al., 2023; Jackson et al., 2021). Two such highly important yet less studied constructs of behaviour are Learning commitment (LC) and Interpersonal Adaptability (IA). LC can be defined as the psychological commitment and the proactive orientation by an individual when it comes to the consistent acquisition of new skills and knowledge that might have been developed specifically within the frames of the social cognitive and the organizational learning theory (Rowden, 2002; Noe et al., 2014). LC provides the prime force of self-directed upskilling in an industry where technological obsolescence is a serious issue. IA, which is one of the fundamental dimensions of personal adaptability, denotes the flexibility that enables individuals to change the behavior and interaction style in accordance with new, dynamic, and complicate social and task-related contexts (Ployhart and Bliese, 2006; Charbonnier-Voirin and Rousnel, 2012). IA is the social lubricant that facilitates proper cooperation and syntending of knowledge in a cross-functional, team-based, and sometimes more so, "cobot"-driven (collaborative robot) workplace of SM.

The originality and mark of this study is many-sided. To begin with, it goes past a siloed perspective of human capital development by both exploring various synergistic impacts of a cognitive-motivational driver (LC) and a social-behavioral competency of (IA). This gives a holier and more integrative concept of the human aspects that would be needed in SM. Second, it extends conceptually the dimension of the idea of interpersonal interactions to the case of human-machine cooperation since in recent years, productive communication with AI interfaces and cobots is turning into a strategic job skill (Gervasi et al., 2020). Third, it presents an empirical study of an emerging economy population (Indonesia) within a relevant natural geographical leaning of the literature, which was mostly based on Western Europe and North America (Moeuf et al., 2018). This is because it is important to learn about these forces in fast industrializing countries to smoothly integrate the global supply chains.

In this way, this study is been informed by the following Research Question (RQs):

- How strongly does learning commitment by employees have a positive impact on human capital development in intelligent manufacturing industries?
- How positively interpersonal adaptability on part of the employees affiliated with creation of human capital in the smart manufacturing sectors?
- So, in which case, learning commitment or interpersonal adaptability has been more linked with the human capital creation?

The rest of this paper is organized in the following way: the literature review which provides a theoretical underpinning and formulates the hypotheses; the part about the methodology that describes research design, measures, and the analysis stages; the part on presentation of the results; the discussion section that would establish how the findings can be connected with the existing literature and practice; conclusion which indicates contributions, limitations, and directions of future research.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT1

The section offers a detailed theoretical framework comprised of smart manufacturing, human resource management, and an organizational literature analysis to develop a strong theoretical framework of the study.

The Transforming the Human Capital in Smart Manufacturing.

Human capital as a content originally introduced by Becker (1964) and Schultz (1961) has been considered to be a major resource providing competitive advantage. In the natural manufacturing, HC had been typically related to employment of usual working skills, technical expertise and experience. Nevertheless, the fresh SM situation requires a radical conceptualization. Due to the widespread application of information, connectivity, and automation, human value is no longer performed automatically but accomplished through the manner of monitoring systems, analytic interpretation, exception imagery, and innovation of ideas (Zhou et al., 2022). The creation of knowledge to support new knowledge stocks was named by Human Capital Creation (HCC), thus the creation process at the organizational level (Khorasani and Almasifard, 2017).

This is a process that is communal in nature. Although personal skills are necessary, the range of SM systems develops and necessitates the incorporation of a variety of knowledge related to mechanical engineering, data science, software development, and supply chain management (Rauch et al., 2022). Therefore, HCC in SM is not just the overall hours of individual training but a qualitative result of the workforce that is able to learn, adapt, and use knowledge collaboratively and in an extremely volatile technological environment (Liao et al., 2023). This paper assumes that, this emergent property is fundamentally contingent upon the prevalence of two personal-level attributes including achievement of learning commitment and interpersonal adaptability.

Learning Dedication: The Intelligent Overview of unremitting upskilling.

Learning commitment (LC) is a particular type of motivation and characterizes a particular devotion of one to the very process of learning. It has been defined by the conviction in the importance of learning, readiness to work hard to attain some new skills, and the propensity to take up self-directed learning processes (Rowden, 2002; Noe et al., 2014). Formal training programs are ineffective in the circumstances of SM, where technological developments such as digital twins or an AI-accompanied predictive maintenance continue to change constantly. The technical skills are getting diminished at a very fast rate (World Economic Forum, 2023).

The high LC employees make an individual effort to counter this knowledge gap. Instead, they will be more interested in attending online courses, experiment with new software, follow trends in the industry, and effectively apply the new knowledge in professionals (Jiang and Hu, 2022; Grosse et al., 2023). This inherent voluntary modernization is one direct contribution to the organizational human capital stock. Once high LC is observed among a large group of the working population, the overall productivity of the organization in relation to comprehending, using, and innovating SM technologies is greatly intensified. It is changing the workforce as instead of passive beneficiaries of the training into agents of its own and the organizational development. According to this argument, we make the following hypothesis:
H1: Human Capital Creation within smart manufacturing industries is influenced significantly positively by Learning Commitment.

The Adaptability of Interpersonal Interaction: The Social Custom of Socio-Technical Systems.
The Interpersonal Adaptability (IA) has been developed as one of the subset of I-ADAPT theory that characterizes adaptability as being a multidimensional concept (Ployhart and Bliese, 2006). In particular, IA is the capacity to properly control own behavior, style of communication and approach to interaction to correspond to new social context and various people (Charbonnier-Voirin and Roussel, 2012; Pulakos et al., 2000). SM environment is a socio-technical system per se, and a success in the system is determined by social integration factors as much as by technical integration (Tortorella et al., 2021).

The IA need shows itself in the critical manner of two ways. To begin with, SM projects are very interdisciplinary. The engineers have to communicate well with data scientists and vice versa since data scientists need to be conversant with the operational limitations provided by the floor managers. Having IA would help people to cross such disciplinary lines, solve conflict positively, and develop social trust to share knowledge (Fang et al., 2023; Rauch et al., 2022). This is mainly the exchange of tacit knowledge and explicit knowledge that forms a core of establishing new and synergistic knowledge, the logos of HCC.

Second, and less established, is the need of the human-machine cooperation. However, with the emergence of cobots and AI-assisted decision support systems as colleagues, employees will have to change their styles of contact and learn to interact with the latter, as a non-human agent (Gervasi et al., 2020). This entails the knowledge of capabilities and limitations of the machine, clear directions and interpretation of the correct output of the machine. This can be a challenge to an employee with a low IA and consequently frustrating, distrustful, and failure to use the technology efficiently. On the contrary, the flexible worker is able to smoothly incorporate the machine as an effective work member and hence, it expands the cognitive capacity of the work unit on the whole. The enlarged perspective of the concept of interpersonal interaction places IA at the core of maximizing the potential of SM technologies thus becoming a significant contributor to the human capital of the organization directly. Therefore, we hypothesize:

H2: Interpersonal Adaptability possesses a powerful positive influence on the Human Capital Creation in the smart manufacturing industries.

III. METHODOLOGY

This section elaborates on the research design, population and sampling, data collection procedures, measures, and the specific data analysis techniques employed, including the handling of data quality issues.

Research Design
The research design used in this study was a quantitative, explanatory, and cross-sectional research. The aim was to estimate the relationships with the constructs that were postulated to relate with each other at one point in time. The mechanism of collecting the data based on surveys was considered the most suitable to gather sufficient information regarding a large and geographically dispersed sample that can be statistically generalized (Saunders et al., 2019). The population, sampling, and data collection method were presented in Chapter 3, Section 2.

The participants chosen in the current study consisted of persons (professional characteristics in manufacturing companies in Indonesia) a category of people like professionals (engineers, technicians, data analysts, operations managers) whose operations are currently undergoing implementation of Smart Manufacturing technologies are under investigation. The choice of Indonesia as an exemplar is explained by the fact that it is a prime emerging economy that has an expanding manufacturing segment and significant governmental backing of the Industry 4.0 processes.

Only a non-probability purposive sampling method was used to make sure that the respondents were directly affected by SM environments. The sampling frame was developed based on the member directories to the Indonesian Association of Manufacturers and using professional networking platforms such as LinkedIn, was created to include persons whose job descriptions or who have LinkedIn profiles listed them as having worked on a digital transformation, automation, or Industry 4.0 program.

A total of eight weeks was the group of weeks during which data was collected. The Qualtrics platform was used to create an online questionnaire. It was through email and professional groups that the survey link would be sent with the help of a cover letter availing information about the purpose of the research, provisions of anonymity, and the informed consent. Two weeks after a follow up was reminded to the participants originally randomly assigned to the intervention group to enhance the response rate.

Sample Demographics

Out of the sent questionnaires (350), 301 returns were gained. Upon finding that 287 responses were complete and could be used, 287 completed and usable responses were kept to do the analysis (effective response rate: 82%). The participants were equal in sex 72 percent males and 28 percent females. Education wise 65 percent were having a bachelor's degree, 28 percent were having a master's degree with 7 percent having a doctorate or other professional certification. Meanwhile work experience was found to be 9.2 years and the mean living experience in their present organization was 7.5 years. The respondents used diverse industries, with 30 percent in the automotive sector, 25 percent in the electronics sector, 20 percent as well as in food and beverage sector, and 25 percent as the chemical processing sector.

Measures and Instrumentation The majority of respondents indicated that they considered the similarity scale suitable for assessing their personalities.<|human|>Measures and Instrumentation Most of the respondents explained that they found the similarity scale appropriate in the test of their personalities.

The indicators of all constructs were measured at reflectively on a five-point Likert scale between 1 (Strongly Disagree) and 5 (Strongly Agree). The scales are based on established literature to be content-valid which has them undergo some changes which involve the alteration of words to suit the SM context. The face validity, clarity, and other issues related to the contextual relevance were evaluated by a pilot test involving 15 industry experts, and academics with only some slight changes leading to changes in the phrasing of certain items.

Selected on the basis of its role in organizational commitment Emphasizes the dedication to personal investment in specific activities. The sample items are: I suppose that eternal learning is a key to my future career in smart manufacturing, and, through my personal initiative, I tend to engage in acquiring new skills in the area of digital technologies without being requested.

Interpersonal Adaptability (IA): Measured by a 6-item scale that has been adhered to Ployhart and Bliese (2006), Pulakos et al. (2000). To get the human-machine aspect, one was included: I can change my approach easily when collaborating with collaborative robots or AI systems. Other products were geared towards the need to adjust to inter dept competition.

Human Capital Creation (HCC): This is a scale at an organization level of analysis and measured using perceptions by individuals using 5-item scale where items are modified on the basis of Khorasani and Almasifard (2017) and Subramanium and Youndt (2005). Examples of such items are: employees in my organization have been equipped with specific data analysis and interpretation skills; the general knowledge in my organization concerning smart manufacturing processes is one of the primary assets.

Data Screening and Data Missing Values.

The data were pre-screened in terms of completeness, lack of engagement, and outliers. Missings values were initially checked among the dataset. The data gap rate was minimal (under 1.5 per cent in regards to any one variable) and would suggest to be totally random (MCAR) as per Little MCAR test (– 12.45, pp = 0.185). Since the percentage of missing values is low and random, Expectation-Maximization (EM) algorithm was adopted to provide the missing values because it offers less biased estimates when compared to listwise and pairwise deletion (Hair et al., 2019). Also, gaze was on the data to check straight-lining (there were the same responses to a considerable number of items) and out of the ordinary response time; no trends of this kind were identified.

Data Analysis Technique

The results were processed with the help of variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM) software using the SmartPLS 4. PLS-SEM has been chosen due to the capabilities to emphasize on intricate relations when small-to-middle sample sizes are required and the importance of prediction, in addition to less constraint requirements on data distribution (Hair et al., 2019). The procedure used to conduct the analysis was based on the two-stage procedure suggested by Henseler et al. (2009) to evaluate reliability and validity of the measurement (outer) model and, subsequently, test the hypotheses based on evaluating the structural (inner) model.

IV. ANALYSIS AND RESULTS

Measurement Model Assessment

In the accompanying table, the assessment of a model was performed using a measurement model that was already developed during the procedure. The assessment of a model has been carried out using a pre-existing measurement model that was created in the course of the procedure in the accompanying table.

Construct validity and reliability involved in constructs were assessed strenuously. It is evident as indicated in Table 1 that all the loading of the indicators was high and exceeded the recommended 0.708 level, which indicates indicator's reliability. The consistency in among the internals was ascertained because Cronbachs Alpha and Composite Reliability (CR) of all the constructs took a

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value over the conservative mark of 0.8. The convergence validity was attested because the Average Variance Extracted (AVE) of all the constructs was greater than 0.5, which implied that constructs weigh up in excess of a half of the indication in every of their indicators (Hair et al., 2019).

Table 1:
Reliability and Convergent Validity

Construct	Items	Loadings	Cronbach's Alpha	Composite Reliability (CR)	AVE
Learning Commitment (LC)	LC1	0.821	0.887	0.919	0.694
	LC2	0.843			
	LC3	0.855			
	LC4	0.812			
	LC5	0.825			
Interpersonal Adaptability (IA)	IA1	0.832	0.901	0.925	0.673
	IA2	0.841			
	IA3	0.825			
	IA4	0.798			
	IA5	0.812			
	IA6	0.815			
Human Capital (HCC)	HCC1	0.845	0.874	0.909	0.667
	HCC2	0.832			
	HCC3	0.812			
	HCC4	0.795			
	HCC5	0.801			

Fornell-Larcker criterion and Heterotrait-Monomethod (HTMT) ratio were the two measures of discriminant validity. The AVE of the square root of each construct (the diagonal values in Table 2a) indicated better relationships with the other constructs, and which are greater than the AVE of other constructs, met the Fornell -Larcker condition. Moreover, Table 2b presents, all HTMT are lower than the high significant threshold of 0.85 indicating a solid piece of evidence of a discriminant validity (Henseler et al., 2015).

Table 2a:
Discriminant Validity (Fornell-Larcker Criterion)

Construct	1	2	3
1. Learning Commitment (LC)	0.833		

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2. Interpersonal Adaptability (IA)	0.587	0.820	
3. Human Capital Creation (HCC)	0.551	0.605	0.817

Table 2b:
Discriminant Validity (HTMT Ratio)

Construct	1	2	3
1. Learning Commitment (LC)			
2. Interpersonal Adaptability (IA)	0.712		
3. Human Capital Creation (HCC)	0.689	0.734	

Structural Model and Hypothesis Testing

The Variance Inflation Factor (VIF) was used to measure collinearity prior to conducting the analysis of the structural model. This implied that there was no threat of multicollinearity as all inner values of VIF were less than 3.0. The statistics used to explain the endogenous variable, Human Capital Creation, at the level of R 2 of 0.512 were significant. This shows that the two independent variables LC and IA account 51.2 percent of the variance in HCC that is regarded a large effect size in the behavioral studies (Cohen, 1988).

Table 3 shows the path coefficients (5) (ною) and the level of significance counted after passing through a bootstrapping process deposited on 5,000 subsamples. The findings indicate that it is adequate to H1 as Learning Committee can affect Human Capital Creation positively (0.381, p = 0.001). A significant positive effect is also shown by Interpersonal Adaptability (= 0.422, p = 0.001) and H2 is proven to be true. On comparison of the standardized Beta coefficients, Interpersonal Adaptability is observed to have a little more pronounced impact on Human Capital Creation as compared to Learning commitment.

Table 3:
Hypothesis Testing Results

Hypothesis	Path	Beta (β)	Standard Deviation	T-Statistics	P-Values	Decision
H1	LC -> HCC	0.381	0.054	7.056	0.000	Supported
H2	IA -> HCC	0.422	0.051	8.274	0.000	Supported

V. DISCUSSION

This study aimed to shed some light on the most critical attributes of human behavior which motivate to build the human capital in the multi-faceted socio-technical landscape of Smart Manufacturing. The results strongly and clearly support the main argument of the study the fact that not only a deep- seated devotion to various learning practices but also an excellent level of interpersonal adaptability are critical preconditions towards the development of a capable workforce in Industry 4.0.

Human Capital Creation (H1) as a positive impact of Learning Commitment (LC) on Human Capitals is a great cause, which supports a profound change in the character of work and skill formation. The skill and desire to learn is more permanent and competent meta-skill in a time when the shelf-life of particular technical knowledge is brief. This observation carries a lot of similarity with the study of Grosse et al. (2023), who opined that the foundation of organizational resilience to digital transformation lies in its learning culture. The thing is that high LC employees are not only a passive consumer of training requirement, but they are active part-takers of their personal improvement in the context of their ongoing search to create the knowledge gaps and fill them with the new knowledge. The overall self-motivated upskilling of the collective increases the common arena of expertise in the organization directly and results in that it keeps its eyes on the technological change.

It is possible that the more delicate and impactful support on the connection between Interpersonal Adaptability (IA) and HCC (H 2) is the most potent contribution made by the study. It proves the fact the technical mastery is not enough. The relevance of IA ($\beta = 0.422$) and LC (0.381) as slight differences in their strengths might indicate that in an integrated and collaborative environment as manifested in SM, the social competence to utilize and integrate knowledge might be a little bit decisive than knowledge acquisition per se. This goes in line with the socio-technical systems theory where social and technical factors are focused on, and they are interdependent (Tortorella et al., 2021). High IA enables the exchange of ideas across the diverse functional silos and individual knowledge into collective intelligence. Additionally, by extending the idea of IA to incorporate the interaction between humans and machines, this article will contribute to validating an increasing degree of assertion in the literature human-intelligent machine interaction interdependence is a novel type of interpersonal ability, and that its operational and innovative gains are directly correlated with its use (Gervasi et al., 2020). When an employee is equipped to work an effectively interact with a cobot or interpret a dashboard that is being machine driven, they effectively increase the overall cognitive ability in the team.

VI. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

Theoretical and Practical Implications

This research will theoretically add to the increased literature on human resource management in Industry 4.0, as the ideas produced by organizational learning and adaptive performance theories are incorporated here. It also presents an empirically proven model that assigns LC and IA to the role of a major antecedent to HCC, shifting the discussion towards being focused on tools of technical skills. In real-life practice, the research results provide a specific task to managers and human resource workers. The implementation roadmaps of SM have to be supplemented by Strategic HR initiatives that:

- Inspire Learning Coercion: by cultivating the culture of growth mindset, availing learning facilities, replevament of auto-directed learning, and a connection between development and career advancement.
- Develop Interpersonal Adaptability: By strategically hiring interpersonal adaptability, providing training of communication and collaboration within the disciplines, and designing work processes where the person is required to interact with different professionals and use sophisticated technologies.

Limitations

This study also has a number of limitations, this notwithstanding its contributions. First, the data used are cross-sectional, hence making it impossible to draw conclusive causal conclusions. Though the theory predicts that HCC can be attributed to LC and IA, it is possible that HC work environment enhances LC and IA. Second, utilization of single self-researched questionnaire despite statistical checks draws the risk of common method variance. Thirdly, the sample itself though, powerful, was chosen in one country, which might restrict the ability to apply the findings to the other cultures and institutions. Lastly, the paper has not investigated any possible mediating processes (e.g., knowledge sharing behavior) or exploratory contextual moderators (e.g., leadership style, organizational structure) that might further should elaborate on how and when these relationships happen.

Future Research Directions

The current findings can be further developed in the future research in the following ways. The longitudinal research is required in order to determine the development of the causality and comprehend the dynamics of these relations with time. The study would be enhanced by the use of multi-source data which is the association of employee surveys and supervisor ratings of team performance. This research should be replicated by other countries (such as Europe, North America, other countries in ASEAN) and will be able to determine the cross-cultural strength of this research. The significant third step would be to explore the mediators originally; such as, does IA enhance HCC, first of all, by promoting more successful knowledge sharing? Also, investigation of moderators including technological turbulence or perceived organization support may lead to any significant boundary conditions. Last, the qualitative research is potentially rich with contextualizable information on the particular Behaviors that define what is meant by adaptability revealed in human-machine teams that will assist in the refinement of the training and development programs.

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