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Leadership Skills for Industry 4.0: Scale Development and Validation

Puja Khatri

University School of Management Studies, Guru Gobind Singh Indraprastha University, India

*Sumedha Dutta**

Department of Business Administration, Maharaja Agrasen Institute of Management Studies, India

Khushboo Raina

Department of Management, Lal Bahadur Shastri Institute of Management, India

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Abstract

Varying impact of digitalization is felt on all organizations irrespective of their sector/industry. The milieu is relatively under researched for the manufacturing sector. Complexity of the situation is further intensified by volatile, unpredictable, complex and ambiguous conditions (VUCA) of the existing environment, announcing onset of the fourth industrial revolution – Industry 4.0. Leading an organization amidst such circumstances calls for a special skill set matching this unique nature. Scholarly work focusing on distinctive features of Industry 4.0 and its effect on several sectors is abundantly available. Nevertheless, an instrument to quantify the skills desired in leaders for effectively leading in Industry 4.0 is left unattended. In the present work, three major 4.0 skill dimensions needed in a leader in Industry 4.0, referred as '4.0 Leader's Skill Set' were identified, namely Digital Comfort, Cognitive Thinking and Team Sensitivity. The study was conducted in two phases wherein the first phase, data from 250 employees of manufacturing sector were taken. An additional sample of 294 employees were taken in Phase II for confirmatory analysis and validation of the scale. Satisfactory values of KMO (0.931) and Bartlett's test of Sphericity: $p<0.05$ were obtained. Overall reliability of scale capturing 4.0 Leader's Skill Set is 0.9. 4.0 Leader's Skills was established as a reflective – reflective second order construct with the identified 3 dimensions; CT, TS and DC wherein reliability and validity of the scale was established by using PLS-SEM.

Keywords: Cognitive Thinking; Digital Comfort; Emotional Efficacy; Industry 4.0; Leadership

JEL Classifications: L2; L6; M15

***Corresponding author:** Maharaja Agrasen Chowk, Sector 22, Rohini, New Delhi, Delhi 110086, India E-mail: sumedha.maims@gmail.com

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1. Introduction

The current era of globalization is characterized by the dynamism of smart business processes. Presently, business organizations operate under the pressure of reducing business cycles, creating interconnected processes, and implementing the latest technologies in operations (BMBF, 2014; Helmrich, 2015). On top of it, the volatility of the markets and a heterogeneous environment created by the customization of the products to cater to the personalized needs of the customers have made it more challenging (Spath et al, 2013). To achieve a competitive edge in this scenario, smart production systems have replaced the traditional ones to achieve the requisite flexibility and capacity. This megatrend is comprised of automation, expansion, digitalization and shifts in consumer demands and has given rise to a new production process 'Industry 4.0' (Development Dimensions International, 2017). In recent years, 'Digital Transformation' has become a popular buzzword owing to the rapid dispersion and development of various digital technologies, leading to radical reforms at all business levels (Klein, 2020).

The digital revolution is the foundation of the Fourth Industrial Revolution, in which technology is an intrinsic component of civilization and a link between the digital, physical, and biological worlds. The labour markets have been put under new strains as a result of the Fourth Industrial Revolution. As a result, lifelong learning, educational reform, and new skill retraining initiatives will be critical in ensuring that individuals have a viable economic opportunity to compete in the new workplace. According to the World Economic Forum, by 2022, at least 54% of all employees will require further training (Samans, 2019). As a result, companies must hire new brilliant workers or train existing employees to gain all of the necessary knowledge to adopt Industry 4's latest technology. This new production focus is commonly known as the 'fourth industrial revolution' or 'the internet of things.' The term Industry 4.0 originates from the German term '*Industrie* 4.0' introduced at the Hannover Fair in 2011 and it became the prime focus of the German government and other European nations (Ghobakhloo, 2018).

When there is a huge ambiguity about the future orientation and available alternatives in technology, it becomes a necessity for the organizations to design an apt strategy to implement technology (Ivanov et al 2016). Strandhagen et al. (2017) analysed numerous elements of repetitive manufacturing environments and concluded that digital technologies are better appropriate in these settings. On both the fronts - strategic and technological, this radical transformation towards Industry 4.0 demands a well laid out strategy highlighting each step falling ahead to attain a complete digital manufacturing enterprise (Sarvari et al, 2018). To stay adaptive to the changes prevailing in the environment, it is imperative for organizations to embrace them with proper systems in place. The employee is the key to getting to the client. Changes in production systems are both a result and a cause of changes in consumer behaviour (both external and internal customers) in the industry 4.0 era (Bonekamp and Sure, 2015; Bartuska, Hanzl and Lizbetinova, 2016).

In the current world of work, the physical world is dependent on the digital world, with cloud computing, the Internet of Things, big data, cybernetic physical systems, and other driving forces (Bonilla, Silva, Silva, Gonçalves and Sacomano, 2018; Fettermann et al, 2018). UNIDO (United Nations Industrial Development Organization) puts forth that amongst the top 10 countries in the world, India is the only country from the middle-income category which is undergoing rapid transformations regarding production systems using ADP (Advanced Digital Production) (Sony & Aithal, 2020). This paradigm shift in the production processes calls for a shift in the required skills of the concerned managers also. Therefore, the skills and qualifications of the concerned manpower have to be in sync with the changes (Klosowski et al, 2016). Wolter et al (2015) opine that this transformation will lead to shifts in the job market. Reduction in jobs, job switching and changes in qualifications will be seen majorly in the manufacturing sector. These depict some of the negative challenges posed by the introduction of Industry 4.0, on the other hand, Drucker et al. (1997) believe that not technology, but the management of human resources efficiently will be required in the new era of production and manufacturing. Also, the major economic and strategic advantages lie with those firms which can readily engage, develop and retain professionals having requisite skills in the marketplace to achieve competitive advantage over others Smith and Kelly (Shiri, 2012). Across the world, leaders are facing the tough task of keeping confidence and respect towards business and leadership intact. They are looked upon as the saviors in turbulent and ambiguous times. This becomes more crucial to address when the global economy is highly disruptive and an environment of cynicism, mistrust and unstable economic conditions is prevailing all around (Bawany, 2018).

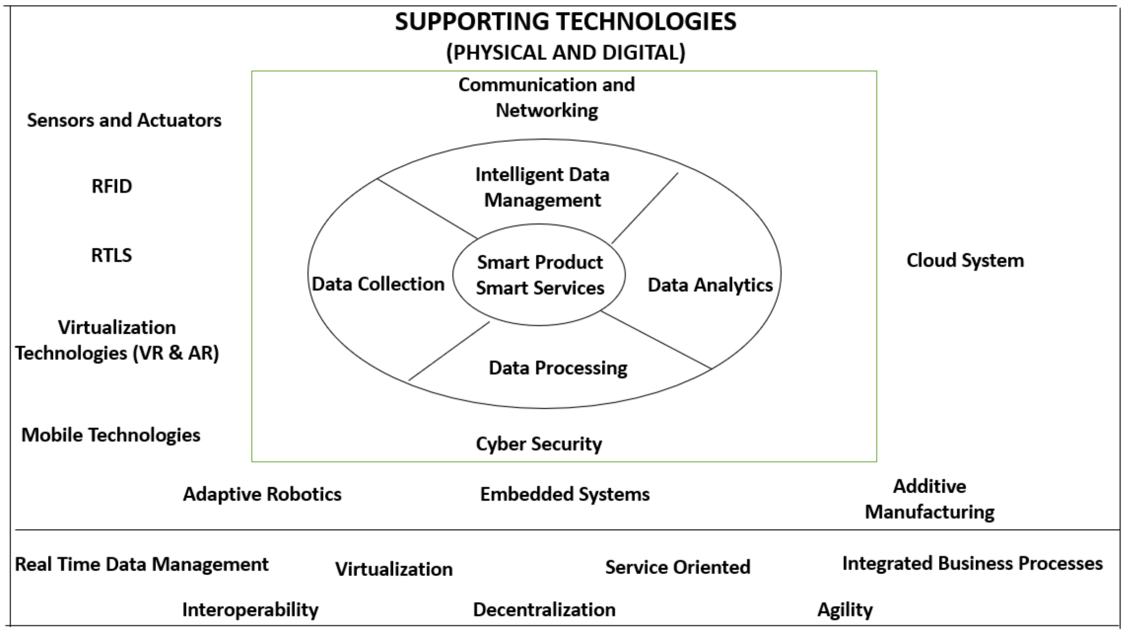
Leaders are needed to be adaptable and ready to welcome and celebrate the change in the future work due to the rapid pace of change. The change will be viewed as an opportunity to grow and innovate by successful leaders during the fourth industrial revolution (Marr, 2019). Arora, Vaishali and Jain (2018) contemplated a list of requisite skills set by the concerned managers in the era of Industry 4.0, which includes critical thinking, social intelligence, adaptive thinking, emotional intelligence, analytical skills, decision making etc. In another study conducted by DDI (2017), leaders are expected to be horizontal thinkers, engagement builders, customer-connectivity drivers, motivators and extreme lean adopters. When all new parameters are coming on a single platter, then it becomes critical to test and evaluate the underlying measures of the drivers responsible to promote the said phenomenon. Currently, Industry 4.0 is a prime concern for majority of the organizations, research centres and academia, still the scholars in this field believe that the term is ambiguous and because of less research in this field, organizations face difficulties in getting their hands on this phenomenon and tracing the steps to be taken for a successful transition (Ghobakhloo, 2018). Organizations across the world are at a crossroads in terms of their future operations. They are implementing Industry 4.0 ideas (Metallo et al, 2018) while simultaneously dealing with the influx of new generations of employees born after 1980. These personnel are from Generations Y and Z, and among them are future leaders in positions of leadership (Ng and Parry, 2016). Both innovations have a significant impact on present organisational practices, as well as the functioning and behaviour of organisations. Multicultural and multidisciplinary characteristics of organizational environment (Erol et al, 2016; Prifti et al, 2017), raise concerns about how future leaders' attitudes and behaviours will align with future organisational leadership roles (Waples and Brachle, 2020). Surprisingly, there is a clear absence of the scientific tool to empirically measure the dimensions of leadership in the era of Industry 4.0. An empirical assessment tool can yield a plethora of behavioral and dispositional data points which can almost accurately predict the leader’s readiness for the era of Industry 4.0. The present study focuses on theoretical work of Industry 4.0 to construct a scale for measuring the skills needed in a leader in Industry 4.0; we refer to these skills as ‘4.0 Leader’s Skill Set’(labelled in Figure 3 as ‘4.0leaderskills’). The study will be beneficial for the leaders, managers, administrators working in the concerned firms and the regulatory bodies to put the requisite framework for the same in place.

2. Literature Survey

The world has come a long way since the advent of first industrial revolution. The first industrial revolution broke in 1800s with the generation of mechanical power. The first ever manufacturing process was started in textile industry. Quality of life remained an issue during the first industrial revolution. Mass production was initiated in the Second Industrial Revolution when electrification was introduced. Customization of the products was an issue to address here. Digitalization started having its impact on the production processes by the third industrial revolution which enabled flexible production on programmable machines. Currently, we are in the Fourth Industrial Revolution where processes are ICT driven and decentralized enabling mass production with all customization and flexibility (Rojko, 2017). Cyber Physical Production System acts as an interface between the machine (computer) and humans during the production processes. Industry 4.0 is the brainchild of the German government as a part of its strategy to promote the computerization process in its manufacturing sector. Now the concept has been widely accepted across Europe, Asia and USA. In most English-speaking countries, alternative terms are also widely used like industrial internet or internet of things (IoT). The fundamental philosophy is to explain the digitalization of the traditional manufacturing and production processes. Since the phrase "Industry 4.0" was coined in 2011, digitalization has gotten a lot of attention. The term refers to a digitalized industry's vision. As a result, it identifies the goal of a development that began slowly but steadily years ago and has become increasingly vibrant and present. Because digitalization in industry affects processes, products, and business models holistically, it is also referred to as digital transformation. As a result, a plethora of expectations arose in tandem with the term "Industry 4.0," resulting in a variety of extremely different and often far-reaching ideas of the future of manufacturing and its products.

The term "Industry 4.0" has yet to be fully defined (Madsen, 2019). Industry 4.0 is currently regarded to be a movement based on developing digital technologies that are being integrated into organisational operations, particularly in manufacturing companies (Brixner, Isaak, Mochi, Ozono, Suarez & Yoguel, 2020). Organizations face a variety of obstacles as a result of these transformative shifts, ranging from concerns with technical implementation (Frank et al, 2019) to issues with personnel in human resources management (Schneider, 2018). On a practical level, Industry 4.0 technologies primarily consist of digitalization-based concepts and automation. The future changes, however, are predicted to effect soft people-related aspects as well as hard technology-related aspects (Erol et al, 2016). It is expected that the organisational environment will become more multicultural, multidisciplinary, agile, collaborative, open, and so on. As a result of these shifts, the question of which values, behaviours, and attributes leaders should embody or prioritise in the Industry 4.0 workplace arises. The phrase ‘Industry 4.0’ is most expected to become a next incremental step in the value chain process of the manufacturing sector (Cerika and Maksumic, 2017). The final aim of Industry 4.0 is to build a smart and open manufacturing platform for the networked information applications across the industries. The vision behind the implementation of this technology is that all manufacturing firms irrespective of their size are enabled to gain quite an easy access to the technologies supporting modelling and analytical capabilities of the systems that can be customized to meet the personalized needs. Further, the concept can be best elaborated by the term ‘smart factory’ which entails the merging of physical and virtual worlds through cyber-physical processes and results from the fusion of both the technical and business processes (William, 2014). The introduction of ICT in these processes has dissolved the boundaries between the real and the virtual world (Pillay, Ori and Merkofer, 2016). The use of state-of-the-art technology is another aspect of this industrial revolution. Earlier, the application of IT tools and techniques was in the simple form called "Material Requirements Planning" (MRP). There were restrictions in the use of technology for production, management of materials or procurement (Menges, Roubanov, & Ernst, 2014). The application of better IT processes across production processes is referred to as "Enterprise Resource Planning" (ERP) which forms the basis of the current digitized manufacturing process. The concept of Industry 4.0 focuses on the interconnection of objects, people and systems in real-time environment (Dorst et al, 2015). Therefore, the products, machines and processes are well equipped with the techniques of Artificial Intelligence to enable its adaptability for the continuous changes in the environment (Porter and Heppelmann, 2015). Primarily, Industry 4.0 is consisted of supply chain network, service information systems and production facility to keep the value-added networks operationalized. Therefore, the upcoming technologies like robotics, simulation, big data analytics, cyber-physical infrastructure, cloud systems, augmented reality,etc. are crucial for the successful implementation of this phenomenon (Satoglu, Ustundag, Cevikcan and Durmusoglu, 2018). Figure 1 elaborates the framework of Industry 4.0 in the given context.

Figure 1: Framework of Industry 4.0



Source: Satoglu, Ustundag, Cevikcan and Durmusoglu, 2018

In order to harness the said advantages, an effective workforce has to be deployed so that resources can be used wisely, and maximum benefits can be drawn. Leaders have this major task of guiding their teams mindfully to leverage the benefits of the current era. They must grab the opportunity to shape the Industry 4.0. In this digitalized global economy, leaders will drive and establish the vision, purpose, and position of future businesses (Carton, Murphy and Clark, 2014), and entire organisations will reflect their personalities in the way they work (Oreg and Berson, 2019). Even more importantly, a leader's cognitive and value qualities have a significant impact on positive organisational results (Hambrick and Mason, 1984). Some indications of the necessary features and actions of transitional leaders have been widely documented in terms of comprehending the critical relevance of leadership. Transitional leaders must be able to acknowledge their emotions (Rubin, Munz and Bommer, 2005), which is linked to openness, and have proactive personalities (which is linked to values of initiative). Building capabilities is critical; what capabilities are now lacking, what is required for AI implementation, and how will the skill gap change if big data and AI are used to create a new product or service? Capability gaps can be divided into three categories; 1. High-level cognitive and technological abilities 2. Emotional and social awareness 3. A basic understanding of manufacturing and processing (Sridhar and Ponniah, 2020).

Bawany (2018) opines that cognitive readiness is a major requirement for the leaders right now, and it has been defined as the mental preparation or advanced thinking skills which enable the leaders to face complex business problems in the much volatile, unpredictable, complex and ambiguous (VUCA) environment. There are 7 components of the cognitive readiness, they are: a) Mental cognition: thoughts and emotions, b) Sensemaking: visualize bigger picture, c) Intuition: gut feeling, d) Problem solving: analytical methods, e) Adaptability: willingness to change, f) Attentional control: focus the attention and g) Communication: creating communication channels. Identification of the requisite competencies is crucial for the development of the workforce to meet the market needs in present times.

Competency models are collections of knowledge, skills, abilities, and other traits required for effective performance in certain jobs, job families, or functional areas (Mavrikios, 2015). Several projects have been undertaken in recent years to establish competency models for manufacturing, ICT, and Industry 4.0. ASME (2015) presented a competency for the future production worker in relation to Industry 4.0. The identified competencies were divided into two groups: technical qualifications and skills, and personal qualifications and abilities. IT knowledge and abilities, organisational and processual awareness, and the capacity to communicate with modern interfaces (human-machine / human-robot) were highlighted as “must haves” in the future Industry 4.0 scenario among the technical ones. Four main types of competencies have been identified which are a) Technical skills: job related, b) Methodological competencies: skills for problem solving, c) Social competencies: attitude to cooperate and d) Personal competencies: individual values and motivation (Becker, 2013). Hecklau et al (2016) developed a competency model for Industry 4.0 in the light of the PESTEL challenges faced by the firms in the era of Industry 4.0. They identified 4 sets of competencies which are: a) Personal competencies: flexible, open to change, ability to work in pressure, b) Social competencies: intercultural and language skills, networking skills and leadership skills, c) Methodological competencies: creativity, entrepreneurial thinking, analytical skills, decision making and d) Technical competencies: media skills, coding skills, process understanding. Grzybowska and Łupicka (2017) identified key managerial competencies for the future leaders and they are: a) Entrepreneurial thinking: ability to identify marketplace and opportunities, b) Creativity: ability to perceive in new ways, c) Problem solving: analytical and logical thinking, d) Conflict solving: self-control and empathy, e) Decision making: process of making choices, f) Analytical skills: gather information and evaluate, g) Research skills: retrieve in-depth information and h) Efficiency orientation: efficient use of resources. DDI (2017) presented a comprehensive list of skills requirements in the traditional and future oriented workers and the same is presented in Figure 2.

Figure 2: Skills Requirements in Traditional vs Future Oriented Workers

Past requirements for workers	Present/Future requirements for workers
Experience	Ability to learn
Physical capability	Mental muscle, ability to adapt quickly to changing roles
Mechanical aptitude	Digital and team-collaboration aptitude
Existing knowledge, basic education	Higher-level education, continuous learning
Single-process motivation	Motivation to work in a team across multiple processes
Detailed assembly tasks	Manufacturing process monitoring
Willingness to follow instructions, with occasional contributions to process improvements	Willingness to own the line and assume responsibility for meeting production and quality goals, and constant improvement
Manual data tracking	Real-time data usage

Source: Development Dimensions International, 2017

There are several types of leadership theories to consider, including leadership attribute theories (which aim to explain specific characteristics that account for leadership success), behavioural leadership theories, and organisational leadership theories. Theories of leadership (which seek to explain the varied leadership styles employed by effective leaders) and Theories of contingency leadership, which aim to describe the best leadership style depending on the situation, the leader, and the following personal qualities are differentiated by traits. Personality is a collection of characteristics that classifies a person's conduct. Personality individual profiles reveal which qualities are stronger and which are weaker. Production, logistics, communication, and human resource management all undergo changes as a result of digitalization (Oberer and Erkollar, 2018). Equipping leaders with all the requisite traits and required elements has to be done through proper systematic training. Knowledge and education are important components of the Fourth Industrial Revolution because they help institutions achieve their objectives. According to the human capital theory, knowledge equips individuals with stronger cognitive skills, hence it is vital to boost their productivity and efficiency in order to expand connected activities. Employees must have a certain level of education, experience, expertise, and skillset. As a result, these are used to build values for an organization's success (Alharbi, 2020). Moreover, the 2030 Sustainable Development Plan and Goals emphasise the role of education in fostering change in knowledge, skills, values, and behaviour in order to attain higher growth sustainability, (Wals, Mochizuki and Leicht, 2017) noted out. The birth of this concept coincided with the recognition of the necessity for a strong educational system to meet the growing difficulties. Since the Fourth Industrial Revolution began to manifest itself in the labour market, graduates must be prepared for it, and quality must be reached within educational and research institutions, as well as the application of current study disciplines.

India is a major hub for the service sector where 16.7% of the GDP comes from the manufacturing (Ministry of Finance, 2018). India has actively been embracing the new technology and techniques to upgrade itself on the global level. Government has been trying its best to improve in manufacturing through various initiatives like Make in India, National Manufacturing Policy, MoU for research, etc.,but the shortage of required skills in the workforce is becoming an obstacle to its progress path (FICCI, 2015). The determination of the skills and acquiring them is the only key to attain maximum benefits of the Fourth Industrial Revolution. The significance of Industry 4.0 is to transform the usual machines to independent self-aware and self-learning systems in order to improve the overall performance according to the interactions with surroundings (Vaidya, Ambad and Bhosle, 2018). The presence of an empirically tested measurement tool will work as a catalyst to this already fast paced sector. The present study will address this shortcoming by developing a scale to empirically identify the skills required by the leaders working in the era of Industry 4.0 so that all the upcoming leaders of this industry can embrace the upcoming changes of this era comfortably.

3. Methodology and Data

The prime objectives of the current study are:

- To identify and confirm the requisite skill sets needed among the leaders in a manufacturing sector in Industry 4.0.
- To determine the reliability and validity of the identified factors of 4.0 Leader's Skill Set in accordance with its reflective nature.

Assigning priority to competing goals is a challenging task. Amongst the various approaches available for dealing with vague and unstructured problems having manifold incompatible objectives, MCDM is the most frequently cited in the published literature (Lee and Eom, 1990). Additionally, in MCDM, various approaches are prevalent, namely, Analytical Hierarchical Process (AHP), fuzzy AHP, Data Envelopment Analysis (DEA), fuzzy TOPSIS, to state a few. In all the above listed approaches, at the very outset, a comparison is drawn among all possible incompatible alternatives or solutions. The decision makers provide specific ratings on the basis of weights assigned to each alternative vis-à-vis other contending alternatives. For the current study, AHP approach, introduced by Saaty (1980) is applied owing to its accepted suitability to solve complex problems by applying various selection norms. The dimensions so identified were further ranked and verified by conducting focus group discussions with experts belonging to academia and industry. Giving regard to the experiences of the experts, a few items suggested by them were included to measure 4.0 leaders' skills set even though they did not emerge from the literature.

The present work is descriptive and cross-sectional in nature. The available repertoire of literature was carefully reviewed for understanding the peculiar environment of Industry 4.0 to identify the relevant set of skills needed in a leader in its context. Then, these items (4.0 Leader's Skill Set) were endorsed through extensive deliberations with experts belonging to academia and industry; the scale thus developed was administered to collect primary data.

The scope of our research includes team leaders or managers working in the manufacturing companies based in Delhi - NCR. Multistage sampling was used to obtain the sample for data collection. At the outset, a list of 63 manufacturing companies based in Delhi - NCR was drawn from the official website of the Ministry of Corporate Affairs (www.mca.gov.in). Companies with paid up capital greater than 0.2 million were selected to reach to a list of 8 companies. Then purposive sampling was used to form a sample from the selected 8 companies. Responses of 40 employees from each company working at the managerial level was sought. The proposed sample was 320 respondents to whom the questionnaires were personally administered in the form of hard copies. A brief overview of the survey's purpose was given to the participants for their ease of understanding. The participants were also extended assurance regarding data confidentiality and their anonymity.

Measure – Adaptation and Finalization of the questionnaire: Our survey questionnaire comprised of two parts – general information about the respondents and the questionnaire. A brief overview of relevant instructions for providing responses was specified at the beginning of the questionnaire. Demographic details, like age, gender, marital status and organizational level occupied by the respondent formed the first section of the questionnaire. This section was followed by specific questions on the measurement of the leader skills relevant for Industry 4.0. The final questionnaire consisted of 32 items which were rated on a 7- point Likert type scale; 1 being 'strongly disagree' and 7 being 'strongly agree'. The rationale for using a 7- point Likert type scale was on account of its potential to yield a better result of various indices of reliability, validity and discriminating power (Preston and Colman, 2000).

Data Collection procedures: The objective of the current work was to develop an instrument for measuring 4.0 leader's skill set and confirm the validity of the scale so developed in Indian context. This purpose was attained by conducting analysis in two phases on two sets of independent samples. In the first phase, Principal component analysis was conducted on data collected from 250 employees of Indian manufacturing sector (n1= 250). An additional sample of 294 (n2 = 294) employees were retaken in Phase 2 for confirmatory analysis and validation of the scale so developed.

Study Population: Phase 1 was conducted between January to April 2019. Data was collected from 250 (male – 145 and female – 105) survey respondents working in the manufacturing organizations. Out of these 250 respondents, 175 were at junior level and 75 were working at the middle level in the organization.

For Phase 2, data collection was conducted between May and August 2019. Out of 475 questionnaires distributed, 294 usable responses were received which were used in the final stage for data analysis. The sample consisted of 186 (63.2%) males and 108 (36.7%) females; with 180 employees at junior level and 114 at the middle level.

4. Data Analysis

The data was analysed by carrying out the following five steps: (i) item analysis, (ii) common method bias, (iii) principal component analysis (PCA), (iv) confirmatory factor analysis (CFA) and (v) reliability and validity assessment. SPSS v.23.0 and PLS-SEM 3 software were used for the statistical analysis of data.

4.1 Item Analysis

Prior to conducting analysis, the researchers conducted sampling adequacy test (K-M-O test) and test for assessing normality of data (Barlett's test of sphericity). In the present work, KMO value was observed as 0.931; a score above the minimum threshold value of 0.50 (Hair et al., 2006). Barlett's measure of 6367.437 was found highly significant ($p < 0.001$) with 378 degrees of freedom. And hence, it was concluded that our sample is acceptable and apt for applying factor analysis on the solicited data.

Table 1: KMO and BARTLETT'S TEST

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.931
Bartlett's Test of Sphericity	Approx. Chi-Square	6367.437
	df	378
	Sig.	.000

Source: SPSSS Output

4.2 Common Method Bias

Application of self-report measures for data collection gives rise to a pertinent issue known as common method variance. To check the same, Harman's one factor technique is utilized wherein all the items are loaded onto a single factor and the un-rotated factor solution is studied (Podsakoff et al., 2003). In our study, it was observed that the total variance described by single largest factor was 47.9 (less than the threshold value of 50); implying that our results are not hampered by common method bias.

4.3 Principal Component Analysis

To extract the initial factors, principal component analysis with varimax rotation was run. In principal component analysis, square multiple correlations were used as estimates of the initial communalities, yielding a set of four factors. These four factors were extracted after removing items having cross loadings and with factor loadings less than 0.50 on the corresponding factors. For factors extraction, eigen value >1 was applied as the criterion. The initial thirty-two items were condensed to four factors with a total of twenty-eight items. As shown in Table 2 below, the total variance explained by the four factors taken together is 67.949%. It can be further observed that all communalities' values fall within the range of 0.531 (lowest communality value- EI1) and 0.845 (highest communality value- Digital_5).

The results offered a four-factor structure (Table 3) for the construct under study- 4.0 Leader's Skillset. The first factor, labelled as 'Digital Comfort' (digitalcomfort), consisted of items pertaining to measure the comfort level of an individual (in our case, a leader) when working on various modern digital platforms. It comprises of statements like 'I feel safe using online applications', 'I have full knowledge of online payment methods', 'I can store and sort data easily', etc. The second factor, labelled as 'Cognitive Thinking' (CT), captured the expertise of a leader to use cognition for assimilating several inputs to establish an understanding. This factor was made up of items like, 'I tend to gather information from as many sources possible', 'I feel "Believing in your own self" is the primary step to solve any problem', 'I follow my gut feeling/intuition', etc. The third factor was labelled as 'Team Sensitivity' (TS), which assess the degree of sensitivity displayed by a leader towards various differences existing among team members. It comprises of items like, 'I always listen to my teammates', 'I am a polite person', etc. The fourth factor was labelled as 'Emotional Efficacy' that measures the capability of a leader to assess the emotional makeup of the team members. This factor was completely dropped during the stage of confirmatory factor analysis.

Table 2: TOTAL VARIANCE EXPLAINED

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.236	40.130	40.130	11.236	40.130	40.130	7.562	27.006	27.006
2	4.404	15.729	55.858	4.404	15.729	55.858	5.929	21.177	48.183
3	2.329	8.317	64.175	2.329	8.317	64.175	2.994	10.693	58.876
4	1.057	3.774	67.949	1.057	3.774	67.949	2.540	9.072	67.949
5	.850	3.034	70.983						
6	.709	2.533	73.516						
7	.656	2.344	75.860						
8	.599	2.139	77.999						
9	.549	1.961	79.960						
10	.521	1.861	81.821						
11	.496	1.771	83.592						
12	.469	1.675	85.267						
13	.443	1.583	86.850						
14	.393	1.402	88.252						
15	.383	1.368	89.621						
16	.361	1.289	90.910						
17	.335	1.196	92.106						
18	.315	1.127	93.232						
19	.288	1.027	94.259						
20	.275	.981	95.240						
21	.241	.861	96.102						
22	.210	.749	96.851						
23	.199	.712	97.563						
24	.177	.631	98.194						
25	.150	.534	98.728						
26	.136	.487	99.215						
27	.122	.436	99.651						
28	.098	.349	100.000						

Note: Extraction Method: Principal Component Analysis.
Source: SPSS Output

Table 3: ROTATED COMPONENT MATRIX

	Component			
	1	2	3	4
I am comfortable in using online applications.	.785			
I communicate with people using online media.	.815			
I feel safe using online applications.	.780			
I am comfortable in using e-wallets.	.804			
I save time by using digitized systems.	.890			
I can access my documents from anywhere and anytime using digital systems.	.858			
I have full knowledge of online payment methods.	.835			
I can easily manage my work in spite of high digitization.	.872			
I can store and sort data easily	.855			
I am aware of digital advertisements	.863			
I tend to gather information from as many sources possible		.738		
I realize the importance of sorting information relevant for the given task.		.719		
I can always draw results from the data.		.723		
I feel "Believing in your own self" is the primary step to solve any problem.		.641		
I feel comfortable working in unpredictable situations.		.706		
Almost all the times, I know what I want from myself.		.838		
I often come up with new ideas while solving a problem.		.792		
I follow my gut feeling/intuition.		.674		
I can suppress my emotions when needed.		.545		
I always listen to my teammates.			.567	
I am comfortable in talking to people with different mindsets.		.554		
I am a polite person.			.796	
I prioritize team work.			.751	
I take criticism positively.			.612	
I remain focussed when going through an emotional phase.				.720
I am approachable.				.802
I don't get offended easily.				.783
I don't get into arguments easily.				.812

Note: Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 6 iterations.
Source: SPSS Output

The overall reliability of scale capturing 4.0 Leader's Skill Set is reported as 0.9. According to the views of Nunnally (1978), the instruments applied in basic research should have reliability of about .70 or higher .

4.4 Stage 2: Confirmatory Factor Analysis (CFA) – Reflective Measurement Model – PLS SEM

The next step in our study is to examine the measures used in our work; their dimensionality and epistemic relationships (link between construct and its indicators). Epistemic relationships can either be formative or reflective (Polites, Roberts and Thatcher, 2012). In our study, we have examined 4.0 leader's skills, a second order higher model, by using a popular approach called, higher component model (HCM) as originally suggested by Wold (1982). Researchers have applied the Type 1 HCM Model – reflective first order, reflective- second order; the first order latent constructs are reflectively measured and are highly correlated with each other and yet are distinctive from each other. 4.0 leader's skill is viewed as a reflective- reflective second order construct with Digital comfort, Cognitive Thinking (CT) and Team Sensitivity (TS) as lower order reflective constructs measured by ten statements in Digital comfort, ten statements in CT and four statements in TS.

4.5 Model Assessment

Measurement model and structural model are the two components in a structural equation model (Henseler, Ringle & Sinkovics, 2009). When assessing measurement model, we first need to study the reliability and measurement validity (convergent and discriminant validity) (Hair, et al, 2014; Chin, 2010), followed by the size and significance of the path coefficients and multi-collinearity.

4.6 Reliability Assessment

Cronbach's alpha and composite reliability (CR) score help in assessing the reliability of reflective measurement models. As we can observe that all the Cronbach's value satisfies the stated criteria > 0.7 as given by Nunnally (1978) and all our Composite reliability values are > 0.70 (Bagozzi and Yi, 1988); thus, establishing the reliability of our reflective model (Table 4).

Table 4: Cronbach's alpha and Composite Reliability

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
4.0leaderskills	**0.950**	**0.954**	**0.466**
CT	**0.919**	**0.933**	**0.581**
TS	**0.880**	**0.918**	**0.736**
digitalcomfort	**0.961**	**0.966**	**0.743**
glo4.0leaderskills	**1.000**	**1.000**	**1.000**

Source: Analysis Output

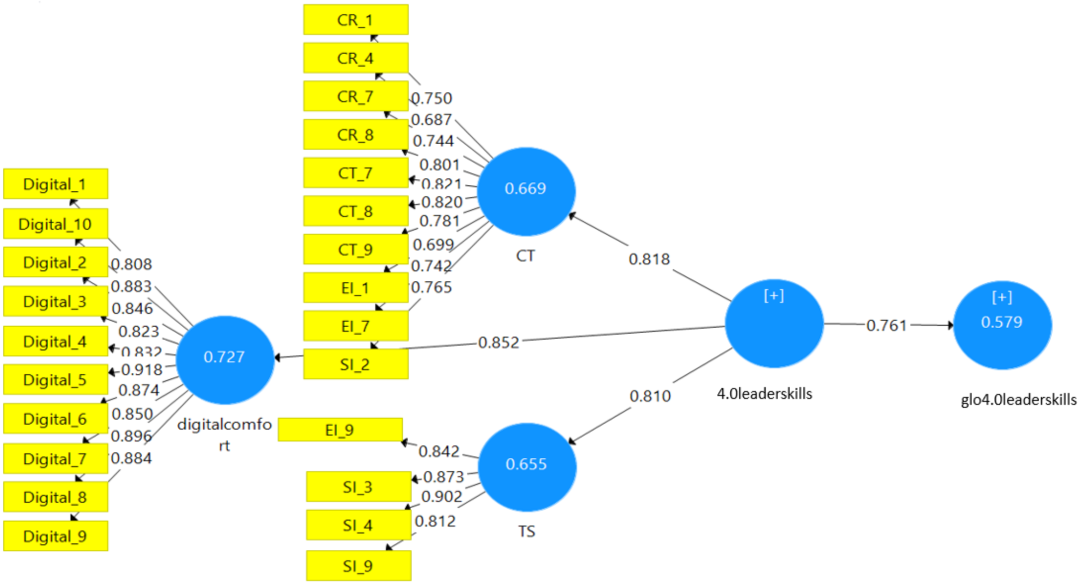
4.7 Validity Assessment

The field of research presents numerous approaches for establishing the validity of the scaling method. One approach to assess the indicator's validity calls for an estimation of correlation of the indicators with an external variable. Inclusion of a global measure summarising the crux of the complete construct was proposed by Diamantopoulos and Winklhofer (2001). Accordingly, we used an outcome variable (external/global) which is an independent reflective indicator and a reflectively – measured construct. One reflective indicator of 4.0leaderskills (glo4.0leaderskills) is used as a global measure or indicator of 4.0 leader's skills. This helps to overcome the problem of under-identification and thus, supports the validity assessment.

One reflective indicator of employee wellness (EmpWellGlobal – I feel complete sense of wellbeing at my job) has been taken as a global measure to help in overcoming the issue of under-identification and help in validation purposes.

The use of glo4.0leaderskills as a global indicator of 4.0 leader's skills resulted in a path coefficient of 0.761 (refer Figure 3) which is above the suggested threshold value of 0.70 (Hair et al., 2017). In addition, the values of outer loadings as given in Figure 1 are all above the acceptable value of 0.70 (Hair, e t., al, 2014). With respect to AVE, Fornell and Larcker (1981) stated that an AVE value > 0.4 can be accepted provided its CR > 0.6 and since all our values of average variance extracted (AVE) given in Table 4 meets the stated criterion; thus, offering support for the convergent validity of the 4.0 leader's skill.

Figure 3: Leader's Skill Set as a reflective – reflective second order construct



Source: Analysis Output

After, establishment of reliability and validity, the other criteria for assessment are size and significance of the path coefficients and multi-collinearity.

4.8 Size and significance of the path coefficients

For evaluating path coefficients, bootstrapping technique is generally suggested (Efron and Tibshirani, 1993). For our analysis of path coefficient (given in Table 5), we have used 5% as level of significance, and we can observe that all the path coefficients are significant.

Table 5: Significance of Path Coefficients

	4.0leaderskills	CT	TS	Digitalcomfort	glo4.0leadertraits
4.0leaderskills		0.872 (β=0.818; α=0.05)	0.883 (β=0.810; α=0.05)	0.890 (β=0.852; α=0.05)	0.780 (β=0.761; α=0.05)

Source: Analysis Output

4.9 Multi – Collinearity

The next step is assessing the issue of multi-collinearity through Variance Inflation Index (VIF) which reflects the degree of variance in the coefficient estimate being inflated due to its existence in the model. It indicates if the correlation between independent variables is high, it will give rise to issues in fitting the model and analysing the results properly (Frost, 2017). In our work, all VIF values are below the stated threshold value of 0.50 (Hair, et. al, 2011; Hair et al, 2012; Henseler et al., 2009; Latan and Ghozali, 2012); implying that our data is free from the problem of multi-collinearity.

The assessment of the construct with supporting results confirms the establishment of 4.0 Leader’s Skill Set as a reflective-reflective second order construct with Digital Comfort, Cognitive Thinking and Team Sensitivity as its lower sub-dimensions.

5. Discussions

The main objective of our study is a systematic two-stage construction and validation of 4.0 Leader’s skill set in Indian context. The instrument was tested on two independent samples; one consisting of 250 responses on which PCA was conducted to determine a specific set of factors. The second sample consisting of 294 responses was taken for carrying out CFA using PLS-SEM3. The –two-stage process was conducted to refine the selected items and validate the model at first and second order levels. The three second order factors identified are digital comfort, cognitive thinking and team sensitivity.

Digital comfort holds great relevance as we step into the cyber-culture of Industry 4.0. In the current scenario, the organizations are integrating their business digitally, giving rise to search for leaders who are competent to drive the digital need of business. Digitalization can be seen on all fronts, reaching every department and infusing across a business at a fast pace. So, a marketing leader must be up-to-date with digital technologies in order to offer an exceptional experience to customers; the IT leader needs to keep abreast of various digital platforms to understand how the data collected can help an organization to take the business to the next level; HR leader must have the requisite skill set for effectively harnessing the power of social networks and digital channels to channelize the efforts of the digitally savvy workforce in the right direction, so on and so forth. Specifically, we can say that a leader high on digital comfort will aid the company to truly leverage its digital assets, that is, digital apps, tools and software.

Cognitive thinking has cognition as its core component. Cognition refers to the process by which an individual acquires knowledge through sensory inputs, thought as well as experience. When such a cognition is put to use by a person to integrate several inputs for the purpose of understanding the concept comprehensively, it is known as cognitive thinking. Cognitive skills aid a leader to grasp, process, recollect and apply the incoming information and this becomes all the more important in the age of digitalization which is witnessing the flow of voluminous information from all directions.

As cultural boundaries lose their relevance, organizations are witnessing a growth of heterogeneous workforce. Thus, a leader should show sensitivity to all the apparent differences existing among the team members. A 4.0 leader should be emotionally as well as culturally sensitive to lead the team effectively.

The study has made use of intensive indicators to constitute a construct that is reflective in nature. The researchers are able to discuss 4.0 leader's skill in detail to discuss the nature of the construct and its validity as reflective construct.

6. Future Research Avenues

Effective implementation of Industry 4.0 technologies offers many concrete implications for the entire manufacturing industry, environment as well as for workforce. Its adoption not only brings economic rewards by taking efficiency, quality, all-round improvement and alliances to the next level, but also contributes towards strengthening safety, sustainability and image of the manufacturing industry. Reaping the maximum advantage of Industry 4.0 offerings demands a high level of preparedness from the industries. They need to prepare themselves for handing numerous economic, political technological, social, legal and environmental challenges in this direction. What are these challenges and what can be the strategic actions to manage these challenges can be source of future research area. For instance, Industry 4.0 dictates companies to handle many organizational and process changes which needs high implementation costs with an unclear estimate of cost savings or a heightened need of data safety and security. An increase in job requirements instils fear about losing a job and, thereby, adding to the mental stress of employees. At the technical front, many unsolved problems emerge owing to an absence of clearly documented standards for various technologies, rise in demand for high-end computer equipments or higher requirements for improved communication networks. Along with these, various legal and regulatory challenges too need to be faced on and off. Such a vivid spectrum of challenges makes it clear that companies must be driven for adopting government directives, initiatives or financial assistance schemes. Additionally, Industry 4.0 helps in attaining digital end-to-end integration and thus, plays a significant role in dropping of internal operating costs (Kagermann, Helbig, Hellinger and Wahlster, 2013). Do these costs offset the paybacks can also be researched? The authors have laid down a platform wherein a comprehensive approach towards Industry 4.0 is undertaken for the purpose of identifying research avenues to be explored by the aspiring researchers.

Nevertheless, embracing Industry 4.0 will make manufacturing industry technologically driven setting up performance benchmarks for other industries to follow. Supplementary steps in science and practice will take the innovative feature of Industry 4.0 in the complex environment of the manufacturing industry to a new horizon. Forthcoming studies should take the outlined challenges and the identified issues presented within the research agenda.

7. Conclusion & Implications

The world is witnessing a grand shift in terms of the business processes that have been deployed in the firms to acquire the maximum market share for themselves. With the advent of the Fourth Industrial Revolution commonly known as Industry 4.0 or Internet of Things, the processes have become smart in approach. The shorter business cycles, flexibility in production processes and customization in the products have become the focal points for the organizations, if at all they want to survive in the given business environment. The automation processes enabled by the Artificial Intelligence are taking a toll on the global operations of the firms. In order to thrive in the given environment, it is imperative for the organizations to develop their human resources especially leaders. Digitalization, networked smart gadgets, and new modes of communication and cooperation require innovative techniques to create value. Competitiveness and innovation are at the heart of Industry 4.0. To deal with new difficulties, businesses must modify their skills. Design thinking, unlike change management, which is a sequential notion, is an iterative strategy that combines creative and analytical methodologies. Designers utilise Design Thinking to address complex challenges and come up with attractive solutions. A design mentality is one that is solution-focused and action-oriented in its approach to achieving a desired future. It could be used as a step-by-step method in business management to develop and implement ideas that improve earnings, efficiency, and customer satisfaction, as well as keep businesses ahead of the innovation curve. Companies must think in new ways as part of Industry 4.0 (Oberer and Erkollar, 2018). The leaders have to play a transformational role in guiding their workers to achieve the best in the given resources along with matching the pace of the industrial revolution for what is relevant today may lose it lustre tomorrow. They have to guide their teams mindfully to achieve targets. Fostering inclusive leaders will almost certainly be just as important to an organization's success in this new era. Today, diversity and inclusion have a growing impact on a company's brand, mission, and performance. Indeed, for companies wanting to recruit and keep top personnel, inclusivity is becoming a critical differentiator. Inclusive leaders embrace the value that a varied environment can provide by drawing on distinctively human attributes like empathy, curiosity, and courage. These leaders listen to their staff and encourage them—qualities that today's workers are increasingly looking for in their bosses.

Leaders with excellent interpersonal skills and knowledge of the intricate interplay between people and new technologies are needed in Industry 4.0. As these tools become more widely used, business leaders should reconsider their talent and leadership development initiatives. Organizations may better position themselves for the challenges and opportunities that this new era is expected to bring by prioritising the development and growth of ethical, inclusive leaders, as well as nurturing technical and human skills across the company (Foutty, 2020).

Government of India is also not leaving any stone unturned in this regard. EEPC (Engineering Export Promotion Council) has been appointed by the Government of India to represent the biggest segment of Indian industry which contributes approx. 25% to Indian total exports. These industries being capital as well as labour intensive will result in competitive advantage, but their readiness needs to be assessed at all levels (Stentoft et al, 2020). With an emphasis on the critical tradition and community of practise, objectivity remains regulatory. Getting accustomed to the education and industrial training systems necessitates more participatory arrangements that allow for a smooth movement of human resources into technical and IT jobs. Manufacturing workforce occupational skills require a high degree of perseverance and predictability, which is dependent on a young and well-educated workforce. Though such a workforce is an asset, it is critical that they acquire the necessary employable skills for future professions (Medtech, 2017).

Various authors have discussed at length about the manifold benefits and expectations from adoption of Industry 4.0 in the manufacturing sector and have also listed competencies sets and skills set that must be present in the leaders in the era of Industry 4.0, but a clear, empirically tested measurement tool is not available. The development and validation of a scale for measuring the skill set of leaders to thrive in the complexities of Industry 4.0 makes it stands apart from the previously published works.India is striving hard to fix its roots in the ground of global manufacturing enabled by ICT, but there is still a long way to go. The lack of required skilled workforce is the major cause of this. Hence, to achieve this, the clarity about the required skills of the leaders is critical for the success of manufacturing in Indian context.

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