Scenario Analysis of Human – Machine Learning in Industry

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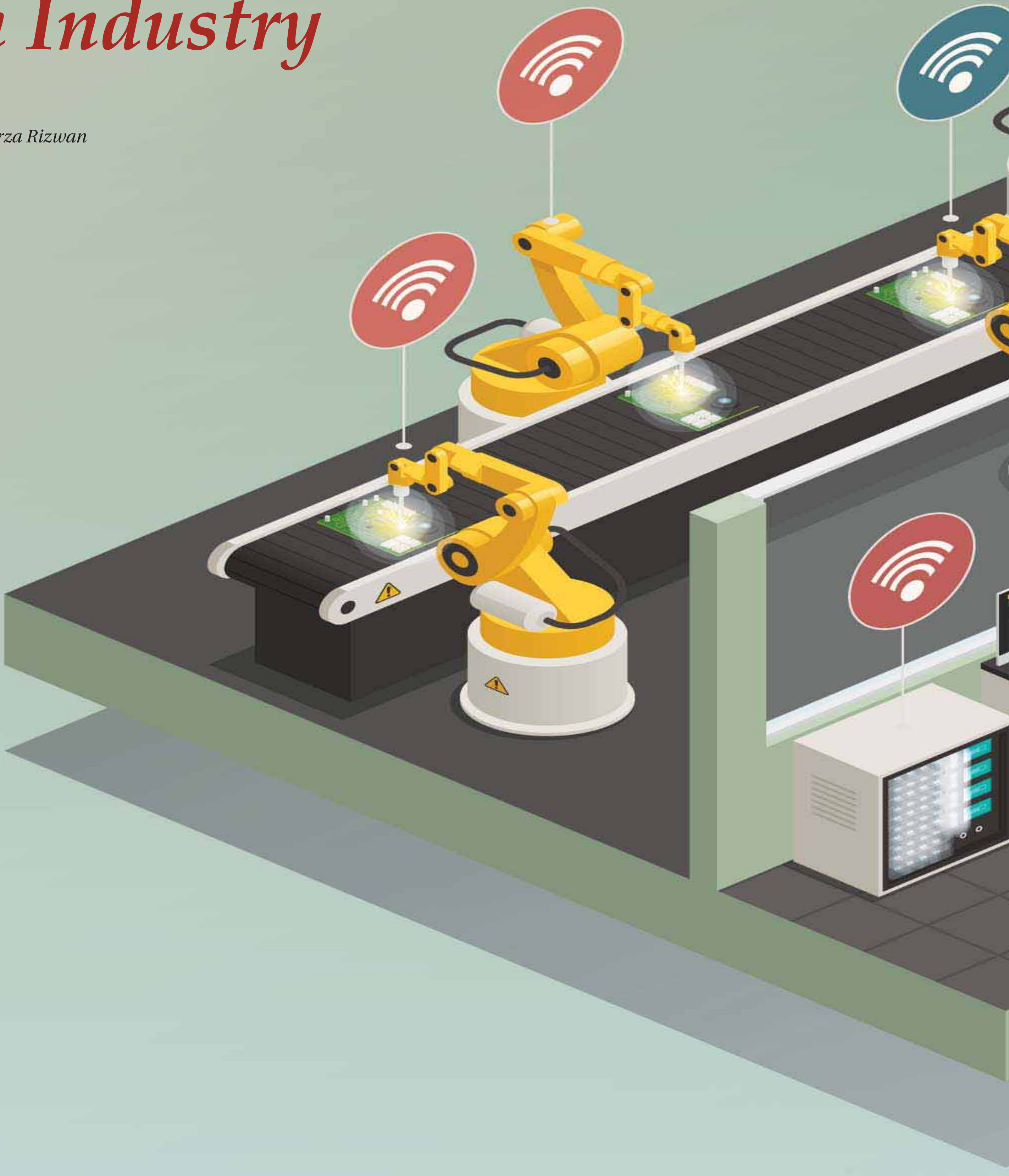

ABSTRACT

Background: *Industry 4.0 characterized by 'smart factories' gave rise to the absolute customized product which has become possible through the creation of new operating models where virtual and physical systems of manufacturing cooperate mutually. The breakthrough technologies such as quantum technology, nanotechnology, machine learning, and others are generated through connected machines and systems. The technological fusion and their integration across physical, digital, and biological domains demand basic to advance levels of human-machine cooperation and collaboration or human-machine learning.*

The research aims: *In this paper, the author applies a scenario analysis process to understand how Industry 4.0 may impact the concepts of learning and propose best learning practices for the future.*

Methodology: *The paper is based on the literature review of experts' work on Industry 4.0 and Human-skilling. Through such literature review, critical factor elements characterizing Industry 4.0 and Human-skilling have been identified. Six steps scenario-analysis process has been adopted to suggest what would be the future of human skilling. It has also been attempted to explore the possibility of theory concerning the role of learning in Industry 4.0.*

Key Findings: *It has been concluded that Leadership with high emotional intelligence and digital mindsets generating innovative ideas will be the future of human skilling in Industry 4.0 and beyond.*

Keywords: *Industry 4.0, human-learning, machine-learning, newer technologies, knowledge management, organisational learning*

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INTRODUCTION

Industry 4.0 characterized by 'smart factories' gave rise to the absolute customized product which has become possible through the creation of new operating models where virtual and physical systems of manufacturing cooperate mutually. The connected machines and systems through digital technologies and cognitive computing generated breakthrough technologies like Machine-Learning, Nanotechnology, Quantum Computing, and many others. These digital technologies and cognitive computing are shifting the traditional boundaries of manufacturing industries. (J. E. Kelly and S. Hamm, 2013).

The fusion of technologies and their interaction across physical, digital, and biological domains demand basic to advance levels of human-machine cooperation and collaboration or humanmachine learning. The connected types of machinery and smart devices generate self-learning solutions and self-directed capabilities as a kind of 'Human Learning' designed to reduce communication cost and time along with the flexibility to manufacture with mass customization capabilities and enhanced production speed and quality as that of 'Smart Factories of Industry 4.0'. (H. Gruber, 2017, C. J. Bartodziej, 2017, J. A. Saucedo-Martínez, et al., 2017).

Learning is critical for individual growth and organizational functioning as educational and skilling standards of nations, companies and individuals are crucial parameters in today's competitive and globalized market or knowledge society (Illeris, 2009). Learning impacts the quality of interactions in an organization, triggers organizational change (Antonacopoulou& Gabriel, 2006), and enables companies to maintain their competitive advantage (Carmeli et al., 2009). However, on the other side, it has been observed in a recent survey that only 13% of workers in OECD countries and economies use key information-processing skills, namely literacy, numeracy, and problem-solving skills on a daily basis with higher proficiency than computers. (S.W. Elliott, 2017).

In the above background, the author intends to understand how Industry 4.0 may impact the concepts of learning and how the best learning practices for the future can be proposed. To find an answer, critical factor elements characterizing Industry 4.0 and Human-skilling have been identified through the literature review. The author then applies the scenario analysis process in terms of the tipping points of the drivers of Industry 4.0 and required human skills and learning after the probable role of applicable machine learning to suggest what would be the future of human skilling. It has also been attempted to explore the possibility of theory concerning the role of learning in Industry 4.0.

POSTULATION OF INDIVIDUAL AND ORGANIZATIONAL LEARNING

Phillips & Soltis (2009) concluded that scholars failed to propose a single comprehensive theory of learning. The complexity of the learning process resulted in at least three major theories of learning, that are behaviourism, cognitivism, and constructivism. (Davis, Edmunds, & Kelly-Bateman, 2010; Wenger, 2009). The genesis of these theories has roots far into the past with two opposing stands on the origin of knowledge – empiricism, and rationalism.

Empiricism views experience as the primary source of knowledge; whereas, Rationalism emphasizes that knowledge derives from a reason beyond the senses (Schunk, 1991). Since the time of Aristotle (384-322 B.C.), empiricists adopted the stand that complex ideas are generated when sensory impressions associate contiguously in time and/or space, and these ideas are subsequently processed into knowledge. Rationalism originated with Plato (c.427347 B.C.) and put the distinction between mind and matter to accentuate the idea that humans learn by recalling or discovering what already exists in the mind. (Ertmer, P. A., & Newby, T. J. 2013). The central belief that knowledge arises through the mind remains the same.

The foremost community in which learning can occur is 'Individual Learning'. An individual acquires new skills or ideas at work and their productivity may increase as they gain expertise. An individual chooses to share their knowledge with the rest of the group. If an individual doesn't share their knowledge, the group loses the particular knowledge. (Wilson, Jeanne M.; Goodman, Paul S.; Cronin, Matthew A. 2007). Group learning is the next largest community (Wenger, Etienne (1998) primarily the processes of interpretation and integration. (Crossan, M.M, Lane, H.W. and White, R.E.1999). Organizational learning occurs during the organization's activities and at different speeds. The goal is to enhance efficiency through productive adaptation to changing environments and adjustment under uncertain conditions. (Dodgson, Mark 1993). The inter-organizational learning will occur leading to improved processes and products by integrating new insights and knowledge. Inter-organizational learning will cut time costs, risk reduction during problem-solving, and help learn faster by modifying ideas and creating innovation. (Tucker, Anita L.; Nembhard, Ingrid M.; Edmondson, Amy C. 2007).

Knowledge Management

With the advent of IT, emphasis has been put on knowledge management systems. Individuals within an organization create, distribute, or apply knowledge in their work and learning is an inherent element of their work routines (Maruta, 2014).The knowledge management system at the organization concentrates on integration and continuous improvement through sharing of lessons learned leading to consistent innovation and competitive advantage. (Gupta, Jatinder, Sharma, Sushil 2004). These efforts are the convergence of organizational learning through knowledge sharing with a greater focus on 'knowledge management as a strategic asset'. (Maier, R. 2007).Knowledge Management is thus a strategic intent to raise the standard of performance of the organization by executing strategic wisdom of sharing the right knowledge to the right people at the right time to put information into action. (O'Dell & Grayson, 1998).

CRITICAL FACTOR ELEMENTS OF INDUSTRY 4.0

During the Hannover Fair in 2011, the term 'Industry 4.0' is coined for the fourth industrial revolution (Schwab, 2017), which come after the three previous industrial revolutions, namely: the first one – mechanization, use of water and steam, the second one – mass production, use of electricity and the third one –digitalisation, use of PC and microprocessors (Kagermann et al., 2013; Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014; Marik et al., 2015).

the real one whereupon integrating IT and production (Gill, 2013).

THE ROLE OF LEARNING IN INDUSTRY 4.0

Industry 4.0 implications on the workforce

Table 1: Features of the Industrial Revolution

The Industrial Revolution	Key Features
First Industrial Revolution 18th/19th century (1760 onwards to be more precise)	Quick change of production technologies New social-economic structures 30X increase in iron production Key invention – steam engine
Second Industrial Revolution 19th century	Mass production assembly lines with electricity 8X increase in car production Key inventions – light bulb, telephone and internal combustion engine
Third Industrial Revolution 20th century (1960 to be more precise)	Partially automated production using electronics and IT First programmable logic controller (1969) Key inventions – semiconductors, PC, and internet
Fourth Industrial Revolution 2011 till now	Digitalization and connection of all actors in the value process, Fusion of the production with ICT Cyber-physical systems are intelligent Connected industrial production and logistics units that are able to communicate together. The gap between the digital, physical, and biological worlds is shrinking Technology is changing faster than ever.

Source: Author

Marik et al. (2015) resolved smart factories as independently automated operational units transformed into a fully integrated and automated environment for continuously optimised production. The global networks of businesses incorporate their machinery, warehousing systems and production facilities in the shape of Cyber-Physical Systems (CPS). These CPS autonomously exchange information, trigger actions and control smart machines, storage systems and production facilities independently (Kagermann et al., 2013). The purpose of Industry 4.0 could be easily understood in the context of the manufacturing environment having the influence of the Internet of Things (IoT) and services (Kagermann et al., 2013) or mergers of the virtual world with

The essential elements to implement Industry 4.0 are high-tech infrastructure, information, and highly skilled people (Shamim et al., 2016; Slavik, 2015). Kagermann et al. (2013) believe that on account of continuous resource productivity in Industry 4.0, efficiency occurs across the entire value network and a new type of interaction between people and machines brings along important changes to the nature of work. Slavik (2015) states that all leaders of the manufacturing sector agree upon this phase of the industrial revolution (4.0) to have advanced and superior robots and the companies need skilled and qualified labour to operate and service these robots. Lorenz et al. (2015) categorize work with high job losses, such as assembly and production planning, and indicates

Table 2: Critical factor elements of Industry 4.0

Nature of Factor Elements	Critical Factor Elements
Extended Digital Technologies	New Computing Technologies Blockchain and Distributed Ledger Technologies The Internet of Things Big Data and Cyber Risks
Reforming the Physical World	Artificial Intelligence and Robotics Advanced Materials Additive Manufacturing and Multidimensional Printing (3D Printing) Upside and downside of Drones
Altering the Human Being	Biotechnologies Neurotechnologies Virtual and Augmented Realities
Integrating the Environment	Energy Capture, Storage and Transmission Geoengineering Space Technologies

Source: Shaping the future of the fourth industrial revolution, Klaus Schwab, 2018 significant job gains in IT and analytics.

Human Learning

Learning is a hypothetical construct; it cannot be directly observed but only inferred from observable behaviour. (Richard Gross, 2015). The learning ability is a natural instinct in humans and animals, and evidently in few machines as well as in certain plants. (Karban, R. 2015). Coon (1983) defined "learning as a relatively permanent change in behaviour due to past experience and Anderson (1995) states learning as the process by which relatively permanent changes occur in behavioural potential as a result of experience. Anderson's definition has an advantage over Coon's that it implies a distinction between learning (behavioural potential) and performance (actual behaviour). Human learning is the

Table 3: Five Stages of Skill Acquisition

Skill Level	Components	Perspective	Decision	Commitment
1. Novice	Context free	None	Analytic	Detached
2. Advanced beginner	Context free and situational	None	Analytic	Detached
3. Component	Context free and situational	Chosen	Analytic	Detached understanding and deciding; involved outcome
4. Proficient	Context free and situational	Experienced	Analytic	Involved understanding; detached deciding
5. Expert	Context free and situational	Experienced	Intuitive	Involved

Source: Dreyfus 2004, Adult Skill Acquisition

Table 4: Four Main Families Machine Learning Algorithms

Learning Approach	Description	Example of Algorithm
Information-based Learning	Employing concepts from information theory to build models	Decision Trees
Similarity-based Learning	Model based on comparing features of known and unknown objects, or model developed through measuring similarity of past and forth coming occurrences	k-Nearest Neighbours (k-NN)
Probability-based Learning	Model based on measuring likelihood of occurrence of some event	Bayesian Network
Error-based Learning	Model based on minimizing the total error through a set of training instances	Multivariable linear regression

Source: Adapted from Kelleher et al, (2015), MIT Press

Table 5a: Human intervention in Machine Learning

Types	Nature	Level of Human Intervention
Supervised Machine-learning	Assumes that training examples are classified i.e., learning relationship between a set of descriptive features and a target feature	High
Unsupervised Machine-learning Semi-supervised Machine-learning	Concerns the analysis of unclassified examples	Low
Semi-supervised Machine-learning	Uses unlabelled data with a small amount of labelled data to improve the learning accuracy	Medium
Reinforcement Machine-learning	Employs different scenarios for discovering the greatest rewarded action in a trial-and-error process by collecting feedback from environment	Nil

Source: Adapted from 'Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies', MIT Press, 2015 acquisition process of the new or modifying existing knowledge, behaviours, skills, values, or preferences. (Richard Gross, 2015). It has been a subject matter in the field of education, pedagogy and cognitive psychology in relation to the learning theories (discussed above), learning styles, pedagogic models, conceptual learning, and educational psychology (Ertmer, P.A and Newby, T.J, 2013). The experience and skill level of a learner are highly correlated in the five-stage model of adult skill acquisition proposed by Dreyfus (2004). It considers learning by creating concepts and meaning from experience. [Table 3] Learning factories proposed by Abele et. al (2017) consider Scenario-Based Learning (SBL) as an effective approach. (Erol et al, 2016). It is an iterative and interactive process, that uses simulative scenarios for structured descriptions of real-world problems and related instructions, to support active learning (Erol et al, 2016).

Machine Learning

Machine learning (ML) constitutes the multiple manifestations of the study and computer modelling of learning processes. (Carbonell, 1983). It is the scientific study of algorithms and statistical models as a subset of artificial intelligence, where computing systems rely on patterns and inferences to perform specific tasks without explicit instructions. ML use sample data to construct a mathematical model to generate automated decisions or predictions without being explicitly programmed (Samuel, 1959), and to perform the task. (Bishop, 2006). Those artificial models and computational algorithms resemble the ability of human learning and reproduce human skills known as cognitive computing. ML algorithms can be classified into four families; namely, information-based, similarity-based, probability-

Table 5b: Capability Comparison of Human and Machine (Learner Groups) based on Quality and Performance Variation

Capability		Human	Machine
Quality and Performance Variation in … .	**Mechanical Job**	• High inter-individual differences and diversities. • Can be improved through training and job satisfaction. • Individual differences and diversities impact problem-solving abilities, competencies, experiences and qualification.	• Very low • It can be degraded over lifetime or due to inappropriate maintenance
	Decision-making	• Personal, societal and institutional interests influence decision-making. • The complexity and sensitivity (risk) of the matter may affect.	• Low to high depending on the quality of data, algorithms, human intervention impact, and problem complexity. • The quality can be improved with relatively large datasets.
	Carrying out a Task	• Relatively high (however, individual capacity, motivation and commitment matters). • High possibility of work fatigue and job dissatisfaction	• Very low.

Source: Adapted from Ansari and Seidenberg, 2016

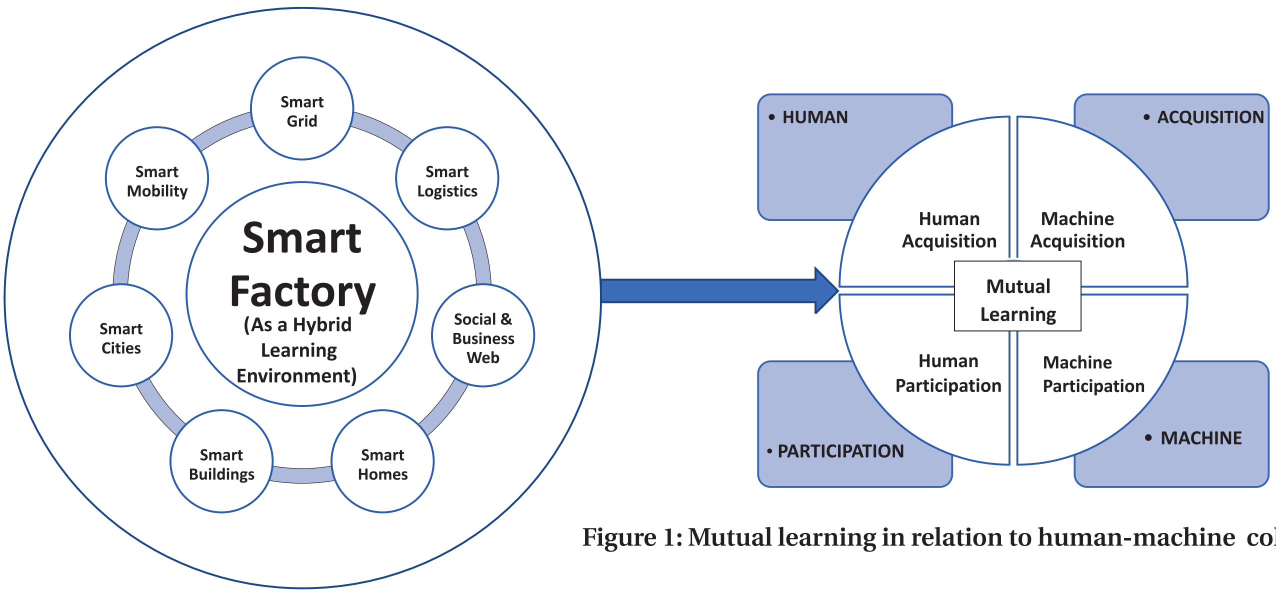

Figure 1: Mutual learning in relation to human-machine collaboration.

based, and error-based learning [Table 4], which can be further distinguished on the parameters of human intervention [Table 5a] as (i) Supervised ML (ii) Unsupervised ML (iii) Semi-supervised ML, and (iv) Reinforcement ML. (Kelleher et al, 2015).

Human-Machine Learning

The two groups of learners (human or machine) interact and closely collaborate to build the ground for hybridization of the learning concepts, in which mutual learning occurs. Quality and performance variation as the key indicators, in carrying out a task that identifies and distinguish the capability of human and machine on performing the assigned task. A comparison of quality and performance variation of the learner groups with respect to an assigned task has been presented in Table 5b. Similar capability can be extended to information processing and problem-solving tasks (Ansari and Seidenberg, 2016). Such differences in capabilities reflect the learning potentials for humans and intelligent machines indicating that the learning process can be independent or dependent.

In the context of Industry 4.0, human-machine learning occurring through human-machine cooperation and collaboration performs mutual learning of human-machine through a shared task which involves exchange, action or influences resulting in a certain degree of dependency. Such hybridization compounds elements of human and machine in knowledge acquisition into a new boundary system where mutual learning takes place. Figure 1 above, depicts the conceptual model of mutual learning inspired by the model of hybrid learning proposed by Zitter and Hoeve (2012).

Table 6: Human Skills in Industry 4.0

Human Skills	Defined	Relevant Competencies
Sense-Making	Ability to determine the deeper meaning or significance of what is being expressed	• State-of-the-art knowledge
Social Intelligence	Ability to connect to others in a deep and direct way, to sense and stimulate reactions and desired interactions	• Networking skills • Ability to be compromising and cooperative
Novel and Adaptive Thinking	Proficiency at thinking and coming up with solutions and responses beyond that which is rote or rule-based	• Creativity • Entrepreneurial thinking • Motivation to learn
Cross Cultural Competency	Ability to operate in different cultural settings	• Intercultural skills • Language skills • Communication skills • Ability to work in a team • Flexibility
Computational Thinking	Ability to translate vast amounts of data into abstract concepts and to understand data-based reasoning	• Technical skills • Ability to work under pressure • Coding skills • Understanding IT security • Compliance
New Media Literacy	Ability to critically assess and develop content that uses new media forms, and to leverage these media for persuasive communication	• Media skills
Transdisciplinary	Literacy in and ability to understand concepts across multiple disciplines	• Conflict solving • Sustainable mindset • Ambiguity tolerance
Design Mindset	Ability to represent and develop tasks and work processes for desired outcomes .	• Problem solving • Process Understanding
Cognitive Load Management	Ability to discriminate and filter information for importance, and to understand how to maximize cognitive functioning using a variety of tools and techniques	• Decision making • Analytical skills • Research skills • Efficiency orientation
Virtual Collaboration	Ability to work productively, drive engagement, and demonstrate presence as a member of a virtual team.	• Ability to transfer knowledge • Leadership skills

Source: Adapted from Institute for the Future, 2011 and Hecklau et. al, 2016

SCENARIO ANALYSIS OF HUMAN-MACHINE LEARNING IN INDUSTRY 4.0

Scenario-analysis involve aspects of systems thinking where many factors combine in complex ways to create sometime surprising futures. The unique feature of the scenario-analysis method is to capture such factors which are complex to formalize, such as paradigm shifts in values, future insights or new inventions or regulations. (Mendona, Sandro; Cunha, Miguel Pina e; Ruff, Frank; Kaivo-oja, Jari, 2009). To formulate specific strategies, scenario analysis are used to change mindsets about the exogenous part of the world. (Schoemaker, 1993)

We present here the six-steps scenario-analysis process adopted to suggest what would be the future of human skilling.

Table 7: Deep Shift through Drivers of Industry 4.0

Drivers		Deep Shift
Digital Technologies	New Computing Technologies Blockchain and Distributed Ledger Technologies The Internet of Things Big Data and Cyber Risks	• Implantable technologies like mobile phone • 80% of people with a digital presence on the internet • Vision as the New Interface, where reading glasses connected to the internet • Wearable Internet • Ubiquitous Computing • Supercomputer in Pocket • Storage for all • The Internet of and for things • Big Data for Decisions • Bitcoin and the Blockchain
The Physical World	Artificial Intelligence and Robotics Advanced Materials Additive Manufacturing and Multidimensional printing (3D Printing) Upside and downside of Drones	• Driverless Cars • Artificial Intelligence and Decision Making • AI and White-Collar Jobs • Robotics and Services • The Connected Homes • Smart Cities • The Sharing Economy • 3D Printing and Manufacturing • 3D Printing and Human Health • 3D Printing and Consumer Products
Altering Human	Biotechnologies Neurotechnologies Virtual and Augmented Realities	• Designer Beings (Human genome deliberately edited) • Neurotechnologies (Artificial memory implanted in brain)
Integrating Environment	Energy Capture, Storage and Transmission Geoengineering Space Technologies	• Soil-less farming through Nanotechnology • Renewable energy • Space tourism • Stable climate

Source: Shaping the future of the fourth industrial revolution, Klaus Schwab, 2018

Step 1: The Deep Shift of Industry 4.0 driving skillsets requirement

Experts predicted five major future production work in general and in manufacturing arising out of the deep shift of Industry 4.0 [Table 7]. (i) *Humans will remain an absolute necessity in future factories* – though automation will decrease the number of jobs in manufacturing, newer jobs will be created to manage machines (Zukunft, 2013). (ii) *Complexity of new tasks will keep happening*– caused by an increasing product and process complexity on the one hand and the required interaction with computational automation devices on the other hand, the human working tasks will be more complex as well. (Dombrowski et. al, 2014) (iii) *The new tasks will be intensely connected to the computing system and devices*– Becker claims that organizational losses in production can be reduced by mobile assistance systems, intelligent automation, expert knowledge, and creativity of workers. (Botthoff et. al, 2015). Becker concluded that future workers need more abstraction and problem-solving capabilities, the ability to perform independent and self-organized work and be communicative. (iv) Repetitive tasks will be automated– Hirsch-Kreinsen claims that the intelligent systems will substitute easy tasks. This leads to the disqualification of workers since only non-automatable tasks remain. (Botthoff et. al, 2015). (v) *Unique human abilities will have a significant role in human task design*–Spath expects combined, hybrid production systems where human flexibility is used to connect automated parts of the production

Step 2: The Viable framework

Industry 4.0 is an era of digitalisation. Everything is digital from business models to environments, production systems to machines, as well as operators, products and services. The entire process or the physical flows are consistently mapped on digital platforms. The higher level of system automation at the factory enables communications through ICT, within and beyond the factory operation system leading to the smart factory where all elements of the value chain are accomplished at real-time engagement. These disruptive impact of smart manufacturing companies allows the smart manufacturing ecosystem paradigm. The conventional centralized applications end with industry 4.0.

Step 3: The Mini Scenario

Adoption of Industry 4.0 brings the following critical changes: (i) Automated production equipped with robots, humanoids & machines (ii) Predictive maintenance to reduce downtime (iii) Big Data – a decision-based on historical data to optimize production (iv) Smart Transport will automate transportation of raw material / final products (v) Machines connected over a network to optimize production (vi) Supply Chain Monitoring and data sharing of complete supply chain (vii) 3D Printing manufacture complex parts in one-go without any assembly (viii) Production simulation and optimization of production lines.

Step 4: The Large Scenario

New machines and tools are deployed towards higher automation and interconnected on a base network. Data to be collected for continuous analysis. Machine parameters to be adjusted based on quality requirements. The supply chain will turn more efficient.

The future manufacturing plants will be flat, flexible, decentralized, and changeable. Different production areas will be interconnected. Workers will be able to move from one shop to the other based on the requirement.

Step 5: Drafting Scenarios: The Way Ahead

Industry 4.0 is driving disruption and presents challenges of its own making. To counter those challenges, we require collective wisdom toward a new cultural renaissance. Contextual intelligence is the first answer, as an ability and willingness to anticipate emerging trends and to connect the dots. Great leaders understand and master contextual intelligence through networking across traditional boundaries.

Industry 4.0 is characterized by persistent and intense change, leaders with high emotional intelligence will be more creative and better equipped to be more agile and resilient to cope with disruption. Inspired intelligence stimulates creativity to lift humanity on collaboration and moral consciousness of a shared sense of destiny. As the pace of change accelerates physical intelligence becomes critical as the complexity increases the need to keep fit and remain calm under pressure becomes essential.

Step 6: Issues Identified: Four major impacts

Industry 4.0 has four major impacts on business across industries – (i) customer expectations are shifting beyond producers' expectations at a faster pace, (ii) products are being enhanced by data, which improves asset productivity, (iii) new partnerships are more than common as companies learn the importance of new forms of collaboration and (iv) operating models are being transformed into new digital models.

CONCLUSION AND RECOMMENDATION

Industry 4.0 demands a shift in mindsets and newer approaches to technology, business or governance, and values. Collaboration of humans and machines instigates mutual learning but humans remain absolutely necessary in smart factories. The unique human skills which can't be replicated or learned by machines will turn out to be the most sought-after human skills. Leadership with high emotional intelligence and digital mindsets generating innovative ideas will be the future of human skilling in Industry 4.0 and beyond. The Decision-making ability of humans has taken a back seat as it is better done by machines with big data. Therefore, Industry 4.0 requires more multi and interdisciplinary skills for handling combined task elements for human-machine tasks.

Finally, the concept of mutual learning needs to be explored further from the current hazy picture through cross-discipline research collaboration of data scientists, cognitive psychologists and educators.

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