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Research Article

# Rebooting employees: upskilling for artificial intelligence in multinational corporations

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## Abstract

Proponents of artificial intelligence (AI) have envisaged a scenario wherein intelligent machines would execute routine tasks performed by humans, thus, relieving them to engage in creative pursuits. While there is widespread fear of corresponding job losses, organizational think tanks vouch for the synergistic culmination of human–machine competencies. Using the dynamic skill, neo-human capital and AI job

es, we contend that the introduction and adoption of AI calls for

ll themselves. To determine the kev skills deemed critical for the

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upskilling of employees, we interviewed 20 experienced professionals in multinational corporations (MNCs) in the information technology sector in India. Deploying Gioia's methodology for qualitative analysis, our investigation revealed five critical skills for employee upskilling: data analysis, digital, complex cognitive, decision making and continuous learning skills.

**Keywords:** Artificial intelligence upskilling future of work multinational corporations MNCs employability

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## Introduction

The impact of technology on the global economy, businesses and societies is exponential and has enabled unprecedented advancement, leading experts to predict that the upcoming decade will witness tremendous changes in the nature of work owing to artificial intelligence (AI) (Butler, 2016; Davenport & Kirby, 2016). AI systems extend human capabilities by sensing, comprehending, learning and acting (Daugherty & Wilson, 2018). Not surprisingly, the discourse on the future of work has drawn contrasting views. While critics of AI firmly believe that machines will replace human beings in many jobs, proponents of AI envision new jobs with value creation (Ågerfalk, 2020; Sullivan et al., 2020). Despite these opposing views, there is agreement on one insight – this wave of technological advancement will disrupt the employment equilibrium, and this disruption of the workforce and displacement of labor is universally applicable as most industries today are enabled by technology (Bughin et al., 2017; Østerlund et al., 2021).

Gradually, artificially intelligent machines are taking over tedious, mechanical and mundane human tasks, such as documenting, scheduling, inspecting equipment,

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conducting preliminary analyses (Huang et al., 2019; Huang & Rust,

i et al. (2020) note. AI is becoming more commonplace in developing nations such as China and India. In China, 77% of the workforce has employed AI in their work in some shape or form while this number is 71% for India.

These technological advances and achievements are possible due to data science, analytics and machine learning becoming central to the AI functioning – indeed, a key characteristic of artificially intelligent machines is that the intelligence is drawn from a constant learning and adaptation process (Akerkar, 2019; Lecun et al., 2015). AI-powered technologies collaborate with humans towards improved decision making and enhancing the quality of life. Today, multinational corporations (MNCs) are investing heavily in logic and knowledge-based AI-tools that are driven by huge amounts of data, information and rules (Corea, 2019). Tools such as logic-based programming, robotic process automation, expert systems, descriptive and predictive analytics, are helping businesses in transforming the workplace tremendously (Akerkar, 2019; Corea, 2019; Hancock et al., 2020; Wilson et al., 2017). As an example, AI-enabled systems depend on internet-of-things and big data as the main ingredient to facilitate data-driven decision making.[1] Further, AI itself comprises a set of algorithms which depends on data for executing the responses (Jaiswal & Arun, 2021; Portugal et al., 2018). Thus, in this paper, we operationalize *AI as data-driven systems that extend human capabilities by enabling faster and better decision making and problem-solving.*

While sophisticated AI-technologies are reducing the need for human labor in multinationals, linking these technologies to the organizational needs and deliverables requires an in-depth understanding of organizational members’ capabilities (Davenport & Kirby, 2016). Clearly, developing competencies related to AI and its applications is extremely important to help employees remain employable in the future. In this study, we operationalize *upskilling as learning new skills to sharpen employee’s abilities to understand and utilize AI-based systems.* According to Hancock et al. (2020), roughly 30–40% of employees would need to upgrade their skills significantly, within the next decade. In this connection, several MNCs such as Amazon,

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almart are developing AI-powered products and services, while also ping the required technical and soft skills of the human capital.

Given the broad applications of AI, and its potential to affect our day-to-day lives in almost every aspect, it is critical that we study the pros and cons of AI applications, especially in the workplace, as it can have a direct effect on the society, since many jobs might become human-redundant. Accordingly, the present study was designed to address the research question: ‘What are the skills that will be deemed critical for the upskilling of employees to remain employable, and thrive, in the era of AI?’

## The Indian context

Given the rapid globalization and technological developments, several MNCs have set up operations in emerging economies (Thite et al., 2014). In this connection, India is considered an emerging economic superpower (see Budhwar et al., 2019), not just due to the low cost of operations but also because of its demographic dividend, foreign language skills, intellectual capital and diversity. In 2018, the Indian government think-tank, National Institution for Transforming India (NITI) Aayog, launched a nation-wide programme on AI and its tremendous industrial applications, thus, driving the entire economy towards digitization and AI. By 2035, AI is projected to add US$957 billion, or 15% of India’s current gross value (Menon et al., 2017). Recently, the INDIAai website was launched by the government to demonstrate India’s journey to global prominence in AI (INDIAai, 2020). Further, since the past three decades, the Indian Information Technology (IT) industry has gained an immense global reputation for deploying the global services delivery model.

Indeed, the global reach of this industry has impacted organizations worldwide as the Indian IT industry powers the digital functioning of major developed and developing nations by providing services in the back-office operations (Jain et al., 2019; Malik et al., 2020; Pereira et al., 2020). Not surprisingly, the practices of the Indian IT industry are benchmarked to global standards (Budhwar & Varma, 2011; Thite et al., 2014). The Indian government’s thrust on technology, data and talent to create and use AI-systems across industries has given an extraordinary boost to the IT firms in India.

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to a significant improvement in employment opportunities in India
responding increase in the return of Indian expatriates to

contribute to the continuing growth of the Indian economy (see, e.g. Varma & Tung, 2020). Relatedly, the Government of India has issued the National Education Policy (NEP) in July 2020 which has laid out clear procedures to disseminate education, especially in Information Technology and Computer Science, to all children across different educational levels (NEP, 2020). Accordingly, we decided to conduct our study in the Indian IT sector.

Finally, even though the human resource discipline is replete with studies on the interface between technology and human resources (Bondarouk & Brewster, 2016; Bondarouk et al., 2017; Marler & Boudreau, 2017), recent developments with respect to AI have received scant attention from academicians (Meijerink et al., 2018). Some scholarly work has been initiated towards a better understanding of how, and to what extent, AI impacts HR (Chaudhuri et al., 2020; Malik et al., 2019). These explorations are primarily in the areas of recruitment and selection of applicants and performance management systems (PMS). Further, the neo-human capital theory (NHCT) highlights the increasing demand for technology-induced skills and the development of human capital in times of rapid technological change (Pereira & Malik, 2015). Accordingly, we believe our study is timely and critical, and it makes four key contributions. First, we use the lens of dynamic skill, neo-human capital and AI job replacement theories, to contribute to the understanding of human resource development in the context of AI. Second, we add to the growing literature on the MNCs operating in India in the IT sector. Third, we identify those skill sets which can potentially help IT MNCs and employees prepare themselves for the sustainable design and implementation of AI. Finally, while identification of key skill sets is the starting point, we suggest practical tools for leaders in MNCs to advance employee learning and competencies towards creating value out of human–machine augmented intelligence.

In the following sections, we briefly review the literature on AI, its impact on human resources and the need for upskilling for the era of AI. This is followed by a detailed description of our research design and method, and a discussion of our analyses and

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ffer practical and theoretical implications, outline the study
uss kev avenues for further research.

## Literature review

In developing the rationale for our study, we employ the theoretical lenses of dynamic skill theory, NHCT and theory of AI job replacement. These theories were specifically chosen, as they help advance the role of skill demand due to technological change in the context of AI.

## AI and its impact on human resources (HR)

In present times, technology has proliferated across human lives and industries, and technological change is unprecedented in its pace, scope and magnitude of impact. With game-changing innovations juxtaposed with technological advancements, organizations need to digitally reinvent themselves at an exponential pace to stay relevant and ahead of competitors. AI-systems have the capability to simulate neural networks that train and learn through experiences embedded in massive data sets at a whirlwind speed (Butler, 2016; Jordan & Mitchell, 2015; Mitchell, 2017). In this connection, Tschang and Mezquita (2020) have noted that some scholars argue that AI may lead to unemployment, while others believe AI could be used to augment existing jobs. Clearly, both views have some merit, but both need to be explored further. Not surprisingly, the understanding of how, and to what extent, AI impacts HR is in its nascent stages (Malik et al., 2019).

Two areas of HR where AI has important applications are recruitment and selection of applicants and PMS (Chaudhuri et al., 2020). By using AI-based bots, organizations have expedited the applicant screening and selection processes. Cappelli et al. (2020) explain that algorithms for recruitment are designed based on established predictors and criteria that satisfy a statistically significant relationship. These algorithms are trained on existing recruitment and selection datasets. The prospective candidates are



based on the training dataset and screened for the criterion PMS determines the rewards (or punishment) for each organizational member based on their competencies, behaviors and task accomplishments. Since the most widely used metric, that is, the performance appraisal score, is subjective and not bias-free, AI-based algorithms can be considered as a suitable HR intervention. With such promising AI applications deployed in organizations, employees need to upskill themselves to understand and appropriately use these tools owing to ethical, legal and contextual considerations that are beyond the scope of this article.

## Need for upskilling for AI

The notion that AI will surpass human intelligence is often voiced with advances in AI creating tipping points triggering significant changes in organizational operations and outcomes (Butler, 2016). For instance, there is a shift in demand in the workforce from basic manual and physical work skills to cognitive competencies. This shift has prompted organizations to change the talent mix. Since human beings note rates of change as linear and not exponential, they often find this pace of technological advancement difficult to align with. Not surprisingly, scholars have cited increased attrition rates and unemployment as AI takes up mundane tasks previously performed by humans (Bughin et al., 2018; OECD, 2012). While a technological revolution may eventually be on the cards, the scale and time frames are currently unknown. Thus, the upcoming era necessitates humans to develop appropriate skillsets for redefined jobs and work closely with AI-technologies to progress well in their employment.

Work in today's MNCs is knowledge-intensive and relies heavily on the interface between AI-enabled technology and employees (Bondarouk et al., 2017; Pereira & Malik, 2015). While technology enables organizational deliverables, employees are the key drivers of value creation and source of sustained competitive advantage. Thus, contemporary MNCs not only focus on developing physical and organizational capital but also on developing human capital which is of utmost importance for organizational sustainability and success, more so, in the upcoming era of AI and the changing nature

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singly reshaping work by performing various tasks and is becoming

nnovation (Rust & Huang, 2014). Most jobs in MNCs comprise mechanical tasks (such as administering daily routines and tracking attendance), thinking tasks (such as analyzing customer preferences and scheduling logistics) and feeling tasks (such as empathizing with customers and advising therapies to patients). These dimensions of tasks may vary from one job to another and the intelligence required thereof. As AI deemphasized mechanical human labor, humans have to upgrade their focus on tasks that are difficult for AI to assume, that is, tasks requiring thinking and feeling skill sets (Huang et al., 2019; Huang & Rust, 2018).

## Theories of upskilling

We draw upon the dynamic skill theory (Fischer et al., 2003), NHCT (Pereira & Malik, 2015) and the theory of AI job replacement (Huang & Rust, 2018) to explicate the need for upskilling. Dynamic skill theory views skill development as a web of activities that is context-specific and outcome-oriented (Kunnen & Bosma, 2003). In a dynamic world, individuals need to be adept in various skills such as social, emotional, technological and physical skills to exhibit good performance or demonstrate appropriate behavior depending upon the context or situation. A web of skills captures the interconnected complexity of skills in diverse contexts. Since dynamic skill theory is a theory for adult cognitive development, we invoked it in the context of skill development for employees in the era of AI.

Further, the NHCT highlights the increasing demand for technology-induced skills and the development of human capital in times of rapid technological change (Pereira & Malik, 2015). Proponents of NHCT argue that individuals with higher levels of human capital concentration (higher level-of-education, experience in training, open to learning and exploration) are more likely to adopt technological changes and develop new skills (Bartel & Lichtenberg, 1987; Wozniak, 1984, 1987). We agree with Pereira and Malik (2015, p. 154) that the need for employee training will not decline with higher levels of technological knowledge. Rather, we believe that with the proliferation

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ıcross industries in the near future, there will be a continuous

l for new skillsets and higher levels of human capital concentration.

While AI’s ability to increasingly perform various tasks is indeed a major source of innovation and value creation, there is also an increased threat of job loss. The theory of AI job replacement (Huang & Rust, 2018) posits that replacement by AI is primarily at the task-level, rather than at the job-level. More specifically, the changing nature of work is largely for tasks that are easy and repetitive and entail mechanical intelligence. Once AI has accomplished the lower-level and subsequently the higher-level mechanical tasks that comprise a job, it will progress to replace human labor in analytical intelligence, that is, tasks that require rule-based and logical thinking. Soft skills, thus, will assume paramount importance for humans. The future workforce would need to acquire intelligence for higher job complexity including intuitive intelligence (for complex, chaotic and context-specific tasks) and empathetic intelligence (for tasks requiring high levels of emotions and empathy). While AI domain experts are relentlessly developing and training machine-learning algorithms to mimic human capabilities, higher levels of skills such as communication, relationship building, problem-solving, reasoning, empathy and sense-making, are extremely difficult to be emulated by AI (Huang & Rust, 2018). Thus, we contend that in the era of AI, employees need to deconstruct existing skills and cultivate new ones to remain employable and competitive.

## Study design

The present study was designed to address a key research question: ‘What are the skills that will be deemed critical for the upskilling of employees to remain employable, and thrive, in the era of AI?’ In other words, in the era driven by AI, the study aims to identify skills that are considered critical for employees’ upskilling. To address our research question, we interviewed 20 seasoned MNC executives in the IT sector in India. These participants were middle to senior-level managers with at least 10 years of

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ce. Further, all participants had an adequate experience of AI
d experience in working with AI-enabled services. The IT sector was

chosen for our study as technology-led innovations and growth are tightly linked to each other in this industry. Further, among all sectors, IT firms are most likely to expect a high level of role disruption and skill shortage due to AI (Agarwal et al., 2020). Despite the acknowledgment that AI-enabled services are the primary source of innovation in the service industry (Rust & Huang, 2014), there is limited research on human resource development of this workforce (Chaudhuri et al., 2020; Malik et al., 2019; Pereira & Malik, 2015).

In the Indian context, IT firms hold notable significance. From humble beginnings in the 1970s, the Indian IT industry has come a long way (Malik & Rowley, 2015). Today, this sector contributes 7.9% to India's economic growth and is expected to contribute 10% by 2025 (IBEF, 2019). The IT industry is a result of the rapid world of change and technological advancement generating revenue of more than US$180 billion and employing 4.1 million professionals, the highest employment provider in the private sector in India (NASSCOM, 2020).[2] With the Indian government's budget allocation (2020) of US$1.13 billion (spread over five years) for developing technologies and AI-based applications and thrust on deploying AI-powered technologies across other industries, the Indian IT sector has immense scope to grow.

India has also attracted global visibility and gained prominence in terms of intellectual capital with several IT MNCs setting up their major hubs and innovation centres in India (Budhwar, 2012). A key aspect of the present study is the focus on IT organizations with global footprints. Technology-based MNCs are heavily investing and engaging in futuristic AI-powered technologies (Akerkar, 2019; Davenport & Kirby, 2016). Further, MNCs are deploying AI-based products and services developed in one location across varied operations in different countries. While national cultural context plays a crucial role in business decisions, AI-powered data facilitate problem-solving and decision making.

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es the participants and their company's characteristics. Twenty
evel employees in both technical and managerial roles were

contacted. The participants were employed in different MNCs spread across different locations in India, while their headquarters were based in Canada, the United States of America, Denmark, Ireland, Switzerland, France and India. In India, these MNCs operated from Pune, Chennai, Bangalore, Noida, Kochi, among many other locations. We chose MNCs of varying sizes, determined by the worldwide employment size, to comprehensively assess the need for upskilling in the IT sector. The MNCs were categorized as small, medium and large, based on employee headcount less than 4999, 5000–59,999 and more than 60,000 employees (Lavelle et al., 2012). Thus, five participants each from small and medium-size MNCs and 10 participants from large MNCs comprised the study's dataset.

Table 1a. Participant's and their company's characteristics.

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We sought an appointment for conducting the interview after providing the purpose and setting the context of the study. The participants were assured of anonymity and post their informed consent to participate in the study, an in-depth interview was conducted. The interview design was semi-structured in nature (please see Appendix A), and the interviews were guided by an indicative list of questions wherein the interviewees had flexibility in responding, thus, providing deeper insights into the study phenomenon (Banihani & Syed, 2020). While conducting the interview, we refrained from including personal questions/preferences, leading words and kept questions simple to understand. Each interview lasted for 25–30 minutes. Hand-written notes yielded a transcript of roughly 8000 words.

## Data analysis

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nature of the study, we coded the transcripts manually following roposed by Gioia et al. (2013).[3] After crafting a well-specified research question, we conducted semi-structured interviews wherein a multitude of informant (participant) terms, codes and categories emerged within the first few interviews. Gioia and colleagues (2013) refer to this stage as *1st-order concepts* in which researchers strictly adhere to the participants' terms, phrases and descriptions, and refrain from drawing specific categories. As we progressed in conducting the interviews, we began recognizing similarities and differences among the categories. We created meaningful clusters of terms and phrases and labelled those categories using the participants' phrases, thus, emerged the *2nd-order themes*. The second-order themes are primarily at the theoretical level and help the researchers in describing and explaining the study phenomenon. The culmination of themes and concepts yielded theoretical saturation (Glaser & Strauss, 1967) and then we proceeded to distill these concepts and themes into *aggregate dimensions*.

The 1st order concepts, 2nd order themes and aggregate dimensions became the basis for building the data structure for the present study (Figure 1). Data structure not only configures the qualitative data into a meaningful visual aid but also provides a graphic representation of the researchers' progress from 1st order raw participants' terms to 2nd order theoretical themes to finally meaningful dimensions that answer the research question. Authors discussed the participants' dialogues, reconciled differing interpretations and finally reached a consensual decision on the themes and dimensions. Constructing the data structure compels researchers to think about the data theoretically and is thus considered as the key component of demonstrating rigor in qualitative research.

Figure 1. Data structure.


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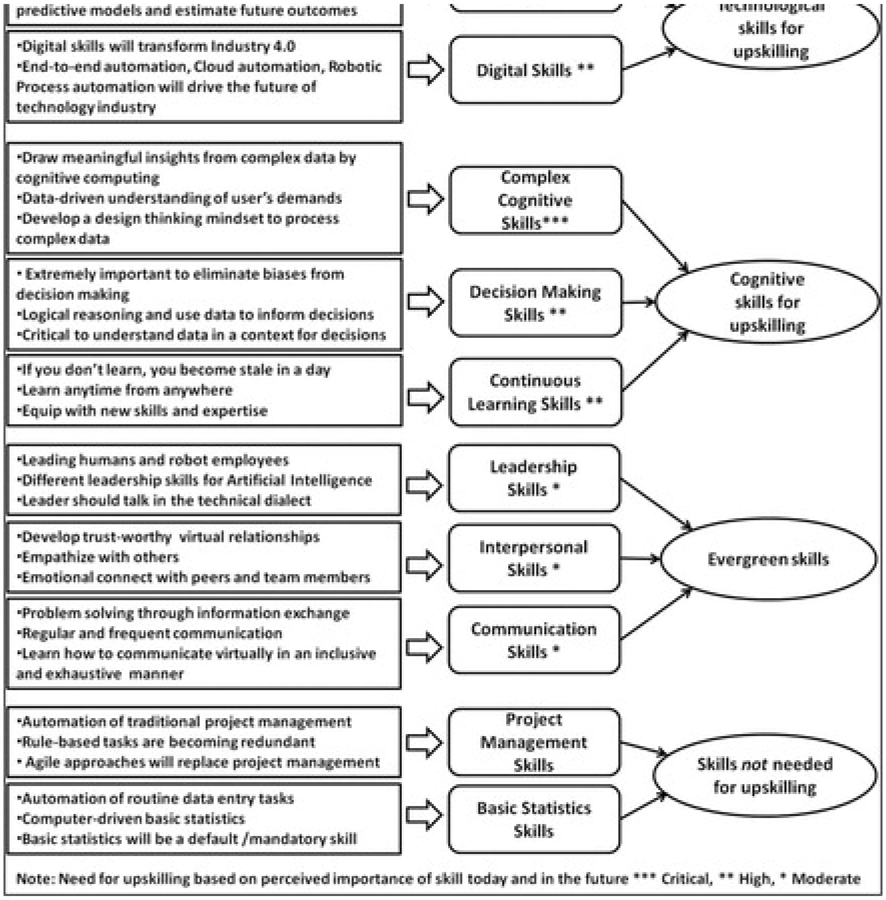


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To validate the accuracy of our concepts, themes and dimensions, we conducted five post-study interviews with senior-level managers (different from the dataset participants) working in MNCs in the IT sector in India. Table 1b describes the profile of the post-study participants.

Table 1b. Post-study participants' profile.

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## Findings

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›ove data analysis, several themes emerged with respect to
›orce for the era of AI. The present study builds an inductive model

grounded in data as exemplified by the data structure model (Figure 1). The data structure demonstrates 1st order concepts, 2nd order themes and aggregate dimensions. The change in perceived importance of the skills in the present and future times is further indicated using asterisks on the 2nd order themes, that is, themes that need upskilling for the future are categorized as Critical, High and Moderate. Table 2 encapsulates additional supporting data in the form of representative quotations for readers to discern and view the evidence for our findings.

Table 2. Data supporting interpretations of skills identification for upskilling for AI.

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## Technological skills essential for upskilling

### Skill 1: Data analysis skills

The past decade has witnessed the generation of huge amounts of data from varied sources such as the Internet, social media, public sources and interaction with clients. Due to the interconnectedness of technologies, big data are being added to the existing data repository in real-time at high velocity. Further, data are available in different formats and structures such as text, video, audio and image. A participant noted, ‘data is the oil’ while another said, ‘data is gold’. Given the enormous amount of data at their disposal today, data analysis tools extensively used in the IT industry including R programming, Python, Power BI, SAS and Tableau, become highly critical for employee upskilling. Further, expertise in the Hadoop framework that facilitates the processing of big data and Full Stack developers for programming languages such as Java and .Net, are important for upskilling for the future IT workforce. From the narratives, we found that data analysis skills were described in many ways. Broadly,

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ewed as a systematic process of understanding the data and
nformation to inform decision making. Participant 2 *explained,*

*'Data analysis is basically….applying statistics to describe and evaluate data'*.

### Skill 2: Digital skills

Most industries and contemporary organizations are increasingly generating footprints in the digital space. The technology industry aims to connect the physical and digital worlds by creating a robust and secure phygital (physical plus digital) ecosystem. As the economy moves towards digitization, processes need to be automated and optimized for efficiency with enhanced security at a reduced cost. Thus, employees must acquire digital skills such as intelligent automation (Blueprism, vision plotting), cloud automation (Slack, Google Cloud Provider), Robotic Process Automation (Kapow, Selenium), cybersecurity (intrusion detection), and runtime applications (Angular, JBOSS). Participant 7 shares, '*The whole IT industry is enabling a digital transformation…there is a move towards a smarter world…with digital metrics, digital strategies, digital tools…so digital will be a core skill…a fundamental skill*'.

## Cognitive skills essential for upskilling

### Skill 1: Complex cognitive skills

With the enormous amount of data in varied formats and structures, it is becoming challenging to make sense of the data. Complex data must be processed to derive meaningful information, visualization and interpretation. Business intelligence needs convergence of data to design simple solutions and draw relevant insights. Most organizations in the technology industry conduct internal training to develop thinking and higher-order skills for employees. Training in skills such as Watson (Discovery, Studio Dashboard), design thinking, story building and Apache Spark, are being encouraged by organizations to upskill employees for complex information processing, cognition development and critical thinking. Participant 12 quotes, '*Our chatbot ABC*[4] *is becoming smarter with data…it breaks each sentence into meaningful information,*

*es and gets intelligent with every new question asked to her…so*

*e their higher level of intelligence for much more complex tasks'*.

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## Skill 2: Decision making skills

Organizations aim to take good decisions for enhancing business performance. Though data are predominantly available for decision making, most contemporary organizations are unable to leverage the power of data. '*Today I have a lot of data and system-generated reports giving me an overview of the data…I should be able to use these [reports] as inputs to inform my decisions',* says Participant 14. Decision making skills are critical for upskilling as decision making is still highly subjective and not as data-driven as it should be. Human biases unconsciously seep into the decisions. Dynamic human behavior, ethical and legal considerations must also be accounted for during decision making. Further, speedy decisions must be taken in real-time such that the decisions reflect current trends and address critical business disruptions. Thus, employees must notably be trained in taking unbiased, rational and evidence-based decisions.

## Skill 3: Continuous learning skills

Engaging oneself in an unceasing learning path while responding to the volatile, uncertain, complex and ambiguous business environment (VUCA) is the key ingredient for employee success in the era of AI. Unlike a few decades back when each technology had a lifespan of at least a few years, in contemporary times, the lifespan of technology has reduced to a few months or weeks. In such a dynamically changing technological era, continuous learning is undoubtedly essential for employees to stay relevant and not become obsolete. As a participant said, '*If you don't learn, you become stale in a day in this industry*'. Continuous Improvement, Continual Learning and Troubleshooting are some of the continuous learning programs internally organized by companies while Full Stack development for Java and .NET are some of the domain-specific skills recommended for continuous learning. '*Learning is the DNA of the organization….we have provided access on all platforms to our employees so that they can learn anytime from anywhere'* (Participant 13).

critical skills for employee upskilling to sustain employment and

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of AI: data analysis skills, digital skills, complex cognitive skills, decision making skills and continuous learning skills.

## Evergreen skills for upskilling

While upskilling in the above-cited technological and cognitive skills is critical for IT sector employees to remain employable and thrive in the era of AI, some other skills were found to be of importance. Social skills, specifically, leadership skills, interpersonal skills and communication skills were mentioned by some participants as important; however, the context will differ. For instance, future leaders must not only be visionaries but also must understand the intricacies of AI and associated technologies. As a participant said, '*the leader should possess algorithmic thinking and talk in the technical dialect in order to drive transformation*'. Further, the need for building strong relationships through trust and interpersonal association would remain essential; however, future employees must also build good virtual relationships without co-locating physically. Likewise, employees will have to become comfortable and conversant in not having in-person communication. A participant notes, '*employees will have to learn how to communicate virtually in an inclusive and exhaustive yet unambiguous manner*'.

Thus, leadership, interpersonal and communication skills were noted to be of importance by most participants. We refer to these skills as 'evergreen skills' because irrespective of time, that is, today or in the future, these skills are deemed crucial for an individual's success. In the present study context of upskilling for AI, the degree to which upskilling in these evergreen skills is needed is not relatively as high as the need for upskilling in technological and cognitive skills.

## Skills not required for upskilling

While our primary aim was to identify the skills critical for upskilling in the context of AI, the participants inevitably highlighted skills that have already or will soon become obsolete. Skills needed for delivering routine, mundane and rule-based tasks are not

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ons are already adopted for these tasks. For instance, data entry, basic statistics, database management and project management are some skills that are gradually losing their lustre. For instance, basic statistics is an important skill in the present for data analysis; however, in the future driven by AI, basic statistics will become a ‘*default/mandatory/fundamental*’ skill as noted by many participants. Further, with changing client demands and faster turnaround times, the role of project management is diminishing exponentially. The Waterfall model for software development life cycle is becoming redundant as the technology industry is moving towards an agile approach. The agile and scrum master processes have stand-up meetings that ensure higher project flexibility, parallel processes, quicker reviews, better product quality, faster delivery, enhanced connectivity with the clients, reduced need for documentation and an integrated development-operations (DevOps) framework. ‘*SAFe 4.0 is the platform for becoming an Advanced Scrum Master*’ shares a participant. Thus, basic skillsets would be managed well by AI-systems; whereas, human beings must elevate to higher-order and complex tasks.

Thus, the key study findings are:

a. Data analysis and digital skills are critical technological skills for employee upskilling.

b. Complex cognitive, decision making and continuous learning are critical cognitive skills for employee upskilling.

c. Leadership, interpersonal and communication are evergreen skills for which the degree of upskilling needed is relatively less than the technological and cognitive skills.

d. Routine skills such as basic statistics and project management will diminish in the future, thus, upskilling is not needed.

The data structure model presented in Figure 1 helped visualize the categorization of the skills into different themes. In the ensuing discussion, the need for upskilling of different skills (2nd order themes) was briefly classified as critical, high and moderate,

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s were found unimportant for upskilling. To present these findings is useful to diagrammatically represent the participants’ perceptions of the importance of different skills at two points in time: at present and in the future (Figure 2). This representation grounded in data is a dynamic model emerging from the qualitative analysis (Gioia et al., 2013). The figure helps to visualize how the importance of each skill is perceived to 'dynamically' change from present to future and underscores the relative need for upskilling.

Figure 2. Relative importance of skills for employee upskilling.

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Figure 2 schematically represents the relative importance of different skillsets for employee upskilling in the IT industry to remain employable and competitive in the era of AI. The vertical axis is a measure of the importance of a particular skill today, while the horizontal axis represents the skills perceived to be important in the future. The extreme bottom right region in the plot represents the theoretical possibility of a skill that is of slight importance today but has the highest importance in the future and thus qualifies as the most critical zone for upskilling. The grayscale color code (see color bar on the right side of the plot) illustrates the relative importance of any skill for upskilling: skills depicted in the lightest background regions of the figure have the highest importance for upskilling whereas; skills marked in the darker background are of diminishing importance for upskilling. The skills marked on the top left quadrant have diminishing relevance in the future. The importance of skills such as basic statistics and project management is diminishing due to AI-enabled systems, thus, they do not require upskilling. The dotted diagonal line is an 'equipotential' and the skills that hypothetically lie on this line are those for which no change is expected in their *relative* importance between today and in the future. Evergreen skills such as leadership, communication and interpersonal skills are of importance today and will continue to be important in the future. However, the future evergreen skills will be

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...rding to AI and thus, the need for upskilling in these skills exists ... extent.

Upon moving further away from the equipotential line towards the bottom right zone, the perceived need for upskilling progressively enhances. The five skills found *critical* for upskilling in the present study are depicted in different quadrants of the figure. The top right quadrant contains one technological skill (i.e. digital) and one cognitive skill (i.e. continuous learning). Participants were unequivocal about their high relevance today as well as their relevance in the future AI-era. These skills are of growing importance for upskilling as we navigate from present to future. Thus, we approximately positioned these skills on the top right quadrant of the diagram to the right of the diagonal. Further, skills including data analysis (technological skills), decision making and complex cognitive (both cognitive skills) were described by the participants to be of moderate importance today but of tremendous importance in the future. The need for upskilling for AI is the highest for these skills which are depicted in the bottom right quadrant of the figure. Thus, Figure 2 represents the skills that are important now, skills that are important in the future and the skills that need the most attention for upskilling for AI.

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## Discussion

Our study provides important insights regarding how the potential adverse impact of AI in terms of job replacement can be meaningfully redirected into an employee's skill development. The demand for skills due to technological advancement will assume unprecedented importance in the near future. We can broadly map the skills identified in the present study to Huang and Rust (2018) model of four intelligences required for service tasks – mechanical, analytical, intuitive and empathetic. We found that tasks related to mechanical intelligence such as basic statistics will be easily taken over by AI in the near future. Analytical tasks such as data analysis and technology-related digital competence will be difficult to be mimicked by AI. Intuitive tasks such as complex



g, decision making and continuous learning, and empathetic tasks
ition, interpersonal and leadership skills will be even more difficult

to be emulated by AI. Thus, the changing nature of work in the IT sector necessitates employees to perform jobs that require more of analytical, intuitive and empathetic skills so that they remain employed and create value for the organization.

Corroborating with the dynamic skill theory and recent Mckinsey report (Agarwal et al., 2020), our study participants highlighted that Indian organizations are dynamically engaging employees in building their skills as a priority activity. With the integration of AI across industry types, there is a shrinking need for basic cognitive skills such as data entry, data processing, scheduling and monitoring. Our findings indicate that there is a significant need for upskilling in technological skills including data analysis and digital skills. Concurrently, the demand for cognitive skills is also on the rise especially for skills such as complex information processing, critical thinking, decision making and continuous learning. It should also be noted that our findings were agnostic of the size of the MNC. The participants included managers from small, medium and large-size MNCs operating in the IT sector in India. Irrespective of the size of MNC, the participants responded alike that employees' skills need to be built to address role disruptions and skill gaps created due to AI. This demonstrates that the orientation and understanding of the IT industry are similar with respect to the challenges, opportunities and avenues that the era of AI will unfold for individual contributors and for organizations.

The proponents of AI do not champion the mass replacement of humans by machines. Rather, they indicate organizational think tanks to nurture the workforce with the right skillsets to augment technological advancements. In view of the current and forecasted changes, contemporary organizations are providing several online and offline learning platforms and opportunities for employees to enhance their current skills portfolio. Increasing tech talent requires upskilling in data analysis including knowledge of advanced statistics, application of predictive modeling and time series forecasting, data interpretation, writing algorithms and familiarization with concepts related to big data, analytics, machine learning and deep learning. Advanced digital

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ed to have strategic importance to the business encompass cloud ent automation, robotic process automation, cybersecurity and internet-of-things.

The rise in demand for complex cognitive and information processing skills is owing to the rapidly changing market trends, consumer preferences and overall business scenario. Changes in the macro-level industry environment impact internal organizational functioning and its employees. For instance, employees need to understand the technical details of products/services and explain to customers. This requires cognitive skills such as deriving insights from complex data, visualizing and interpreting it in a meaningful manner. Further, AI-powered technology needs to be embedded in the employees' way of thinking. Developing systems thinking, design thinking, enhancing creativity, and data-driven decision making comprise sharpening thinking skills. Big data analytics, decision support systems and contextual sensemaking by AI-technologies are providing insights to managers, thus, enabling them to take decisions in a better, faster and more precise way. Finally, there is an emphasis on enhancing the learning curve in a cross-functional and team-based work environment as the nature of work will be redefined with a heightened need for agility. Thus, flexibility, continuous learning and agile ways of working are foreseen as top-priorities by organizations. Scrum master, agile coach and DevOps are the critical skills enabling organizational sustenance in the era of disruption and AI.

While there is a major need for upskilling employees in cognitive and technological skills, the need for upskilling in social skills such as leadership, communication and interpersonal remains, thus, we refer to these skills as evergreen skills. Leaders' crucial role lies in thoughtfully redesigning existing jobs and encouraging employees to enhance their skills. Across levels, communication is imperative to inspire employees in creating a mindset of continuous learning and skill enhancement. Further, in an era of digitization, there is a threat of treating people as numbers and dehumanizing them. Thus, developing empathetic and interpersonal skills is needed to enable employees' strengths and capabilities.

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skilling will reap the requisite benefits only if organizations

hools and colleges to develop appropriate curricula to address the issue of lack of talent and skill mismatches. Relatedly, educators should redesign the curriculum and develop new metrics to measure broad-based skillsets in tandem with industry requirements.

AI has not only impacted organizations but has set the ball rolling to develop a ‘learning and feeling economy’. A learning economy is characterized by a workforce that continues to learn, upskill and reskill based on advances in technology and innovation (Bughin et al., 2018). A feeling economy is an economy in which the employment attributable to feeling tasks such as interpersonal and empathy exceeds the employment generated by thinking and mechanical tasks (Huang et al., 2019). While AI-systems continuously learn and perform thinking and mechanical tasks, humans can spend more time on empathetic and feeling tasks. Thus, managers must restructure the jobs to more people-oriented, feeling-conscious and emotionally intelligent. This requires developing employees on feeling intelligence and people skills.

Finally, the present skills scenario in the sampled IT firms does not demand the need for upskilling in routine or rule-based skills such as data entry, scheduling, coding, basic statistics, database management and project management. As data are being generated continuously and voluminously, AI-powered systems are increasingly becoming capable of analyzing data based on algorithms and making sense of structured data in real-time. Rule-based cognitive systems have the ability to learn and improve performance through continuous analysis of real-time data and user feedback. Thus, AI can automate many repetitive, mundane and high-risk tasks giving human beings more scope for engaging in complex tasks. Further, AI’s greater power lies in collaborating with humans and complementing human being’s capabilities. In today’s highly dynamic industry environment, changing decision criteria powered by real-time data and machine-learning approaches are creating immense business value, thus, necessitating the workforce to develop skills to work proficiently alongside AI-enabled machines.

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In order to capitalize on the benefits of AI, organizations must proactively re-tool their policies, practices and philosophies to accept AI-enabled mechanisms as partners in their operations. More specifically, leaders must raise the capacity of employees in these skills to prepare and perform well in the era of AI. Advancing the NHCT, we suggest using a high commitment human resource (HCHR) strategy towards creating a firm's competitive advantage by building human capital concentration (Collins, 2020). HCHR is a philosophical approach focusing on investment in employee skill and capability development. HCHR outlines the employer–employee relationship by creating an organizational climate that encourages organizational members to build their resources and human capital. Investment in the intangible human capital presents strategic leverage points that drive an organization's competitive advantage (Chadwick & Flinchbaugh, 2020).

The AI job replacement theory necessitates employees to upskill themselves in skills deemed critical for the future such as analytics, predictive modeling, intelligent automation, agility and digital skills. This investment in human capital will not only preserve the in-house functional knowledge and expertise but also boost employee motivation, loyalty, organizational commitment and citizenship. Organizational support towards upskilling is critical in encouraging employees to develop new skillsets. Changes in context require cognitive development and hence the dynamic skill theory helps explain how an individual can adapt to the changing tasks, needs and environment. Developing a habit of lifelong learning is the most important ingredient to develop oneself for the future of work. But, such learning must be supported and rewarded by the organization, so that employees' learning behavior is reinforced.

The future of work embedded in AI requires a transformational change in an individual's previously accepted worldviews and perspectives. Additionally, leaders should enable agility among organizational members, that is, the ability to renew, adapt and change quickly to facilitate their learning and capacity building while ensuring success in the turbulent business environment. Leaders must help

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and lifelong employability, that is, continuous adaptation and

onomy evolves. Upskilling should not be considered as an end in itself, but as a means to grow and remain employable.

As organizations aim to leverage the benefits of AI, a basic understanding of technological advancements and their application is binding across all managerial levels. It is necessary to highlight here that upskilling is not just needed for the large proportion of the workforce but also for the top management and senior executives. Dynamic managerial capabilities (DMC) theory (Augier & Teece, 2009; Helfat & Martin, 2015) highlights the impact of varied characteristics and behaviors of senior leaders on the resource advantages in multinational organizations. DMC theorizes the processes through which organizational leaders acquire, develop, deploy and reconfigure capabilities to drive strategic behavioral change among other organizational members. Organizational leaders' acceptance and adoption of technology is critical as it will help them to orchestrate digital changes in a better manner. This does not necessarily mean that they should become AI-experts; however, process redesigning and organizational transformation towards digitalization can be facilitated by top management only if they equip themselves with adequate and updated skill sets.

Furthermore, our study demonstrates the need for developing a symbiotic relationship between humans and machines. Huang and Rust (2018) suggest human–machine integration towards building collaborative intelligence such that AI will enhance human connectivity. Individual employees have limited intelligence, whereas, collectively employees support each other. Likewise, human intelligence can be augmented by the collective intelligence of machines. While AI has the capability to process large amounts of data, the key to remaining important for humans lies in the understanding of data, interpreting the results and decision making. Since, the human brain processes data in a holistic way and AI processes data in a logical way, computational methods on which AI is built will make humans more powerful (Huang & Rust, 2018). Hence, employee upskilling must emphasize the importance of a collaborative relationship between man and machine to surf the AI revolution.

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## plications

Our findings offer several theoretical implications for future research. As we noted earlier, human resource literature is lagging when it comes to examining the intersection of AI and human resources. While the published literature is fairly advanced in investigating how technology has helped speed human resource processes, there is a need to examine how AI is impacting the practice, process and philosophy of human resources. For example, one critical aspect of AI is that individuals will increasingly deal with robots as colleagues and technological platforms as managers. This will necessitate re-visiting our understanding, and revising theories, of supervisor–subordinate relationships and team cohesiveness, for example. As we noted earlier, the dynamic skill theory proposes that individuals would need to be adept in a whole range of skills including social, emotional, technological and physical skills to survive and thrive in the new workplace. In addition, individuals would now also need to become comfortable with human–machine interactions and be willing to update and/or upgrade their skills in this area, as AI-enabled machines and processes get upgraded/upskilled.

Similarly, NHCT and AI job replacement theory both address the issues involved with how AI will impact the ability of human beings to use their skills for finding gainful employment in the workplace and retaining that employment. Our findings of the need for upskilling offer support for these theories while at the same time suggesting that the theories will need to evolve as AI keeps evolving.

Finally, since AI may eliminate or reduce the need for humans in numerous jobs, academics would need to re-visit the classical theories of work and motivation, for example, to better understand how the growth of AI is impacting how humans see their work. In a recent examination of how the technological platforms impact employee control and motivation, Norlander et al. (2021) found that Uber drivers reported greater intrinsic motivation and enjoyment of work compared to taxi drivers, even though they were subject to higher levels of monitoring and control *via* AI

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here is a need to further investigate the AI and human resource

arious angles.

## Limitations and future directions

The limitations of our study highlight new avenues for further research. The preliminary ideas that emerge from the current study prompt further data collection, thus, strengthening the qualitative work. Future researchers may generate hypotheses based on the present study, gather new data, and test the propositions using quantitative research design towards generating an explanatory model for skills upgradation in the context of AI. Further, while AI-systems facilitate problem-solving, it is critical to account for the national cultural context for business decision making. AI-based products and solutions are primarily data-driven and data is highly contextual. As there are cultural differences across countries, this may be interesting to investigate in more depth. The current study focused on employee upskilling for AI in a sample of informational technology multinational corporations in India. Future research could explore the adequate skill needs across different sectors with different types of business ownership. MNCs in the IT sector may have a different orientation as compared to a public limited company in the automobile sector, for example.

Next, given that India has been in the lead of developing AI applications and in AI implementation, it is critical that scholars examine the evolution of AI applications in the Indian context. This is critical since India presents a paradoxical environment – a country with a large population with the need for millions of jobs is also in the forefront of developing AI-enabled applications that can replace human labor – as in the case of a restaurant in Bengaluru using robots as waiters and a school using robot as a teacher.

While our focus in the present study was primarily on the upskilling of employees, future studies may examine other options to build the workforce for the future, for instance, redeploying some employees with specific skills within the organization to make better use of their skillsets. Alternatively, since redeploying does not upskill employees, recruiting people with the desired skills maybe another worthy option.

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so using the services of freelancers or contract employees than

employee. These independent workers not only bring the necessary expertise but also seamlessly integrate into the organization due to increased agility. Thus, future work may explore what works best for organizations – upskilling existing employees or redeploying existing employees or hiring new employees or outsourcing the task. Finally, scholars should also examine the social and psychological impact of AI on those whose employment is made redundant by these technologies, especially in a developing nation such as India.

## Conclusion

The present study aimed to unearth the skills deemed critical for the upskilling of employees to sustain employment and thrive in the era of AI. Contemporary organizations do not consider AI as a competitor to humans, rather they believe in the human–AI complementarity. Technology complements and augments human capabilities towards enhancing business growth. The study highlights five critical skills for employee upskilling including data analysis, digital, complex cognitive, decision making and continuous learning skills. Thus, the proposed shift in skill sets emphasizing the development of higher cognitive and technological skills is a pivotal step towards human–AI collaboration. Completely outsourcing intelligence to machines will neither be useful nor ethical owing to the complex socio-economic-political–cultural milieu in which the organizations are fabricated. Evolving to a higher collective intelligence with techno-cognitive skills deems to be the most promising way forward. We are confident that the present study has provided a roadmap for future research in this nascent yet promising domain.

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## Disclosure statement

The authors have no potential conflict of interest.

## Geolocation information

The study was conducted in India (Asia).

## Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article. Further details may not be available as it will compromise the privacy of the research participants. For further clarifications, please contact the lead author.

# Notes

1 We thank an anonymous reviewer for this suggestion.

2 NASSCOM (National Association of Software and Services Companies) is the agency responsible for IT and ITeS sector in India).

3 We thank the Editors and an anonymous reviewer for this methodology.

4 Name of the chatbot is disguised to maintain organizational anonymity.

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## APPENDIX A Interview schedule

1. Which skills according to you are critical for your upskilling to remain employable and succeed in the AI era? What is the relevance of the skills you mentioned today?
2. Within the past 3 years, have you been upskilled/undergoing upskilling to prepare for changes due to AI? Please provide some details such as the nature of the upskilling program, module(s), and keywords.
3. Among the skills of relevance today, which skills will not require upskilling for the AI era?
4. Company's information: Headquarter, worldwide employee headcount, headcount in India.
5. Personal information: Gender, job function, total years of work experience, experience of AI implementation, and experience working with AI-enabled services.

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