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Sustainability accounting and reporting in the industry 4.0

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A B S T R A C T

Industry 4.0 is the fourth industrial revolution. It is formed on the building blocks of Industrial Internet of Things, real-time data collection and predictive analytics using big data analytics, artificial intelligence, and cloud manufacturing. The complexity and value of Industry 4.0 is established by the existing research studies. Some of the research studies have proposed the design elements and contribution of Industry 4.0 to achieving sustainability objectives. This research delves deeper into this area to evolve a new research challenge on contribution of Industry 4.0 to sustainability accounting and reporting. Through a methodology of two focus group discussions and interviews, this research derived an empirical formulation presenting a mapping between Industry 4.0 attributes and selected material topics and their disclosures in Global Reporting Initiative framework. The empirical formulation divided the Industry 4.0 framework in India into three levels of maturity each mapped with the appropriate triple bottomline topics under the Global Reporting Initiative. This empirical formulation requires further research to establish its validity as it appears to be not-to-optimistic representation by the members of the two focus groups. The Interview respondents suggested cautious approach as AI-based predictive analytics and automation may need a long maturity path. Soft aspects of reluctance to complexity and new technology adoption may need continuous evolution of technical and other training programmes with the maturity of Industry 4.0 for sustainability accounting and reporting in an organisation.

1. Introduction

Sustainability accounting and reporting (SAR) is a framework for defining sustainability variables based on the triple bottom line model (TBLM), defining and implementing measurement techniques, and reporting the actual status of the variables in the public reports by a company (Bebbington and Larrinaga, 2014; DEFRA, 2013). The SAR framework is developed by Global Reporting Initiatives comprising of universal standards of disclosures and management approaches of the TBLM variables. Reliable and valid measurement approaches of TBLM variables have been a challenge for industries (Burritt and Christ, 2016). Industry 4.0 provides a new approach to this challenge as advancements in information and communication technology and IP-enabled industrial cyber-physical systems (Industrial Internet of Things) can form a value chain under this framework facilitating real-time data sharing on the variables under monitoring and controlling (Burritt and Christ, 2016; Kiel et al., 2017; Stock and Seligar, 2016). This level of system facilitating real-time awareness was not possible using the legacy technologies. This research is a study of SAR modelling under Industry 4.0 and is an attempt to develop a reliable and valid model showing the most significant Industry 4.0 variables influencing the GRI principles facilitating SAR.

The business case for sustainability was proposed by Porter and van der Linde (1995), and the Industry 4.0 was first conceptualised by few industrial organisations in Germany (Burritt and Christ, 2016). SAR has been long criticised for the green wash effect based on poorly conceptualised and prepared baselines for measurements, unreliable measurements following manual or semi-automatic processes affected by delays and errors, and manipulation of results and analysis to hide the weaknesses in the corporate environmental performance of an organisation. The GRI framework has provided a new perspective to sustainability measurements and is the most popular framework for sustainability reporting worldwide (KPMG, 2015, 2017). However, there is a lack of empirical evidence on effectiveness in measurements methods and scientific methods followed in reporting of environmental performances. Dahl (2012) had highlighted the problem of insufficient indicators of sustainability targets and their measurement for meeting company-level sustainability goals and contribution to

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national and global sustainability goals. The indicators need to be scientific (for example, the indicators measured over a time series should clearly reflect a trend of improvements). Kwatra et al. (2020) highlighted the need for bottoms-up approach emphasising that national or global indicators are not sufficient to assess the sustainability goals of an individual company. For example, technical efficiency in low carbon production needs to be mapped with the spatial zone directly influenced by a manufacturing plant (Li et al., 2020). A spatio-temporal mapping of a zone for capturing indicators of green performance of industries in the zone can reflect the differences in their green performances.

KPMG (2015) published a three step formula for reliable and valid carbon reporting: identification of the materiality and measurements data clearly, reporting on steps taken and demonstration of reduction of carbon emissions and footprints, and demonstration of how the steps taken have helped in achieving climate protection goals of the company. Such a framework requires comprehensive technology and process capabilities dedicated to SAR. How can Industry 4.0 help? The Industrial Internet of Things (IIoT) and big data analytics (BDA) are at the core of Industry 4.0 (Kiel et al., 2017). Currently, manufacturing organisations are adopting the IIoT and big data systems for solving their gaps in industrial process data collection and analysis. However, the core and features of IIoT technology and architecture are not appropriately positioned for SAR of triple bottom line variables in literature.

The research questions investigated in this research are the following:

(a) What technology and architectural features of Industry 4.0 can enable reliable and valid measurements of SAR variables in the triple bottom line model?
(b) How can industries implement these features in practice to ensure reliable and valid measurements of SAR as per the GRI framework?

The highlights of this research are the following:

(a) A detailed review of the key SAR variables under Global Reporting Initiatives and other relevant literature;
(b) A detailed review of Industry 4.0 technology and architectural features;
(c) Mapping of Industry 4.0 capabilities with SAR variables in a multivariate model
(d) Collecting primary data from two Focus Groups working on Industry 4.0 solutions in Delhi NCR region (details of Focus Groups are in Section 5: Methodology);
(e) Conducting interviews with five manufacturing operations heads in the city of Kanpur and Lucknow (details in Section 5: Methodology);
(f) Evolving an empirical model showing relationships between the Industry 4.0 capabilities and the relevant triple bottom-line topic areas of the Global Reporting Initiative;
(g) Critical analyses of the empirical model, their relevance, and significance for theory and practice;

In the next two sections, a review of literature is presented for building the two foundation pillars of knowledge essential for this research:

(a) About Industry 4.0 framework and the roles of Industrial Internet of Things (IIoT), Big Data Analytics (BDA), and Artificial Intelligence (AI) in it;
(b) The role of the Industry 4.0 in achieving sustainability.

2. Industry 4.0 framework and the roles of Industrial Internet and Things, Big Data Analytics, and Artificial Intelligence in it

Industry 4.0 is conceptualised as the fourth industrial revolution benefitting from digital innovations in industrial processes and engineering applications, latest communication technologies, service-orientation (servitisation) of knowledge-based integrated and automated manufacturing systems, and evolving ways of digitally offering products and services through new forms of markets and exchanges (Roblek et al., 2016; Yao et al., 2017). This concept is also called smart manufacturing, which is delivered by integrating manufacturing systems through cloud computing riding on integrated cloud-based manufacturing applications. These applications are specialised production flows offered by cloud manufacturing integrators allowing manufacturing companies to plug-in their processes with the cloud workflows and begin taking and processing production orders (Wang and Xu, 2013; Wu et al., 2013).

Adopting cloud-based services-oriented manufacturing is a new innovation driven by the modern industrial market dynamics, changing customers' demand patterns, and the need for real-time visibility into demands and supplies for building dynamic quick response and agile capabilities (Cegielski et al., 2012; Oliveira et al., 2014). Capability building in this direction requires significantly large scales of data collection, storage, and analysis. This requirement created the roles of IIoT and BDA systems deployed on cloud computing within the Industry 4.0 framework (Gabriel and Pessl, 2016; Kiel et al., 2017; Tao et al., 2014). The framework of cloud-based manufacturing integration under Industry 4.0 allows large manufacturers to open their job working assignments to smaller manufacturers through cloud-based service-oriented manufacturing integration (Cegielski et al., 2012; Oliveira et al., 2014). This framework can also allow multiple small manufacturers to collaborate through a manufacturing applications integrator to manufacture products flexibly as per the market demands and quickly deliver them to the intended marketplaces.

As the Industry 4.0 framework rides on real-time flow of demand and supplies data, manufacturers collaborating through the cloud-based manufacturing integrators can deliver product and services just-in-time following the demands pull strategy (Cegielski et al., 2012; Oliveira et al., 2014; Wu et al., 2013). The manufacturing applications can facilitate performance-oriented design and allocation of costing per design component, process planning and production sequencing, plugging in physical production resources providers, identification and allocation of resources, testing and quality assurance, and delivery of products to the end customers by matching with the demands (Wu et al., 2013). Fig. 1 presents the framework:

The Industry 4.0 requires two separate sections to be integrated within the manufacturing system: the traditional materials requirements and enterprise resources planning software (MRERPS) and the production planning and control of smart manufacturing system (PPCSMS) powered by cyber-physical (IIoT) system deployed at the machine controls and data collection, optimisation and control systems supported by big data (Trstenjak and Cosic, 2017). The process variables' sensors and robotics controlling the manufacturing machines are made of different varieties of IIoTs deployed as separate clusters (Wang et al., 2016). Numerous robotics task allocation algorithms have evolved under the Industry 4.0 framework following a hybrid of centralised and distributed resource allocation and sensing/control mechanisms. The cloud-based data centres host the programming and control logic integrated with PPCSMS software system. The data flow mechanism from the IIoT sensors follow a flow of scheduling, buffering, filtering, and logging/querying. The PPCSMS calculates multiple

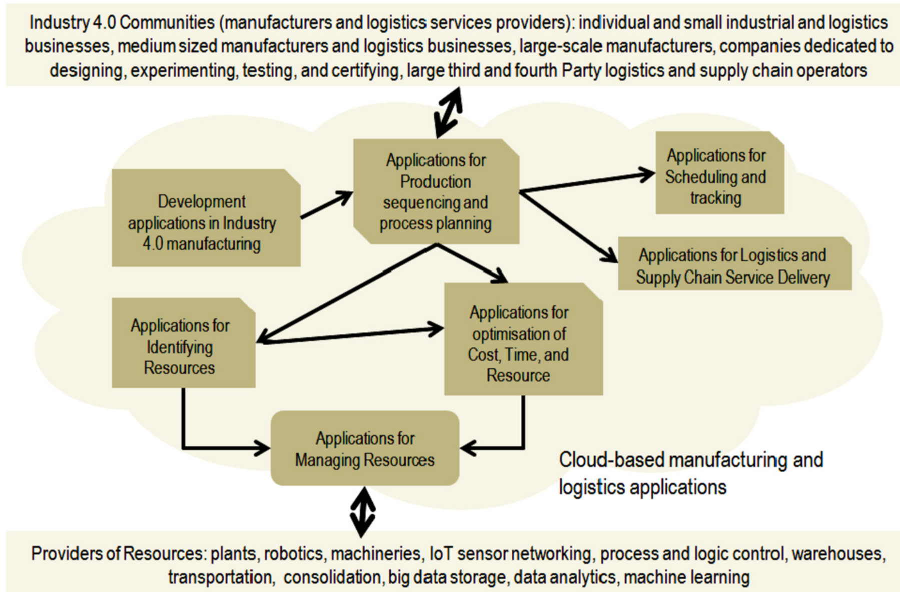

Fig. 1. Cloud-based integrated manufacturing in Industry 4.0 (Redrawn figure based on Wu et al., 2013: 566).

combinations of resources and their scheduling and selects the most cost-optimised one for the MRERPS system to handle.

The IIoT sensors and actuators are deployed in three layers: sensors, middleware, and actuators (Abdmeziem et al., 2016). Sensors are deployed in massive-scale farms with the central role of data collection, harvesting, and communication to big data servers (ITU-T, 2012; ITU-T, 2017). Sensors provide vital information from the running processes needed for decision-making on actuation of robotic controls. Many IIoTs possess both sensing and actuation capabilities. Sensors are small autonomous devices with multilayered architecture as per the IoT reference model for collecting data and storing in the solid state memory within their microchips (ITU-T, 2012). Sensors are interconnected via wireless sensor networks (WSNs) for multiple industrial purposes (like, keeping multiple backups of the real time data) (ITU-T, 2017). They provide their stored data to the central big data servers whenever request are made by the centralised PPCSMS (ITU-T, 2017; ITU-T, 2018). However, actuation is not autonomous. It is tightly controlled through highly secured signalling protocols and communication channels. A middleware is an integral component of the PPCSMS that interfaces a large cluster of sensors with the big data servers (Abdmeziem et al., 2016). It serves as an intermediate buffering station before data is finally committed into the big data tables. It also has security controls to identify compromised sensors and take corrective actions.

Actuation is a complex robotics process for fulfilling the physical roles of the cyber-physical IIoTs (Abdmeziem et al., 2016). Actuation commands are programmable and are linked with a carefully crafted subroutine of resource allocation and activation within a manufacturing process chain. The key design considerations for deploying the IIoTs for the PPCSMS are: protocol support, battery life and energy efficiency, allocation of IIoT to manufacturing resources (actual field robots), identification and authorisation of the IIoTs, IPv6 addressing, quality of service, data storage, security and privacy, and communication systems (Aazam et al., 2016). The BDA is deployed inside the core of the PPCSMS. It is integrated with the MRERPS at the database level (Khan et al., 2016; Lee et al., 2014). Fig. 2 presents a schematic of BDA in the Industry 4.0 PPCSMS framework:

BDA system with artificial intelligence (AI) can command cyber-physical IIoT systems controlling multiple fleets of machines and facilitates remote operator to machine interactions at mass scales. It helps in smart analytics, like machine health awareness, and optimal decision support for automated and self-controlled maintenance of machines. The big data servers maintains multiple information items collected from the IIoTs, like data for monitoring machine conditions, parameters controlled by the robotics, machine performance measurements data, model and make information, machines' components' configurations, and data on tasks executed and utilisation of resources. Artificial intelligence (AI), as an Industry 4.0 layer over BDA, is related to autonomous decision-making by machine learning algorithms designed to control robots and machines (Dopico et al., 2016).

Standardised machine communication languages and BDA systems have made AI more robust and accurate (Dopico et al., 2016). Using the power of BDA, AI can now simulate the whole life cycle of manufacturing of a product providing a three dimensional view on how a digital factory can work. AI adds the capability of intelligence-assisted manufacturing and process execution using the evolving features of robotics and machine tools controllable through entire algorithmic cycles of mathematical expressions invoking numerous activations based on data streams (Li et al., 2017). This capability reduces the role of operators in controlling robots through individual commands issued through their manual decision-making (Romero et al., 2016). Modern communication systems and cloud computing play a significant role in digital transformation of AI-controlled robotics.

With AI support, robots have become more collaborative, cognitively and ergonomically aware, conscious and knowledge-driven within their augmented reality environment, adaptive to environmental changes, and adaptive to multiple complex control strategies (Avishay et al., 2019; Romero et al., 2016; Yao et al., 2017). The human operators need not guide and control the robots at every step of their operations. They can now play the role of an analytical operator powered by BDA and multiple decision options provided by AI actively collaborating with robots using them as smart cyber-physical assistants. This capability of Industry 4.0 may be viewed as the next giant step of innovation beyond computer-aided designs (CAD), computer-aided engineering (CAE), and computer-aided manufacturing (CAM). Traditional industrial

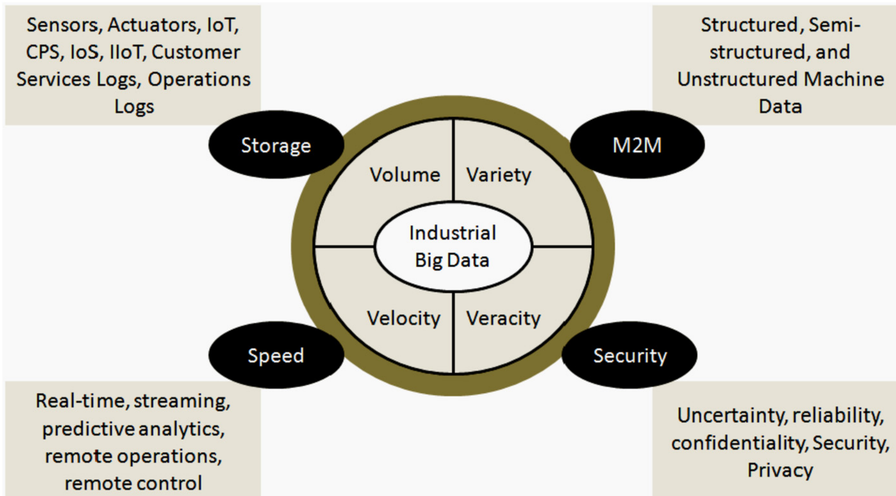

Fig. 2. Big data Analytics system in the Industry 4.0 framework (Khan et al., 2016: 2).

communication protocols had limited the networking capabilities between control systems and robots. Industry 4.0 on IPv6 has broken this barrier making the control systems smarter.

3. Industry 4.0 for sustainability

Sustainability is a highly complex subject dealing with numerous variables under the scope of the TBLM objectives (Golini et al., 2014). Managing sustainability goals, especially related to environmental protection, is a competitive priority as there is a strong emphasis on integrating environmental protection technologies into manufacturing systems and technologies (Jabbour et al., 2012). Manufacturing organisations have recognised the value of TBLM objectives for their business in the longer-term, and are investing in technologies and standards for achieving those (Jabbour et al., 2012; Golini et al., 2014). However, the effectiveness of TBLM in a manufacturing network can be achieved only when each site in the network is prepared as per the established standards at the network level (Golini et al., 2014). Standalone sites can lack capabilities in meeting TBLM. Further, manufacturing organisations may implement environmental practices as a preventive measure with focus on eco-efficiency, which may limit its potential competitive priority in spite of positive influence on quality, cost, delivery, and flexibility (four fundamental manufacturing priorities) (Jabbour et al., 2012). A systemic approach towards integrating green supply chain and environmental management practices with the quality management practices shall enable enhancement of green performance of manufacturing organisations (de Sousa Jabbour et al., 2014). A good opportunity in this context is to implement ISO 14001 standard and its controls.

These crucial findings by Golini et al. (2014), Jabbour et al. (2012), and de Sousa Jabbour et al. (2014) link the Industry 4.0 to TBLM as networked manufacturing and achievement of fundamental manufacturing priorities (systemic improvements, quality, cost, delivery, and flexibility) are key components of its fundamental design. The traditional manufacturing models lacked delivery effectiveness and flexibility for dynamic systemic improvements (Golini et al., 2014). The traditional Peripheral, Onion, and Complex Control System (CCS) models of manufacturing plants treated a manufacturing facility as a standalone system (Golini et al., 2014; Herrmann et al., 2014). A standalone manufacturing plant takes energy inputs (electricity, gas, oil) to drive production machines and their technical building services that transform raw materials into finished goods (Herrmann et al., 2014). Such complex systems generate lots of heat, wastes, exhausts, emissions, and provide highly difficult working environments for the workers. For decades, such manufacturing plants have flourished across the world in thousands. They are unsustainable by design. It is very difficult to develop capabilities in them in their traditional model designs for achieving TBLM objectives unless the model itself is changed.

The future model of manufacturing plants is the Manufacturing Ecosystem Model (MEM) in which, plants are integrated in a network that can facilitate flows-based processes for governing production, energy, resources, and people skills based on a symbiosis driven by cyber-physical systems and modern information and communication technologies (Alcacer and Cruz-Machado, 2019; Golini et al., 2014; Herrmann et al., 2014). In this model, plants do not work at their maximum efficiencies (fully stressed utilisation of capacities) (Herrmann et al., 2014). Instead they work at optimal efficiencies. The focus is on maximising collaborative outcomes of multiple plants to meet the demands instead of pushing an individual manufacturing plant to produce the maximum that it can achieve to push mass products in the markets. This model can be achieved effectively following the Industry 4.0 design (Alcacer and Cruz-Machado, 2019). TBLM objectives are natural outcomes in this model as the per-plant consumption of energy and natural resources reduces significantly, and the stress on workers reduces.

The Industry 4.0 design requires transformation in multiple features of a manufacturing plant, like modularity in design, scalability, compatibility, mobility, and universality (Alcacer and Cruz-Machado, 2019; Herrmann et al., 2014). For example, small plant locations in the proximity of end customers are preferred over large and remote manufacturing plants (distributed manufacturing) (Rauch et al., 2015). Plants with modularity capable of mass customisation are preferred over in-flexible and non-modular assembly lines capable of mass manufacturing (Shim et al., 2017). The workstations (machineries) are deployed in such a way that they can handle multiple product designs, can follow complex heuristic rules of production scheduling, can auto-adjust to varying lot sizes (workloads) and bottlenecks, and can process a combination of multiple despatching rules (like, first in first out, modified due date rules, minimum setup rules, and slacking rules) (Shim et al., 2017).

As researched by de Sousa Jabbour et al. (2018), the Industry 4.0 design effectively supports the ReSOLVE (Regenerate, Share, Optimise, Loop, Virtualise, and Exchange) model of a sustainability-friendly economy, popularly known as the Circular Economy. de Sousa Jabbour et al. (2018) presented a five-step approach to achieving the ReSOLVE model of a circular economy following a framework of sustainable operations management using suitably selected Industry 4.0 technologies and cooperation among supply chain agencies in achieving clearly defined performance indicators and achievable targets. Two aspects of Industry 4.0 design are critical for achieving a circular economy – value creation and its capturing through technologies, processes, practices, performance measurements, and continuous improvements (de Sousa Jabbour et al., 2018; Nascimento et al., 2019). The regeneration of energy resources and shared manufacturing activities among multiple facilities for optimising per-plant energy consumption can be achieved through the multi-plant flows-based processes and careful measurements and monitoring in Industry 4.0 design (Alcacer and Cruz-Machado, 2019; Herrmann et al., 2014; de Sousa Jabbour et al., 2018).

The looping attribute of the ReSOLVE model requires infrastructure for recycling and reuse of the products reaching the end of life cycle (de Sousa Jabbour et al., 2018; Nascimento et al., 2019). The looping process involves careful storage and sorting of reusable materials, treating them for reusability preparations, and then feeding them into a system of remanufacturing (Nascimento et al., 2019). Virtualisation and exchange requires virtual integration of flow-based manufacturing processes spanning across multiple plants located globally (Herrmann et al., 2014). In the research by Rosa et al. (2019), the Industrial Internet of Things and Additive Manufacturing are highlighted as the most useful technologies for circular economy under the Industry 4.0 framework. IIoT can sense the TBLM variables and provide the data needed by big data systems and artificial intelligence to assess the key problem areas for improvements (Rosa et al., 2019). Cyber Physical Systems (CPS) with attached IIoTs can help in multiple enhancements in the product life cycle management for reducing wastes and also for making products recyclable. Further, additive manufacturing can contribute to circular economy by reducing wastes significantly because it does not leaves residues of unused raw materials.

Industry 4.0 system performance is centred at effectiveness of each process and all the equipment (control systems, robotics, machinery, and processors) that play their roles in it (Alcacer and Cruz-Machado, 2019; Yazdi et al., 2018). Reduced rejections and wastage leading to high production efficiency is one of the core objectives of Industry 4.0. The factors influencing effectiveness are performance (total cycles executed/total runtime), quality (accepted goods/total goods), and availability (total runtime/planned production runtime) (Yazdi et al., 2018). These factors can be maximised by conducting a time-series analysis of machine-generated data about what is happening in each component (such as, control system, robot, machine, and processor) in a process cycle (Sivri and Oztaysi, 2018; Zhong et al., 2017). Maximising these factors can help in achieving multiple TBLM objectives because the overall intensity of many variables (like, energy consumption, natural resources consumption, wastage, stress on workers, emissions, and heat generation) will reduce as a result of squeezed timelines (Yazdi et al., 2018). Enhanced production effectiveness is directly proportional to enhanced sustainability.

Industry 4.0 model is designed to achieve all of these for targeted demand fulfilment (Kiel et al., 2017; Yazdi et al., 2018), and the culture of lean manufacturing acts as a moderator (Iranmanesh et al., 2019; Resta et al., 2016). The IIoTs provide time-series data about process performance attributes in real-time to BDA, which uses AI to determine and fine tune factor variables determining production effectiveness (Kiel et al., 2017; Ren et al., 2019). The maintenance reports and daily operating performances of each component, such as controller, machine, and robot are monitored remotely by collecting real-time relevant data from the IIoT sensors (Sivri and Oztaysi, 2018; Zhong et al., 2017). The next maintenance cycle or urgent repairs of a component is determined dynamically based on its running and past performances relative to other similar components. The AI decision-making engine analyses massive big data repositories and determines the minimum required performance scoring for each component based on the targeted demands and their deadlines (Kiel et al., 2017; Ren et al., 2019). The entire system is fully dynamic as the AI drives the triggers for repairs, maintenance, and replacements. All fixed human-configured triggers and schedules are replaced by AI-controlled big-data-driven dynamic triggers and schedules in Industry 4.0.

The Industry 4.0 technological change is a revolution, which can influence the key principles of the environmentally-sustainable manufacturing processes through its core feature-based technological capabilities deployed in globally connected virtual manufacturing plants through cloud manufacturing (de Sousa Jabbour et al., 2018a; Lu et al., 2019; Perez-Lara et al., 2018). Design for environment, cleaner production, green supply chain management, sustainable procurement, and circular economy variables under the ReSOLVE model are the key principles of environmentally-sustainable manufacturing processes. The cyber-physical systems, big data analytics, cloud manufacturing, additive manufacturing, and artificial intelligence systems in Industry 4.0 framework enable the real-time visualisation and actuation capabilities, which in turn enable automated operations-level decision-making capability, automated fault finding and corrections and prevention capability, optimisation of tasks and maintenance capability, automatic prioritisation capability, and many such new capabilities over the Industry 3.0 framework. As the cyber-space addressing and connectivity is extended to physical equipment, machinery, and robotics, manufacturing facilities across the world can be part of a network allowing flow-based networked execution of manufacturing processes. The key principles of environmentally-sustainable manufacturing processes can be built as quality targets to achieve multiple TBLM objectives automatically.

A crucial yet overlooked capability needed for sustainability under the TBLM framework is about integrating human skills with technology. The TBLM training, technical training related to TBLM, customers' involvement in TBLM initiatives in an organisation, developing green content based on established standards (notably, ISO 14001), and inducting sustainable practices in the skills and practices of suppliers are key influencers of effectiveness of meeting TBLM objectives in organisational operations (Jabbour et al., 2013; Jabbour et al., 2015; Kannan et al., 2014; Teixeira et al., 2012; Teixeira et al., 2016). HR practices relevant to TBLM and lean manufacturing practices are joint influencers in the same model achieving goodness of fitment in the research by Jabbour et al. (2013). In a later study, it was shown that technology practices relate statistically significantly with market, environment, operational performance for sustainable production but lacks relationship with human resources and organisational performance (Jabbour et al., 2015). Perhaps, the gap is in the lack of adequate TBLM training practices. This gap is highlighted in the research by Teixeira et al. (2012) and Teixeira et al. (2016) identifying misalignment between TBLM training and the required content as a significant cause. As specifically highlighted by Teixeira et al. (2012), there should be co-evolution between the training content and organisational TBLM practices. This means that the training should become deeper and involved to align accurately as per the needs for meeting TBLM objectives in the organisation. These findings are expected to apply in effectiveness of Industry 4.0 in meeting TBLM objectives. Keeping in mind about technical aspects of Industry 4.0, the sophistication in training content is expected to be much higher. This reveals that training employees on Industry 4.0 systems for TBLM practices will be a much bigger challenge in the future.

The next section presents details of the methodology followed in this research.

4. Methodology

Currently, there is little empirical evidence on contribution of Industry 4.0 framework to SAR. This research is viewed as one of the earliest efforts in building this new field of empirical knowledge. Hence, an exploratory qualitative method was preferred to collect primary data in this research diving deeply into the experiences of industrial experts in “Production Engineering through Networked Controllers” and “Information and Communications Technology for Production Engineering” fields. The components of Industry 4.0 are being implemented in the Delhi NCR industrial regions in North India. In the quest for reliable and valid industrial evidences on the subject of interest in this study, a focus group discussion and analysis approach was followed in this research (Nyumba et al., 2018). Focus group is recognised as one of the approaches in qualitative methodology targeted to build collective consensus on a focussed subject through collaborative narratives of the individuals having in-depth experience in that subject (Flick, 2010). It can be achieved through focus group interviewing (Yin, 2011) and focus group open discussion and analysis in the form of a debate (Barry et al., 2009; Kitzinger, 1995). This research did not rely only on the focus group albeit followed a multi-method approach for deriving more effective scientific outcomes (Mura et al., 2020).

Conducting a focus group discussion and analysis in the form of a debate requires expert moderation skills. The participants should be kept focussed on the subject matter, should be motivated to reveal deep facts, and everyone in the group should get a fair chance to contribute (Barry et al., 2009; Flick, 2010). Given the university teaching experience of the author, he was able to use this method effectively treating it as a classroom debate on a highly complex and sophisticated subject matter. The sampled group should have both homogeneity and heterogeneity characteristics (Kitzinger, 1995). For example, the group members should have experienced a common phenomenon in different work environments.

A good focus group design should have 8 to 12 members, sessions of not more than 2 h, multiple sessions till a consensus is reached, very carefully selected group members, and defined protocols for discussion, data collection, data analysis, consensus building, and moderation (Grudens-Schuck et al., 2004). In this research, two focus groups were formed as summarised in Tables 1 and 2:

The Focus Group A was formed of employees of three large-scale global companies that have collaborated to offer Industry 4.0 solutions in India. These companies have a long presence in India. The second focus group was formed by some of their prominent clients in the Uttar Pradesh side of Delhi NCR region (comprises five heavily industrialised districts: Noida, Greater Noida, Ghaziabad, Meerut, and Gajraula). The researcher approached the members of the first focus group through a senior representative of one of the companies that he had met in the proceedings of a conference. On learning about his research interest and his design of focus group discussion, the senior representative invited him to conduct the two focus groups using one of the conference rooms in his Noida office. He also helped in recruiting the members for the two groups. The Focus Group A was interested in exploring how the existing Industry 4.0 solutions can contribute to SAR and the Focus Group B was interested in the existing Industry 4.0 solutions offered by global vendors in India could be applied for effective and credible SAR. Their interests in the outcomes of this research were purely academic for enhancing their knowledge about influence of Industry 4.0 solutions on SAR capabilities.

Both the focus group discussions were conducted separately. The respondents were requested to conduct an active brainstorming to write down definitive facts on flip-charts pertaining to the two research questions of this research (Section 2) presented to them. The definitive facts were related in the form of an empirical structural construct, which was discussed critically pertaining to their relevance, and practical application in the industries studied in this research.

The results of the focus group discussion were used as foundation knowledge to conduct interviews with the individuals in the head of production and similar roles reflecting seasoned operations experience. Five such individuals agreed for interviews. To test the outcomes of the focus group discussion through independent perspectives, this time the respondents were chosen from the manufacturers in the cities of Kanpur and Lucknow (both these cities are about 500 km away from the Delhi NCR region). Out of the five respondents, four were heading operations in Kanpur-based industries and one was heading operations in a Lucknow-based industry. Kanpur is a heavily industrialised city. Lucknow is not as heavily industrialised but has the benefit of hosting multiple head offices of industrial plants located in Kanpur and other cities. The researchers could meet their respondents in Lucknow itself.

Each respondent was asked the same two questions as discussed in the focus group discussion:

(a) How the existing Industry 4.0 solutions (in-general) can contribute to SAR?
(b) What existing Industry 4.0 solutions offered by global vendors in India could be applied for effective and credible SAR?

The next section presents the results of both the methods followed in this research.

Table 1
Focus Group A — information and communications technology for production engineering.

S. No.	Age	Current role	Organisational Profile
1	32	Systems Architect	One of the largest networking manufacturer and software solutions global company
2	35	Systems Architect	Same as above
3	33	Systems Architect	Same as above
4	34	Product Specialist	Same as above
5	33	Account Manager	Same as above
6	39	Solutions specialist	One of the largest ICT manufacturer and industry automation solutions global company
7	37	Client Manager — Smart Manufacturing Solutions	A joint venture of one of the largest process engineering manufacturers of the world and a prominent industrial software automation company

Table 2
Focus Group B – production engineering through networked controllers.

S. No.	Age	Current role	Organisational Profile
1	37	Production control	Local Manufacturing Plant of a medium-scale pan India manufacturing company producing specialised chemicals; operating Industry 4.0 model for slightly more than one year;
2	35	Production management	Local Manufacturing Plant of a large-scale global manufacturing company working on global specialised production contracts; operating Industry 4.0 model for more than four years;
3	42	Production management	Same as above
4	41	Production management	Same as above
5	40	Production management	Same as above
6	44	Supply chain management	Same as above
7	39	Managing Director and one of the Owners	Two manufacturing plants of precision glass cutting and fitting; running a ICT vendor-managed pilot on Industry 4.0 for more than six months
8	40	Director and one of the Owners	One manufacturing plant of electrical fittings; running a pilot on Industry 4.0 for more than six months and now planning for its full-scale rollout

5. Industry 4.0 for sustainability accounting and reporting (SAR) – A primary analysis

In this section, the results of the two Focus Group discussions and a primary analysis of the influence of Industry 4.0 on SAR following the GRI framework are presented. Before delving deep into the attributes of Industry 4.0 influencing SAR, a brainstorming session was held by both the focus groups for highlighting the key material topics in the GRI framework that are expected to be influenced by Industry 4.0. After multiple rounds and rejecting the choices based on collaborative debate, the finalised version after combining the outcomes of the two focus groups are presented in Fig. 3. The choices (underlined) were common in both the focus groups. The primary analysis is focussed on these material topics only.

Three key industrial solutions were discussed by both the focus groups: A global IT and networking MNC's Industry 4.0 communication systems, a leading factory automation equipment manufacturing MNC's Smart Manufacturing, and a global IT MNC's Industry 4.0 and Cognitive Manufacturing. These industrial solutions are combined by the focus groups as they are synergised for Indian markets. These solutions were used by the focus groups as baselines for their debating because the participants were familiar with them. The purpose of this research is not to position them albeit is to use them for creating a list of key Industry 4.0 attributes and analysing their possible influences on SAR of the material topics identified (underlined) in Fig. 3.

Using the flip charts method mentioned in Section 5, the attributes of these industry solutions were listed and their influences on SAR of one or more material topics in the GRI framework were debated. As the author was the moderator of both the focus groups, he could standardise the names of attributes and their encodings. The final outcome was two constructs in which, the influences of the attributes were shown on the material topics highlighted in Fig. 3. The two constructs were produced by the two focus groups. Given that this research is interested in the construct coming out from a final consensus between the two groups, only those attributes of the industry solutions debated and their influences on GRI material topics were retained that were common in the outcomes of the two focus groups. The finalised construct showing the Industry 4.0 mapping with GRI material topics and GRI disclosures is presented in Table 3:

To understand how the two focus groups arrived at Table 3, their pattern of analysis is presented in Fig. 4. The focus groups analysed the GRI standards in the context of the level of investments proposed by the vendors over a longitudinal plan. Initial investments

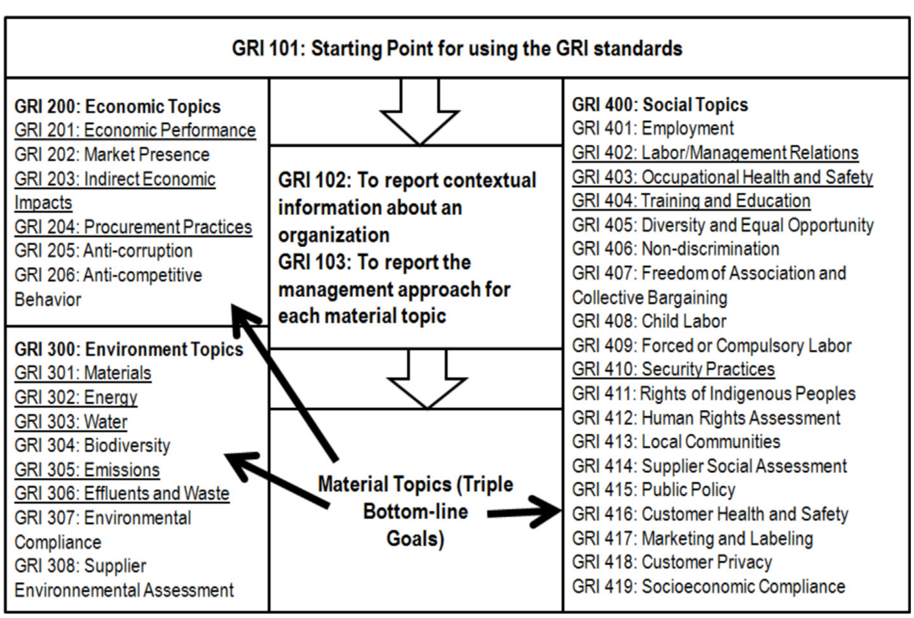

Fig. 3. SAR areas in the GRI framework expected to be affected by Industry 4.0 framework – an outcome of the two Focus Group Discussions and Analysis.

Table 3
Mapping of the Industry 4.0 attributes with the GRI material topics with reasons, as reflected in the finalised construct.

S. No.	Industry 4.0 Attribute	Mapping with GRI Material Topics	GRI Disclosures under the Material Topic
1	Digital Signature of each component and material	GRI 301: Materials	Disclosure 301-1 Materials used by weight or volume Disclosure 301-2 Recycled input materials used Disclosure 301-3 Reclaimed products and their packaging materials
2	Multi-functional IIoT Sensors on each component and material packaging	GRI 301: Materials	Same as Serial No. 1
3	Cognition (smartness; self-awareness and self diagnosis) of each component	GRI 301: Materials GRI 302: Energy GRI 303: Water GRI 305: Emissions GRI 306: Effluents and Waste	Disclosure 302-1 Energy consumption within the organisation: data collected from sensors Disclosure 302-2 Energy consumption outside of the organisation: data collected from sensors Disclosure 302-3 Energy intensity: data collected from sensors Disclosure 302-4 Reduction of energy consumption: data collected from sensors Disclosure 302-5 Reductions in energy requirements of products and services: data collected from sensors and some tests conducted Disclosure 303-1 Water withdrawal by source: data collected from sensors Disclosure 303-2 Water sources significantly affected by withdrawal of water: data collected from sensors Disclosure 303-3 Water recycled and reused: data collected from sensors Disclosures 305-1 to 305-7 All forms of emission disclosures identified by GRI: data collected from sensors Disclosure 306-1 Water discharge by quality and destination: data collected from sensors and some tests conducted Disclosure 306-2 Waste by type and disposal method: data collected from sensors Disclosure 306-3 Significant spills: data collected from sensors Disclosure 306-4 Transport of hazardous waste: data collected from sensors Disclosure 306-5 Water bodies affected by water discharges and/or runoff: data collected from sensors
4	Machine-to-machine Communication through Internet	Same as Serial No. 3	Same as Serial No. 3: All sensory and testing data can be communicated freely through the Internet
5	Real-time data collection from sensors	Same as Serial No. 3	Same as Serial No. 3: the cognition data from each component and material package can be collected in real time from sensors
6	Predictive analytics	Same as Serial No. 3	Same as Serial No. 3: Predictive analytics shall help in time-series forecasting on all the variables collected through sensors and test reports
7	Common communication language and protocols	Same as Serial No. 3	Same as Serial No. 3: Every sensory data can be communicated and stored through common language and protocols
8	Prescribed corrective and preventive actions for best performance	Same as Serial No. 3	Same as Serial No. 3: Predictive analytics shall help in taking strategic and operations-level actions to continuously improve GRI performance
9	Dynamic scheduling through flexible machining	Same as Serial No. 3 + GRI 402: Labor/Management Relations GRI 404: Training and Education	Same as Serial No. 3 + Disclosure 404-1 Average hours of training per year per employee Disclosure 404-2 Programs for upgrading employee skills and transition assistance programs Disclosure 404-3 Percentage of employees receiving regular performance and career development reviews Intensive programs shall be needed to migrate the employee skills to the new automated systems and processes of Industry 4.0; thereafter, training and education will also become an automated process given the significant visibility into the running components and processes;
10	Dynamic production engineering processes	Same as Serial No. 9 + GRI 204: Procurement Practices	Same as Serial No. 9 + Disclosure 204-1 Proportion of spending on local suppliers Continuous replenishment shall become an automated capability, which will also reflect breakup of suppliers receiving replenishment orders.
11	Individualisation through customer-specified production specifications	Same as Serial No. 10	Same as Serial No. 10
12	Continuous control systems and engineering	Same as Serial No. 10	Same as Serial No. 10
13	Dynamic and continuous scheduling	Same as Serial No. 10	Same as Serial No. 10
14	Autonomous dynamic and flexible automation	Same as Serial No. 10	Same as Serial No. 10
15	End-to-end global integration and visibility of operating clusters of components	Same as Serial No. 10	Same as Serial No. 10
16	Automated robotic loops of sensing and actuation	Same as Serial No. 10	Same as Serial No. 10
17	Model-driven production engineering	Same as Serial No. 10	Same as Serial No. 10
18	Continuous data collection and storing in cloud big databases	Same as Serial No. 10	Same as Serial No. 10
19	Real-time dashboards showing real-time production insights	Same as Serial No. 10 + GRI 201Economic Performance + GRI 203 Indirect Economic Impacts	Same as Serial No. 10 + Disclosure 201-1 Direct economic value generated and distributed Disclosure 201-2 Financial implications and other risks and opportunities due to climate change Disclosure 203-1 Infrastructure investments and services supported Disclosure 203-2 Significant indirect economic impacts Real-time production insights shall provide in-depth analytics on economic performance of the components and processes running on them, which will not only justify efficiency of operations albeit, will also justify efficiency of sustainable value generation. At a larger

Table 3 (*continued*)

S. No.	Industry 4.0 Attribute	Mapping with GRI Material Topics	GRI Disclosures under the Material Topic
			scale, integration of global plants and distributing production processes across global units can reduce global carbon footprints and emissions caused by a large-scale globally spread manufacturing company.
20	Cloud-based integrated global operations	Same as Serial No. 19	Same as Serial No. 19
21	Continuous health monitoring of each component	Same as Serial No. 19	Same as Serial No. 19
22	Predictive forecasting of repairs, maintenance, and replacements	Same as Serial No. 19	Same as Serial No. 19
23	Virtual Engineering with Machine Learning	Same as Serial No. 19	Same as Serial No. 19

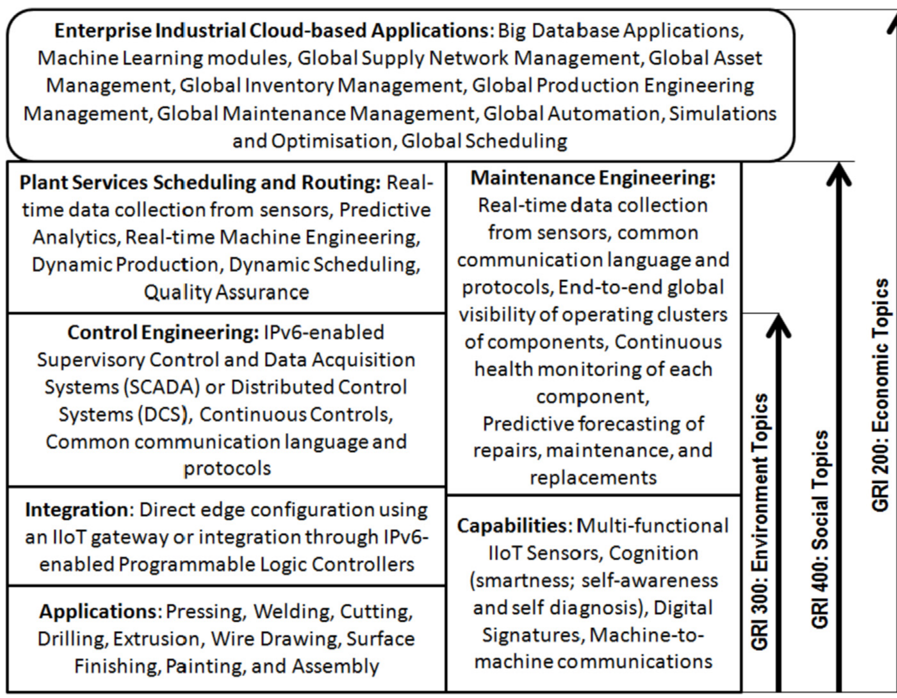

Fig. 4. Simplified attributes of cloud-based Industry 4.0 framework – an outcome of the two Focus Group Discussions and Analysis.

require setting up new IIoT sensors or modifying the existing programmable logic controllers (PLC) infrastructures to IPv6 based sensing technologies and integrating them (through SCADA or DCS), deploying systems for protocol conversions and real-time data collection, deploying big databases, and deploying applications for real-time health monitoring, real-time machine engineering, and dynamic production and scheduling. The Focus Group B concluded that this system is sufficient to collect and view the data needed for reporting the selected material topics and their GRI disclosures under "GRI 300: Environmental Topics". Although, Focus Group A proposed better analytical abilities for reporting the environmental material topics GRI 301 and GRI 306 (Fig. 3), overall both focus groups agreed that investments up to real-time monitoring capabilities can improve GRI 300 reporting significantly. For example, equipment with longer runtimes causing longer cycle times of emissions and other environmental hazards, and needing operations fine-tuning, maintenance, or parts replacements can be easily identified.

The next level of investments is required in predictive analytics and forecasting, which involves multiple sub-modules, such as predictive health monitoring, predictive forecasting for repairs and maintenance, and predictive machine engineering, production, procurement, and scheduling. This level will involve multiple industry-standard data engineering applications but may or may not involve artificial intelligence (depends upon architectures made by different vendors).

At this level, improvements can be made at much larger scales extending numerous benefits to workers. They shall be exposed to significantly lower stress and danger times because the maximised production strategy can be migrated to optimised production strategy without losing on outputs. Both the focus groups agreed that this level of investments can potentially develop capabilities for collecting and reporting the data needed for the selected material topics and their GRI disclosures under "GRI 300: Environmental Topics" as well as "GRI 400: Social Topics". Large scale enhancements in production systems can improve the working lives of employees exposed to difficult work routines. The management – labour relationships (GRI 402) can improve by implementing organised and predictive processes for identifying potential threats and equipment predicted to be causing excessive stress thus reducing risks to health and safety of workers (GRI 403) and reducing security threats (GRI 410). Industry 4.0 will require new training and skill-building under the new automated operations environment (GRI 404). There may be some time needed for settling down in the new automated framework.

The two focus groups proposed that in absence of cloud-based integration and analytics conducted by artificial intelligence, the "GRI 200: Economic Topics" are difficult to report. Although, Focus Group B felt that GRI 204 (procurement practices) can be improved with predictive analytics as the requirement is merely to report on opportunities given to local suppliers, Focus Group A argued that an honest reporting of the larger economic benefits extended to society will require longitudinal training of machine learning algorithms. Data collected without cloud computing integration will be insufficient to gain such insight. Both the focus groups argued that getting an overall insight into direct and indirect economic impacts will require longitudinal analytics using data integrated through cloud computing and longitudinal training of machine learning.

The next step followed in this research was an interview process involving five respondents as discussed in Section 4. The two questions as stated in Section 4 were presented to them along with the results of the focus group discussions. The respondents provided explanatory responses, which were converted into definitive facts at the end of the individual interviews by involving each respondent and achieving their agreements. The duplicate definitive facts were merged and the final outcomes were as presented below:

(a) Industry 4.0 solutions in-general and the specific offers made by multinational companies in India may be more effective for environmental measurements and reporting (GRI 300).
(b) The aforesaid solutions may be useful for economic measurements and reporting (GRI 200) if contextual analysis and clear benefits relevant to the company can be conducted objectively.
(c) The solutions may not be effective for social measurements and reporting (GRI 400) in their current form because almost all the GRI topics under GRI 400 requires predictive monitoring and involvement of AI-based decision making.
(d) Involvement of AI is essential for meeting the objectives of economic (GRI 200) and social (GRI 400) topics.
(e) The foundation level of solutions comprising of cyber-physical systems and Internet of Things may be used for operations and environmental parameters monitoring.
(f) Predictions of possible machine failures and timely maintenance using data collected from machines shall be among the most useful value additions.
(g) The AI-driven automation capabilities will require prolonged maturity periods as AI will need loads of historical data to make error-free actuations. It is possible that automated actuations may seldom happen in small to medium scale Indian industries in of fear malfunctions.
(h) Body wearables may be a good idea for monitoring health and safety, but their feasibility and longevity in the work environments need to be assessed.
(i) The fundamental solutions comprising cyber physical systems, IIoT, and basic software solution for monitoring and decision-making can be adopted after some customisations. Advanced predictive analytics and AI-based automation may not provide any fruitful results for a long time; until the data sizes and AI training is sufficient enough to trust its automation capabilities.
(j) Global integration, flow-based automated capabilities, and global sustainability monitoring and localised resources control will require long periods of maturity. It may be viewed similar to ERP and MRP implementation, which were matured after decades of continuous improvement efforts. Industry 4.0 technologies may not be any different.

These results have provided an insight into the perspectives of practitioners regarding role of Industry 4.0 in SAR following the GRI standards. Keeping these perspectives and the results from focus group discussion and interviews in mind, an empirical formulation is presented after critical discussion in the next section.

6. Critical discussion and empirical formulation

Industry 4.0 is a good solution for sustainable manufacturing. The framework requires significantly large scales of data collection, storage, and analysis on cloud computing (Gabriel and Pessl, 2016; Kiel et al., 2017; Tao et al., 2014). The MRERPS and PPCSMS capabilities require complete multi-plant integration for achieving effective automation in production and machine engineering, and in scheduling (Trstenjak and Cosic, 2017; Wang et al., 2016). Sensing and actuation driven by real-time data collection and analysis is the foundation of Industry 4.0 (Abdmeziem et al., 2016). However, they are not enough to develop predictive capabilities. The end-to-end machine engineering systems need to be aware, conscious and knowledge-driven within their augmented reality environment, adaptive to environmental changes, and adaptive to multiple complex control strategies (Avishay et al., 2019; Romero et al., 2016; Yao et al., 2017). This level of capability can only be achieved through implementing the complete framework. The role of Industry 4.0 in achieving the circular economy ReSOLVE model will require sensing, actuation, predictive analytics, and automated decision-making capabilities (de Sousa Jabbour et al., 2018; Nascimento et al., 2019). As reflected in the focus group discussion and interviews, sensing and actuation, predictive analytics, and automated decision-making are three levels of Industry 4.0 requiring three different levels of investments. The solutions from multinationals operating in India comprise of all the three levels, but the practitioners recommend beginning with sensing, actuation, and basic levels of real-time monitoring and control as an optimum solution to begin with. The academic research studies view predictive analytics and automation as critical capabilities needed for sustainable manufacturing (de Sousa Jabbour et al., 2018; de Sousa Jabbour et al., 2018a; Kiel et al., 2017; Ren et al., 2019; Sivri and Oztaysi, 2018; Zhong et al., 2017). The full system prescribed by academic researchers involves machine-level data collection from the IIoT sensors, which needs to be fed to advanced big data analytics systems for training the AI algorithms. However, the practitioners have suggested taking a cautious approach based on their past experiences of slow and tedious maturity paths of ERP and MRP systems.

Overall, Industry 4.0 appears to be fulfilling a crucial variable of integrating environmental quality practices into planning and operations of an industry as suggested by Diabat and Govindan (2011). In another research, Govindan et al. (2014) highlighted the challenge of industries sticking to their existing inflexible practices and hesitating in adopting complex designs, technologies, and processes. These are softer challenges of sustainable manufacturing practices, which can be addressed through in-depth trainings and workshops (Jabbour et al., 2013; Jabbour et al., 2015; Kannan et al., 2014; Teixeira et al., 2012; Teixeira et al., 2016). If the technical and soft trainings evolve with the maturity of sustainable manufacturing operations of an organisation, the challenge of resistance to implementing Industry 4.0 technologies shall be addressed. Companies in India would (possibly) never implement a complete framework. They will prefer phased implementation based on evidences of maturity in the system. From sustainability perspective, there will always be a tendency in India to implement systems with lower investments amidst lack of complete understanding of the benefits of sustainability practices on businesses (Govindan et al., 2014).

The global vendors targeting Indian industrial markets perhaps know about these challenges in the Indian markets. From the focus group discussions, the concept of multi-level solutions offered by vendors is clearly visible. However, on the basis of the concepts of MRERPS and PPCSMS (Trstenjak and Cosic, 2017; Wang et al., 2016) and the capabilities of globally integrated manufacturing, engineering, maintenance, repairs, and replacements (Kiel et al., 2017; Rauch et al., 2015; Ren et al., 2019), targeted demand fulfilment (Kiel et al., 2017; Yazdi et al., 2018), and lean manufacturing as a moderator (Iranmanesh et al., 2019; Resta et al., 2016), Industry 4.0 needs to be implemented up to the third level defined by the two focus groups. The actual implementation plan may be prolonged but this research, at a theoretical and empirical level and agreeing with the recent studies by de Sousa Jabbour et al. (2018), de Sousa Jabbour et al. (2018a), Kiel et al. (2017), Ren et al. (2019), Sivri and Oztaysi (2018), and Zhong et al. (2017), proposes the need for complete yet maturity-driven implementation approach of Industry 4.0 technologies at the three levels for achieving the goals of sustainable manufacturing and the objectives of the circular economy ReSOLVE model. For SAR following the GRI framework, even the complete implementation of the three levels of Industry 4.0 (sensing and actuation, predictive analytics capabilities, and AI-driven automation) will not be sufficient to cover all the topics in the TBLM.

The three levels of Industry 4.0 and their attributes are presented in Fig. 5. This design of Industry 4.0 indicates that Indian companies might prefer a phased approach, and there will always be differences between vendors and industrial reports and the actual field-level benefits derived from each level. The challenge highlighted by Govindan et al. (2014) may be realised if industries implement Industry 4.0 either at Level 1 only or at Levels 1 and 2.

The empirical formulation in Fig. 5 is an attempt to justify what can be expected by a particular level of investments in Industry 4.0. This formulation is an outcome of in-depth and focussed discussion by professionals in the Indian industry, who are involved in decision-making and implementation projects. Realisation of limitations of the three levels of Industry 4.0 capabilities positioned in India is a practical outcome. Further, the realisation that Industry 4.0 is not a complete solution for sustainability is also a practical outcome, as the capabilities of all the levels of Industry 4.0 are projected as contributing to a limited number of GRI disclosures under the GRI material topics. This may be a pessimistic projection, however, and hence its validity needs to be studied further in future studies. The next section presents the implications for theory and practice of the empirical formulation and these practical outcomes.

7. Implications for theory and practice

Industry 4.0 presents a significant opportunity to achieve the goals of sustainable manufacturing, and achieving the objectives of the circular economy ReSOLVE model. The recent studies by de Sousa Jabbour et al. (2018), de Sousa Jabbour et al. (2018a), Rosa et al. (2019), and Nascimento et al. (2019) presented the role of Industry 4.0 technologies in achieving different goals of circular economy. The role of IIoT and cyber physical systems is widely recognised as the most critical, but real-time visualisation, predictive analytics, and automation are recommended to approach maturity in sustainable manufacturing through gradual integration with quality management practices, and operational decision-making. This research study has elaborated that approach through an empirical formulation of three levels of Industry 4.0 implementation. To meet the empirical models presented by majority of the existing researchers (such as de Sousa Jabbour et al., 2018; de Sousa Jabbour et al., 2018a; Kiel et al., 2017; Ren et al., 2019; Sivri and Oztaysi, 2018; Zhong et al., 2017), Industry 4.0 technologies need to be implemented as a complete solution. However, when analysing in the context of measurements and reporting of sustainability variables under the GRI topics, only a partial coverage has evolved from the focus group discussion. The interview respondents have further cautioned against much optimism in investing in Industry 4.0 given that the analytics and automation parts are driven by artificial intelligence, which may take a long time to mature, provide accurate predictions, and make correct decisions. As maturity of artificial intelligence requires

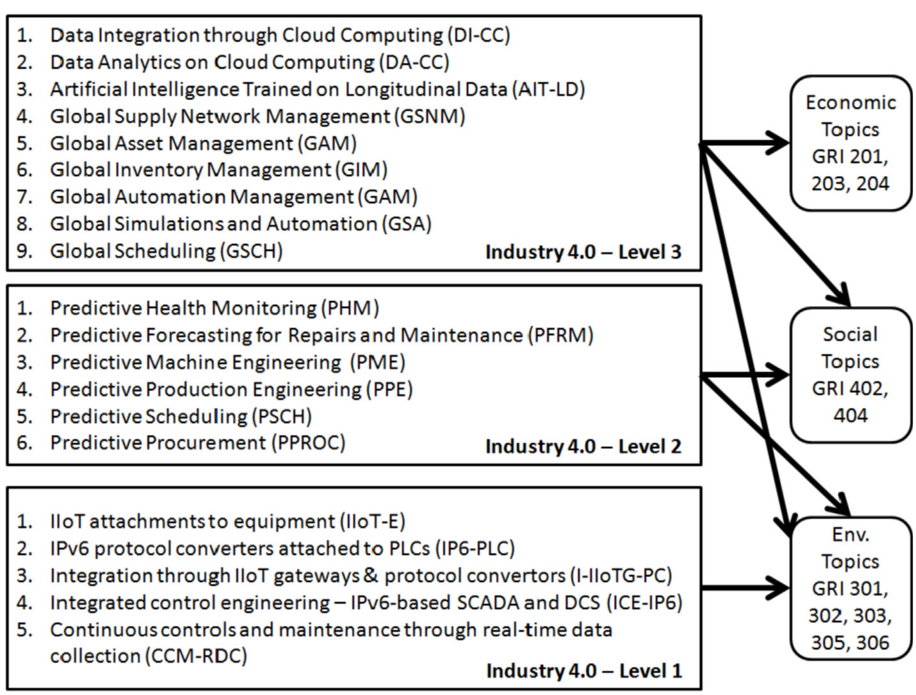

Fig. 5. Empirical formulation of contribution of attributes of cloud-based Industry 4.0 framework to GRI reporting.

training data collected from historical records, the path may be much longer for small to medium manufacturers than large companies. The lowest layer of Industry 4.0 technologies as per the empirical formulation has been mapped with measurements and reporting of environmental topics as per the GRI standard. To achieve measurements and reporting of economic and social topics, the layers of predictive capabilities and AI-driven global practices are needed, even if their maturity might take a long time.

Further, the research by Govindan et al. (2014) regarding reluctance by Indian companies in adopting new technologies and practices is reflected in the results of both focus group and interviews outcomes. Another group of researchers have tried to address this challenge through their studies on the softer aspects of achieving sustainable practices (such as: Jabbour et al., 2013; Jabbour et al., 2015; Kannan et al., 2014; Teixeira et al., 2012; Teixeira et al., 2016). These studies have found gaps in significance of human resources management in meeting sustainability goals amidst lack of appropriate content and its depth for training. To implement the empirical formulation of Industry 4.0 for SAR, the training programs need to be aligned closely with the maturity level achieved by an organisation. The depth and quality of the training content need to be enhanced continuously to meet the softer challenges in implementing Industry 4.0 for SAR. The empirical formulation may be used as a high level guideline on the way the training content needs to be enhanced with maturity when an organisation transitions from Level 1 to Level 3.

This research is based on focus group discussion and interviews involving small groups in Indian small scale industries. The solutions proposed by prominent multinational organisations in India were discussed in the focus group discussions. The perspectives evolving have some credible validation from existing research studies. However, these groups are too small to evolve recommendations having larger impacts. The perspectives may differ significantly within India and multiple other developing countries. Further, there may be differences between perspectives of manufacturing professionals in developing and developed countries. For example, in countries like China and USA having matured manufacturing practices, companies may prefer to invest in big data and artificial intelligence along with IIoT and cyber physical systems in early stages of implementation knowing the time span they need to mature through continuous data collection and training. Further, mapping of the three levels of Industry 4.0 with SAR TBLM topics under GRI framework may be more exhaustive than what has evolved in this research. However, there may be some aspects in this research achieving global acceptance. For example, the design of the three levels of Industry 4.0 technologies based on their maturity may be accepted globally after minor changes. Further, the strengths of these technologies in meeting the specified GRI TBLM topics may be accepted globally although perceived as incomplete and non-optimistic.

Future validation of the mapping of empirical formulation of Industry 4.0 levels with GRI topics may be undertaken by researchers in different economies. Varying perspectives are expected; but more importantly, the reasons for change in perspectives need to be recorded. The empirical world needs to draw a line between mere reluctance to adopt a complex technological framework like Industry 4.0 and grounded theories on why and why not a mapping between an Industry 4.0 level and a GRI topic can be validated. With the perspectives captured from multiple economies, the mappings on the either side of this line will get clearer and accepted globally.

8. Conclusion

This research presented a study of the influence of Industry 4.0 capabilities on the material topics of Global Reporting Initiative (GRI) model of sustainability reporting. Two focus groups were formed to study this topic through in-depth group discussions. The Industry 4.0 capabilities were derived in the form of attributes at three levels of implementation evident in India. The two focus groups mapped the attributes carefully with individual GRI disclosures under the GRI material topics. The final empirical formulation reflects that Industry 4.0 is not a complete solution for comprehensive GRI reporting because only a limited number of disclosure requirements can be implemented even if all the three levels of Industry 4.0 positioned in India are implemented. Further, limitations of partial implementation are clearly reflected from the final empirical formulation. Level 1 of Industry 4.0 is projected to contribute to disclosures related to five material topics under GRI 300 (environmental topics), Level 2 of Industry 4.0 is projected to contribute to disclosures related to the stated material topics under GRI 300 (environmental topics) and two material topics under GRI 400 (social topics), and Level 3 of Industry 4.0 is projected to contribute to the stated material topics in GRI 300 and GRI 400, and three material topics under GRI 300 (economic topics).

The above findings were presented to five operations heads and the questions used for focus group discussion were asked. The respondents credited IIoT and cyber physical systems to mostly environmental performance monitoring, but were not optimistic about body wearable sensors for health and safety monitoring. Especially, they cautioned against optimism in deploying AI-based predictive analytics and automation. In their view, the traditional ERP and MRP systems took ages to settle down and the Industry 4.0 technologies cannot be rushed, as well. Companies will need to set their expectations right and allow them to mature gradually.

It is difficult to judge the validity of this empirical formulation because this is a new area of research. However, the formulation appears not too optimistic when compared with the empirical results of existing studies in sustainable manufacturing and circular economy modelling. Hence, future research studies are recommended to validate the mappings in this formulation to judge its validity. There is a possibility that contributions of Industry 4.0 attributes to additional material topics and their disclosures might appear through future studies.

In India, cautious and restrictive investments for meeting triple bottom-line sustainability goals, and sustainability accounting and reporting will always be a barrier. Industry 4.0 offers dual benefits in the areas of automation and operations efficiency, and in sustainability accounting and reporting. However, the empirical formulation reveals that economic benefits will only be visible after implementing Level 3 of Industry 4.0. Hence, the usual "what-if" doubt will be a significant barrier in investing in complete implementation of 4.0. Perhaps, industries will attempt to truncate the overall framework of Industry 4.0 in their respective settings citing internal feasibility analytics. Pessimistic empirical formulations like the one derived from the outcome of this research may only add to this barrier. It is essential that the validity of this empirical formulation is tested further. If appropriate, its expansion is needed to drive better confidence in Industry 4.0 for developing capabilities for sustainable accounting and reporting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Kamlesh Tiwari: Conceptualization, Investigation, Methodology, Data curation, Writing - original draft. **Mohammad Shadab Khan:** Visualization, Formal analysis, Writing - review & editing, Validation, Supervision, Resources.

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