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Cyber-Physical Process Monitoring Systems, Real-Time Big Data Analytics, and Industrial Artificial Intelligence in Sustainable Smart Manufacturing

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ABSTRACT. The aim of this paper is to synthesize and analyze existing evidence on cyber-physical process monitoring systems, real-time big data analytics, and industrial artificial intelligence in sustainable smart manufacturing. Using and replicating data from Capgemini, Forrester, McKinsey, PwC, and World Economic Forum, we performed analyses and made estimates regarding how networked integrated production equipment and sensors and machine learning tools configure the predictive monitoring of manufacturing plants. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate.
JEL codes: E24; J21; J54; J64

Keywords: cyber-physical; process monitoring; sustainable smart manufacturing

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1. Introduction

Attaining a high level of resilience is pivotal in smart manufacturing through data acquisition and management. (Peng et al., 2021) A smart factory is a big data-driven industrial integrated networked assembly, aiming mass customization, supplying customers with sustainable items and services, and facilitating instantaneous adjustment (Costea, 2020; Konhäusner et al., 2021; Nica et al., 2018; Popescu et al., 2018) for flexible alterations of user demand, shop floor environments, and value networks. (Cohen et al., 2019) Sustainable manufacturing Internet of Things has a part in circular economic purposes by attaining social, economic, and environmental upsides. (Khan et al., 2021)

2. Conceptual Framework and Literature Review

Typified by self-control and agile adjustment to swift dynamics in intricate production environments (Bailey, 2021; Kliestik et al., 2021; Lyons and Lăzăroiu, 2020; Popescu et al., 2017a, b, c; Vătămănescu et al., 2020), sustainable manufacturing Internet of Things optimizes the reliability of production output. (Zhang and Gao, 2021) Industry 4.0-based manufacturing systems configure networked embedded smart assembly stations, cognitive reconfigurable equipment, and data-driven assemblies and parts that integrate the physical operations with virtual data to neutralize mismanagements, and optimize the production process. (Cohen et al., 2019) Predictive models are articulated within cyber-physical production systems for the monitoring of industrial plants (Croitoru and Coșciug, 2021; Kral et al., 2019; Mihăilă et al., 2016; Rowland et al., 2021), resulting in the demand for extensive supervision of model performance and pattern adjustment (Andrei et al., 2016; Dawson, 2021; Lăzăroiu et al., 2017; Pelau et al., 2021; Svabova et al., 2020) if surrounding conditions are altered and the aimed prediction precision is not satisfied. (Bachinger et al., 2021) Cyber-physical systems and Internet of Things facilitate enhanced output and time management, carrying out heterogeneous digital manufacturing processes entailing sensors and networked technologies by use of deep learning-assisted smart process planning, automated production systems, and industrial big data. (Khan et al., 2021)

3. Methodology and Empirical Analysis

Using and replicating data from Capgemini, Forrester, McKinsey, PwC, and World Economic Forum, we performed analyses and made estimates regarding how networked integrated production equipment and sensors and machine learning tools configure the predictive monitoring of manufacturing plants. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate.

4. Study Design, Survey Methods, and Materials

The interviews were conducted online and data were weighted by five variables (age, race/ethnicity, gender, education, and geographic region) using the Census Bureau's American Community Survey to reflect reliably and accurately the demographic composition of the United States. The precision of the online polls was measured using a Bayesian credibility interval. Confirmatory factor analysis was employed to test for the reliability and validity of measurement instruments. An Internet-based survey software program was utilized for the delivery and collection of responses. Panel research represents a swift method for gathering data recurrently, drawing a sample from a pre-recruited set of respondents. This survey employs statistical weighting procedures to clarify deviations in the survey sample from known population features, which is instrumental in correcting for differential survey participation and random variation in samples. Results are estimates and commonly are dissimilar within a narrow range around the actual value. If a participant began a survey without completing it, that was withdrawal of consent and the data was not used. To prevent missing data, all fields in the survey were required. Any survey which did not reach greater than 50% completion was removed from subsequent analysis to ensure quality. The data was weighted in a multistep process that accounts for multiple stages of sampling and nonresponse that occur at different points in the survey process. Test data was populated and analyzed in SPSS to ensure the logic and randomizations were working as intended before launching the survey. To ensure high-quality data, data quality checks were performed to identify any respondents showing clear patterns of satisficing (e.g., checking for high rates of leaving questions blank). The cumulative response rate accounting for non-response to the recruitment surveys and attrition is 2.5%. The break-off rate among individuals who logged onto the survey and completed at least one item is 0.2%. At each step in the survey research process, best practices and quality controls were followed to minimize the impact of additional sources of error as regards specification, frame, non-response, measurement, and processing. Question wording and practical difficulties in conducting surveys can introduce error or bias into the findings of opinion polls. The sample weighting was accomplished using an iterative proportional fitting process that simultaneously balanced the distributions of all variables. Stratified sampling methods were used and weights were trimmed not to exceed 3. Average margins of error, at the 95% confidence level, are +/-2%. The design effect for the survey was 1.3. For tabulation purposes, percentage points are rounded to the nearest whole number. Addressing a significant knowledge gap in the literature, the research has complied with stringent methodology, reporting, and data analysis requirements.

5. Statistical Analysis

Sampling errors and test of statistical significance take into account the effect of weighting. Throughout the research process, the total survey quality approach, designed to minimize error at each stage as thus the validity of survey research would be diminished, was followed. An informed e-consent was obtained from individual participants. Study participants were informed clearly about their freedom to opt out of the study at any point of time without providing justification for doing so. All data were interrogated by employing graphical and numeric exploratory data analysis methods. Descriptive analyses (mean and standard deviations for continuous variables and counts and percentages for categorical variables) were used. Descriptive statistical analysis and multivariate inferential tests were undertaken for the survey responses and for the purpose of variable reduction in regression modeling. Multivariate analyses, and not univariate associations with outcomes, are more likely to factor out confounding covariates and more precisely determine the relative significance of individual variables. Independent *t*-tests for continuous variables or chi-square tests for categorical variables were employed. To ensure reliability and accuracy of data, participants undergo a rigorous verification process and incoming data goes through a sequence of steps and multiple quality checks. Descriptive and inferential statistics provide a summary of the responses and comparisons among subgroups. Only participants with non-missing and non-duplicated responses were included in the analyses. Individuals who completed the survey in a too short period of time, thus answering rapidly with little thought, were removed from the analytical sample. Behavioral datasets have been collected, entered into a spreadsheet, and cutting-edge computational techniques and empirical strategies have been harnessed for analysis. Groundbreaking computing systems and databases enable data gathering and processing, extracting meaning through robust deployment.

6. Results and Discussion

Smart manufacturing resilience represents the capacity to predictively evaluate and organize before the unpredicted consequences, convert production capacity with respect to impact, and judiciously recycle and recondition surplus production capacity in a financially rewarding and systematized fashion. (Peng et al., 2021) Data quality and pattern interpretability (Andronie et al., 2021; Ionescu, 2020; Lăzăroiu et al., 2020; Poliak et al., 2021a, b; Valaskova et al., 2021) constitute a barrier for the broad implementation of deep learning-enabled manufacturing for concrete deployment. (Zhang and Gao, 2021) The advancement of cyber-physical system-based manufacturing requires strategies for sustainable development. (Khan et al., 2021) (Tables 1–6)

Table 1 Extensive implementation of artificial intelligence and advanced analytics has enabled industrial competitiveness in the digital era. (%, relevance)

Advanced analytics for quality monitoring	97
Digital supplier performance management	96
Fully automated inbound logistics	95
Production planning powered by advanced analytics	94
Advanced Industrial Internet of Things applied to process optimization	93
Predictive maintenance aggregating equipment and process data	95
Visual inspection powered by artificial intelligence	94
Logistics powered by real-time tracking, unmanned operations and automatic planning	95
Real-time digital performance-management system for production and maintenance	92
Robot data analytics	93
Predictive maintenance	93
Internet of vehicles-enabled fleet performance management	94
Internet of Things-enabled manufacturing quality management	92
Quality warranty reduced by advanced analytics	94
Biometric authentication for operators	93
Real-time production performance monitoring and visualization	95
Advanced analytics-based machine performance improvement	92
Deep learning image recognition to detect quality defects	93
Artificial intelligence-guided machine throughput optimization	94
Digital twin planning	92
Cycle time monitoring and visualization digital tool	91
3D digital twin for product development and testing	93
Digital twin of sustainability	91
Digitally enabled operator performance management	93
Digitally enabled equipment performance management	91
Internet of Things infrastructure for control systems	94
Digital twin to simulate customer systems	90
Internet of Things-enabled manufacturing system	93
Automated material-handling and process automation	90
Advanced analytics-enabled scheduling and dispatching	93
Real-time visibility on production network	92
Industrial Internet of Things-enabled advanced process automation	88
Vision-guided robotics order fulfillment	89
Automation of production and maintenance	86
Industrial Internet of Things-enabled smart factory	89
Deep-learning optical defect detection	87
Machine-learning predictive maintenance	87
Artificial intelligence to accelerate scaling of digital applications across fleet	86
Advanced analytics-enabled process monitoring system	87
Flexible robotics to ensure high productivity and agility for continuous new ramp-ups	87

Cloud-based digital data control enabling real-time process management	86
No-touch internal logistics automation via connected mobile robots	85
Machine learning 3D quality inspection	84
Digital maintenance system using predictive analytics	85
Al-based automatic control	86
Digital twin in production	85
Digital performance management tools	83
Control system to plan and schedule manufacturing processes from raw material to customer	86
Predictive maintenance deployment	85
Advanced analytics for quality prediction	84
Robotic process automation	85
Smart device maintenance management system	83
Digitally enabled product development	85
Real-time asset performance monitoring	82
Digital supplier quality management	82
Sensor network and data architecture	81
Real-time process monitoring and control	80
Dynamic simulations-based scheduling	82

Sources: World Economic Forum; McKinsey; our survey among 6,700 individuals conducted February 2021.

Table 2 Methods adopted to scale automation programs (%, relevance)

Systematic process redesign (modifying legacy processes by employing a combination of traditional levers, such as reduction of bottlenecks, and automation solutions, such as robotic process automation bots)	77
Human-in-the-loop solutions (training automation platforms using reinforcement learning methods over time)	72
Tactical interventions (deploying adequate solutions to address specific pain points within processes)	59
Cleansheeting and/or replatforming (building organizational processes from scratch to incorporate automation technologies)	45

Sources: McKinsey; our survey among 6,700 individuals conducted February 2021.

The capability of big data collection, inspection, and intelligent service by use of cloud-based platforms configures omnipresent networking, resilient supply, and flexible upgrading of production resources. (Peng et al., 2021) Smart manufacturing leverages deep learning, big data analytics, and operational simulations to enhance the production process in collaborative virtual enterprises by use of production equipment and sensors and machine learning prediction tools. (Bachinger et al., 2021) Aided assembly optimizes the timescale and safety of fastening and picking undertakings by use of collaborative robots, automated numeric monitoring equipment, and reconfigurable tools, all assimilated through robust supervision in an open architecture setting to manufacture a certain set of tailor-made parts, ensuring a flexible, convertible, and cost-effective production process. (Cohen et al., 2019)

Table 3 Which of the following business or operational benefits have you realized or would expect to realize by deploying edge Internet of Things for analytics? (%, relevance)

Business benefits	
Cost reduction	75
Improved security and privacy capabilities	65
Improved products/services	59
Improved use of data and analytics in business decision making	55
Improved customer experience	54
Operational benefits	
Improved real-time decision making	73
Improved business processes/operations	60
Improved visibility into processes and operations	54
Improved safety through surveillance, monitoring, and tracking capabilities	53
Automated information collection and flow between business processes	49

Sources: Forrester; our survey among 6,700 individuals conducted February 2021.

Table 4 How relevant are the following concepts for your company? (%, in use today)

Predictive maintenance	40
Big data-driven process and quality optimization	38
Process visualization/automation	36
Connected factory	35
Integrated planning	39
Data-enabled resource optimization	58
Digital twin of the factory	29
Digital twin of the production asset	27
Digital twin of the product	26
Autonomous intra-plant logistics	25
Flexible production methods	25
Transfer of production parameters	24
Modular production assets	27
Fully autonomous digital factory	19

Sources: PwC; our survey among 6,700 individuals conducted February 2021.

Table 5 Organizations’ focus on manufacturing intelligence. (%, relevance)

Our analytics platforms are specialized by area (process or product family, quality, maintenance, energy, etc.).	57
We have a horizontal data collection and aggregation platform.	55
Cloud reversibility (option to modify or roll back solutions in cloud) is critical for our smart factory initiatives.	53
We have an end-to-end integrated platform from device to analytics.	49

Sources: Capgemini; our survey among 6,700 individuals conducted February 2021.

Table 6 How companies can increase operational flexibility and start achieving impact at scale by use of Industrial Internet of Things (%, relevance)

Off-the-shelf Industrial Internet of Things tools support the continuation of operations with fewer employees on site, since they facilitate remote work in direct and indirect functions.	97
With machine breakdowns Industrial Internet of Things tools can receive input from sensors that help pinpoint problems, such as broken components or oil leakage, that could interfere with production.	96
Industrial Internet of Things-based software solutions can provide a real-time dashboard of key performance indicators to support shop-floor performance dialogs, increasing transparency, allow the tracking of improvement actions, and send alerts to operators via mobile devices.	94
Similar to inventory management, Industrial Internet of Things can provide transparency about the waste created during the production and its root cause.	93
For mass production, companies can achieve significant savings by installing basic measurement devices, such as scales and in-line sensors that send information via Industrial Internet of Things.	95
Industrial Internet of Things tools can help companies optimize procurement by using real-time information on inventory levels and production capacity to determine what quantities must be ordered and assist with rapid contract renegotiations.	92
Industrial Internet of Things-enabled pricing tools can analyze data on supply and demand from connected assets in near-real or real time, including information on stock levels, available capacity, production schedules, and anticipated delivery dates.	91
Industrial Internet of Things facilitates real-time data exchange between all supply-chain participants, creating an integrated view of production programs, scheduling, inventories, quality, and anticipated delivery times.	94
Industrial Internet of Things can increase production efficiency of single machines or entire production lines by using advanced analytics to optimize process parameters.	92

Sources: McKinsey; our survey among 6,700 individuals conducted February 2021.

Industrial Internet collects data throughout a significant span by use of omnipresent sensing and cross-domain networking, covering the manufacturing terminal input from processing machines and autonomous robots, tracking and collecting real-time information. (Peng et al., 2021) The complex environment application prospects, machine learning harnessing, hardware-restricted Industrial Internet of Things platforms, and the heterogeneity of enterprise systems necessitate sound and error resilient ways out, enabling the automated adjustment of predictive models. (Bachinger et al., 2021) The design and management of Internet of Things-based decision support systems configure a streamlined, dynamic, and modular manufacturing of customized items by use of sustainable Industry 4.0 technologies through monitoring algorithms and upgrading models. (Cohen et al., 2019)

7. Conclusions, Implications, Limitations, and Further Research Directions

Deep learning algorithms develop the state of technology for data-driven supervision, diagnosis, and prognosis. (Zhang and Gao, 2021) Smart production processes necessitate heterogeneous networked patterns of distinct components to simulate and monitor the entire operations, and to configure the predictive monitoring of manufacturing plants. (Bachinger et al., 2021) This article focuses only on cyber-physical process monitoring systems, real-time big data analytics, and industrial artificial intelligence in sustainable smart manufacturing. Limitations of this research also include a convenient sample, small sample size, and cross-sectional data collection, thus limiting generalizability. Certain variables were dichotomized because of small cell sizes throughout the analysis. The sample size and the richness of the cohort study dataset enable the control for numerous potential confounders in the multivariable analysis, and provide novel data on the topic. More data gathered either cross-sectionally or longitudinally that utilize larger study populations are required to check and support the conclusions drawn in this study. Further research should consider artificial intelligence-driven big data analytics, real-time sensor networks, and product decision-making information systems in sustainable manufacturing Internet of Things.

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Research method
Cross-sectional design using self-report questionnaires.

Data analysis
The gathered data were entered into a spreadsheet and analyzed.

Compliance with ethical standards

Ethical approval
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent
The ethical consequences of this research have been carefully considered. Best practices have been respected so as to inform the participants and protect the data and integrity of the interviewees whose participation was voluntary and who were given a plain language document with information as regards the research. The data have been processed in a way that ensures appropriate security of personal data against unauthorized or unlawful processing, accidental loss, destruction or damage, employing appropriate technical or organizational measures. All the information provided by the interviewees has been anonymized for confidentiality reasons.

Animal studies statement verification
This article does not require animal studies verification.

Code availability
This project has employed statistical analytical techniques standard in all statistical packages.

Data and materials availability
All research mentioned has been published and datasets used and analyzed during the current study are available from respective outlets. All raw, results, and key source data supporting the conclusions, statistics, models, and codes generated or used during the study appear are provided with this article. Note: The publisher is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing content) should be directed to the corresponding author for the article. Other modeling input assumptions are available on reasonable request.

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Author contributions
All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication. The authors take full responsibility for the accuracy and the integrity of the data analysis.

Conflict of interest statement
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Disclosure by the editors of record
The editors declare no conflict of interest in the review and publication decision regarding this article.

Transparency statement
The authors affirm that the manuscript represents an honest, accurate, and transparent account of the research being reported, that no relevant aspects of the study have been left out, and that any inconsistencies from the research as planned (and, if significant, registered) have been clarified.

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