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Cyber-Physical Process Monitoring Systems, Artificial Intelligence-based Decision-Making Algorithms, and Sustainable Industrial Big Data in Smart Networked Factories

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ABSTRACT. This paper analyzes the outcomes of an exploratory review of the current research on cyber-physical process monitoring systems, artificial intelligence-based decision-making algorithms, and sustainable industrial big data in smart networked factories. The data used for this study was obtained and replicated from previous research conducted by Algorithmia, Capgemini, Forrester, Management Events, and PwC. We performed analyses and made estimates regarding how big data-driven algorithms and tools can enable product realization by use of networks of smart connected devices and sensors, pattern-detecting decision-making equipment, and machine learning-based tools, leading to precise and real-time data gathering and analysis, while big data analytics applications across industrial plants are decisive in configuring digital manufacturing options for automated production. Data collected from 5,600 respondents are tested against the research model. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate.
JEL codes: D53; E22; E32; E44; G01; G41

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1. Introduction

Industry 4.0-related digitalization processes have led to disruptive breakthroughs across cyber-physical system-based manufacturing. (Tortorella et al., 2021) Big data-driven algorithms and tools can enable product realization by use of available industrial plant resources while reducing manufacturing, planning, and logistics expenses. (Saniuk et al., 2021) Industry 4.0 furthers digital manufacturing options for automated production, integrating the deployment of networked technologies to share data to processing stations and of cloud-based computational resources in input mining. (Turner et al., 2021)

2. Conceptual Framework and Literature Review

Industry 4.0-based manufacturing systems enable the production of inexpensive customized items swiftly through a gradual productivity and efficiency optimization. (Saniuk et al., 2021) Big data analytics and circular economy performance can shape sustainable manufacturing. (Awan et al., 2021) Industry 4.0 automation systems require technological and organizational reconfiguration, digitalization, and interconnection. (Cirillo et al., 2021) The networking of ubiquitous edge computing and blockchain technologies is pivotal in Industrial Internet of Things applications. (Yu et al., 2021) Smart manufacturing systems can organize, develop, and adapt an elaborate production process coherently (Adams et al., 2021; Dușmănescu et al., 2016; Lăzăroiu et al., 2019; Vătămănescu et al., 2020), enhancing the synergistic design of manufacturing resources on industrial plants. (Wang et al., 2021) Precise and real-time data gathering and analysis are crucial in the sustainable performance of manufacturing processes (Barbu et al., 2021; Kovacova et al., 2018; Novak et al., 2021; Stefko et al., 2019) throughout smart and collaborative production and logistics environments by use of predictive maintenance.

3. Methodology and Empirical Analysis

The data used for this study was obtained and replicated from previous research conducted by Algorithmia, Capgemini, Forrester, Management Events, and PwC. We performed analyses and made estimates regarding how big data-driven algorithms and tools can enable product realization by use of networks of smart connected devices and sensors, pattern-detecting decision-making equipment, and machine learning-based tools, leading to precise and real-time data gathering and analysis, while big data analytics applications across industrial plants are decisive in configuring digital manufacturing options for automated production. Data collected from 5,600 respondents are tested against the research model. 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.

⬇

Data sources: Algorithmia, Capgemini, Forrester, Management Events, and PwC.
Study participants: 5,600 individuals provided an informed e-consent.

⬇

All data were interrogated by employing graphical and numeric exploratory data analysis methods. 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. An Internet-based survey software program was utilized for the delivery and collection of responses. 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). Sampling errors and test of statistical significance take into account the effect of weighting. 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. 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%.

⬇

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. Addressing a significant knowledge gap in the literature, the research has complied with stringent methodology, reporting, and data analysis requirements.

Flow diagram of study procedures

5. Statistical Analysis

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. Independent *t*-tests for continuous variables or chi-square tests for categorical variables were employed. 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.

⬇

Mean and standard deviation, *t*-test, exploratory factor analysis, and data normality were inspected using SPSS. 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. AMOS-SEM analyzed the full measurement model and structural model.

⬇

Panel research represents a swift method for gathering data recurrently, drawing a sample from a pre-recruited set of respondents. 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. Non-response bias and common method bias, composite reliability, and construct validity were assessed. Results are estimates and commonly are dissimilar within a narrow range around the actual value.

Flow diagram of statistical parameters and reproducibility

6. Results and Discussion

Machine learning-based software systems can transfer real-time decision-making performance to integrating plant automation. (Turner et al., 2021) Smart products with embedded intelligence, sensor-fusion for big data-driven machining and analysis (Pelau et al., 2021; Poliak et al., 2021; Wallace and Lăzăroiu, 2021), conjoint intelligent process planning and scheduling (Andronie et al., 2021a, b, c; Kafel et al., 2021; Nica et al., 2020; Popescu et al., 2018), and preventative and predictive maintenance of production machinery (Andrei et al., 2016a, b; Ginevicius et al., 2020; Lu et al., 2020) are pivotal in agent-based collaborative cyber-physical process monitoring systems by use of cognitive automation. (Tables 1–9)

Table 1 Expected benefits of Internet of Things investments.
Select all that apply. (%)

Improved customer service quality	62
Creation of new digital products and services	59
Creation of new business models and revenue streams	55
Improved decision making through the efficient use of data	53
Reduced operational costs	49

Sources: Management Events; our survey among 5,600 individuals conducted November 2020.

Table 2 Artificial intelligence's potential to increase efficiencies
with automated communications (%, relevance)

Virtual personal assistants	61
Automated data analysts	59
Automated communications like email and chatbots	57
Automated research reports and information aggregation	55
Automated operational and efficiency analysts	52
Predictive analytics	50
Systems used for decision support	49
Robotics	47
Automated sales analysts	45
Machine learning	42

Sources: PwC; our survey among 5,600 individuals conducted November 2020.

Table 3 The impact of machine learning operations on organizations (%, relevance)

Improving customer experience	95
Automating processes	94
Generating customer insights and intelligence	93
Increasing long-term customer engagement	93
Generating financial insights	91
Acquiring new customers	92
Interacting with customers	91
Increasing customer loyalty	92
Managing logistics	90
Retaining customers	89
Supply chain optimization	87
Building brand awareness	86
Detecting fraud	85
Reducing costs	87
Back office automation	84
Financial planning	85
Recommender systems	86
Managing inventory	84
Reducing customer churn	87

Sources: Algorithmia; our survey among 5,600 individuals conducted November 2020.

Table 4 Incorporating edge Internet of Things for analytics can help organizations overcome the limitations of a fully centralized analytics approach (%, relevance)

Many organizations embrace Internet of Things solutions to optimize operational processes, differentiate products and services, and enhance digital capabilities.	95
Many firms use cloud platforms to analyze their Internet of Things data by applying advanced analytics models and leveraging clouds' extensive processing power, connectivity, and storage capabilities.	94
Internet of Things solutions often enable digital transformation by extending software control of physical assets and providing a rich source of data including location, status, and presence of connected assets, products, and processes.	94
Internet of Things provides opportunities to optimize assets, differentiate products, and reimagine business models for strategic advantage.	93
Manufacturers can use Internet of Things-enabled quality and compliance solutions to analyze machine data and external data in real time to help deliver actionable insights, limit exposure, and reduce the impact of compliance and quality issues that arise in the manufacturing plant.	92
Edge computing refers to moving compute as close to the data sources as is necessary and feasible, enabling real-time decisions and insights to drive better outcomes.	94
Enterprises in various industries are proactively deploying a diverse array of Internet of Things use cases to enable digital transformation initiatives which address mission critical processes, enhance operations, and differentiate customer relationships.	93

Sources: Forrester; our survey among 5,600 individuals conducted November 2020.

Big data analytics can network data management effectiveness and circular economy operations by use of Internet of Things-based real-time production logistics, deep learning-assisted smart process planning, artificial intelligence-based decision-making algorithms in cyber-physical system-based smart factories. (Awan et al., 2021) Technological change can be strategically deployed by industrial plants to configure a lean system and a robust, demand-led, manufacturing flow through cyber-physical system-based real-time monitoring and artificial intelligence-driven big data analytics. (Cirillo et al., 2021) When a manufacturing process is disrupted by unpredictable situations (e.g., machine failure, order modification, and transitory insertion), production systems can react instantaneously and carry out distinct manufacturing tasks. (Wang et al., 2021) Smart connected devices and operational processes, advanced production scheduling, equipment maintenance, and remote operation and maintenance services are decisive in optimized resource sharing through automated data collection. The manufacturing process can be integrated and networked by use of deep learning-based algorithms, digital data flows, computer vision technologies, and artificial intelligence-assisted process automation.

Table 5 Internet of Things, big data, and automation can be the catalyst for a smarter and sustainable supply chain future. (%, relevance)

Automation of tasks through robotic process automation and machine learning will be key to reduce processing errors and cut overall costs.	95
Global supply chain management adopts data-driven technology to further improve its supply chain monitoring and overall performance.	94
Data-driven supply chain management plays a pivotal role in boosting operational efficiency and reducing overall costs.	94
With real-time or near-real-time data on dynamic pricing, dynamic sales data, weather patterns, and product quality testing and dynamic replenishment, organizations are able to extrapolate trends, better understand future scenarios and make profitable recommendations.	93
Automation of time-consuming, repetitive, and lower-value processes can be a massive boon for organizations by integrating robotic process automation and machine learning into their systems.	93
The data captured from Internet of Things provide real-time tracking and monitoring of assets through continuous feedback loops, giving asset-intensive organizations the ability to link data across enterprises and to suppliers.	91

Sources: Management Events; our survey among 5,600 individuals conducted November 2020.

Table 6 Share of organizations with advanced data capabilities. Select all that apply. (%)

We can store, retrieve and analyze the data at all levels of the value chain.	62
We have the required methods and tools to scan and create digital mock-ups of our existing assets.	57
We have established a data governance framework governing the data flow, access control, and data retention.	55
We have accurate digital mock-ups of our plants.	54
We have complete view of the data flows across all processes and all IT-OT systems.	52

Sources: Capgemini; our survey among 5,600 individuals conducted November 2020.

Table 7 Organizations that have mastered their smart factory transformation. (%)

The level of scalability of the technologies or platforms

Robotics/Cobotics	91
Analytics and artificial intelligence	89
Track-and-trace technologies	87
Industrial Internet of Things systems	85
Remote monitoring	84

The level of benefits from the technologies or platforms

Robotics/Cobotics	92
Analytics and artificial intelligence	91
Track-and-trace technologies	90
Industrial Internet of Things systems	91
Remote monitoring	89

Sources: Capgemini; our survey among 5,600 individuals conducted November 2020.

Table 8 Applying automation and robotics to increase cost efficiency and enable accuracy (%, relevance)

Reusable code and functionality are helping enterprises deal with massive spikes in volumes of calls, emails and forms.	89
During a period of high operational pressure and changing production levels, the accelerated adoption of flexible robotics, additive manufacturing, and other automation tools can improve the efficiency of standard processes and speed up output levels and shift product mix at reasonable cost.	88
Robotic process automation solutions can help in achieving higher productivity by enabling highly accurate data entry, taking over repetitive tasks and freeing up personnel capacities for value-adding activities.	85

Sources: PwC; our survey among 5,600 individuals conducted November 2020.

Table 9 How relevant are the following concepts for your company? (%, in use today)

Predictive maintenance	43
Big data-driven process and quality optimization	40
Process visualization/automation	39
Connected factory	38
Integrated planning	41
Data-enabled resource optimization	59
Digital twin of the factory	33
Digital twin of the production asset	30
Digital twin of the product	28
Autonomous intra-plant logistics	27
Flexible production methods	26
Transfer of production parameters	25
Modular production assets	24
Fully autonomous digital factory	22

Sources: PwC; our survey among 5,600 individuals conducted November 2020.

Big data analytics applications across industrial plants are decisive in configuring digital transformation and advancing and analyzing data insights as regards circular economy capabilities (e.g., manufactured item design, optimization of product-to-service strategies, and fashioning reverse logistic business models) by use of artificial intelligence data-driven Internet of Things systems, Internet of Things smart devices, robotic wireless sensor networks, and cyber-physical system-based real-time monitoring. (Awan et al., 2021) Concerning human–machine networking and personnel's authority to discontinue manufacturing operations, Industry 4.0 decreases employees' self-governance and consolidates ways of management supervision. (Cirillo et al., 2021) Artificial intelligence-based decision-making algorithms can replicate the task execution operation, identify anomalous conditions throughout the production process, and recreate the undertaking execution procedures to detect possible issues in advance. (Wang et al., 2021)

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

Big data-driven algorithms and tools can enable product realization by use of networks of smart connected devices and sensors, pattern-detecting decision-making equipment, and machine learning-based tools, leading to precise and real-time data gathering and analysis, while big data analytics applications across industrial plants are decisive in configuring digital manufacturing options for automated production. This article focuses only on cyber-physical process monitoring systems, artificial intelligence-based decision-making algorithms, and sustainable industrial big data in smart networked factories. 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 robotic wireless sensor networks, industrial artificial intelligence, and deep learning-assisted smart process planning in sustainable cyber-physical manufacturing systems.

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

Data analysis
The gathered data were entered into a spreadsheet and analyzed. The analytical procedures included heterogeneous descriptive statistics for all employed variables in the tables.

Software information
To process and inspect the collected data, IBM SPSS 24 and AMOS 20 tools were used.

Survey result aggregation
Responses were classified into categorical variables for quantitative analysis.

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

Regression analysis and significance testing

Throughout this research, regression analysis was employed to report on the statistically relevant features (independent variables) of survey respondents with regard to key question responses (dependent variables). The survey analysis required the configuration of various socioeconomic respondent categories from demographic data. Consistency was checked by applying reverse coding to some items. Statistical remedies after data gathering were carried out to evaluate potential common method errors (e.g., Harman's single factor test, partial correlation procedures, and checking the consequences of unassessed latent methods factors).

Data and materials availability

All research mentioned has been published and datasets used and inspected 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, together with the details of the study design and the procedures for information analysis, 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.

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. 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. 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. 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. 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. 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.

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

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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
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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. The study questionnaires were carried out in an inclusive manner.

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