

Autonomicity in Cyber-Physical Systems: Proposing a Theoretical Concept and a Scale Divided into Levels of Automation

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Abstract

The rapid advancement of Industry 4.0 has positioned Cyber-Physical Systems (CPS) as key enablers of intelligent and autonomous manufacturing. While automation and autonomy are widely discussed, the concept of autonomicity—the system's ability to self-manage, adapt, and make decisions independently—remains theoretically underdeveloped and lacks a structured framework for assessment. This study addresses this gap by defining the concept of autonomicity in CPS and proposing a five-level evaluation scale. A theory development approach was adopted, supported by a systematic literature review and a bibliometric analysis conducted using the Scopus database and VOSviewer software. The resulting scale classifies CPS autonomicity from total human dependence to full self-management, incorporating criteria such as AI capabilities, self-learning, fault tolerance, and autonomous decision-making. The findings contribute to both theory and practice by refining the conceptual understanding of CPS autonomicity and offering a structured tool for its assessment. This work provides a foundation for future empirical research and supports strategic planning in autonomous industrial environments.

Keywords- Industry 4.0, Cyber-physical systems, Autonomicity, Automation levels, Internet of things (IoT).

1. Introduction

The global technological landscape has undergone a profound transformation in recent years, driven by the emergence of disruptive digital technologies and the widespread integration of computational intelligence into everyday life. Innovations such as smartphones, smart TVs, autonomous vehicles, and integrated information systems exemplify the digital convergence that has reshaped how individuals and industries interact with technology (Cavata et al., 2020). Within this evolving context, enterprises face increasing competitive pressure to enhance operational efficiency and respond to market demands with greater agility. In response, Industry 4.0 (I4.0) technologies have become instrumental, instrumental in reducing operational costs and cycle times while simultaneously fostering innovation and productivity (He & Jin, 2016).

Recognized as the core of the Fourth Industrial Revolution, I4.0 represents a paradigm shift in manufacturing, characterized by the transition from partially automated to fully digitized and intelligent production environments (Nafich & Mohelská, 2020). This shift is underpinned by an array of advanced technologies, including Big Data, autonomous robotics, the Internet of Things (IoT), cybersecurity, cloud computing, 3D printing, and augmented reality (Faria et al., 2019). Among these, CPS play a central role, acting as the interface between the physical and digital domains. CPS integrate mechanical components with embedded computational intelligence and communication capabilities, enabling real-time sensing,

actuation, and autonomous control (Zheng et al., 2021).

In this environment, CPS are often organized into Cyber-Physical Production Systems (CPPS), where interconnected sensors and intelligent machines form autonomous production ecosystems capable of self-monitoring and adaptation (Salazar & Heuser, 2022). Through sophisticated architectures and control algorithms, CPS are expected to evolve in terms of scalability, resilience, security, and performance—surpassing traditional embedded systems in responsiveness and intelligence (Hu et al., 2021).

Despite the extensive focus on automation and autonomy in CPS, the notion of autonomicity—defined as a system's capacity to self-manage, self-optimize, and make independent decisions—remains conceptually underdeveloped in the current literature (Sanchez et al., 2020). Autonomicity is not merely a synonym for automation or autonomy; it encompasses a higher-level capability for self-regulation, learning, and adaptation in dynamic and uncertain environments.

In this context, the lack of a standardized framework for assessing different levels of autonomicity in CPS represents a critical gap in both academic research and industrial practice. Without a structured understanding of how CPS evolve from fully dependent to fully autonomous behavior, it becomes difficult to guide technological implementation and strategic decision-making in I4.0 ecosystems.

Accordingly, this study seeks to address the following research questions:

- (1) How can the concept of autonomicity be theoretically delineated within the context of Cyber-Physical Systems (CPS), and what are its defining characteristics?
- (2) What methodological framework can be employed to develop and validate a robust scale for assessing varying levels of autonomicity in CPS?

To address these questions, this study adopts a theory development approach, which enables both the conceptual clarification of autonomicity and the structured construction of a scale for its assessment in CPS. Specifically, the research aims to construct a theoretical concept of autonomicity and propose a five-level assessment scale, grounded in a systematic and bibliometric literature review. The main contributions include: (i) the development of a structured framework to define and assess CPS autonomicity; (ii) the proposition of a conceptual model integrating CPS, IoT, and I4.0 enablers; and (iii) the design of a preliminary diagnostic tool for classifying CPS according to their level of autonomous behavior.

The structure of this paper is organized as follows. Section 2 outlines the research methodology, including the theory development approach and the bibliometric analysis procedures employed to support the conceptual foundation. Section 3 presents the theoretical background, discussing key constructs such as autonomicity, I4.0, CPS, and IoT, and culminates with a proposed conceptual model that integrates these elements. Section 4 proposes a theoretical definition of autonomicity specifically tailored to CPS and details the conceptual development process that supports the construction of the assessment framework. Section 5 introduces the proposed five-level autonomicity scale, describing its structure, components, and functionalities, followed by a critical discussion of its theoretical and practical implications. Finally, Section 6 presents the study's conclusions, summarizes its main contributions, addresses its limitations, and offers directions for future research.

2. Materials and Methods

In response to the research questions outlined above, this study adopts the Theory Development approach. As emphasized by Gregor (2006), this approach plays a fundamental role in advancing scientific knowledge by enabling the creation of robust explanatory models that can be empirically tested and applied across

diverse fields. It is characterized by the systematic construction and refinement of conceptual frameworks through critical analysis of both emerging and consolidated ideas.

According to Lynham (2002), theory development unfolds through the stages of conceptualization, operationalization, and iterative refinement of theoretical constructs. In this study, these stages guided the definition of the concept of autonomicity and the development of a multi-level scale for assessing the degree of autonomy in CPS, ensuring both theoretical depth and practical applicability.

The theoretical development undertaken here is grounded in a structured literature review that seeks not only to synthesize existing knowledge but also to highlight conceptual gaps and future directions. Creswell and Clark (2017) argue that theory development involves the formulation of propositions or hypotheses that emerge from an extensive review of the literature. Such reviews serve to identify unresolved questions in the field and inspire the development of innovative frameworks that address these deficiencies.

To support the theoretical proposition of autonomicity in CPS, a bibliometric analysis was conducted using the Scopus database, a comprehensive and authoritative source of peer-reviewed literature (Harzing & Alakangas, 2016). The analysis focused on publications from 2012 to 2022, allowing a longitudinal perspective on the development of the field (Mariano et al., 2015). Only scientific journal articles were included; other types of publications such as thesis, dissertations, and conference proceedings were excluded. The selection process followed a predefined set of keywords associated with CPS and autonomicity to ensure the relevance and accuracy of the data corpus.

The bibliometric analysis utilized key indicators to characterize the field, including publication growth over time, most cited authors and collaboration networks, leading journals, keyword cooccurrence patterns, and impact indices such as citation counts and journal impact factors. These metrics allowed for the identification of research trends, influential contributors, and emergent themes over the last decade. As highlighted by López et al. (2019), bibliometric methods have become increasingly relevant for measuring research productivity, quality, and evolution.

The analysis was supported by VOSviewer, a software tool developed by Waltman and Van Eck, known for its capacity to generate visual representations of bibliometric networks. VOSviewer's interface enables the identification of relationships such as co-citation, co-authorship, and term cooccurrence. It also allows for the clustering of keywords into thematic groups represented by different colors, with the size of each node indicating frequency of occurrence (Agudo et al., 2022).

In this study, VOSviewer version 1.6.18 was employed under the following configuration (Van Eck & Waltman, 2022): data were extracted from the Scopus database; the period of analysis was 2012–2022; the type of analysis was cooccurrence of terms from titles and abstracts; the normalization method applied was the force association method; and the minimum threshold for term inclusion was five occurrences.

In addition to bibliometric mapping, the research also incorporated a longitudinal analysis aimed at identifying shifts in thematic focus over time. Results indicate that earlier publications (2012–2016) concentrated primarily on the structural and architectural aspects of CPS. In contrast, more recent studies (2017–2022) increasingly address issues related to artificial intelligence and cybersecurity, revealing the dynamic evolution of research interests within the field. This temporal segmentation was crucial to understanding the transformation of scientific discourse over time (Mariano et al., 2015).

The literature review followed a systematic protocol based on the methodology proposed by Junior and Filho (2010), and refined by Mariano et al. (2015). This protocol includes: the identification of relevant literature through predefined keywords in selected databases; filtering based on abstract analysis; the construction of a classification system to encompass the main dimensions of the research topic; and the synthesis of scientific output, highlighting major findings, challenges, and opportunities. This method enabled a clear mapping of the current state of research and provided a foundation for the next stages of this study.

A mind map was developed to illustrate the methodological flow of the bibliometric review, depicting each step taken in the initial phase of the research (**Figure 1**). This figure helps clarify the logic and progression of the methodological approach adopted in this work.

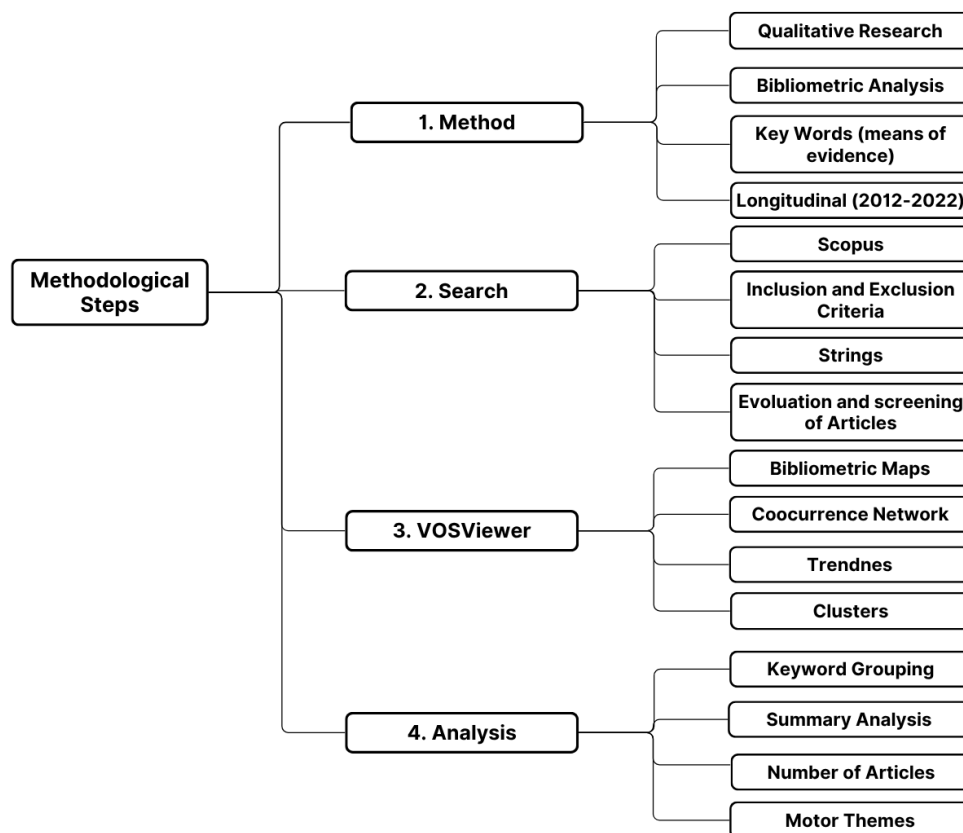


Figure 1. Methodological steps. Source: by the author (2025).

It is important to note that the bibliometric analysis presented here constitutes the first phase of a broader research agenda. Based on the results of this phase, it is possible to define the concept of autonomicity in CPS and proceed to the development of a multi-level evaluation scale. In the next stages of the research, this work will advance toward the creation of a matrix of relationships between system components and the design of an empirical instrument to assess CPS autonomicity. The complete methodological roadmap—including past, current, and future phases—is illustrated in **Figure 2**.

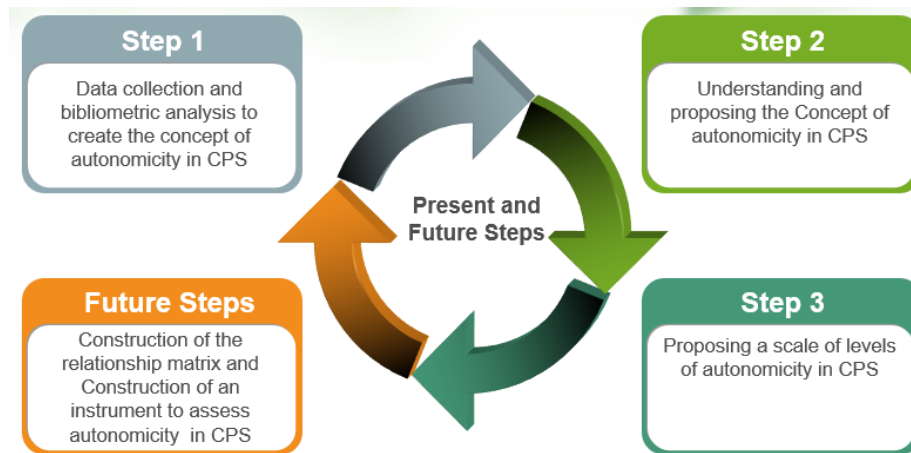


Figure 2. Present and future research stages. Source: by the author (2025).

Finally, the process of theoretical development carried out in this study aims to provide the conceptual foundation for the autonomicity scale in CPS. This scale represents the main theoretical and methodological contribution of the article, offering a structured tool to guide future research and practical implementation in the field of CPS.

3. Emerging Themes for Autonomy in Cyber-Physical Systems (CPS)

3.1 Autonomicity

The concept of autonomy has become increasingly prominent in scientific and industrial domains, particularly in light of the growing sophistication of Artificial Intelligence (AI) applications at both subsystem and system levels. An autonomous system is defined as one capable of operating independently from initiation to completion, without the need for human intervention. The etymology of "autonomy" traces back to "autonomous" and finds metaphorical resonance in biology—specifically, in the functioning of the Autonomic Nervous System, known for generating involuntary responses (Janiesch et al., 2020).

Traditionally, autonomy has been interpreted as a system's capacity for self-regulation. However, this broad interpretation often leads to confusion between automation and true autonomy. Systems that merely follow predefined routines are frequently mislabeled as autonomous. In contrast, genuine autonomy involves self-governance and self-direction, encompassing advanced capabilities such as self-healing, self-protection, self-configuration, and self-optimization (Janiesch et al., 2020).

This distinction is further emphasized by Sanchez et al. (2020), who argue that while automation focuses on reducing human intervention, autonomy implies situational awareness and responsiveness to real-world consequences based on practical data or models. Autonomous systems thus extend beyond data processing and decision modeling, necessitating an ongoing debate about how autonomy should be defined and measured across diverse technological fields.

In this context, the term autonomicity, borrowed from the biological sciences, has been adapted to information technology to denote systems with the capacity for self-management. Such systems can recover autonomously from failures, defend against cyber threats, reconfigure based on environmental stimuli, and enhance their own performance (Sterritt & Hinchey, 2005). Colman (2007) adds that autonomicity should be understood less as an intrinsic property of system components and more as an emergent attribute resulting from their interrelationships.

From a software engineering perspective, autonomicity also serves as a metric to gauge the extent of a system's autonomous functionalities. Dehraj and Sharma (2020) assert that understanding and quantifying these capabilities is critical for fostering user trust in autonomous applications.

The automotive industry, while not typically using the term "autonomicity," offers practical examples of its implementation. Vehicles can range from fully manual to entirely self-managed systems. Frameworks like SAE J3016 have become standard references for classifying levels of vehicular autonomy (Hopkins & Schwanen, 2021). The evolution of this classification system reflects the broader maturation of knowledge in this domain. As Varga (2017) highlights, autonomous vehicles promise several societal benefits, including improved mobility for vulnerable populations, optimized traffic flow, decreased urban congestion, and enhanced fuel efficiency.

Common to both the information technology and automotive sectors is the recognition that autonomic systems must possess the ability to self-configure. This adaptation may result from direct human input—particularly from experienced operators—or arise from the system's capacity to learn from contextual variables (Hopkins & Schwanen, 2021). Nevertheless, as Colman (2007) reminds us, even the most advanced models remain limited in their predictive power, as many variables and scenarios can only be addressed through exposure in real-world contexts.

This evolving understanding of autonomicity serves as a foundational element for interpreting the technological advancements introduced by I4.0. As industrial systems increasingly incorporate interconnected devices, intelligent automation, and real-time data processing, the demand for autonomous capabilities becomes more pressing. In this context, autonomicity not only underpins the operational logic of CPS, but also plays a pivotal role in enabling the self-managing, adaptive, and resilient infrastructures envisioned within I4.0 paradigms.

3.2 Industry 4.0

The concept of I4.0, formally introduced at the Hannover Messe in 2011, represents a transformative evolution in manufacturing and production systems. By leveraging advanced digital technologies, I4.0 redefines industrial efficiency, adaptability, and resource optimization through the digitization of entire value chains (Liao et al., 2018). It initiates a dynamic shift from traditional production models to integrated, intelligent, and autonomous systems.

According to Delke et al. (2023), this paradigm shift is propelled by technologies such as digitization and robotization, which reshape organizational interconnectivity and generate wide-reaching economic and societal impacts. I4.0 fosters a systemic transformation that extends beyond technological adoption, demanding the reconfiguration of managerial, operational, and strategic dimensions within organizations.

I4.0's core lies in the integration of advanced technologies—including CPS, the Internet of Things (IoT), and Cloud Computing—into production environments. These technologies enhance the performance and responsiveness of industrial systems, allowing for real-time data acquisition, process optimization, and decentralized decision-making (Sony, 2018; Sitepu et al., 2020). The concept of the "smart factory" encapsulates this transformation, wherein interconnected machines, products, and systems collaborate to achieve high levels of automation, flexibility, and customization (Rossini et al., 2019).

Nonetheless, despite its disruptive potential, the practical implications and conceptual boundaries of I4.0 are not always fully grasped. According to Shafiq et al. (2015), the depth of its integration and its impacts

on industrial practices often remain ambiguous, underscoring the need for clearer frameworks and definitions.

Technologies such as Digital Twins (DT), Virtual Reality (VR), and Smart Objects contribute significantly to this innovation landscape. DTs enable the virtual simulation of CPS, enhancing predictive capabilities and system resilience, while VR offers immersive visualization of industrial environments. Together with Big Data analytics and intelligent automation, these tools expand the possibilities of sustainable and collaborative production systems (Gutiérrez et al., 2023; Jabbour et al., 2018).

Junior et al. (2018) emphasize that I4.0 should be understood as an emergent and evolving concept within production systems, one that depends on the seamless convergence of technologies to generate intelligent, autonomous, and responsive environments. Recent global events—such as the Barcelona New Economy Week (Bnew, 2024)—illustrate this trajectory by showcasing the role of digital transformation and technological convergence in shaping the future of manufacturing.

However, the realization of I4.0's full potential depends not only on the adoption of advanced technologies but also on the organizational capacity to effectively implement and manage them. As Delke et al. (2023) notes, successful integration demands competent professionals and strategically aligned implementation processes. Biazi & Marques (2023) further argue that the capacity to collect, analyze, and act upon real-time data requires leadership capable of navigating dynamic contexts, demonstrating self-regulation, cognitive flexibility, and rapid value signal adaptation.

Finally, Wagner et al. (2017) highlight that the effective deployment of I4.0 technologies requires an initial evaluation of each organization's sociotechnical baseline, the integration of innovation within lean production systems, and the continuous adaptation of business processes to technological evolution.

Building on the transformative potential of I4.0, the integration of CPS represents a crucial pillar in achieving intelligent and autonomous industrial environments (Tancredi et al., 2022). CPS serve as the backbone for the realization of smart factories, enabling seamless interaction between computational elements and physical processes. Their capability to sense, analyze, and respond autonomously within dynamic contexts underscores the increasing importance of autonomic features in modern industrial systems. The following section delves deeper into the emerging characteristics of CPS and explores how these systems embody and extend the concept of autonomic behavior within I4.0 frameworks.

3.3 CPS - Cyber Physical Systems

In the context of I4.0, CPS are central technologies that integrate physical assets with computational capabilities to manage interconnected systems. These systems are fundamental for achieving digital transformation in production lines, as they enable the integration of physical objects and equipment with decision-making processes (Seeger et al., 2022).

The concept of CPS emerged in 2006 at a workshop in Austin, Texas, USA (Jiang, 2018), and has since evolved to combine software and hardware components with internet connectivity and user interaction. CPS operate across multiple spatial and temporal scales, adapt to a range of behaviors, and are capable of contextual interactions (Matsunaga et al., 2022). Their capacity to manage real-time connections between physical and computational resources has driven innovation in areas such as smart manufacturing, autonomous vehicles, smart cities, and homes (Katina et al., 2017).

CPS aim to replicate physical environments through the development of cybernetic components aligned with real-world functionalities (Alhafidh & Allen, 2017), and are widely applied to connect devices to the internet within the I4.0 ecosystem (Afrizal et al., 2020). Control elements and sensors are embedded in machines, devices, networks, and human interfaces to monitor and interact with various systems (Salman & Salih, 2019).

However, the development of distributed CPS is complex and error-prone due to their heterogeneous nature, involving diverse components, languages, and tools. One of the major design challenges lies in embedding security mechanisms early in the development process to enhance system simplicity and maintainability (Pinto et al., 2022).

A widely referenced CPS architecture is the 5C model proposed by Lee & Kao (2015), considered a practical guideline for implementing I4.0 systems. It is composed of five hierarchical levels:

Level I – Connection: Raw data collection from machines and components via sensors;

Level II – Conversion: Transformation of data into meaningful information;

Level III – Cyber: Integration of digital models, including digital twins;

Level IV – Cognition: Generation of system-level knowledge based on the processed information;

Level V – Configuration: Autonomous decision-making for self-configuration, self-adjustment, and self-optimization.

This structure provides a systematic workflow to support the implementation of CPS in manufacturing environments (Bruton et al., 2016). At the base level, the connection between sensors and machines ensures precise data acquisition. The conversion level processes this data into actionable information, while the cybernetic layer enables deeper insights through data analysis (Jiang, 2018).

Sensors are essential for CPS functionality, as they provide real-time data that supports processing and control decisions (Zheng et al., 2021). These sensors are integrated with machines, networks, and human operators, and monitor key operational parameters such as voltage, temperature, vibration, speed, oil concentration, and visual attributes of components (Jiang, 2018). Additionally, they track environmental variables such as humidity, lighting, and atmospheric pressure, which are crucial for maintaining optimal industrial performance (Jiang, 2018).

Nonetheless, CPS development still faces challenges related to portability, time constraints, and connectivity reliability, all of which can affect predictability and data integrity (Alhafidh & Allen, 2017).

Security is another critical aspect in CPS and encompasses two domains: information security and control security. The former focuses on protecting data throughout its lifecycle—collection, processing, and sharing—particularly in open, distributed networks. The latter safeguards control systems from targeted attacks on evaluation and decision-making algorithms (Mbiriki et al., 2018).

CPS are often conceptualized as feedback systems that merge computing, networking, and physical processes. These intelligent systems apply artificial intelligence to monitor and regulate their environments, enabling precise and timely decision-making and influencing how organizations are structured and operate (Varadarajan et al., 2022).

The consolidation of CPS within I4.0 has laid the groundwork for even broader integration between physical devices and digital systems. In this context, the Internet of Things (IoT) emerges as a

complementary and essential technology, enabling continuous communication among connected objects and enhancing real-time monitoring, control, and decision-making capabilities. The synergy between CPS and IoT empowers intelligent industrial environments, providing robust connectivity that supports more autonomous, efficient, and responsive production operations.

3.3.1 IoT - Internet of Things

The Internet of Things (IoT), in conjunction with CPS, refers to the interconnection of physical devices capable of collecting data, communicating information, and being remotely monitored or controlled. These devices—such as smart vehicles, drones, household appliances, and industrial machines—are embedded with sensors that enable the integration of physical and digital environments (Mbiriki et al., 2018). Within the context of I 4.0, CPS play a central role in the digital transformation of manufacturing, while the IoT provides a foundational infrastructure that significantly influences modern lifestyles (Varadarajan et al., 2022).

One of the major contemporary challenges in industrial environments is the transition of manufacturing processes toward IoT-enabled or CPS-based architectures. This transformation demands not only the networking of physical objects but also the creation of their digital counterparts, forming integrated ecosystems (Salau et al., 2022). The acceleration of digitalization and the demand for intelligent, adaptive manufacturing systems have driven the evolution of the IoT, facilitating machine-to-machine communication and the handling of large-scale, mission-critical data flows (Kebande, 2022).

The International Telecommunication Union (ITU) (2024) defines the IoT as a global infrastructure for the information society, enabling advanced services through the interconnection of “things” (both physical and virtual) based on information and communication technologies (ICT). This definition underscores the centrality of connectivity and device integration in promoting technological advancement across multiple domains.

Historically, the development of IoT and CPS has been driven by the pursuit of economic and social benefits, with applications now extending across smart transportation, industrial logistics, and personalized healthcare. In the healthcare domain, for instance, CPS enable smart hospitals to remotely monitor patients, issuing automatic alerts to family members, emergency services, or hospitals in the event of critical incidents (Ramasamy et al., 2022).

According to Magomadov (2020), the IoT is a transformative technology designed to revolutionize industrial practices by integrating predictive analytics and artificial intelligence through sensor-based device interconnectivity. It forms a unified system that allows for seamless transmission of data between machines, devices, and users in both human-to-human and human-to-computer interactions (Laghari et al., 2021). Furthermore, the IoT enables real-time data collection, cloud-based storage, and analytical processing, supporting both immediate and predictive decision-making (Banerjee, 2022). This makes it an indispensable component of I 4.0, especially in manufacturing environments where sensors and connected systems enhance operational efficiency and responsiveness (Magomadov, 2020).

Looking ahead, the IoT is expected to encompass a vast array of interconnected devices and sensors, each generating substantial volumes of data. This expansion will require reliable and scalable communication protocols, as well as robust hardware and software infrastructures to ensure interoperability, security, and responsiveness (Salau et al., 2022).

Given the central role of IoT in enabling communication, data exchange, and real-time responsiveness within CPS, it becomes evident that these technologies not only support system functionality but also lay the groundwork for autonomous behavior. However, despite the technological advancements observed, a clear and structured framework for understanding and evaluating autonomicity in CPS remains absent. This gap highlights the need for a comprehensive conceptual model that integrates key elements of I4.0 and addresses the progressive nature of autonomy in these systems. The following section presents a model designed to meet this need, offering a systematic approach to analyze and classify levels of autonomicity in CPS.

3.4 Proposed Conceptual Model for Autonomicity in Cyber-Physical Systems (CPS)

The literature on CPS and their autonomic capabilities reveals significant conceptual and methodological gaps that limit the effective assessment and application of autonomicity. A major limitation is the absence of a structured and universally accepted framework capable of categorizing the degrees of autonomy that CPS can attain. Although discussions about the relevance of autonomic behavior in these systems are growing, there is no precise definition or measurement scale that enables systematic evaluation. Furthermore, many existing models overlook the dynamic interplay between emerging technologies—such as the Internet of Things (IoT), artificial intelligence (AI), and communication infrastructures—that are fundamental to the evolution of CPS under the I4.0 paradigm.

To address these limitations, this study proposes a conceptual model of autonomicity in CPS. The model seeks to integrate key elements of I4.0 with the structural features of CPS to provide a coherent framework for understanding and evaluating different levels of autonomy. It is composed of four main components: Autonomicity: Defined as the system's capacity for self-management and independent decision-making, this element is influenced by capabilities such as AI, machine learning, redundancy, self-healing, and adaptive behavior. The model incorporates five distinct levels of autonomicity—ranging from total dependence to full autonomy—building on the framework proposed by Kivrak et al. (2024).

- **I4.0 Enablers:** These include enabling technologies such as IoT, AI, cloud computing, and big data analytics. These tools are essential for enhancing the cognitive and responsive capacities of CPS, enabling dynamic adaptation, decentralized control, and higher degrees of system independence (Aceto et al., 2020).
- **Cyber-Physical Systems:** As the core of the model, CPS represent the integration of physical components (e.g., sensors, actuators) with computational intelligence. Through real-time data collection, processing, and action, CPS form the operational foundation upon which autonomy can be developed (Kivrak et al., 2024).
- **Internet of Things (IoT):** The IoT provides the infrastructure that allows CPS to continuously gather data from the physical environment and transmit it to the cyber layer. This connectivity enables real-time analysis and autonomous decision-making, serving as the communication backbone of the system (Kumar et al., 2022).

These components are interconnected in a feedback loop: data collected through IoT-enabled sensors is processed by intelligent algorithms, which guide autonomous responses in real time. This interaction enables the system to continuously learn, adapt, and optimize itself without direct human intervention.

The proposed model advances previous approaches—such as those by Broy (2013) and Salazar & Heuser (2022)—by offering a structured scale that classifies CPS autonomicity into five progressive levels. Unlike

prior models that focus mainly on automation, this framework integrates contemporary I4.0 technologies to reflect the current landscape of CPS development. It also aligns with the adaptive systems perspective, incorporating the complex interaction between CPS, IoT, and AI (Sundarakani & Tan, 2022; Zhang & Lee, 2023).

By consolidating these elements into a unified framework, the model provides a theoretical foundation for evaluating and guiding the development of autonomous capabilities in CPS. It also contributes to closing the gap between technological evolution and conceptual clarity, offering practical value for future empirical research and system design.

3.4.1 Contributions and Applications

The proposed conceptual model of autonomicity in CPS offers significant practical contributions for both academia and industry. It establishes a comprehensive foundation for future research aimed at understanding the progressive evolution of CPS autonomy and their integration with emerging I4.0 technologies. By providing a structured framework, the model facilitates the assessment, benchmarking, and enhancement of autonomy levels across diverse application domains, including smart manufacturing, autonomous transportation, and smart cities.

From an industrial perspective, the model assists organizations in identifying the current autonomy level of their CPS implementations, guiding strategic decisions for technological upgrades and innovation. The proposed five-level autonomy scale serves as a diagnostic and evaluative tool to measure the influence of key enabling technologies—such as IoT and artificial intelligence—on system performance and operational independence.

Moreover, the model encourages the development of new metrics and parameters to evaluate critical system attributes such as reliability, robustness, and adaptive capacity, which are essential for designing and deploying advanced autonomous solutions. By linking theoretical constructs with practical needs, this model contributes not only to the conceptual understanding of autonomicity but also to its tangible application in the I4.0 context.

Importantly, the model integrates core themes of I4.0 and CPS, underscoring their interdependence in driving autonomous capabilities. It offers a clear and systematic progression of autonomy levels, which elucidates how CPS evolve from human-dependent systems to fully autonomous entities. This clarity enables researchers, engineers, and practitioners to focus on the critical components and enabling technologies that must be developed and optimized to achieve higher autonomy.

Figure 3 illustrates the model as a circular interconnection, highlighting the continuous feedback loop among Autonomicity, CPS, IoT, and I4.0 drivers. This representation emphasizes real-time data flow and decision-making processes, capturing the dynamic and adaptive nature of modern autonomous systems.

Complementing the conceptual model, an Autonomous Feedback Hub (AFH) has been developed to serve as an intelligent intermediary among CPS, IoT, and I4.0 drivers. This hub dynamically processes real-time data, optimizes decision-making, and ensures the adaptive behavior of the entire system.

The proposed AFH represents a transformative advancement in enhancing autonomicity within CPS under I4.0 paradigms. By integrating AI-driven real-time analytics, self-healing capabilities, and predictive adaptation, the hub optimizes industrial processes dynamically, fostering resilient and intelligent manufacturing operations. These contributions facilitate the broader adoption of autonomous industrial

ecosystems, paving the way toward a new era characterized by intelligent automation and self-managed production systems.

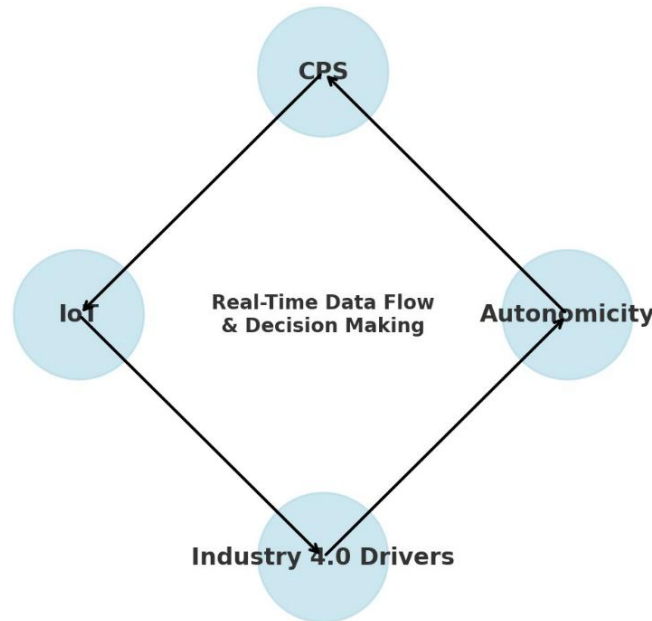


Figure 3. A circular interconnection model of CPS autonomicity. Source: by the author (2025).

Functioning as an intelligent mediator, the AFH continuously optimizes industrial interactions by enabling real-time data exchange and autonomous responses. Its architecture is built around three core components: AI-driven analytics, self-healing mechanisms, and predictive adaptation coupled with autonomous decision-making. Together, these elements ensure that CPS can respond proactively to environmental changes and operational challenges, maintaining efficiency and robustness.

Figure 4 illustrates the conceptual model of the Autonomous Feedback Hub. In this diagram, the hub acts as the processing core, collecting and analyzing data streams from IoT devices and intelligent systems. It employs advanced AI algorithms for autonomous decision-making and self-correction, reinforcing autonomicity as a fundamental enabler for self-management within CPS. The cyclical flow depicted in the figure highlights the continuous interaction among system components, emphasizing the dynamic and evolving nature of autonomy in I4.0 intelligent systems.

The implementation of an autonomous feedback hub will significantly enhance the autonomy, efficiency, and adaptability of I4.0 systems. Key expected outcomes include: Improved decision-making capabilities through AI-driven insights; Reduced downtime and operational disruptions via self-healing mechanisms; Enhanced adaptability to fluctuating industrial conditions through predictive adaptation; Optimization of resource utilization, improving energy efficiency and cost-effectiveness.

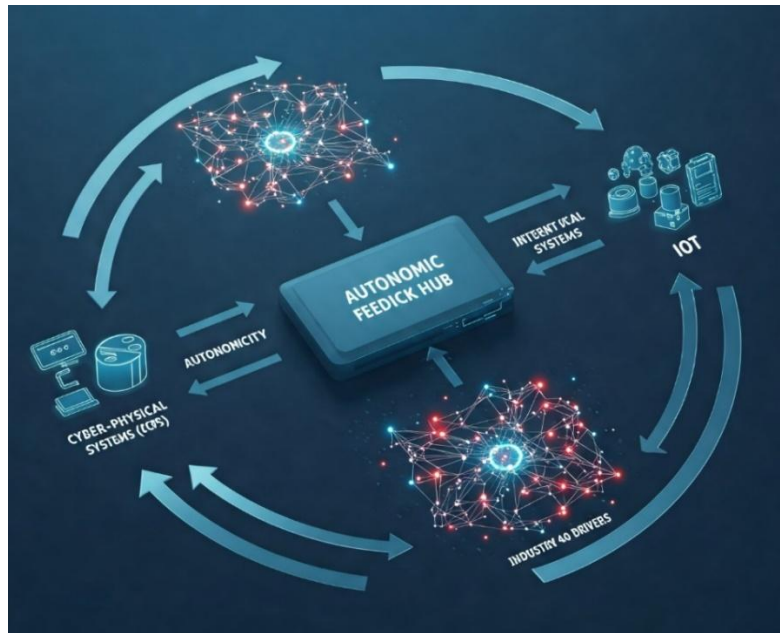


Figure 4. Proposed autonomous feedback hub (AFH). Source: by the author (2025).

4. Understanding and Proposing the Concept of Autonomicity in Cyber Physical System (CPS)

The aim of this study was to develop a scale of autonomicity levels for CPS, based on criteria that have already been defined, as well as to develop and introduce a theoretical concept of autonomicity for these systems. This proposal aims to broaden understanding, facilitate practical application and promote theoretical progress in the field of research.

The analysis is bibliometric and longitudinal and retrospective (2012-2022), with the main means of evidence for this analysis being keywords. The search strings were centered on three basic research areas and themes, namely: A-) "Autonomicity"; B-) "Cyber-Physical System"; C-) "Cyber-Physical System" AND "Autonomicity", with each research block detailed below.

- A) Autonomicity
 - A1 – Autonomicity.
 - A2 - Autonomicity AND Autonomous.
 - A3 - Autonomicity AND Autonomous OR Autonomy.
- B) Cyber-Physical System
 - B1 - Cyber-Physical System.
 - B2 - Cyber-Physical System AND Industry 4.0.
- C) Cyber-Physical System AND Autonomicity
 - C1 - Cyber-Physical System AND Autonomicity.
 - C2 - Cyber-Physical System AND Autonomous.
 - C3 - Cyber-Physical System AND Autonomy.

The search and selection procedures were conducted in four main stages:

- (i) Initial database search and preliminary analysis;
- (ii) Refined search based on defined inclusion and exclusion criteria;
- (iii) Compilation of a list of authors (including areas of concentration and associated keywords);
- (iv) Execution of the bibliometric analysis and formation of thematic clusters.

The inclusion criteria adopted in steps A, B, and C were as follows: type of material (articles and conference papers), publication status (final or in press), language (English), and source type (conference proceedings and journals). These filters were chosen to ensure that the selected materials were peer-reviewed and of academic quality. Subsequently, exclusion criteria were applied, which included: articles related to medical subfields and a temporal limitation covering the period from 2012 to 2022.

The primary rationale for selecting this time frame lies in the increasing relevance of topics related to Cyber-Physical Systems (CPS), automation, and, by extension, I 4.0. In most databases, publications on these themes begin to appear more consistently from 2014 onwards. Although the term "I4.0" was first introduced at the Hannover Messe (Germany) in 2011, it gained wider traction in the country around 2016, through initiatives aimed at pushing the technological boundaries of its manufacturing sector (Liao et al., 2018).

The bibliometric procedures described above provided the basis for a structured and evidence-based understanding of the field. The following section presents a detailed analysis of the bibliometric findings, including visual mappings and cluster interpretations that reveal the central themes and evolving research directions related to CPS and I4.0.

4.1 Analysis of the Bibliometric Review

The analysis began with criterion A1 (Autonomicity), as shown in the figure below (**Figure 5**).

Based on the search criteria described above, the initial sample was narrowed down to 49 articles (referred to as A1 – Autonomicity). The analysis of this sample is illustrated in **Figure 6**, which also presents the keyword co-occurrence network generated using the VOSviewer software. The visualization reveals the formation of three distinct clusters, each represented by a different color: red (application aspects), blue (approach-related aspects), and green (autonomicity).

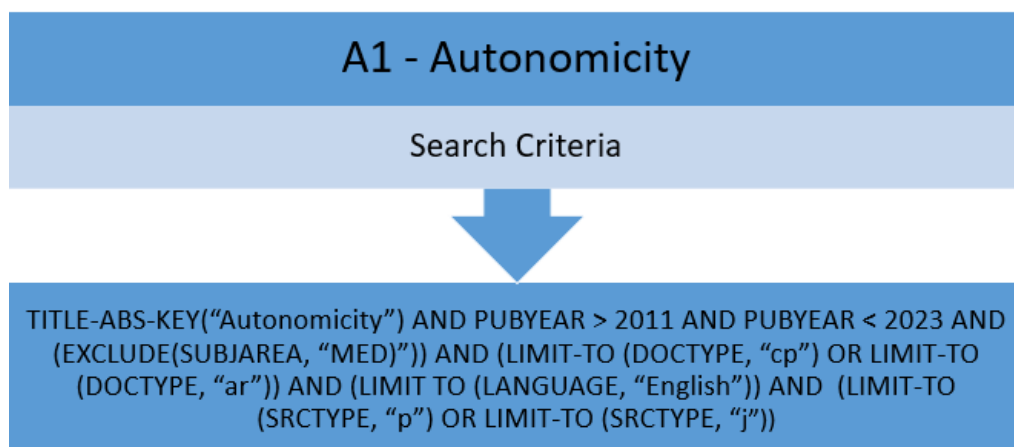


Figure 5. Search criteria A1 (Autonomicity). Source: by the author (2022).

The objective of this analysis is to identify prevailing research trends by organizing related studies into thematic clusters. VOSviewer processes bibliometric data from multiple studies in related fields and maps them into broader research domains, segmenting them based on the frequency and co-occurrence of keywords.

The visual representation of the co-occurrence network in **Figure 6** was further analyzed through the classification of keywords into thematic clusters. These clusters represent three distinct dimensions observed in the bibliometric mapping. The red cluster, associated with application-related aspects, includes the terms: application, internet, paper, solution, system, and thing. the green cluster, which reflects the concept of autonomicity, encompasses the terms: autonomicity, architecture, network, SDN (Software Defined Networks), and self-management. lastly, the blue cluster, corresponding to approach-oriented aspects, comprises the terms: agent, approach, complexity, and sensor. This categorization reinforces the thematic segmentation observed in the network and highlights the central position of autonomicity in relation to technological infrastructure and application domains within CPS.

Following the cluster mapping presented in **Figure 6**, a more detailed analysis was conducted, justified by the centrality of the concept of "autonomicity" to this research. All 49 articles from the A1 sample were read, critically analyzed, and tabulated. Based on the relevance and alignment with the proposed theme, 22 articles were excluded, resulting in a refined sample of 27 articles.

The same systematic procedure was applied to all search groups: initial screening, application of inclusion and exclusion criteria, cluster generation based on keyword co-occurrence, and identification of trend lines through color-coded clusters. In all cases, the selected articles were read in full, analyzed, and organized in a structured table.

The search strategy illustrated in **Figure 3** was consistently applied across all subsequent analyses and cluster constructions. For clarity and focus, only the main clusters identified in each group are graphically presented in this article.

In the A2 analysis (Autonomicity AND Autonomous), the initial sample comprised 10 articles. After the refinement process, 7 articles remained, resulting in four clusters: red (complexity aspects), green (network), blue (system aspects), and yellow (approach aspects).

In the A3 analysis (Autonomicity AND Autonomous OR Autonomy), the initial sample consisted of 12 articles, which was reduced to 7 after assessing thematic adherence. These articles were distributed across four clusters: red (autonomous), green (system), blue (network), and yellow (approach).

Finally, in the B1 analysis (Cyber-Physical System), a broader search yielded a total of 16,334 articles. **Figure 7** illustrates the keyword co-occurrence network resulting from this bibliometric analysis, in which four thematic clusters were identified: red (technology), green (security), blue (protocol), and yellow (approach).

These clusters represent a multidimensional structure of research themes within CPS. The red cluster, comprising 171 articles and related to technology-oriented aspects, includes keywords such as artificial intelligence, automation, autonomy, big data, blockchain, cybersecurity, digital technology, industrial internet, innovation, production process, and smart manufacturing. The green cluster, associated with security-related topics and comprising 168 articles, contains terms like attack, control system, cyber physical, defender, error, failure, information flow, security, and strategy. The blue cluster, linked to

protocols and connectivity, includes terms such as authentication, battery, deep learning, edge computing, IoT device, mobility, privacy, protocol, smart city, and vehicle. finally, the yellow cluster, formed by 48 articles and reflecting approach-related themes, gathers keywords such as behavior, benchmark, complex cyber-physical, development process, formal verification, modelling, simulation, tool, and workflow. This categorization enhances the reader's understanding of the visual data and underscores the interplay between technological innovation, cybersecurity challenges, and system-level approaches in CPS research.

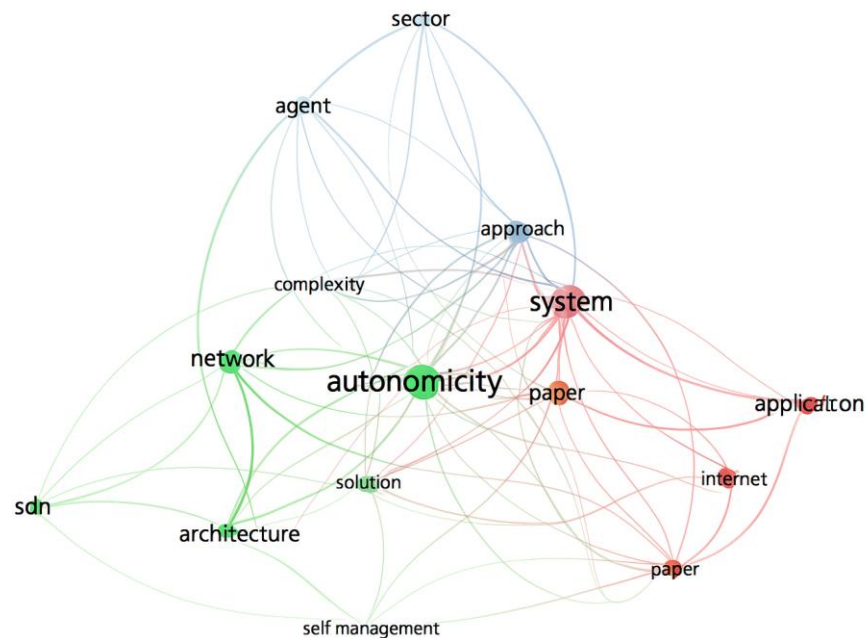


Figure 6. Cooccurrence network of keywords in group A1. Source: by the author (2022).

Table 1 displays the number of articles published each year throughout the analyzed period.

Table 1. Number of articles per year (B1 analysis).

Year	Number of articles
2012	399
2013	562
2014	659
2015	890
2016	1166
2017	1568
2018	2094
2019	2470
2020	2384
2021	2558
2022	1584
Total	16.334

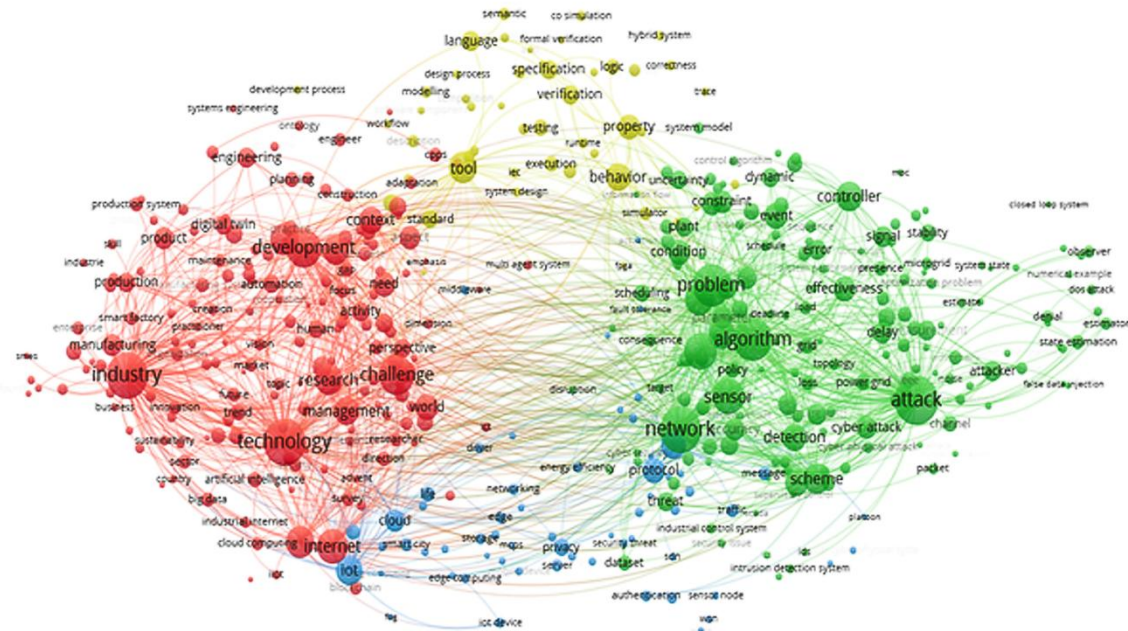


Figure 7. Cooccurrence network of keywords in group B1. Source: by the author (2022).

Following the analytical framework proposed by Alkubati et al. (2023), the results indicate a consistent annual increase in the number of publications related to Cyber-Physical Systems (CPS). This growth is particularly evident during the period when I 4.0 began to receive more focused attention from the academic community, with a notable peak in publications occurring between 2019 and 2021. It is important to note that the data for 2022 were incomplete at the time of the survey, and therefore the total number of publications for that year cannot be considered definitive.

In the B2 analysis (Cyber-Physical System AND Industry 4.0), a total of 1,252 articles were identified, resulting in the formation of nine clusters: red (implementation protocols), green (organizational aspects), blue (CPS aspects), yellow (adoption areas), purple (social impacts), cyan (academic aspects), orange (managerial aspects), violet (types of organization), and lilac (digital aspects), as shown in **Figure 8**.

Figure 8 illustrates the keyword co-occurrence network generated from this bibliometric analysis. Each color represents a distinct research perspective. The red cluster, associated with implementation protocols, includes terms such as blockchain technology, CPS architecture, deep learning, IoT system, and sensor data. The green cluster, focused on organizational aspects, highlights terms like automotive sector, big data analytics, human factor, and supply chain management. The blue cluster, related to the core structure of CPS, contains keywords such as cyber physical production, mobile robot, reference model, and system model. The yellow cluster, linked to adoption areas, includes 4th industrial revolution, construction industry, digital transformation, and intelligent machine. The purple cluster, representing social impacts, lists terms such as adaptation, cyber security, intelligent manufacturing, and society. Additionally, the cyan cluster gathers academic aspects, including engineering education, learning factory, and university; the orange cluster addresses managerial aspects, with terms such as control process and decision making process; the violet cluster groups types of organization, including computer science, stakeholder, and measurement system; and finally, the lilac cluster focuses on digital aspects, with terms such as meta model,

virtual world, and CPPSs. This comprehensive categorization reflects the multidimensional scope of CPS research in the context of Industry 4.0, encompassing technological, managerial, social, academic, and digital domains.

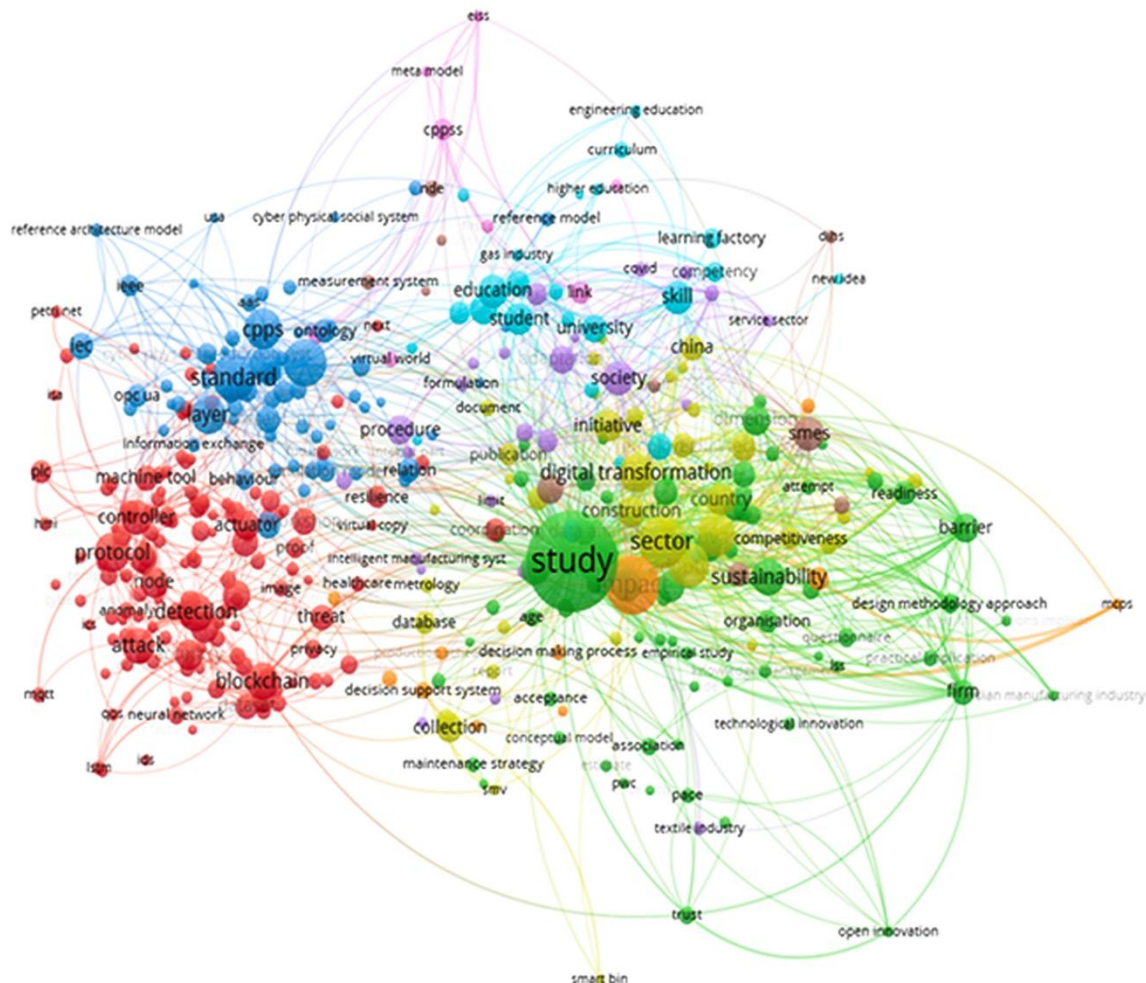


Figure 8. Cooccurrence network of keywords in group B2. Source: by the author (2022).

The C1 analysis (Cyber-Physical System AND Autonomicity) revealed a notably limited set of results, with only two articles meeting the inclusion criteria. This scarcity underscores the conceptual and academic novelty of the term “autonomicity” within the context of CPS. Despite its theoretical potential, the term has yet to be widely adopted or consistently applied in empirical research. Nevertheless, the cooccurrence network generated from this small dataset produced two distinct clusters: one represented in red, focusing on the relationship between CPS and autonomicity itself, and another in green, emphasizing communication aspects. This limited representation reinforces the need for deeper theoretical exploration and broader dissemination of the concept, suggesting that autonomicity remains an underexplored dimension in the broader discourse surrounding CPS and I4.0.

In contrast, the C2 analysis (Cyber-Physical System AND Autonomous) demonstrated substantial academic engagement with the theme, yielding a sample of 1,218 articles. The co-occurrence network derived from this dataset depicted in **Figure 9**, resulted in the formation of seven clearly defined clusters. This indicates that the notion of autonomy within CPS is significantly more consolidated and explored in the literature compared to autonomicity.

For the C3 analysis (Cyber-Physical System AND Autonomy), the sample was 262 articles, and seven clusters were generated (**Figure 10**).

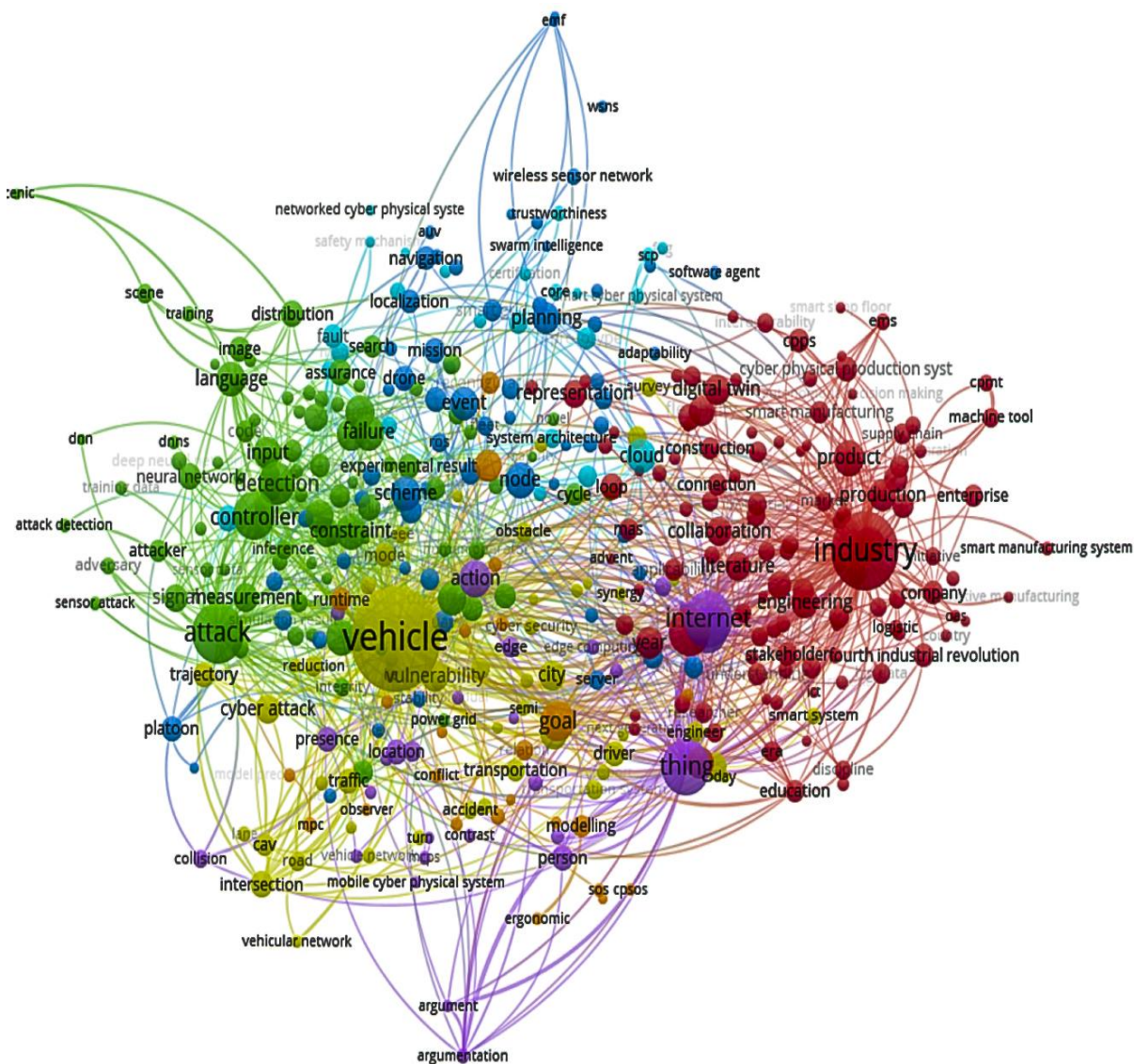


Figure 9. Cooccurrence network of keywords in group C2. Source: by the author (2022).

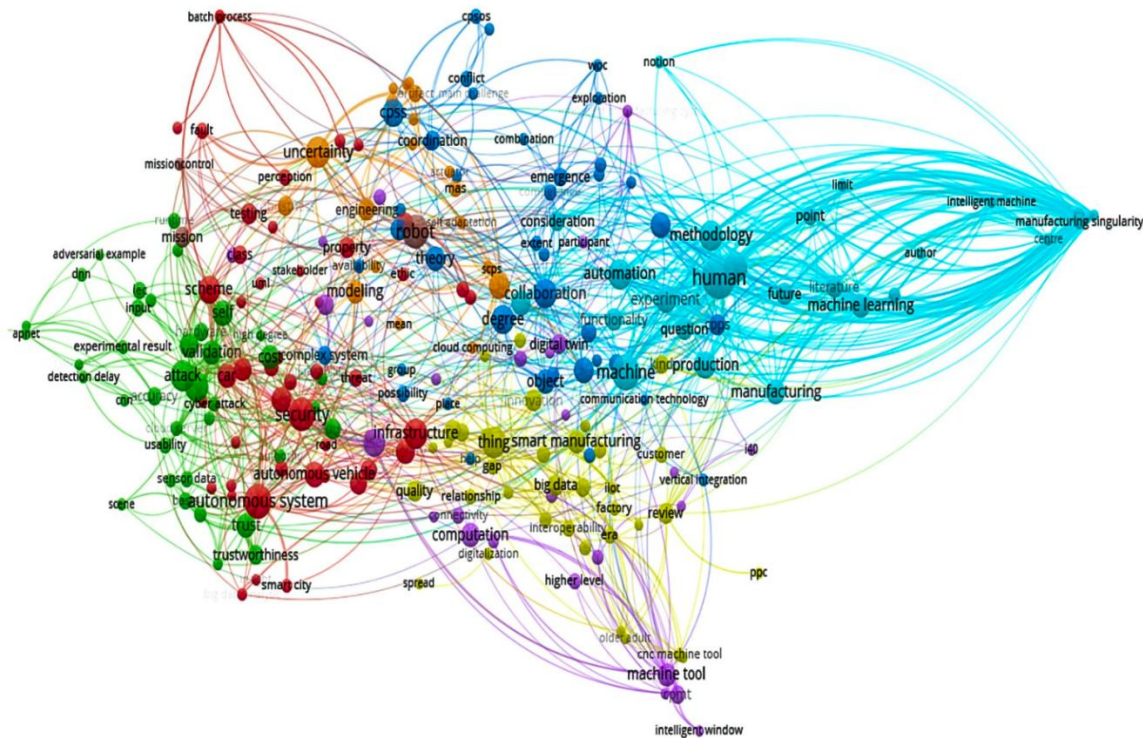


Figure 10. Cooccurrence network of keywords in group C2. Source: by the author (2022).

After a comprehensive and systematic search using keywords closely aligned with the central theme of this study, it becomes evident that the chosen topic—autonomicity within CPS—is both promising and underexplored. While the concept holds significant theoretical and practical potential, especially in relation to autonomy, there remain substantial gaps in the literature. These gaps highlight the need for deeper investigation, particularly concerning the consolidation of autonomy-related concepts in CPS contexts. Given this landscape, the continuation of this research appears both timely and valuable, with the potential to generate meaningful theoretical contributions and practical applications.

It is important to note that this article is part of the bibliographic investigation supporting a doctoral thesis in the field of Production Engineering. All the data collected throughout the bibliometric review will serve as the foundation for the development of the final research proposal and framework.

The analysis uncovered several noteworthy findings. For instance, the number of publications related to CPS increased steadily between 2012 and 2022, particularly during the period when I4.0 began to receive greater attention from the academic community. A publication peak was observed between 2019 and 2021. Interestingly, a decline in publications occurred in 2020, likely due to the disruptions caused by the COVID-19 pandemic.

Regarding the theme of autonomy, the number of publications was not only lower in volume but also in emphasis. The term “autonomy” remains theoretically fragmented and has yet to be fully integrated into the core frameworks of CPS-related research. This presents a critical theoretical gap—one that this study seeks to explore and address more systematically.

The most frequently associated and structuring themes identified in the literature between 2012 and 2022 include: Internet of Things (IoT), Sensors, Artificial Intelligence (AI), Cybersecurity, Machine Learning (ML), Innovation, Autonomous Vehicles (AV), Digitalization, Automation, Smart Cities, and the 5C Architecture. These recurring terms reflect the technological ecosystem within which autonomicity and CPS are situated, and they offer a foundation for future interdisciplinary exploration.

In-depth keyword-based bibliometric research such as this contributes to academic literature by clarifying the dominant themes, gaps, and evolution of research in autonomicity and CPS. A summary of the total number of articles retrieved under each search criterion is presented in **Table 2**.

Table 2. Total articles according to keyword searches. Source: by the author (2022).

Keyword search criteria (2012-2022)	Initial search (without criteria)	Search with inclusion and exclusion
A1 - Autonomicity	162	50
A2 - Autonomicity AND Autonomous	38	10
A3 - Autonomicity AND Autonomous OR Autonomy	45	12
B1 - Cyber-Physical System	23.643	18.748
B2 - Cyber-Physical System AND Industry 4.0	2456	1252
C1 - Cyber-Physical System AND Autonomicity	3	2
C2 - Cyber-Physical System AND Autonomous	1697	1218
C3 - Cyber-Physical System AND Autonomy	347	262
Total articles returned	28391	21554

4.2 Basic Theories for Developing the Concept

A theory, in general, has the capacity to describe phenomena and provide structured guidelines for conducting empirical investigations (Sovacool & Hess, 2017).

Following the approach proposed by Agudo et al. (2022), a bibliographic survey was conducted to identify theories related to autonomics and autonomous systems. The adopted strategy involved constructing a research trends diagram (**Table 3**), which maps the selected theories alongside their respective authors. This consolidation of frequently used theoretical foundations into a single document serves as a valuable resource for scholars interested in conducting more comprehensive and targeted investigations into the field of autonomicity.

By examining the main theoretical underpinnings and their connection to the driving themes of automation and autonomy, it is possible to identify key frameworks that may serve as theoretical pillars for future studies. These include: fuzzy control theory, theory of planned behavior in autonomous vehicle–pedestrian interaction, viability theory, game theory, graph theory, car-following theory, theory of autonomous load control, diffusion of innovations theory, and scale-free network theory.

The autonomicity aspects presented in **Table 3** were derived from a detailed literature review, in which themes such as connectivity, networks, human factors, artificial intelligence, infrastructure, and mathematical modeling emerged as the most recurrent. Among the theories identified, Fuzzy Control Theory stands out due to its strong alignment with the concept of autonomicity, particularly because it mimics human decision-making through artificial intelligence. Additionally, the trend diagram reinforces the relevance of these aspects by visually representing their recurrence across the selected theories.

Beyond listing theoretical contributions, **Table 3** also reveals how these frameworks align with recurring autonomicity elements, such as human interaction, network architecture, intelligent decision-making, and

adaptive behavior. For example, fuzzy control theory is frequently cited due to its applicability in modeling decision processes under uncertainty—a central characteristic in autonomous systems. Likewise, theories such as game theory and graph theory offer robust tools for analyzing strategic interactions and interconnected system behavior, respectively. The inclusion of theories related to infrastructure diffusion and planned behavior further underscores the relevance of socio-technical factors in the evolution and implementation of autonomous technologies. As such, **Table 3** serves not only as a theoretical foundation for this study, but also as a roadmap for future empirical applications and conceptual refinements in the field of autonomicity.

Table 3. Trend diagram: related theories. Source: by the author (2022).

Theory	Theory concepts/Objectives	Aspects of autonomicity					Mathematical model
		Connectivity	Network	Human aspect	Artificial intelligence	Infrastructure	
Fuzzy Control Theory	It addresses a driving control system for Av, which can simulate driving behavior (Zheng et al., 2021). The authors adopt the fuzzy theory approach integrated with Analytic Hierarchy Process (AHP) to measure the subjective attribute of Autonomy (Deharaj & Sharma, 2020). Fuzzy control theory is used to control an autonomous mobile robot for parallel parking, and fuzzy rules can be derived by modeling conventional car driving actions. The theory has been used in the fields of control, artificial intelligence, expert systems and so on (Miyata et al., 1996). Fuzzy logic is an area of AI that is widely used in expert systems. Its principles of uncertainty are capable of improving the control techniques used in industrial automation. The theory simulates human intelligence and is a solution for non-linear processes (Tarso & Bezerra, 2009).	✓			✓		
Theory of Planned Behavior in AV Pedestrian Interaction	The theory of planned behavior is one of the most dominant theoretical frameworks applied to predicting human behavior. This theory predicts pedestrian behavior (Hafeez et al., 2022). The requirements for pedestrian models increase in level, with the initial model requiring detection, the higher model requiring recognition and tracking, and the full interaction model requiring psychological and social resources and understanding to interact in any situation (Hafeez et al., 2022). This theory seeks to capture the highly complicated reality of travel mode choice in a framework consisting of attitudes, subjective norms and behavioral control (Jing et al., 2019). This theory is the extension model of the Theory of Reasoned Action and is widely used to investigate behavioral intention (Jing et al., 2019).	✓				✓	

Table 3 continued...

Viability Theory	Viability theory characterizes the controllability of a range of constrained non-linear systems (Pinto et al., 2022). It can be applied to autonomous vehicles (Pinto et al., 2022). In autonomous driving of miniature racing cars, viability theory is used to generate finite anticipation trajectories that maximize progress while recursively feasible with respect to static obstacles (Liniger & Lygeros, 2019).	✓				✓	✓
Game Theory	According to game theory, agents prefer certain states of the environment, which is modeled with a utility function. If the agents do not cooperate, then the rational agent selects that action which has the highest value between the worst possible utilities of the results of its own action and the actions of other agents. Classical game theory is concerned with equilibrium (Varga, 2017). Game theory provides the basis for the design and analysis of energy systems. Classically, games involve players whose strategies are coupled only through the dependence of utility functions on the strategies of other players (Kulkarni, 2017). The authors used game theory to run an autonomous vehicle and determine its actions in near real time, relying only on spatial and temporal data and electromagnetic information (Kusyk et al., 2021). Game theory in engineering can be effective in computer communications, especially for multi-objective optimization problems in network resource allocation, routing efficiency and intrusion detection systems (Kusyk et al., 2021).	✓				✓	✓
Theory of Graphs	Discrete mathematics covers the field of graph theory, which solves various graph problems using algorithms such as colored graphs. Part of graph theory focuses on algorithms that solve the passage through labyrinths (Coufal et al., 2021). A graph is nothing more than a representation of the interdependence between elements that are represented by nodes. Elements that meet the imagined relationship are symbolically joined by a line called an edge (Souza et al., 2017).					✓	✓
Car-Following Theory	Car-following (CF) theory is a platooning control strategy for vehicles based on sliding mode control theory. This strategy can be applied to achieve fast platooning of multiple autonomous vehicles and maintain the steady state of the platooned vehicle (Jing et al., 2019).	✓			✓	✓	

Table 3 continued...

Theory of Aut. Load Control	This theory transforms the remote control system that receives operating instructions and controls the units into a task-oriented charging system that receives tasks to perform automatic/autonomous control. The authors tested the effectiveness of this theory by a real vehicle test on a particular type of unmanned vehicle (Liu et al., 2021).	✓					✓
Diffusion Theory of Innovations	In this theory, each individual member goes through the five stages of the innovation-decision and process, which are as follows: knowledge stage; persuasion stage; decision stage; implementation stage and confirmation stage. Diffusion being the process by which an innovation is communicated through specific channels over time among the members of a social system; and innovation being an idea, practice or object that is considered new in an individual's life (Shaikh et al., 2020). The diffusion of innovation theory is widely used to identify information technology adoption. It is commonly used to examine communication innovation, the innovation-decision process and the impact of innovation (Shaikh et al., 2020). The authors used the theory of diffusion of innovation with an innovation-decision approach, as a process model with indicators of knowledge, persuasion, decision, implementation, and confirmation (Shaikh et al., 2020). The persuasion phase describes the evaluation of the innovation. The decision phase illustrates how the individual makes the choice to accept or reject the innovation. The implementation stage reveals the use of the innovation by those who accept the innovation. And the confirmation stage explains whether the adopter will continue with the innovation or not (Badri, 2021).	✓					✓
Scale free network theory	Albert - László Barabási was the first person to identify a network as scale-free. He discovered that the distribution of nodes in the Internet tele information network does not correspond to the usual distribution. He used his mathematical model of a global network to analyze different phenomena and discovered that the distribution of nodes is atypical only for the Internet. In this way, it is possible to analyze many other social, technological or biological phenomena. Each phenomenon, which has a network structure, and the system's communication connections can be analyzed (Kowalczyk et al., 2014).	✓					✓

4.3 Proposing a Concept of Autonomicity in CPS

While the terms automation and autonomy are widely employed in discussions surrounding CPS, the notion of autonomicity remains conceptually fragmented and poorly defined. This gap presents a challenge both to academic research and to practical implementations in I4.0 environments, where systems are increasingly expected to operate with minimal human intervention, adapt to changing conditions, and make decisions independently.

Unlike automation, which typically refers to task execution without real-time human input, or autonomy, which implies some level of decision-making capacity, autonomicity denotes a more advanced and comprehensive property: the system's ability to self-manage, self-configure, self-heal, and self-optimize within complex and dynamic contexts. This concept stems from autonomic computing theories (Kephart & Chess, 2003), but its application to CPS requires theoretical refinement and contextual adaptation.

The absence of a clear and structured definition of autonomicity in the context of CPS limits our capacity to assess, compare, and evolve intelligent industrial systems. It also hinders the development of standardized frameworks that support maturity assessments, performance benchmarking, and decision-making in digital transformation processes.

Drawing from the analysis of emerging themes in the literature and the integration of interdisciplinary perspectives—including systems engineering, AI, and control theory—this study proposes the following theoretical definition:

Autonomicity in CPS is the level of autonomy and autonomous capacity achieved within a CPS system, encompassing the ability of these systems to operate, make decisions and adapt autonomously, based on information obtained from the physical environment and cyber data, and can go from the level of zero autonomy to the level of maximum autonomy and self-management, where in this case, there is no human intervention.

To achieve high degrees of autonomicity, systems must integrate various enabling technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Cloud Computing (CP), Machine Learning (ML), and Cybersecurity. When effectively combined, these technologies enhance CPS capabilities to operate independently, adapt to change, and function in dynamic and unpredictable environments. Nevertheless, autonomy must be pursued in conjunction with ethical principles, safety requirements, and transparency to ensure secure and trustworthy operations.

Based on the bibliometric analysis conducted and the foundational theories explored, this concept serves as a necessary theoretical foundation for the creation of the autonomicity scale presented in the following section. By clearly defining autonomicity in CPS, this work supports the main objective of the study: to provide a structured and actionable tool for assessing levels of autonomic behavior in CPS.

In a hypothetical state of total autonomicity, CPS would function entirely independently, even in highly complex and unforeseen scenarios. Such systems must transcend traditional automation by incorporating real-time adaptation, continuous learning, and self-improvement capabilities aimed at maximizing efficiency, resilience, and safety under any operating condition. This level of sophistication demands not only advanced computational architectures but also adaptive decision-making mechanisms and robust feedback control.

Future research should further investigate how organizations can practically attain maximum autonomicity and which system components are critical for achieving full operational independence. These inquiries are essential for guiding implementation strategies, risk management, and performance assessment in highly autonomous industrial environments.

As CPS advance toward higher levels of autonomicity, significant questions arise: Should these systems operate without any human oversight? What are the technical, regulatory, and societal implications of such capabilities? Achieving full autonomicity is not only a technical ambition but also a philosophical and

ethical frontier, demanding rigorous interdisciplinary inquiry.

This definition also opens pathways for deeper theoretical inquiry into the boundaries, risks, and implications of full autonomicity, which remain topics of ongoing academic and industrial debate. The theoretical development presented in this section constitutes the first phase of a broader research initiative. The next section introduces a five-level scale designed to classify CPS according to their degree of autonomicity. This will be followed by the proposal of a relationship matrix and the design of an evaluation instrument, aiming to operationalize the theoretical model developed herein.

5. Development of a CPS Autonomicity Scale Separated into Levels

The analogy between Autonomous Vehicles (AVs) and Machine Learning (ML) was adopted as the conceptual foundation for the proposed scale. These subjects were previously introduced in general terms in the theoretical framework of this study and are now examined in greater detail, serving as the structural basis for the development of a multi-level scale for evaluating autonomicity in CPS.

AVs initially emerged as a topic of interest within engineering domains but have since garnered attention across a wide array of disciplines, including insurance, urban planning, public policy, and social sciences. To describe the varying degrees of automation and task distribution between humans and machines, the concept of automation levels was introduced (Hopkins & Schwanen, 2021). By 2025, it is expected that nearly half of newly produced vehicles will incorporate autonomous functionalities reaching Level 5 automation, as defined by the Society of Automotive Engineers (SAE), potentially enhancing safety, reducing congestion, and alleviating driver stress (Gluck et al., 2022). Similarly, ML can also be categorized into hierarchical levels of autonomy, reflecting increasing complexity in learning and decision-making capabilities.

According to Lee et al. (2017), ML autonomy ranges from Level 1 to Level 5, with each level defined by specific requirements, including the availability of training datasets and input attributes. At Level 1, AVs are fully controlled by the driver, with no automation support—comparable to manual labor environments devoid of technological assistance. Although still common on roads today, Level 1 vehicles are gradually being replaced by models equipped with basic driver-assistance systems (Dias et al., 2021; Smith et al., 2021).

At the base of the ML spectrum lies supervised learning, where algorithms are trained on labeled data under human supervision. This setup is analogous to Level 1 AVs, where constant and targeted human input is necessary to guide learning processes. Supervised ML is widely utilized in applications such as image recognition and natural language processing (Mitchell, 1997).

In Level 2 AVs, vehicles can manage both steering and speed, though human drivers must remain attentive and ready to intervene. These vehicles typically include features like adaptive cruise control and parking assistance, representing a transitional phase toward automation, but still presenting reliability and safety concerns (Cooper et al., 2023). Correspondingly, semi-supervised ML—which trains models on a mix of labeled and unlabeled data—mirrors this intermediate state. Although it allows partial independence, human oversight remains essential for improving system performance, especially in data-scarce environments (Bengio et al., 2021).

Level 3 AVs are capable of partial automation, handling acceleration, braking, and steering, but still requiring the driver to monitor the environment and intervene when necessary. This phase reflects ML models that demonstrate high adaptability but still rely on human supervision in complex or uncertain scenarios (Bengio et al., 2021).

In Level 4, vehicles operate autonomously in most environments, requiring human intervention only in exceptional cases (Cooper et al., 2023). This stage parallels ML models with strong autonomy capabilities, capable of executing complex tasks with minimal external input.

Finally, Level 5 AVs are fully autonomous, capable of operating in all conditions without human intervention (Dias et al., 2021). These vehicles represent a major innovation in the automotive sector by replacing driver tasks with intelligent software systems (Cooper et al., 2023). Similarly, Level 5 ML systems exhibit complete decision-making independence across various contexts and environments (Russell & Norvig, 2020).

The recent discourse on automation levels, particularly within the context of I4.0, underscores the importance of adaptive systems that blend the flexibility of manual processes with the efficiency of automated ones. These systems promote productive human-machine collaboration and contribute to significant improvements in cycle time and operational efficiency (Bortolini et al., 2021).

On the human side, the perception of autonomy levels and user trust in autonomous systems are influenced by a variety of technical and social factors. While automation advances rapidly, higher levels of autonomy may paradoxically decrease user confidence, especially when cognitive and psychological factors are not adequately addressed (Yang et al., 2024).

Grounded in the analogies drawn from the extensive literature on AVs and ML, a five-level scale was developed to categorize the degrees of autonomicity in CPS. As presented in **Table 4**, the levels are defined as follows:

Level 1 – Total Dependence;
Level 2 – Moderate Dependence;
Level 3 – Partial Autonomy;
Level 4 – Substantial Autonomy;
Level 5 – Total Autonomy.

Level 1 - Total Dependence:

At Level 1, systems are entirely dependent on external commands and constant human intervention. Automation is minimal, and all operations are executed manually, with no ability to autonomously respond to environmental changes or system events. Achieving Level 1 autonomy in a CPS involves the integration of essential components such as:

- Sensors and Actuators: Capture environmental data and execute physical actions based on manual commands.
- Human-Machine Interface (HMI): Facilitates operator interaction via input/output devices like screens and buttons.
- Direct Human Control: All critical decisions and actions are made manually using specific interfaces.
- Network Connectivity: Enables system communication with operators through local or internet-based networks.
- Monitoring and Alert Systems: Provide real-time status tracking and notifications of critical events.
- Security Protocols: Protect the system against unauthorized access and malicious activity.
- Manual Interruption Capability: Allows emergency shutdown in the event of failure or hazard.

Level 2 - Moderate Dependence:

At this stage, reliance on external commands is reduced, and some degree of automation is introduced. Systems begin to execute predefined tasks autonomously but still require human oversight for complex or unexpected situations. Additional components are integrated to support limited autonomy, including:

- Decision-Making Algorithms: Enable basic data analysis and decision-making using control logic, expert systems, or ML techniques.
- Predictive Models: Utilize historical data to anticipate events and support proactive responses.
- Sensory Feedback Mechanisms: Monitor and adjust actions based on environmental feedback.
- Human Supervision: Maintained to intervene when decisions exceed system capacity.
- Adaptation to Change: Adjusts operational strategies in response to dynamic conditions.
- Redundancy and Fault Tolerance: Ensures operational continuity even during component failures.
- Learning Capacity: Improves performance over time through experience and human input.

Level 3 - Partial Autonomy:

Systems at Level 3 are capable of autonomous operation under predefined conditions, with more advanced automation, yet still dependent on human intervention in unforeseen scenarios. Key components enabling this level include:

- Advanced AI: Employs complex algorithms such as deep neural networks and fuzzy logic for decision-making.
- Self-Learning and Adaptation: Continuously improves through real-time data and accumulated experience.
- Self-Diagnosis and Repair: Identifies and resolves issues autonomously, or alerts operators when necessary.
- Autonomous Communication: Interacts with IoT devices and other CPS systems without human mediation.
- Multifaceted Decision-Making: Incorporates multiple variables and constraints to optimize performance.
- These features significantly reduce dependence on human oversight, though supervisory functions remain necessary to ensure safety and ethical compliance in exceptional situations.

Level 4 - Substantial Autonomy:

At Level 4, systems demonstrate high autonomy, operating independently in most scenarios and adapting to unforeseen events with minimal human input. The range of automated functions expands significantly and is supported by the following components:

- Advanced AI (*)
- Self-Learning and Adaptation (*)
- Autonomous and Multidimensional Decision-Making: Considers multiple, sometimes conflicting, factors to autonomously optimize outcomes.
- Communication and Coordination: Collaborates with IoT and CPS entities to perform distributed tasks.
- Self-Diagnosis and Repair (*)
- Advanced Security: Implements real-time threat detection, encryption, and system protection protocols.
- Simulation and Testing: Conducts rigorous performance and safety validations in varied and extreme scenarios.

Level 5 - Total Autonomy:

The highest level of the scale represents full autonomy, with systems capable of operating in any condition without human intervention. These systems manage complex decisions, adapt continuously, and perform reliably in unpredictable environments. Critical components include:

- Super AI (*)
- Self-Learning and Adaptation (*)
- Autonomous and Multidimensional Decision-Making (*)
- Advanced Communication and Coordination: Utilizes cutting-edge protocols to interact with a range of cyber-physical entities.
- Self-Diagnosis and Repair (*)
- Extreme Security and Resilience: Employs advanced cryptography, real-time intrusion detection, and cyber-resilience strategies.
- Simulation and Testing (*)

(*) Previously described components in earlier levels, here employed with higher performance and independence thresholds.

Table 4. Proposal for a scale of autonomy in CPS and its components and expected functionalities. Source: by the author (2024).

Levels	Description	CPS components	Expected functionalities
Level 1	Total dependence	Sensors and Actuators; Human-Machine Interface; Direct Human Control; Network Connectivity; Monitoring and Alert Systems; Security Protocols; Manual Interruption Capability.	The CPS requires human intervention for all operations. Operators are responsible for all stages of the production process, from controlling the machines to making decisions about maintenance and logistics. It can provide basic information on the status of machines and processes, but all actions are carried out by the operators.
Level 2	Moderate dependence	Decision-Making Algorithms; Predictive Models; Sensory Feedback; Human Supervision; Adaptation to Change; Redundancy and Fault Tolerance; Learning Capacity.	It can perform simple, repetitive tasks without direct human intervention. Operators still have control over the system, but it can automate some stages of the process, such as transporting materials between different areas of the factory. It can alert operators to problems or exceptional situations that require human intervention.
Level 3	Partial autonomy	Advanced Artificial Intelligence; Self-Learning and Adaptation; Self-Diagnosis and Repair; Multifaceted Decision-Making; Autonomous Communication; Simulation and Testing.	The CPS can make decisions within predefined parameters and deal with routine situations without human intervention. It can adapt production processes in response to real-time data, like changes in market demand or raw material availability.
Level 4	Substantial autonomy	Super Advanced IA; Advanced Self-Learning and Dynamic Adaptation; Advanced Autonomous and Multidimensional Decision Making; Advanced Autonomous Communication and Coordination; Advanced Self-Diagnosis, Repair and Maintenance; Advanced Security; Advanced Simulation.	It is highly autonomous and can operate efficiently with little human supervision. It is able to optimize production, carry out predictive maintenance and deal with variations in the production environment without direct intervention from operators. Operators play a more strategic role, monitoring system performance and intervening only in exceptional cases or for high-level decisions.
Level 5	Total autonomy	Super Advanced Artificial Intelligence; Advanced Self-Learning and Dynamic Adaptation; Advanced Autonomous and Multidimensional Decision Making; Advanced Autonomous Communication and Coordination; Advanced Self-Diagnosis, Repair and Maintenance; Advanced Security and Extreme Resilience; Advanced Simulation in Virtual and Real Environments.	It works completely independently, without requiring human interference. It has the ability to constantly learn and adjust, improving all aspects of production, from resource management to the quality of the end product. Meanwhile, operators have an advisory role, offering high-level guidance and overseeing the system in strategic terms, but are not directly involved in day-to-day operating activities.

The primary objective of this phase was to define clear metrics and structural elements that allow the assessment of autonomy levels in CPS. This scale serves as the foundation for the development of a future assessment instrument, enabling the empirical evaluation of autonomicity in complex systems and facilitating deeper understanding of the interactions among the involved technological and human factors.

Having defined the levels and components required to assess autonomicity in CPS, it becomes essential to critically analyze the theoretical and practical implications of this proposed scale. The following section discusses how the structure of the scale aligns with the technological maturity of CPS, the conceptual gaps identified in the literature, and the interdisciplinary nature of autonomy-related capabilities. This discussion also aims to position the scale within the broader context of I4.0 and intelligent automation, emphasizing its potential for application in both academic and industrial environments.

5.1 Discussions

The primary objective of this study is to develop a scale for assessing different levels of autonomicity in CPS. Accordingly, its implications are both wide-ranging and significant, encompassing theoretical advancements and practical applications. This section addresses the conceptual contributions and potential uses of the proposed scale, highlighting its relevance across multiple domains of I4.0.

From a theoretical standpoint, the articulation of autonomicity in CPS fills a critical gap in the existing literature. Although automation and autonomy have been extensively studied within CPS contexts, the notion of autonomicity—understood as the system’s capacity for self-management, optimization, and independent decision-making—remains under defined and largely unstandardized. By proposing a structured and operationalized definition, this study contributes meaningfully to the conceptual development of CPS, particularly within the I4.0 paradigm. The framework presented offers a foundation for future academic inquiry, enabling the creation of more precise models and tools for evaluating autonomous behaviors in complex systems.

Beyond theoretical advancements, the scale also demonstrates strong practical relevance. Within I4.0 environments—characterized by the integration of CPS in manufacturing, logistics, and smart infrastructures—the ability to assess autonomicity is essential for optimizing performance and innovation. The proposed scale can serve as a diagnostic and strategic tool for both researchers and practitioners. For example, industrial stakeholders can use the scale to evaluate the current level of autonomy in their CPS implementations, identify bottlenecks, and prioritize investments in technologies such as artificial intelligence and machine learning.

The potential applications of the scale span multiple domains of the I4.0 ecosystem, including smart manufacturing, supply chain management, and autonomous robotics. In smart factories, for instance, CPS equipped with higher levels of autonomicity can enable real-time decision-making, increase production efficiency, and enhance operational safety. In logistics, autonomous CPS can support dynamic routing, adaptive inventory management, and greater responsiveness to environmental or market fluctuations.

Nonetheless, it is important to acknowledge that the concept of autonomicity in CPS is still evolving. The scale introduced here should be seen as an initial framework—one that requires empirical testing and refinement. Further studies are needed to validate the scale across diverse industrial contexts and to investigate how varying levels of autonomicity affect performance metrics, cost-effectiveness, and system adaptability. While the scale was developed with I4.0 applications in mind, its relevance to adjacent sectors—such as healthcare, energy, or transportation—should also be explored in future research.

In summary, this study offers both a theoretical framework for understanding autonomicity in CPS and a practical scale for its assessment and enhancement within the I4.0 context. The contributions extend beyond academia, offering actionable insights for professionals seeking to harness the full potential of autonomous systems. Importantly, this work forms part of a broader research project aimed at developing, applying, and empirically testing a CPS Autonomicity Assessment Instrument. The phases outlined in this article lay the groundwork for subsequent stages, which will involve real-world applications and further refinement of the scale through empirical validation.

6. Conclusions

This article aimed to advance the academic understanding of autonomicity in Cyber-Physical Systems (CPS) by addressing two central research questions: (1) how the concept of autonomicity can be theoretically delineated within the CPS context and what its defining characteristics are, and (2) what methodological framework can be used to develop a robust scale for assessing different levels of autonomicity in these systems. To answer these questions, the study proposed a theoretical definition of autonomicity and introduced a five-level assessment scale that classifies CPS according to their degree of self-management and autonomous decision-making. These contributions were supported by a bibliometric review, a structured theory development process, and analogy-based modeling, which together provided a coherent methodological foundation for conceptual clarification and scale construction.

The rapid advancements driven by I 4.0 have underscored the central role of CPS in modern industrial environments. These systems—characterized by the integration of computational intelligence with physical processes—offer unprecedented levels of automation, efficiency, and adaptability. However, despite the growing relevance of autonomy in CPS, the concept of autonomicity remains insufficiently defined and structurally underdeveloped in the existing literature. This study sought to address this conceptual gap by proposing a theoretical framework and introducing a five-level scale to classify CPS according to their degree of self-management and decision-making independence.

The findings contribute meaningfully to both theory and practice. The proposed autonomicity scale offers a structured mechanism for assessing levels of autonomy in CPS, providing a clearer distinction between automation, autonomy, and autonomicity. This differentiation not only advances academic discourse but also presents practical value for optimizing industrial processes, enhancing system resilience, and improving autonomous decision-making across various I4.0 applications.

Critically, the literature review revealed a fragmented understanding of autonomicity in CPS. Many existing studies emphasize automation or general autonomy without clearly articulating criteria for system self-governance. This absence of a unified conceptual and operational framework has led to inconsistencies in how autonomy is interpreted, measured, and applied across industrial sectors. The framework proposed in this study represents an initial step toward addressing this gap; however, its refinement and empirical validation in diverse real-world contexts remain essential.

Future research should prioritize the empirical testing of the proposed scale through case studies and pilot applications in industrial settings. Incorporating interdisciplinary approaches—particularly those integrating artificial intelligence, machine learning, and human-machine interaction—could deepen the understanding of autonomicity in increasingly complex CPS environments. Furthermore, the ethical, regulatory, and societal implications of highly autonomous systems warrant careful consideration. Issues such as workforce displacement, cybersecurity vulnerabilities, and governance challenges must be addressed alongside technical advancements.

By laying the groundwork for a structured and scalable approach to evaluating autonomicity in CPS, this study contributes to both the academic literature and industrial innovation. The scale and framework presented here offer a practical foundation for researchers and practitioners aiming to implement autonomous technologies in a more deliberate, safe, and informed manner. As I4.0 continues to evolve, ongoing exploration of the intersections between autonomy, intelligence, and self-management will be crucial to ensuring that CPS remain effective, ethical, and sustainable.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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During the preparation of this work, the author(s) used generative AI to improve the English language and assist in the generation and enhancement of some of the images included in the article. After using these tools, the author(s) thoroughly reviewed and edited the content and visuals as needed and take full responsibility for the final version of the publication.

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