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Organisational Transformation Enabled by Smart Industrial Products: Unveiling Evolutional Path, Structural Hierarchy of Production Planning & Control, Inter-Functional Synergy and Barriers to Adoption

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Doctoral dissertation presented to the Post Graduate Program in Production Engineering of the Federal University of São Carlos, as part of the requirements for obtaining the title of Doctor of Science in Production Engineering.

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DEDICATORY

I dedicate this work to the heavenly father and my wife and son for all they faced while conducting this work.

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"If you could sell your experience by the price that it cost you, would be rich"

J. P. Morgan

"If I have been able to see further, it is only because I stood on the shoulders of giants"

Sir I. Newton

ABSTRACT

Within the realm of contemporary industry, the Industry 4.0 concept has ushered in a paradigm shift. In this regard, Smart Industrial Products (SIPs), encapsulating a spectrum of cutting-edge technologies, integrated within smart industrial ecosystems develop a central role. This doctoral dissertation aims to explore the evolutional path of main organisational functions, structural hierarchy between capabilities enabled to Production Planning and Control (PPC) function, inter-functional synergy that organisational functions should undergo to achieve full autonomy through the adoption of SIPs and, finally, the relationship between barriers to SIPs adoption. Initially, we identify the capabilities and barriers that SIPs provide for main organisational functions through an extensive Systematic Literature Review (SLR). Subsequently, we investigate the structural hierarchy relationship between the capabilities enabled by SIP adoption and the PPC Function. In sequence, we examine the inter-functional synergy resulting from SIPs adoption across organisational functions. Finally, we investigate the relationship between barriers, proposing a roadmap to strategically mitigate them. Our research comprises a mixed-method study, incorporating elements of SLR, Expert Interviews, Interpretive Structural Modelling (ISM), and the Fuzzy *MICMAC* approach. The first phase of our investigation culminates in a theoretical model outlining the evolutional path for organisational functions to become smart-enhanced, as well as the barriers faced at each stage of SIPs implementation. The second phase proposes a framework for achieving a fully autonomous PPC function, while the third one presents a model illustrating synergistic relationships among main organisational functions. Lastly, in the fourth phase propose a roadmap to strategically mitigate barriers that organisations should surpass to fully adopt a SIP.

Keywords: Smart Industrial Products; Industry 4.0; Production Planning and Control; Interpretative Structural Modelling; Cross-Impact Matrix Multiplication Applied to Classification; Capabilities; Barriers.

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LIST OF ABBREVIATIONS

ACATECH	German Academy of Technology
AM	Accounting Management
BDRM	Binary Direct Reachability Matrix
CNC	Computer Numerical Control
CPPS	Cyber-Physical Production System
ERP	Enterprise Resource Planning
FDRM	Fuzzy Direct Reachability Matrix
FRM	Final Reachability Matrix
ICTs	Information and Communication Technologies
I/O Bandwidth	Input/Output Bandwidth
IoT	Internet of Things
IRM	Initial Reachability Matrix
ISM	Interpretive Structural Modelling
IT	Information Technology
MES	Manufacturing Execution System
MM	Maintenance Management
MICMAC	*Matrice d'Impact Croisé Multiplication Appliquée à un Classement*
M2M	Machine-to-Machine Communication
PPC	Production Planning and Control
QM	Quality Management
RFID	Radio Frequency Identification
ROI	Return On Investment
RQ	Research Questions
SCADA	Supervisory Control and Data Acquisition
SIPs	Smart Industrial Products
SLR	Systematic Literature Review
SO	Specific Objective
SSIM	Structural Self-Interaction Matrix
SUS	Sustainability
WISP	Wireless Identification of Sensing Plattform

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1 INTRODUCTION

This chapter provides a general overview of the thesis, encompassing the subject under study, the main and specific objectives, the research inquiries, and the study's significance. It also offers a concise summary of the research methodologies utilised in this thesis.

1.1 RESEARCH GAP, QUESTIONS AND GOALS

The emergence of disruptive technologies, featuring extensive computational storage and cognitive capabilities, is poised to revolutionise various industry sectors and societal domains. These emergent technologies will create opportunities never before imagined in health, education, agriculture, manufacturing, and services (SCHWAB; DAVIS, 2018).

Within the organisational context, the advent of Intelligent Products is set to redefine how organisations conduct their operations. In this regard, the autonomy level of an organisational function is defined by the autonomy level of the Smart Industrial Products (SIPs) that are working in the shop floor. The SIPs concept, adopted in this research, is defined as “Products incorporating elements of the physical, connected, and smart dimensions, integrating physical and digital components. These products feature embedded systems enabling smart functionality, including the recognition, analysis, and autonomous exchange of customer data pertaining to the customer, goods in production, processes, and the environment in real time. Furthermore, SIPs offer innovative integrated services through self-improvement of their configuration to optimise performance and maximise value for the organisation”. This definition was done based in the main definitions found in literature and, that comprised only parcial aspects of the SIPs considered in our thesis (e.g.: Luo; Jiang; Song (2023); Wong et al. (2002); Kärkkäinen et al. (2003); Ventä (2007); Holmström et al. (2009); Rijsdijk; Hultink (2009); Hoffman; Novak (2015); Fabiano; Martens (2018); and Tomiyama et al. (2019)). So, a traditional function should evolute through 3 different levels to become completely autonomous. First, SIPs goes from traditional to connected, transparent and, after that, fully autonomous. This autonomy allows organisational functions to acquire specific capabilities, which makes it becoming more prescriptive, proactively reacting to the expected and unexpected events.

Despite an increasing volume of research in this field, as demonstrated in chapter 2, there remains a paucity of studies addressing the capabilities enabled by adopting SIPs within an organisation's manufacturing environment. Similarly scarce are the documented challenges organisations encounter when endeavouring to embrace this category of products, herein referred to as SIPs. Therefore, although several studies have highlighted diverse capabilities, they are typically discussed within the specific context of the authors' research, making generalisations biased.

This discrepancy prompts a fundamental question: *What evolutional path should an organisational function follow to become completely autonomous?*

To answer this question, three sub-questions should be answered:

1) What are the capabilities provided by SIPs for each of the main organisational functions?

2) What barriers do organisations face in implementing SIPs, and at what moment do these barriers directly impact SIP adoption?

3) What differentiates a traditional organisational function from a smart-enhanced organisational function, and what is the evolutional path such a

function should follow?

To answer these research questions, we adopted a multi-method research, composed of a SLR, Experts Interview and Content Analysis. At first moment, the SLR was conducted to identify the capabilities and barriers enabled by SIPs adoption in Operations. Then, 05 specialists were consulted to validate the constructs found in the literature. For this, a questionnaire was sent asking them to answer three main questions about these capabilities and barriers. Subsequently, Content Analysis was used to associate each capability/barrier with their respective level.

The main results included a list containing 20 Capabilities and 23 Barriers faced by organisations to adopt a SIP. Through Content Analysis, it was possible to classify the Capabilities into 3 categories: Connected, Transparent and Autonomous Decision-Making. Applying the same method to the Barriers, it was possible to classify them into 3 different moments of the SIPs adoption: Before, During and After implementation. Such classification culminates in a final framework presenting the Evolutional Path that a function should follow when organisations adopt SIP in their operations.

In the following, by examining the main areas of study within this field, we identified diverse research designs and research relating SIP with other concepts such as circular economy (EVERTSEN et al., 2022) and even industrial context (KIM; LIM; HSUAN, 2023; LIU; MING, 2019). These researches, however, have a predominant focus on practical investigations that emphasise standalone solutions. Besides, having identified the main capabilities and barriers to adopting a SIP and, realising that most of the capabilities were related to the PPC function, we identified that there was still a need to deeply explore this point, investigating the relationship between PPC enabled capabilities as a premise for achieve autonomous PPC function.

In the face of such arguments, three new questions arose:

4) Which are the capabilities enabled by SIPs' adoption in the PPC function?

5) How are these capabilities interrelated within the PPC function context?

6) Which path should organisations follow to successfully achieve autonomous decision-making PPC through acquiring SIP's capabilities?

To answer these three interrelated research questions, we used a multi-method approach, composed of the SLR, Experts Interview, ISM and finally Fuzzy *MICMAC* approaches. The SLR was used to raise the capabilities. Through content analysis we selected and refined the description of 12 PPC-enabled capabilities. The ISM was performed to analyse the interrelationship between each pair of capability, culminating in the development of a structural model. After identifying the structural model from the ISM, we performed the Fuzzy *MICMAC* to develop a cluster diagram. This final approach complements the ISM method (BIANCO et al., 2021) since it allows an understanding of the relationship intensity between these capabilities (MOTA et al., 2021), refining the structural model previously identified.

As a result, research question 6 was answered with a proposal of a framework. The proposed model illustrates the hierarchical structural relationship between these 12 capabilities, delineating which should be prioritised to enhance and amplify others. This is a valuable roadmap to assist managers and organisations in efficiently allocating resources for SIPs adoption, according to the current level of their SIPs. In addition, by highlighting the synergy between PPC-enabled capabilities, results demonstrate the existence of a path for optimising SIPs adoption, firstly achieving connectivity and then transparency, followed by autonomous decision-making I to finally achieve autonomous decision-making II, where the PPC function becomes a fully autonomous function.

In sequence, we observed that certain capabilities were linked to different organisational functions, and over time, these capabilities directly impacted the relationships between these functions. Additionally, upon reviewing the main studies on cross-functional synergy, we noticed a narrow focus, such as the role of cross-functional teams in value creation across firms (PETRIK; HERZWURM, 2019), enhancing monitoring capabilities through cross-functional integration (ZERMANE; DRARDJA, 2022), concept clarification, and scale development (PELLALTHY et al., 2019), among other specific areas. Consequently, we recognised the need to incorporate all organisational functions into a single model, aiming to elucidate how the adoption of SIPs would influence inter-functional synergy.

Thus, to the best of our knowledge, no research has evaluated the role of SIPs in shaping inter-functional synergy. In light of these arguments, three new questions have arisen:

7) What capabilities are enabled by SIPs' adoption for the main organisational functions?

8) How can SIP-enabled capabilities be prioritised to enhance synergy among main organisational functions?

9) How does the sequential development of SIP-enabled capabilities facilitate the integration of diverse management functions, enhancing organisational synergy and efficiency?

To address these interconnected research questions, we adopted a multi-method approach, encompassing SLR, Expert Interviews, ISM, and Fuzzy *MICMAC* analysis. The SLR was utilised to identify 20 capabilities enabled by organisational functions (answering question 7), while ISM was employed to scrutinise the inter-functional synergy among each pair of capabilities associated with distinct organisational functions, leading to the construction of the Structural model. Subsequently, Fuzzy *MICMAC* analysis was conducted to generate a cluster diagram.

This final methodological step complements the ISM approach (Bianco et al., 2021) by offering insights into the intensity of relationships among these capabilities (Mota et al., 2021), thereby refining the previously identified structural model. Consequently, question 8 was addressed by proposing a framework that delineates the synergistic enhancement of organisational functions through SIPs adoption. The proposed model illustrates the virtuous cycle enabled by SIPs adoption within organisations, leveraging 20 identified capabilities and highlighting those that should be prioritised to bolster and magnify inter-functional synergy.

The contribution of the model was exactly the answer of question 9, by aiding managers and organisations in effectively managing the interface between distinct organisational functions, through prescriptive approaches provided by their SIPs. Moreover, by emphasising inter-functional synergy, the results demonstrate that SIPs adoption engenders a virtuous cycle of continuous improvement. Initially, this is achieved by synchronising PPC and Maintenance, followed by advancing PPC through analytics, responsiveness, and complexity management. Subsequently, inter-functional collaboration extends to Quality control, Accountability, and adaptive PPC. Finally, environmental stewardship is nurtured through data-driven Sustainability.

To conclude this thesis, our research journey highlights that, although substantial progress has been made in understanding barriers, further investigation is required. Although the study of capabilities provides important insights into the organisational functions' evolutional path, in achieving a fully autonomous PPC, and in understanding how SIPs adoption shapes inter-functional synergy, organisations also face some structural barriers to implementing SIPs in their operations, thus hindering the adoption of such a category of products. Therefore, the exploration of such barriers has shed light on significant challenges hindering the adoption of advanced technologies within industrial settings. In light of the current scenario, three new questions have arisen:

10) What barriers do organisations face to adopt a SIP?

11) How are these structural barriers interrelated?

12) Is there a logical roadmap that organisations should follow to make the process of implementing a SIP more secure, sustainable, and efficient?

To address these three interrelated research questions, a multi-method approach, composed of SLR, Expert Interviews, ISM, and Fuzzy *MICMAC* approaches, was adopted. The SLR was used to identify the barriers in the literature. Content analysis was employed to select and refine the description of the structural barriers. ISM was then used to analyse the interrelationship between each pair of barriers, culminating in the development of a structural model. Following this, Fuzzy *MICMAC* was used to create a cluster diagram, supporting ISM results. This approach aimed us to answer question 10.

By applying ISM and Fuzzy *MICMAC* we identified the structural relationship between barriers, answering question 11. Afterward, we answered research question 12 by proposing a roadmap for mitigating structural barriers. The proposed model presented the relationship between the structural barriers, delineating which barriers should be prioritised to make the SIPs adoption process more efficient. This is a valuable tool to assist managers and organisations in efficiently allocating resources for SIPs adoption through a structured concentration of efforts. Additionally, by highlighting the structural relationship between barriers, we demonstrate the existence of a logical path for mitigating barriers to SIPs adoption.

To provide a clearer insight into the structure and content of this thesis, it is important to distinguish the four articles comprising it. Article 1 focuses on identifying the capabilities and barriers associated with SIPs for organisational functions, proposing a framework that delineates the Evolutional Path these functions traverse to become Smart-Enhanced. Conversely, Article 2 aimed to establish a Structural Relationship Hierarchy between capabilities enabled by SIPs for the PPC function. The proposed framework defines a sequence of capability dependencies, offering a structured pathway for organisations to attain a fully autonomous PPC function. In sequence, Article 3 identifyed how the adoption of SIPs shapes Inter-functional Synergy. And finally, Article 4 avalueted the structural relationship between barriers, proposing a practical guide to help managers in driving their efforts to structurally mitigate these barriers. This distinction between the articles provides a clearer understanding of the scope and specific objectives of each part of this research.

Given the presented context, to summarise, the main goal of this thesis was **to understand how SIPs enhance organisational autonomy by revealing the evolutional path of key organisational functions — particularly the PPC function — thereby clarifying the interfunctional synergies they enable and the structural barriers that must be strategically mitigated for their effective adoption in industrial operations.**

To achieve this general objective of the present thesis, specific objectives (SO) were proposed. The first (SO1) is to identify capabilities and barriers associated with SIPs for organisational functions, proposing a framework that delineates the Evolutional Path these functions traverse to become Smart-Enhanced ones. The second (SO2) is to establish a Structural Relationship Hierarchy framework that defines a sequence of capability dependencies, offering a structured pathway for organisations to attain a fully autonomous PPC function. Moreover, (SO3) was to identify how the SIPs' adoption shapes inter-functional synergy. Last but not least, (SO4) was to propose a structured and practical guide for organisations and managers to strategically move efforts in overcome structural barriers faced to adopt a SIP in organisational operations. Table 1.1 shows the research questions and methods related to the proposed specific objectives.

Table 1.1 – Relationship between RQ, SO, Research Method and Thesis Chapter

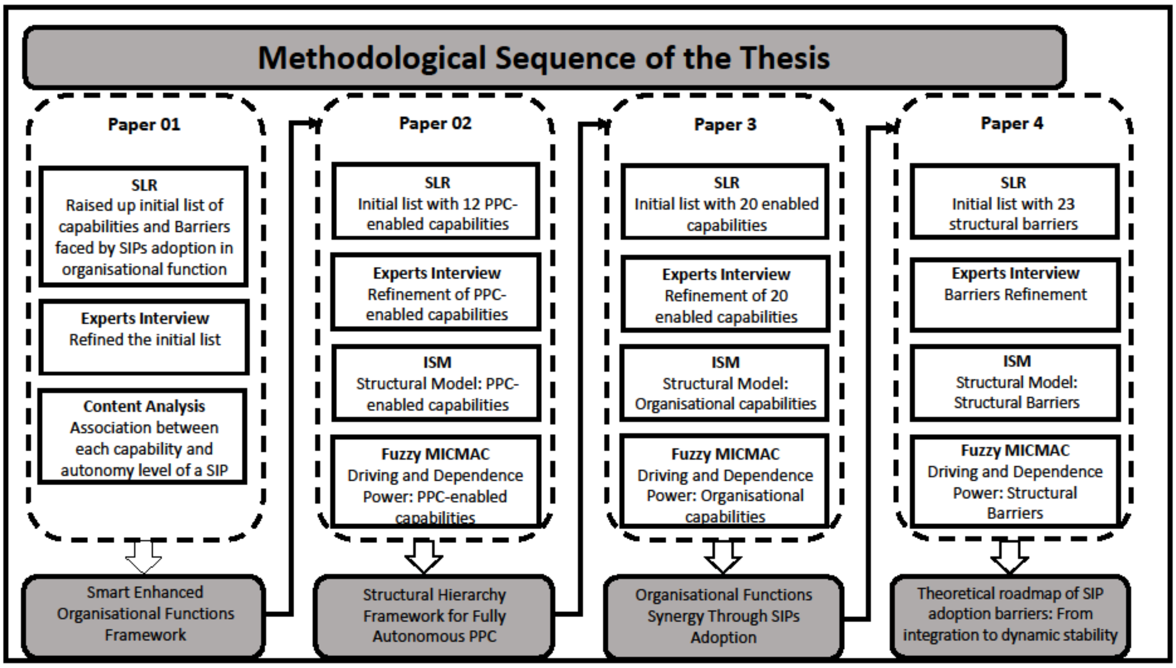
Research Questions	Specific Objectives	Research Method	Thesis Chapter
1) What are the capabilities provided by SIPs for each of the main organisational functions?	SO1	Systematic Literature Review Experts Opinion Content Analysis	**3. Smart-Enhanced Organisational Functions: A Framework Comprising Barriers, Capabilities, and Evolutional Path**
2) What barriers do organisations face in implementing SIPs, and at what moment do these barriers directly impact SIP adoption?		Systematic Literature Review Experts Opinion Content Analysis	
3) What differentiates a traditional organisational function from a smart-enhanced organisational function, and what is the evolutional path such a function should follow?		Systematic Literature Review Experts Opinion Content Analysis	
4) Which are the capabilities enabled by SIPs' adoption in the PPC function?	SO2	Systematic Literature Review Experts Opinion Content Analysis	**4. Exploring Capabilities enabled by Smart Industrial Products Adoption: A Framework for Fully Autonomous Production Planning and Control**
5) How are these capabilities interrelated within the PPC function context?		Interpretive Structural Modelling Fuzzy *MICMAC*	
6) Which path should organisations follow to successfully achieve autonomous decision-making PPC through acquiring SIP's capabilities?		Interpretive Structural Modelling Fuzzy *MICMAC*	
7) What capabilities are enabled by SIPs' adoption for the main organisational functions?	SO3	Systematic Literature Review Experts Opinion Content Analysis	**5. Organisational Functions Synergy Through Capabilities-enabled by SIPs: A Multi-method Study**
8) How can SIPs-enabled capabilities by prioritised to enhance synergy among main organisational functions?		Interpretive Structural Modelling Fuzzy *MICMAC*	
9) How does the sequential development of SIP-enabled capabilities facilitate the integration of diverse management functions, enhancing organisational synergy and efficiency?		Interpretive Structural Modelling Fuzzy *MICMAC*	
10) What barriers do organisations face to adopt a SIP?	SO4	Systematic Literature Review Experts Opinion Content Analysis	**6. Barriers to the Implementation of SIPs in Organisations: Conceptualisation and Relationships**
11) How are these structural barriers interrelated?		Interpretive Structural Modelling	
12) Is there a logical roadmap that organisations should follow to make the process of implementing a SIP more secure, sustainable, and efficient?		Interpretive Structural Modelling Fuzzy *MICMAC*	

Source: Elaborated by the author (2025)

1.1 OVERVIEW OF THE RESEARCH METHODS THAT COMPOSES THIS THESIS

This thesis is composed of four interrelated papers. The option for this model of building has the purpose of streamlining the publication of this work's results and contents. The choice of the methods utilised in each one of the chapters (papers) was associated with the research development and the details of each method utilised are in Chapters 2, 3, 4 and 5. The papers have a logical relationship to each other and papers 2, 3 and 4 present a similar methodological sequence, which justifies any repetitiveness in the text of these three chapters. The methodological sequence of this research is shown in the figure 1.1.

Figure 1.1 Overview of the Research's Methodological Sequence



Source: Elaborated by the author (2025)

This thesis is classified as a multi-method approach. The multi-method term is utilised to represent research that is composed of qualitative and quantitative methods in the same project. The qualitative research of this thesis comprised a SLR, Experts Opinion and Content Analysis. This kind of research has as its main feature data collection in a textual form instead of the numerical form to analyse data. According to Teixeira (2003), the data analysis is configured in an important phase in the investigation achievement in the applied social sciences, especially in the study field of development, management, and organisations. The same author points to the fact that administration and organisational theory studies have been characterised, fundamentally from analytical instruments. These approaches are grounded in mechanical and organic models of the organisation (typical of the qualitative approaches), which does not allow the researcher to interpret reality under new dimensions.

So, the conduction of a literature review systematically substantiates the conduction of unprecedented research. The objective, according to Tranfield; Denyer; and Smart (2003) is to allow the researcher to map and evaluate the state of the art, specifying a research question for the evolution of the existing knowledge. Besides, Denyer; and Tranfield (2009) point out that a SLR is an essential endeavour by itself and not merely a review of previous writing. Moreover, it responds to specific questions and is a “methodology that locates existing studies, selects and evaluates contributions, analyses and synthesises data, and reports the evidence to allow reasonable, clear conclusions about what is and is not known (TRANFIELD; DENYER; SMART, 2003). The SLR approach, performed in this thesis followed the steps proposed by Denyer; and Tranfield (2009), composed by Planning, Conduction and Dissemination. Each specific step is detailed in the third chapter of this thesis.

Regarding the experts' interviews, the data collection for the empirical research and results validation of the SLR were grounded by the expert’s opinions. For the capabilities and barriers validation, we consider adopting the opinion of 05 academical experts. Among the advantages of interview experts, Bogner et al. (2009) points three that comprises:

1. Talking to experts in the exploratory phase of a project is more efficient and concentrated method of gathering data than, for instance, participatory observation or systematic quantitative surveys;
2. Conducting expert interviews can serve to shorten time-consuming data-gathering process mainly when they are seen as surrogates for a wider circle of players;
3. Expert interviews can also be useful when data is difficult to gain access to a particular social field;

Content analysis is a technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use (KRIPPENDORFF, 1989).

So, as a research methodology, it comprises specific procedures that should be both learnable and divorceable from the researcher's judgement. Besides, it should provide new insights, increase the researchers' understanding of a particular phenomenon, or inform practical actions (KRIPPENDORFF, 1989).

Although the term is about 60 years old, today’s content analysis is significantly different, in aim and method, from that performed in the past (KRIPPENDORFF, 1989). According to the author, contemporary content analysis has three distinguishing characteristics:

First, it is an empirically grounded method, being exploratory in process and predictive or inferential in intent. Second, it transcends the traditional notion of symbols, contents, and intents, which surpass the natural evolution of the way content is being disseminated in the computational times, where the processing of digital data in place of cognitive and social practices, along with the ability to reproduce these data in visual and textual forms for reading, rearticulating, disseminating by and to ideally everyone is encouraging an entirely new literacy that undercuts traditional organisational structures, including national boundaries (KRIPPENDORFF, 1989). And third, it has been forced to develop a methodology of its own. Three phenomena corroborate for this third reason: 1) Content analysts now face larger contexts; 2) Great numbers of researchers need to collaborate in the pursuit of large-scale content analyses; 3) The large volumes of electronically available data call for qualitatively different research techniques, for computer aids.

The content analysis was used in our research to verify the existence of any semantical similarity between different constructs (e.g.: Capabilities and Barriers) identified in the SLR. To perform the content analysis, we codify and create a brief description for each capability and each barrier. In sequence, we used the software NVivo to verify which capabilities and which barriers had the same conceptual meaning. The code and its respective description were inserted in the NVivo, and the semantical similarity analysis was performed. The constructs with an index of 75% or above, in terms of semantical similarity, were clusterised in a single construct, avoiding data redundancy and giving reliability to the research.

The quantitative research of this thesis was built through ISM and *MICMAC* analysis. Quantitative research, emphasises the quantification in the data collection and analyses, having by consequence, a much more objective character. The adoption of a quantitative design in research presupposes some specific conditions that should be present since the problem formulation, which implies the preponderant role of the literature review, the collection and data analyses and the results report relation (SAMPIERI, COLLADO and LUCIO, 2013).

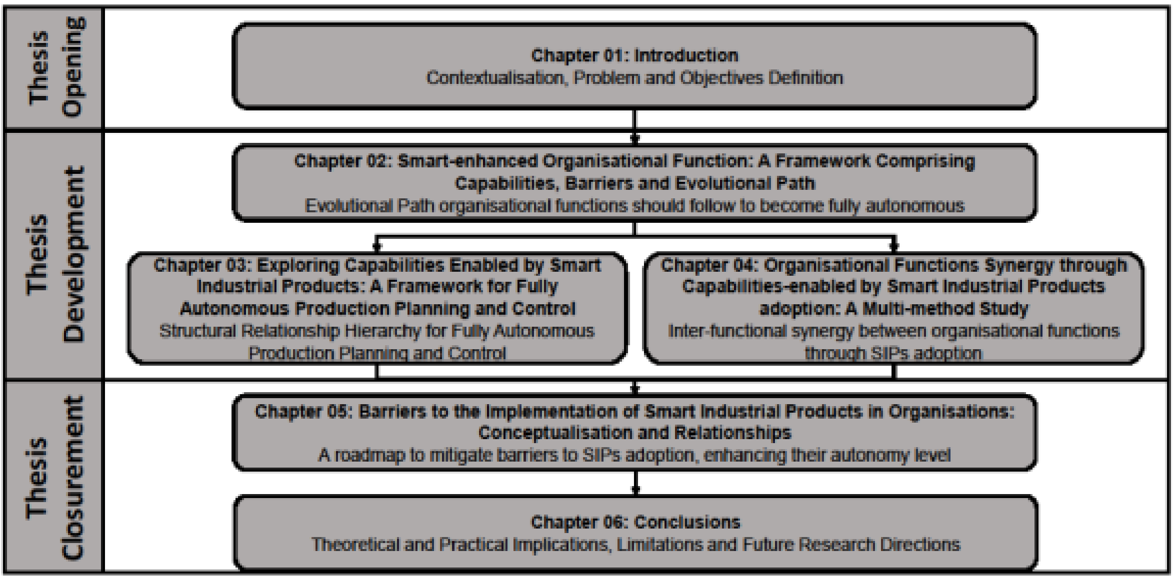
The empirical research of this thesis utilised the ISM approach to collect and analyse data. The complexity of the issues or systems is due to the presence of a large number of elements and interaction among these elements. The presence of directly or indirectly related elements complicates the structure of the systems which may or may not be articulated clearly (ATTRI; DEV; SHARMA, 2013). Farris; Sage (1975) defines ISM as a process aimed at assisting the human being to better understand what he/she believes and to recognise clearly what he/she does not know. The most essential function is organisational. The information added (by the process) is zero. The value added is structural. Hence the ISM process transform unclear, poorly articulated mental model of systems into visible and well-defined models (ATTRI; DEV; SHARMA, 2013).

Furthermore, the *MICMAC* analysis was used to study and identify the driving and dependence power of the variables, determining which variables will guide the model in several categories. Our variable classification follows the model proposed by Attri; Dev; and Sharma (2013), being allocated into 4 clusters: Autonomous, Dependents, Linkage, and Independents.

1.2 THESIS STRUCTURE

The organisation of this thesis follows the logical sequence of state-of-the-art identification and development. Chapter 2 presents a SLR of the SIPs field, seeking to raise capabilities enabled by SIPs adoption for the main organisational functions as well as barriers faced by organisations to adopt a SIP. Chapter 3 presents a framework for a fully autonomous PPC through the use of SIP. Chapter 4 presents the interfunctional synergy between the main organisational function through SIPs adoption. Chapter 5 unvail the structural relationship between barriers to SIPs adoption, proposing a model organisations strategically move efforts to mitigate them. Finally, Chapter 6 closes this thesis bringing the general conclusions and future research directions.

Figure 1.2 Overview of the thesis structure



Source: Elaborated by the author (2025)

2 SMART-ENHANCED ORGANISATIONAL FUNCTIONS: A FRAMEWORK COMPRISING BARRIERS, CAPABILITIES AND EVOLUTIONAL PATH

This chapter is composed by the first paper of the thesis and was published on the journal **Expert Systems With Application**. https://doi.org/10.1016/j.eswa.2024.124530. **Impact Factor Ranking:** Q1 - Web of Science

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Integrating smart industrial products (SIPs) into production processes introduces new dynamics of capabilities and challenges within organisations. However, a prevalent issue is the ad hoc adoption of SIPs without a cohesive strategy, resulting in isolated solutions that do not effectively enhance main organisational functions. Our research fills this critical gap by identifying and combining the capabilities and barriers posed by SIPs. Our findings allow us to propose a framework comprising the stages each main organisational function needs to develop to move from a traditional to a completely autonomous decision-making function. This evolutional path requires that each organisational function acquires selected capabilities and overcomes specific barriers. Our approach encompasses a multi-method methodology, commencing with a SLR encompassing 44 papers, leading to the identification of 20 capabilities and 23 barriers. Subsequently, through rigorous content analyses and expert interviews, we formulate the framework. This paper contributes to academia by providing a framework with an evolutional path that main organisational functions may follow according to the capability they acquire from the SIP and which barriers should be surpassed at each level. For managers in practice, the proposed framework enables a better understanding of the stage of their operations and which capabilities will take their main organisational function from traditional (level 0) to autonomous (level 3) stages.

Keywords: Barriers; Capabilities; Connected Products; Smart Production; Smart Industrial Products

2.1 INTRODUCTION

The last decade has presented disruptive advances in the realm of smart products, especially with the emergence of Industry 4.0 in 2011, supported by the German government and led by the German Academy of Science and Engineering (LEE et al., 2022). In their early days, smart products were mainly the subject of philosophising in technology think tanks or were used for cutting-edge marketing technology at trade fairs (RAFF; WENTZEL; OBWEGESER, 2020). However, smart products have become a tangible reality for both the customer and the organisational environment, enabling new ways to develop and commercialise goods. Besides, the increasing adoption of disruptive technologies and SIPs has transformed organisational standards and product features across various sectors. However, many companies are adopting SIPs without a clear strategy, resulting in isolated solutions that do not directly contribute to their main organisational functions. Moreover, the lack of systematic and strategic identification of capabilities and barriers related to SIPs hinders the evolution of organisational functions towards fully autonomous decision-making processes.

In an organisational context, this tendency of the evolution of products towards smart products has entailed the necessity for further studies to deeply understand these products' impacts on the manufacturing environment since this new industrial stage is affecting competition rules, industry structure, and customer demands (BARTODZIEJ, 2017). In this context, our main motivation in this study is to develop a comprehensive framework that systematically identifies and combines capabilities and barriers associated with adopting SIPs. This framework aims to provide key organisational functions with a clearly defined and structured evolutional pathway, facilitating the transition from traditional to fully autonomous decision-making functions. This paper focuses on the following organisational functions: Accounting, Sustainability, Maintenance, PPC and Quality Management.

While the field of smart products has gained popularity in research, there remains a lack of consensus and clarity regarding the definition of a smart product (RAFF; WENTZEL; OBWEGESER, 2020). Addressing this gap, our paper offers a precise definition of SIPs as follows: "Products incorporating elements of the physical, connected, and smart dimensions, integrating physical and digital components. These products feature embedded systems enabling smart functionality, including the recognition, analysis, and autonomous exchange of customer data about the customer, goods in production, processes, and the environment in real time. Furthermore, SIPs offer innovative integrated services through self-improvement of their configuration to optimise performance and maximise organisation value." This definition was synthesised by analysing key aspects of SIPs outlined by various authors: Luo; Jiang; Song (2023); Wong et al. (2002); Kärkkäinen et al. (2003); Ventä (2007); Holmström et al. (2009); Rijsdijk; Hultink (2009); Hoffman; Novak (2015); Fabiano; Martens (2018); and Tomiyama et al. (2019). Its importante to highlight that this topic has several practical and academic contributions and has been studied recently worldwide, for example, (Li et al., (2024); Yang et al. (2024) among a lot of others.

Our research is focused on identifying the capabilities and barriers associated with SIPs for organisational functions, culminating in a framework that delineates the evolutional path these functions traverse to become smart, based on their acquired capabilities. Capabilities can be understood from two different perspectives. The first perspective comprises the capabilities that the product needs to have to be considered smart or intelligent for the final customer, also referred to as smart consumer products (DAWID et al., 2017; MICHLER; DECKER; STUMMER, 2020). These products include smartwatches, smart bands, smart cars, smartphones, etc. Raff; Wentzel; Obwegeser (2020) proposed a framework containing these capabilities. The second capability perspective considers the abilities that an organisation (specifically its main organisational functions) acquires when adopting SIPs in its processes to create value for itself and its customers. Our study focuses on this second perspective, having a technology-enabled capability perspective rather than a simple technology adoption approach. In our research, we also address barriers, in line with Sarkar; Bhuniya (2022) assertion that comprehending these obstacles is crucial, even when organisations are equipped with the capabilities offered by SIPs.

Our research identifies the capabilities and barriers entailed by SIPs for organisational functions, proposing a framework that presents the evolutional path followed by an organisational function to become smart, according to the level of the acquired capability. Although some research has been carried out on capabilities and barriers related to SIPs adoption, there is a gap in the literature regarding this topic. SIPs require a completely new technology infrastructure, known as the "technology stack," which acts as a conduit for data exchange between the product and the user, incorporating data from various business systems, external sources, and interconnected products (PORTER; HEPPELMANN, 2015). Researchers such as Bueno et al. (2022) and Pardo; Ivens; and Pagani (2020) have emphasised the transformative potential of embedded technologies in creating and capturing value. This technology stack serves as a multifunctional platform within SIPs, facilitating data storage, analytics, application execution, and ensuring secure access to products and the associated data flow (PORTER; HEPPELMANN, 2015). While it is evident that enabling technologies empower SIPs to function effectively, the specific impact of these capabilities on various organisational functions remains a subject that requires further investigation.

Aiming at contributing to bridging this research gap, our paper collects and critically analyses the existing knowledge in the SIP field, presenting and clarifying which capabilities impact each organisational function, identifying the barriers faced by companies in implementing SIPs in their operational environment and organising these capabilities and barriers in a framework that reveals an evolutional path for the functions impacted. Therefore, this study addresses the following main research question:

RQ: What evolutional path should an organisational function follow to become completely autonomous?

To answer this RQ, first of all, three sub-questions should be answered, stated below:

SRQ1. What are the capabilities provided by SIPs for each of the main organisational functions?

SRQ2. What barriers do organisations face in implementing SIPs, and at what moment do these barriers directly impact SIP adoption?

SRQ3. What differentiates a traditional organisational function from a smart-enhanced organisational function?

Concerning the innovation aspects of this research, our framework offers a practical guide for companies interested in adopting SIPs efficiently and effectively. Therefore, the main contributions of our paper are threefold. First, we propose a novel definition for the SIP construct, expanding the definition proposed by Raff; Wentzel; Obwegeser (2020). Second, we identify in the literature the capabilities enabled by SIPs and the barriers to adopting smart products in the industrial context and validate them with experts. This rigorous analysis ensures a thorough examination of the literature and the experts' knowledge in the field, making our findings robust and reliable. Third, we propose an evolutional path that companies should follow to improve the level of decision-making in their different traditional functions. This proposed path is not merely theoretical since experts with empirical knowledge about smart products validated it. Thus, our framework is grounded in practical strategies and actions organisations can implement at each stage. Based on these motivations and contributions, we believe this research provides valuable insights for the academic and professional community, driving the successful implementation of SIPs in organisations across diverse sectors and preparing them for a smarter and more strategic approach to their operations. Moreover, for managers in practice, it provides an enhanced understanding of the current stage of their operations, the necessary capabilities to achieve autonomous decision-making and which barriers will be faced according to the autonomy level of an organisational function. In addition, the multi-method approach was considered to answer the proposed research question, contemplating a SLR and interviews conducted with experts. This combination of methods fits the need to ensure an exhaustive literature review to identify capabilities and barriers, as well as interviews with experts to ensure the validity of the findings. Finally, to the best of our knowledge, our proposed framework is the first framework found in literature, which delineates the evolutional path each main organisational function needs to develop to move from a traditional to a completely autonomous decision-making function.

Our paper is organised as follows. Section 2 presents the literature review and the research gap this work seeks to fill. Section 3 presents the research method. Section 4 presents and discusses the results. Finally, Section 5 provides concluding remarks and suggestions for future research.

2.2 LITERATURE REVIEW

This section begins with a discussion of the smart products literature. Next, an overview of the SIP literature is presented. Finally, the research gaps are discussed based on the current literature analysis, and the study motivations are explained.

2.2.1 An Overview of the Smart Industrial Product Literature

Various technologies are critical in the Industry 4.0 landscape (AWAN et al., 2022). Notably, smart products, such as IoT-based systems, have garnered significant attention (KUMAR et al., 2022; WANG; RANSCOMBE; EISENBART, 2023). Many studies on smart products have been conducted in recent years, including the secure and reliable operation of smart products in various domains (SONG et al., 2023a, 2023b), prototyping in smart product design (WANG; RANSCOMBE; EISENBART, 2023; ZHANG et al., 2023), and analysis of the use of a smart product-service system (CHANG et al., 2023; FENG et al., 2023; LE-DAIN et al., 2023; YU; SUNG, 2023).

A comprehensive literature review of smart products reveals four fundamental types of research in this field. (1), exploring smart products in conjunction with other concepts. For example, Lopez; and Garza (2023) studied consumer bias related to artificial intelligence-generated evaluations in the context of smart product usage. Evertsen; Rasmussen; and Nenadic (2022) analysed the circular economy innovations commercialised by academic spin-offs, including smart products, and Ren et al. (2024) studied the concept of a metaverse in the industrial context; (2) described the development or use of a specific smart product (e.g., CHANG et al., 2023; CONG et al., 2022). (3), analysing smart products acceptance by consumers (ROCHI, 2023; SABATINI; PASCUCCI; GREGORI, 2023). Finally, examining the utilisation of smart products in the industrial context (KIM; LIM; HSUAN, 2023; LIU; MING, 2019).

Within the SIP literature, existing studies provide guidelines for developing or implementing smart industrial product-service systems. For example, Kim; Lim; and Hsuan (2023) provided a multi-level architecture for a smart product-service system in the context of Industry 4.0. Similarly, Liu; and Ming (2019) proposed a thorough framework for identifying and assessing the smart industrial product-service system requirements. However, notably the academic landscape predominantly focuses on using smart products for the final consumer, while research dedicated to the industrial sector remains comparatively limited.

2.1.2 Research Gaps

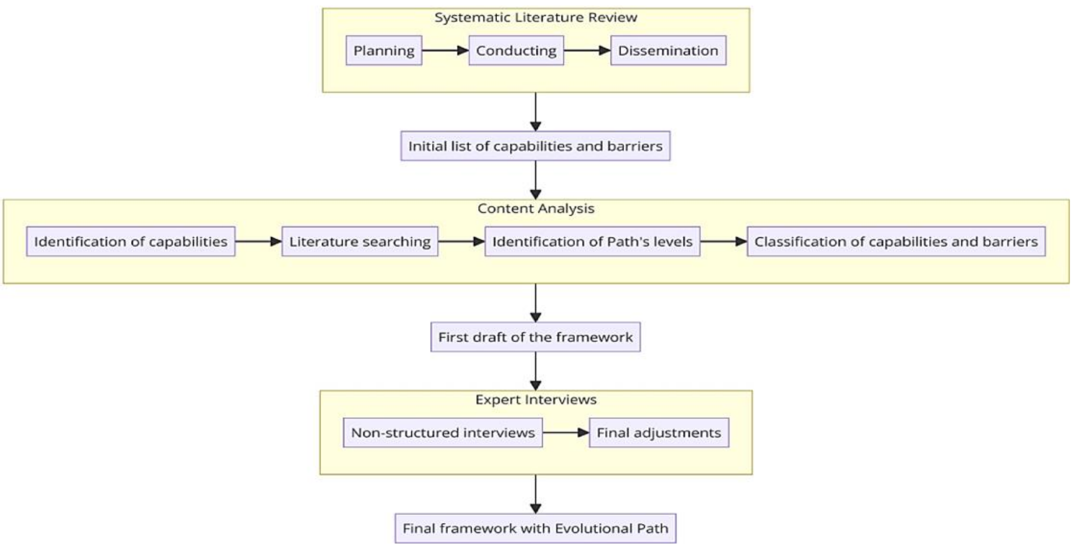
Our study explores SIPs within an industrial context, an area still relatively uncharted compared to the extensively studied consumer-focused SIPs in the existing literature (e.g., Yang et al. (2024). Kim; Lim; and Huan (2023) highlight the importance of smart products within the industrial settings yet a comprehensive literature review reveals a notable gap in research dedicated explicitly to SIPs. While Akhtar et al. (2024) examine the potential of AI and Generative AI in smart product platforming, the integration challenges of different technologies within existing indus- trial systems are less emphasised. The prevailing research primarily focuses on developing and adopting smart product-service systems without adequately exploring crucial factors such as the capabilities SIPs enable and the barriers to their implementation. Akhtar et al. (2024) identified capabilities related to smart products but did not focus on the industrial sector. Additionally, our extends the analyses conducted by Li et al. (2024) who only investigated quality improvement and consumer valuation through SIPs. The existing literature also outlines a product's capabilities to be deemed "smart" without addressing the specific capabilities that the SIPs enable.

In this regard, it can be observed that no research has analysed in depth the benefits (capabilities) that a SIP can enable for industries, nor is there any discussion on the difficulties these companies may face when adopting a SIP (barriers). Therefore, to the best of our knowledge, our study is the first to address the theme of SIP-enabled capabilities and the barriers associated with adopting these technologies. By identifying and deepening discussions about these SIP-related capabilities, valuable insights can be gained to guide the effective adoption of these technol- ogies in various organisational functions. Simultaneously, understanding the adoption barriers to SIPs becomes essential, as it facilitates the recognition of factors that prevent companies from successfully implementing these technologies.

2.3 RESEARCH METHOD

The main objective of this study is to provide a clear and structured framework with the evolutional path that organisational functions may follow when adopting SIPs, streamlining the transition from a traditional to a fully autonomous decision-making function. Thereby, we performed a process comprising three different methodological steps. The first step consisted of an SLR, where we identified each capability's barriers, capabilities, and examples. Next, content analysis was con- ducted to identify semantical similarities between capabilities and barriers. This enabled us to classify the barriers according to when the SIP was adopted, their related capabilities in the organisational function, and their autonomy level. After that, we interviewed five experts (practitioners and academics) to validate the classification and propose the final framework containing the evolutional path. A summary of methods and steps is presented in Fig. 2.1.

Fig. 2.1 Summary of the methodological approach and steps in this research



Source: Elaborated by the author (2024)

2.3.1 Identifying the Initial List of Capabilities and Barriers

The first step was conducting an SLR to enable the identification of an initial list of capabilities and barriers. The justification of an SLR for this first methodological step is that from the SLR, it is possible to respond to specific research questions from a robust methodology for locating, selecting, and evaluating existing studies Denyer; and Tranfield (2009).

Based on the guidelines presented by Denyer; and Tranfield (2009), it was considered that the conducted SLR comprised three main stages: planning, conducting, and dissemination. Thus, the research protocol was defined first (Table 2.1), which included the main research points, the string searched, the databases used, the research topics, the research questions, and the inclusion and exclusion criteria.

Table 2.1 - Research protocol

Research protocol		
Objective		To identify barriers and capabilities provided by smart industrial products (SIPs) for the main organisational functions
Guiding Questions		*RQ1.* What are the capabilities provided by SIPs for each of the main organisational functions? *RQ2.* What barriers do organisations face in implementing SIPs, and at what moment do these barriers directly impact SIP adoption? *RQ3.* What differentiates a traditional organisational function from a smart-enhanced organisational function, and what is the evolutional path such a function should follow?
Databases		Engineering Village, Scopus, Web of Science
Publication years		From 2010 to 2024
Document type		Articles, Articles in Press, Reviews
Language		English
Strings		((Smart AND Product) OR (Smart AND Products) OR (Connected AND Product) OR (Connected AND Products) OR (Smart AND Connected AND Product) OR (Smart AND Connected AND Products) OR (Intelligent AND Product) OR (Autonomous AND Product) OR (Autonomous AND Products) OR (Autonomous AND Device) OR (Autonomous AND Devices))
Criteria explanation		
I/E	*Criteria*	
Exclusion	Non-related (NR)	NR-1: Articles considering smart product-service systems NR-2: The definition of “smart product” is not related to the organisational environment
	Loosely related (LR)	LR: Articles that cite “smart product” but do not discuss the impacts of the capabilities in operations
Inclusion	Closely related (CR)	CR: Articles featuring SIP studies, pointing out capabilities and their relationship with internal organisational functions

Source: Elaborated by the author (2024)

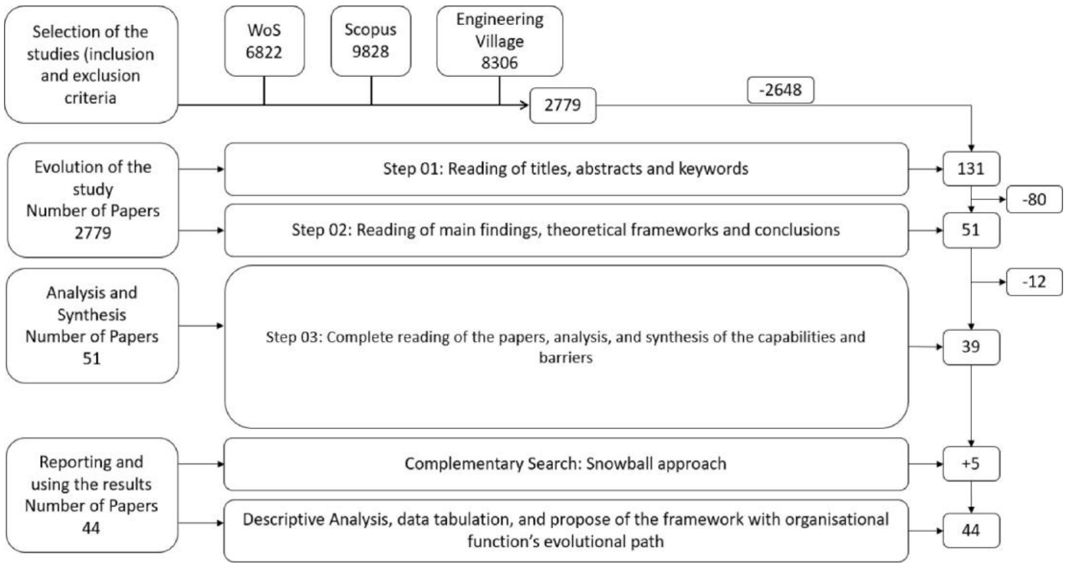
The protocol was implemented in three academic databases: Scopus, Engineering Village, and Web of Science, converging the most relevant available academic articles on the research topic. After choosing the databases, the search strings were defined. A broad search string was specified because of the heterogeneous nature of smart products and the absence of consistent terminology within the sector due to its novelty. The main objective was to include the majority of studies in this field. The search strings defined for this purpose are shown in Table 2.1.

This initial search yielded 24,956 papers. Only documents from 2010 to 2023 were selected, which included articles, press articles, or reviews written in English, and covering areas such as industrial, manufacturing, electrical, and electronic engineering, multidisciplinary, computer science, interdisciplinary, artificial intelligence, operations research, and management. It should be mentioned that duplicated articles were excluded. Considering this, the total sample was reduced to 2,779 papers. The initial year was chosen based on the emergence of Industry 4.0 in 2011 when most of the disruptive technologies that comprise smart products started to be commercially available and further adopted in the industry. Furthermore, only publications from peer-reviewed academic journals were considered, excluding articles from conferences and magazines. The justification for this decision not to consider conference articles is that many of these articles present partial results, anecdotal cases, or low rigour in validation (ROSSINI; POWELL; KUNDU, 2023).

In the next step, the title and abstract of the remaining 2,779 articles were read to assess whether they met the inclusion and exclusion criteria previously defined. Due to the lack of terminological consensus in the field, in this step, each paper was individually analysed to verify whether the research focus was SIPs. After this, 2,648 papers were rejected based on the exclusion criteria. From the 131 remaining articles, the main findings, the theoretical framework, and the conclusions were read, applying the inclusion and exclusion criteria, resulting in 51 articles being selected. Since this work focuses on revealing the capabilities and barriers that SIPs entail for operations, only papers addressing these topics were included. In this process, the thematic positioning of each article is pivotal for the evaluation (RAFF; WENTZEL; OBWEGESER, 2020), and reports not showing any capability or barrier provided by SIPs were therefore not selected. Furthermore, articles focusing on any technical aspects of the product or emphasising product capabilities were not selected as the objective of this review is to assess the benefits of the process.

Following the review, another 9 papers were identified in the references of the initial set of papers (i.e. a snowball approach), which were also read in their entirety. This step resulted in adopting 5 additional documents in the final sample. Thus, after applying the inclusion and exclusion criteria, our final sample comprises 44 articles. When studying smart products' capabilities through a similar method, other studies (e.g. Callefi et al. (2023), (2022); Raff; Wentzel; Obwegeser (2020) have also arrived at a similar number of selected articles. A summary of the filtering process results is shown in Fig. 2.2. Moreover, the 44 selected articles is available in the Table 2.4.

Fig. 2.2 Summary of article selection



Source: Elaborated by the author (2024)

2.3.2 Content Analysis and Expert Interviews: Proposing the First Draft of the Framework for Organisational Functions' Evolutional Path

The framework is proposed based on content analysis and validated through expert interviews. The assessment elements comprised: 1) capabilities provided by the SIP for the organisation; 2) a brief description of these capabilities; 3) the function impacted (benefitted) by implementing the SIP; 4) a practical example (i.e. how the impact happens); and 5) the moment when the barriers directly impact SIP adoption.

Regarding capabilities, each of them represents a benefit that the process acquires when the organisation adopts the SIP. Thus, a codification and a description were provided to improve understanding and enable the grouping process for capabilities cited differently but with the same meanings. This process is based on how the capabilities impact the operations of the acquired ability. Subsequently, each report describes how the acquired ability changes a current process.

2.3.2.1 Content Analysis

The content analysis procedure involved identifying capabilities associated with each organisational function, drawing upon practical examples cited in the analysed papers. Thus, each capability and barrier was codified and briefly described. These descriptions were then input into NVivo 11 software to analyse semantic similarities among constructs, following a procedure similar to that conducted by Bianco et al. (2023), who performed a semantic analysis of factor descriptions for categorisation. This step aimed to recognise instances where a capability or barrier might have been mentioned using different terminologies across various papers but held the same conceptual meaning. In addition, a sensitivity analysis was conducted to determine whether one or more of the analysed factors (capabilities and barriers) could be grouped into a single factor. In this regard, an adequate preliminary list of capabilities and barriers was guaranteed. Subsequently, three other researchers manually analysed the remaining barriers and capabilities. This thorough analysis sought to identify any remaining semantic similarities, ensuring the method's robustness.

Second, we also analysed self-citation effects to ensure the comprehensive coverage of relevant literature and identify potential biases in assessing capabilities and barriers. During this analysis, we observed that only two articles within our sample contained self-citations. These two studies did not address the same capabilities or barriers. Consequently, it can be inferred that there is no significant bias related to self-citation effects.

Third, we identified theoretical models and frameworks that pointed to classification stages for the functions according to the level each would have in terms of autonomy. For this analysis, we used an adaptation of the framework proposed by Oluyisola; Sgarbossa; Strandhagen (2020) as it proposes a classification for SIPs according to the autonomy level that their functions have. This model presents three classification levels according to the function's autonomy index, namely connected, transparent, and autonomous decision-making.

Fourth, we identified which words used in the reviewed capabilities descriptions were related to each framework level. Table 2.2 presents the levels, their respective definitions, and the keywords each capability definition or description should have to allow capability classification within an organisational function. These categories represent indicators related to the performance of capabilities in a practical context.

Table 2.2 - SIP capabilities classification by category level

Category	Definition	Features that a capability must have to be classified within each category
Connected	The connected category comprises the capability provided for a SIP when it is in its first stage of maturity (it is connected but does not have any level of integration or even autonomy in decision-making)	To be considered within this category, the capability description should contain terms such as data gathering, connectivity, or data acquisition
Transparent	The transparent category comprises the capabilities provided for a SIP when it is connected and integrated with other machines, systems, and resources.	To be considered within this category, the capability description should contain terms such as visibility, interoperability, real-time information management, M2M communication, connected, integrated, or networked
Autonomous decision-making (adaptability)	The autonomous decision-making category comprises all the capabilities that are provided by a SIP when it is in its highest stage of development, being connected, integrated, and making use of the data and the identified behavioural parameters of all the production systems to feedback to the SIP, continuously improving its configurations and predicting and planning for future events	To be considered within this category, the capability description should contain terms such as data usage, self-managing information, reconfiguration, algorithm application, analytics, change reaction, and historical data application

Source: Adapted from Oluyisola et al. (2020)

Fifth, after identifying the levels, we used Table 2.2 to identify the capabilities within each level. For instance, as later addressed, the capability MA3 comprises the ability to collect and carry information concerning the product during its lifecycle. This capability contains terms such as collect and carry; thus, these terms are associated with passivity and can be classified in the connectivity level of the maintenance function. Finally, the same procedure was used to identify the barriers to be classified at each level.

2.3.2.2 Experts Opinion: The Final Framework Proposition

The process of refining and verifying validity was conducted by interviewing five experts, including both practitioners and academics. This number of experts was chosen non-probabilistically via purposive sampling. This strategy has been used by several authors (CALLEFI et al., 2021; LOPES et al., 2023; NAEEM, 2020). Furthermore, it was specified that the experts must be academic researchers with more than 10 years of experience in the field of PPC to satisfy the criteria for selection. The experts' profiles are presented in Table 2.3.

Table 2.3 – Experts' profiles

Expert	Position	Academic education	Experience in PPC or Industry 4.0
1	Researcher/ Professor/ Consultant	PhD in Production Engineering	20 years
2	Researcher/ Professor	PhD in Production Engineering	13 years
3	Researcher/ Professor/ Consultant	PhD in Production Engineering	13 years
4	Researcher/ Professor	PhD in Production Engineering	11 years
5	Researcher/ Professor	PhD in Production Engineering	15 years

Source: Elaborated by the author (2024)

Three aspects were considered while validating and refining the barriers and capabilities: title and description; correlation with the research objective, and association with the defined category. The interviews were conducted via videoconference and lasted an average of 50 minutes.

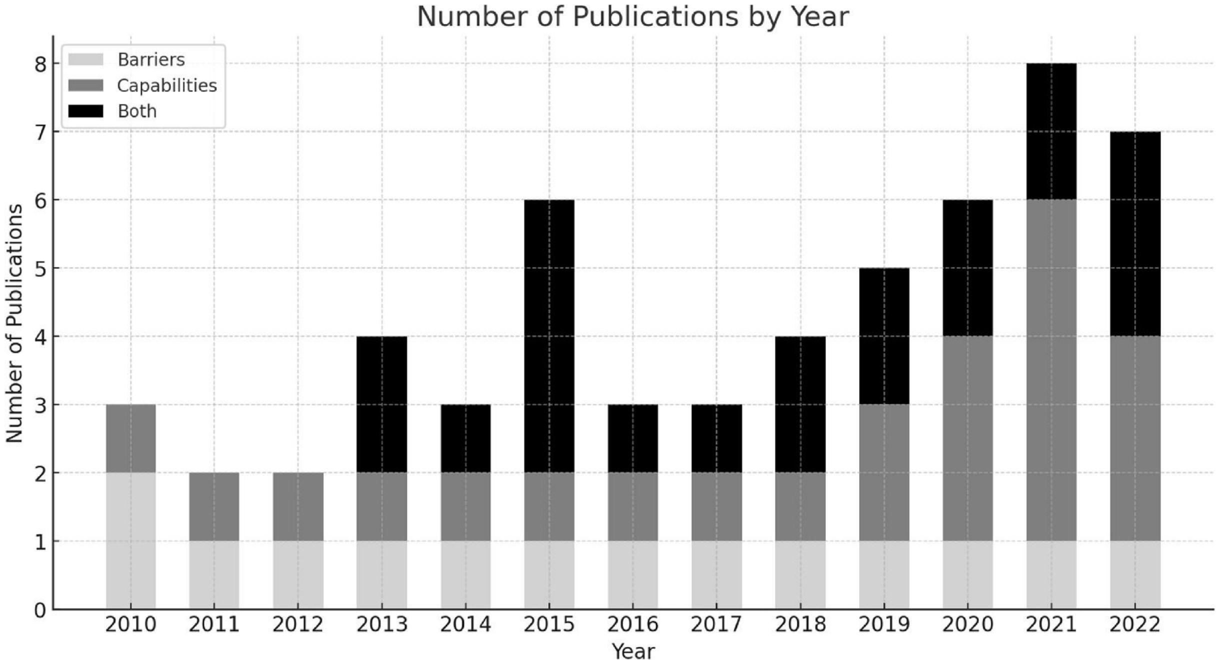
2.4 RESULTS AND DISCUSSION

This section presents the results of this paper, showing the responses to the proposed research questions. We start with a brief descriptive analysis of the papers composing our final sample, later introducing the capabilities and barriers that allow us to introduce a framework for smart-enhanced organisational functions.

2.4.1 Descriptive Analysis

This research identified 44 papers that pointed out the capabilities or barriers SIPs provide for the process when organisations decide to adopt it in production. Of these, 18 papers (40.91%) provided insights into capabilities and barriers to SIP adoption. Furthermore, 14 papers (31.82%) focused solely on capabilities, while 11 papers (25.00%) exclusively addressed barriers. Notably, one paper (2.27%) neither demonstrated specific capabilities nor barriers; however, it was pivotal in spotlighting future challenges within the SIP field. This analysis reveals a trend of increasing publication count during the examined period, possibly catalysed by the assimilation of disruptive Industry 4.0 technologies. Another important aspect is the significant increase in the volume of articles published during the last five years, which accounts for more than 60% of the papers in our sample. According to Wang; Ranscombe; Eisenbart (2023), this tendency is due to practitioners' increased interest in SIP implementation. Figure 2.3 shows the 44 papers' publishing distribution throughout time.

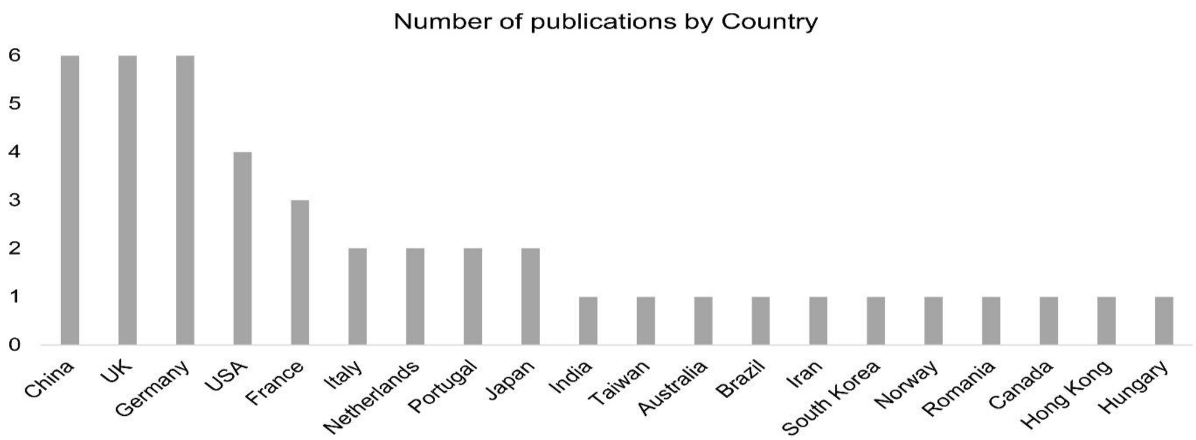
Fig. 2.3 Growth of publications in the SIP field



Source: Elaborated by the author (2024)

Considering the geographical applications of the studies (country of the corresponding author), Fig. 2.4 shows that publications are widespread in four continents (America, Asia, Oceania, and Europe). Most of the research, however, is centred in Europe (54,55%), Asia (29,55%), America (13,64%), and Oceania (2,26%). Another point to note is that authors from developed countries wrote most of the studies. Nevertheless, no emerging country had more than one article identified. It seems that the SIP research field follows the worldwide trend, in which the majority of Industry 4.0 research is concentrated in developed countries (OESTERREICH; TEUTEBERG, 2016).

Fig. 2.4 Distribution of the papers by geographical location



Source: Elaborated by the author (2024)

2.4.2 Analysis of Capabilities and Barriers for SIPs

2.4.2.1 Capabilities Provided by the SIP for the Main Organisational Functions

In this SLR, the term capability was adopted to consider the ability that the SIP adoption brings to the process. In Table 2.4, we present the 20 capabilities identified by the SLR. Table 2.4 also presents, for each capability, the description, the authors who highlighted each one, a practical example (i.e., how the impact happens), and the main function impacted. In this process, the capabilities were classified within each organisational function. To classify the capabilities, we analysed the description of each one with the terms associated with each organisational function. This content analysis was performed using NVivo 11 software. Table 2.4 presents all the capabilities identified and their functions and provides examples of these capabilities, illustrating how they improve the current operations in a real operational environment. The examples were extracted from the papers composing the final sample of this SLR.

Table 2.4 - Capabilities provided by SIPs for the main organisational functions

Capabilities	Code	Description	Authors	Examples	Main functions impacted
Improved efficiency in terms of asset investment	AM1	Ability to improve the efficiency in asset investment through data gathering concerning, for example, the use frequency, quantity, and other variables	3, 30	Bowen Engineering used a tool-tracking solution that combines both identification and tracking. The improved utilisation of assets and a significant reduction in tool investment (3) were achieved	AM
The process becomes more sustainable	SUS1	Ability to use integrated data to produce goods without causing environmental impacts or diminishing them	3, 23, 31, 40, 44	Energy consumption might be reduced by understanding the machine's condition. Better accuracy in predicting failures early will prevent unnecessary operation stoppage, guarantee the best resource use, and reduce waste. Understanding the usage over the life cycle will support better decisions for end-of-life treatment, thereby achieving a circular economy (36, 37). It is also the case that once end-of-life and recycling information is provided by SIPs, enhanced procedures may be followed in the act of disassembly to respect the optimal course of action in terms of overall sustainability and carbon reduction goals (44)	SUS
Improvement in maintenance accuracy, including preventive and prescriptive maintenance by viewing, drawing, and designing data	MM1 / PPC1	Ability to use integrated real-time information about the machine's use to anticipate breaking probability, improve maintenance planning and other factors related to the machine's efficiency	3, 6, 13, 23, 29, 30, 39, 40, 44	Patients need different types of care depending on their conditions. Attaching a Smart-It device to a mobile medicine cabinet can facilitate the health care of young patients with chronic diseases. Smart-It is a small-scale computing device connected to everyday objects to provide sensing, computing, and communication capabilities. The caregiver can track medicine use and drug compliance, reminding patients to take their medicine (23)	MM/ PPC
Remote repair services	MM2	The integration between the SIP and the organisational systems allows staff to execute repairs on the SIP remotely	13, 31	Sysmex originally added connectivity to its instruments to allow remote monitoring but now also uses it to provide servicing. Service technicians can access just as much information about a machine when off-site as when on-site. Often, they can fix it by rebooting it, delivering a software upgrade, or talking an on-site medical technician through the process. As a result, service costs, equipment downtime, and customer satisfaction have improved dramatically (13)	MM
Collecting and carrying information about itself during its lifecycle	MM3	The ability of the SIP to collect data about its use to facilitate several services and its better use	5, 30, 31, 37, 42, 44	In the middle of the life phase, remote diagnostics seems to be one of the main promising services provided by SIPs. This diagnostics service facilitates services such as better problem diagnosis, improvement of condition-based maintenance and scheduling of service personnel, sourcing spare parts (38), and defect identification in product design and manufacturing procedures	MM
Integration of sensing technologies into passive RFID tags	PPC2	Ability to use sensors to detect physical, chemical, or biological properties/ quantities, converting them into readable signals through the use of sensors, integrating data with the system	1	The Wireless Identification and Sensing Platform (WISP) project, carried out at Intel labs, has been used to measure quantities such as light, temperature, acceleration, strain, and liquid level in a particular environment (1)	PPC
Interoperability among various autonomous	PPC3	Ability to communicate among different SIPs that work under different	2, 13, 40, 41,	Attributes (e.g. location, type, quality, and version) and the physical operations through which it has been transformed can be stored. The item location can be	PPC

intelligent resources inside/outside the organisation		protocols, self-managing information to meet the PPC objectives	42, 43, 44	more specific once there is no need to aggregate over fixed locations. This enables monitoring and controlling individual products where disturbances often happen (2)	
Automatic reconfiguration of the SIP/ production line	PPC4	Ability to improve/ upgrade SIPs during the use phase according to the production process requirements, reacting to data collected to self-adapt to the new current scenarios, reducing set-up times for different variants of standard goods, increasing speed, reducing errors, and improving change-over time	3, 16, 18, 24	SIPs in intelligent production lines and assembly will automatically reconfigure themselves in response to customised smart requirements, interacting with production engineers based on intelligent manufacturing technology, which seeks to improve production time and quality and to reduce costs in the physical end, achieving manufacturing process monitoring and production quality control in the cyber end for SIPs (24)	PPC
Dynamic reconfiguring of the team's resources within the production process	PPC5	Ability to reconfigure the team's resources to provide agility to frequent changes in production, fault-tolerance to resource breakdowns, and adaptability to material flow variations through information integration	4	When applied in a production system, this approach allows better and automated decision-making at the resource level based on the following strategies: 1) hierarchical strategy; 2) negotiated heterarchical strategy; and 3) non-negotiated heterarchical strategy. Each one provides better decision-making according to specified criteria (4)	PPC
Complete integration among physical, cyber, and social environments with a high autonomy level, improving the performance of organisational information systems	PPC6	The ability of the SIP to autonomously make decisions acting in coordination with other SIPs, systems, and customers, improving information systems accuracy through automatic monitoring and context awareness	5, 8, 11, 17, 18, 27, 28, 29, 37, 41	A case study was performed to validate the proposed cyber-physical social system (CPSS). The agility, flexibility, responsiveness, and coordination capability of the CPSS-enabled personalised product production system was enhanced through multi-role interactions. The proposed CPSS platform and distributed production control mechanism were feasible (17)	PPC
Remote process control	PPC7	Ability to control the product through integration between the SIP and remote commands/ algorithms that are built into the device or reside in the product cloud	8, 20, 30, 36	In a production process, commands such as "if the pressure gets too high, shut off the valve" or "when traffic in a parking garage reaches a certain level, turn the overhead lighting on or off" can be added (8)	PPC
Self-performance optimisation through the reuse of experiences to enhance decisional performance	PPC8/ QM1	Ability to apply algorithms and analytics to both in-use or historical data, enabling a remarkable enhancement in output, utilisation, and efficiency. Through the expertise gained from past decision-making, SIPs make optimal choices that align production parameters with customer requirements, continuously feedbacking and improving it by applying self-* methods	8, 10, 12, 18, 29, 36, 43	In wind turbines, a local microcontroller can adjust each blade on every revolution to capture maximum wind energy. Each turbine can be adjusted to not only improve its performance but also to minimise its impact on the efficiency of those nearby (8) The integration of process and quality control aiming at implementing feedback control loops for the self-adaptation of process and product configuration is achieved by interacting with these agents. The benefits include increased production efficiency and scrap reduction from 3% to 5% (12)	
Machines linking together	PPC9	The ability of networked machines to	13, 20,	GE's Brilliant Factories initiative uses sensors (retrofitted on existing equipment	PPC

in systems		fully automate and optimise production	39, 40, 43	or designed into new equipment) to stream information into a data lake, where it can be analysed for insights on cutting downtime and improving efficiency. This approach doubled the production of defect-free units in a plant (13)	
Data collection capability is improved	PPC 10	Ability to collect and communicate data throughout the manufacturing process to continuously update the process plan	26, 30, 37, 39, 40	Incorporating SIPs capable of providing real-time data regarding their state, progress, and current whereabouts in the value chain through accurate "process fingerprint" models of each manufacturing process, the connectivity and data provided by the sensor system enable automated tracking of the intelligent products' state and the creation of a seamless, item-level manufacturing history (batch-size-1) (26)	PPC
More robust and flexible production systems	PPC 11	Ability to react to changes such as demand and production scheduling, and also to share information among SIPs as a way to bring robustness to the production process	2, 3, 5, 30, 36, 39	Adopting an autonomous product-driven control strategy in a production cell improves performance levels, especially in cases where disturbance factors occur (39). A system performs better in terms of robustness when it deploys an intelligent product approach in its operations (2, 40). Other demonstrations include the impact of information sharing among products and the system on the perturbations handling in FMS (41) and the effect of a role-based logic in an intelligent product approach on the real-time management of priority changes (42)	PPC
Better complexity management is associated with the combined offer of products and services within and between organisational units	PPC 12	Ability of a SIP to join and facilitate the complexity management of daily tasks associated with the provision of products and services of the goods produced	31, 32, 43	Intelligent devices have advantages such as a high-speed start-up, power-saving features, excellent operability on the user interface, improving presentation quality and reducing meeting times (32)	PPC
Increased visibility of ongoing operations	PPC 13 / QM2	Ability to have real-time information about ongoing operations, performing operational control	6, 7, 29, 30, 40, 43	A company created an intelligent layer, allowing real-time information to make products like trucks and pallets smarter. Tracking technologies in products such as pallets and trucks were used to make them autonomous. Hence, every smart product should have access to all the information the tracking technology provides related to the physical object it represents. The negative impact of unexpected events in both its own and its customer's operations was mitigated, and the precision of information was improved in the enterprise resource planning system (7)	PPC/ QM
High-value aggregation	QM3	Ability of the process to make decisions based on generated/gathered data identifying new patterns in thousands of readings from many products over time	13, 28, 29	1) In a farm setting, data from humidity sensors can be combined with weather forecasts to optimise irrigation equipment and reduce water use. 2) In fleets of vehicles, information about each car or truck's pending service needs and location allows service departments to stage parts, schedule maintenance, and increase the efficiency of repairs. 3) Data on warranty status becomes more valuable when combined with product use and performance. Knowing that a customer's heavy use of a product will likely result in a premature failure covered under warranty, for example, can trigger pre-emptive service that may preclude later costly repairs (13)	QM
Ongoing quality management	QM4	Ability to identify and address design problems that testing failed to expose through operational quality control	13, 30, 36, 40	In 2013, batteries in two Tesla Model S cars were punctured and caught fire after drivers struck metal objects on the road. The road conditions and speeds leading to the punctures had not been simulated in testing. However, Tesla was able to	QM

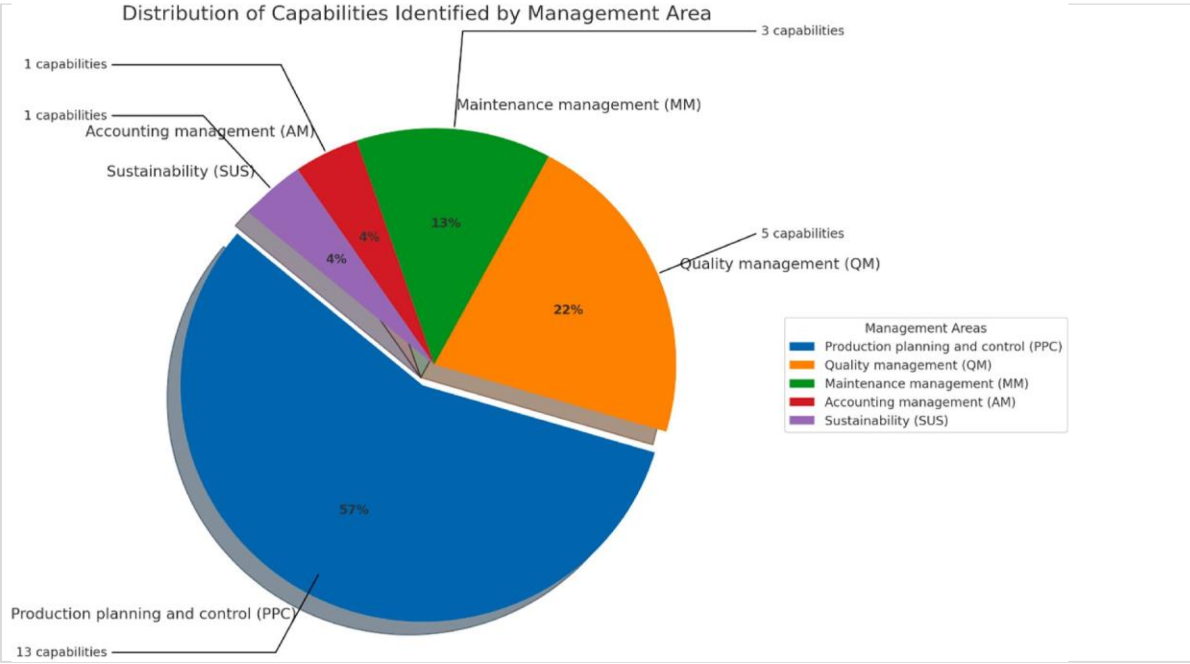
				reconstruct them through a software update to all vehicles that would raise their suspension under these conditions, significantly reducing the chances of further punctures (13)	
High process security	QM5	Ability to manage information about the process, such as a way to readily identify failures that can cause future severe damage	26, 29, 31	Jet engine blades are advanced products manufactured using several layers of materials sandwiched together using a thin heating profile and high pressure. An internal sensor monitoring the temperature curve could provide additional insights and reduce quality issues and scrap (26)	QM

Source: Elaborated by the author (2024)

Notes: 1. (ATZORI; IERA; MORABITO, 2010); 2. (MEYER; FRÄMLING; HOLMSTRÖM, 2009); 3. (MEYER; HANS WORTMANN; SZIRBIK, 2011); 4. (BORANGIU et al., 2012); 5. (MCFARLANE et al., 2013); 6. (TAKAHARA; YASAKI, 2013); 7. (MEYER et al., 2014); 8. (PORTER; HEPPELMANN, 2015); 9. (HERNÁNDEZ; REIFF-MARGANIEC, 2014); 10. (BOUAZZA et al., 2015); 11. (PUTNIK et al., 2015); 12. (LEITÃO et al., 2015); 13. (PORTER; HEPPELMANN, 2015); 14. (DUFFY et al., 2016); 15. (DAWID et al., 2017); 16. (ABRAMOVICI; GÖBEL; SAVARINO, 2017); 17. (DING; JIANG, 2018); 18. (CENA et al., 2019); 19. (SILVERIO-FERNÁNDEZ; RENUKAPPA; SURESH, 2018); 20. (SOROURI; VYATKIN, 2018); 21. (JURIC; LINDENMEIER, 2019); 22. (KESHAVARZI; VAN DEN HOEK, 2019); 23. (TOMIYAMA et al., 2019); 24. (ZHANG et al., 2020); 25. (KAHLE et al., 2020); 26. (LENZ et al., 2020); 27. (RAFF; WENTZEL; OBWEGESER, 2020); 28. (PARDO; IVENS; PAGANI, 2020); 29. (HUNGUD; ARUNACHALAM, 2020); 30. (YI et al., 2021); 31. (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021); 32. (RUHUL AMIN et al., 2021); 33. (RATHEE et al., 2021); 34. (LIN et al., 2021); 35. (THÜRER et al., 2021); 36. (IMAD et al., 2022); 37. (LIU; ZHENG; XU, 2023); 38. (OLUYISOLA et al., 2022); 39. (ANTONS; ARLINGHAUS, 2022a); 40. (ANTONS; ARLINGHAUS, 2022b); 41. (TRAN et al., 2022); 42. (ATTAJER et al., 2022); 43. (LEI et al., 2022); 44. (TURNER et al., 2022).

As shown in Fig. 2.5, PPC was the main function impacted, containing 13 out of 20 capabilities identified (65%), followed by quality management (QM) with five capabilities (25%), and maintenance management (MM) with three capabilities (15%). Accounting management (AM) and sustainability (SUS) functions were impacted by one capability for each function (5%). The total percentage exceeds 100% because two capabilities directly affect two functions simultaneously.

Fig. 2.5 Capabilities by organisational function



Source: Elaborated by the author (2024)

From this analysis, we identified some strengths and weaknesses of the literature concerning SIP barriers and capabilities. Regarding strengths, the practical nature of the works allows us to find examples of applications and their impacts, as well as the temporal moment of impact of structural barriers when adopting a SIP. On the other hand, concerning a weakness in the literature, we perceive that different authors address different capabilities according to specific contexts of SIP applications, resulting in a somewhat myopic managerial perspective. We believe this SLR helps to bridge this gap once it organises the field, proposing a list of capabilities and barriers provided by SIPs for the main organisational functions.

2.4.2.2 Barriers Faced by Organisations in Implementing a SIP

Initially, 23 barriers were identified (Table 2.5), demonstrating many factors influencing SIP implementation. The barriers were classified into three groups according to the temporal moment of their impact on the SIP implementation process. The classification process was undertaken through content analysis (using NVivo 11), considering the association among the terms contained in each barrier's description and the level it impacts. Table 2.5 contains the barriers and their main characteristics.

Table 2.5 - Barriers faced by organisations in implementing SIPs

Barriers	Code	Description	References
Communication difficulties	BA1	Refers to the different types of communication difficulties, such as vertical [among organisational levels over a short time (control) until the decision-making level (planning)] and horizontal levels [communications difficulties throughout the supply chain (suppliers to customers)]	1, 2, 3, 5, 6, 12, 15, 16, 22, 23, 25, 26, 29, 36, 37
Vulnerability in data security	BA2	Refers to the high vulnerability in the evolving IoT scenario. The kind of data being collected, with whom they are being shared, and how they can be manipulated by all levels (horizontal and vertical) can be decisive issues when an organisation decides to adopt a SIP	1, 3, 6, 8, 9, 12, 13, 16, 17, 21, 22, 23, 25, 26, 34
Decreased planning efficiency when control is decentralised	BA3	The decentralisation of production control increases the system's robustness; however, its efficiency decreases once decentralised systems react to some unexpected events, such as a machine breaking down or failing and other disruptions	2, 20, 39
Difficulties in integrating many different SIP	BA4	Refers to the way to operationalise IoT, allowing many systems with many components, built under different protocols, to work harmonically, adapting to the world's physical changes	3, 30, 36, 37
Difficulties in aligning old industrial technologies with the implementation of a new SIP	BA5	Refers to the coexistence of new and old technologies, mainly in areas where transformation processes are evolutionary and not revolutionary (e.g. medicine)	5, 13, 16, 23, 25, 38
Lack of technological maturity	BA6	Many building blocks for supporting product intelligence are either in place or under development. Deployment on an industrial scale can also be considered within this barrier	5, 37
Full adoption difficulties and lack of system stability (operational practicality and decision execution)	BA7	Initial deployments are likely to be partial rather than full deployments. In the case of full deployment, the complete stability of the entire system also needs to be considered	5
Contractual and revenue-sharing challenges	BA8	Most companies fear having their ideas and confidential information leaked and prefer to compete individually	5, 13, 19, 24, 25
Social, psychological, and cultural individualistic behaviour barriers	BA9	Refers to the existence of resistance in process substitution or change, mainly if this process is rooted in the organisation. Cultural behaviour comprises the fears faced when people in the organisation need to share their knowledge and ideas	5, 23, 24, 25
Lack of technical and economic feasibility in the early stage of utilisation	BA10	The term feasibility is understood as the possibility of an undertaking being achieved or is reasonable. In the context of the early stage of utilisation of an SIP's data, feasibility is a measure of the technical and economic viability	5, 22, 24, 26, 36, 37
Complicated system introduction or even its affinity with already existing business systems	BA11	When connecting a SIP with business systems, procurement and deployment work for system introduction are necessary for each component of the service platform, network, and its own SIP. Most systems currently used by corporate users (e.g. Windows) are assumed to be devices' operating systems. Considering this situation, some failures associated with differences in operational systems and browsers could occur among each layer when connecting the SIP with existing business systems	6, 12, 36
Tracking technology remains a fundamental challenge in transforming the abundance of operational information into accurate and timely control decisions	BA12	The commonly held perception that tracking technology will improve the ability to perform operational control can be equivocally wrong. Without specific mechanisms and technologies, such as big data and analytics, it would be impossible for human minds to deal with the large amount of data generated as well as to identify patterns among the data	7, 37

Lack of infrastructure, including network and/or network latency, in some regions of the country where industries are based	BA13	Refers to the lack of network and multi-layer infrastructure required for new entrants in the market or not being available in the region where an organisation is set up	8, 16, 22, 24, 25, 34, 36, 38
Uncertainty about ROI, payback, high costs and investments to (internally) develop a SIP	BA14	Uncertainty regarding ROI and payback are crucial issues. The investment can only be justified if the period is shorter and greater than the short natural life cycle of the goods produced. The total cost can involve factors such as time, specialised labour payment, and others	5, 9, 21, 22, 23, 25, 26
Self-adaptation difficulties among the SIP and its environment (plug-and-play technologies)	BA15	Refers to the lack of the product's ability to recognise standards within the process or how it is used (which is normally possible to achieve through other technologies, such as Big Data and Analytics) and to self-adapt to these newly recognised patterns. The product needs to readily deal with different technologies and software without needing installation or any other product upgrade	12, 36
High energy consumption	BA16	The energy consumption of the SIP is proportional to the complexity of the operation it performs, and not all the products can store energy, requiring other technologies to capture it	1, 12, 29, 34, 36
Risk of bad event propagation	BA17	The product can replicate not only learning obtained through good events but also that obtained from bad events	12, 34
High complexity of management	BA18	The complexity of the product/ service can directly influence the management tasks, the way it interacts with the good being produced, with the other agents of the process, and with its ecosystem	12, 29
Lack of security and trust in using data	BA19	Refers to how much we can trust in the SIP's decision-making, as well as issues such as the use of the (private or shared) cloud and the level of trust concerning the data collected by a competitor's product that the organisation could not access	12
High complexity of system management due to the increase in the number of agents used	BA20	Refers to difficulties related to the infrastructure robustness required when the number of agents (e.g. tags RFID, sensors) acting in a determined environment (and even outside it) significantly increases	16, 30, 38
Cost strategy is not adherent to innovative SIP solutions	BA21	High focus on cost reduction and not on aggregate value for itself and its customers	25, 36, 38
Cyber-attack vulnerability	BA22	The high level of network connectivity dependence can bring new cyber-attack threats	33
Lack of adequate computational resources	BA23	Refers to insufficient computational power, battery, storage, and I/O bandwidth to host and manage IoT applications and services	29, 34, 35, 36

Source: Elaborated by the author (2024)

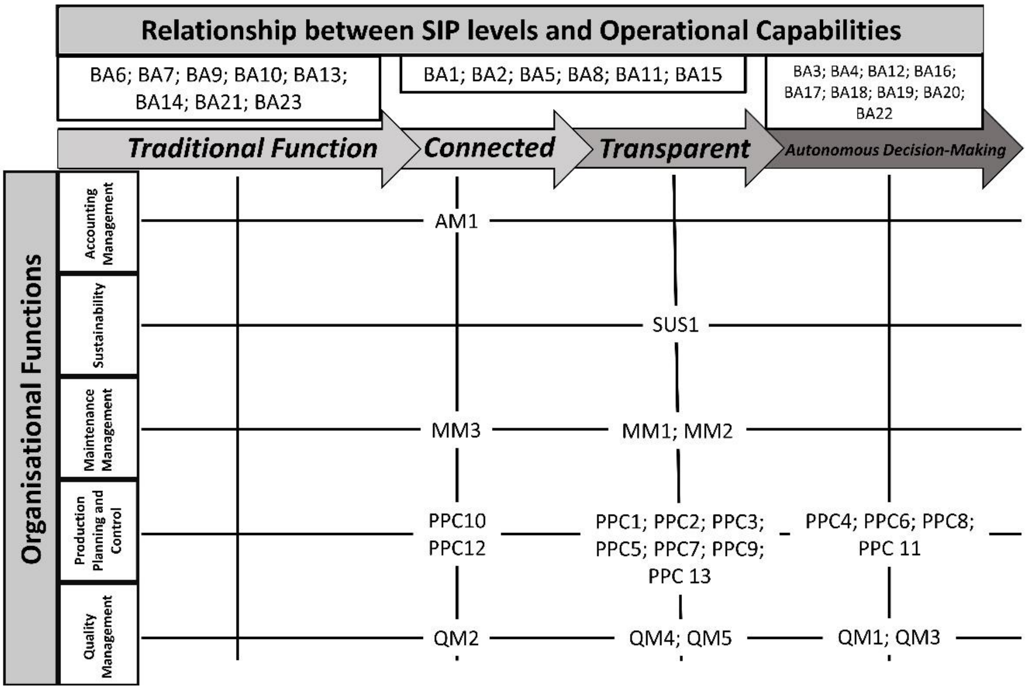
Notes: 1. (ATZORI; IERA; MORABITO, 2010); 2. (MEYER; FRÄMLING; HOLMSTRÖM, 2009); 3. (MEYER; HANS WORTMANN; SZIRBIK, 2011); 4. (BORANGIU et al., 2012); 5. (MCFARLANE et al., 2013); 6. (TAKAHARA; YASAKI, 2013); 7. (MEYER et al., 2014); 8. (PORTER; HEPPELMANN, 2014); 9. (HERNÁNDEZ; REIFF-MARGANIEC, 2014); 10. (BOUAZZA et al., 2015); 11. (PUTNIK et al., 2015); 12. (LEITÃO et al., 2015); 13. (PORTER; HEPPELMANN, 2015); 14. (DUFFY et al., 2016); 15. (DAWID et al., 2017); 16. (ABRAMOVICI; GÖBEL; SAVARINO, 2017); 17. (DING; JIANG, 2018); 18. (CENA et al., 2019); 19. (SILVERIO-FERNÁNDEZ; RENUKAPPA; SURESH, 2018); 20. (SOROURI; VYATKIN, 2018); 21. (JURIC; LINDENMEIER, 2019); 22. (KESHAVARZI; VAN DEN HOEK, 2019); 23. (TOMIYAMA et al., 2019); 24. (ZHANG et al., 2020); 25. (KAHLE et al., 2020); 26. (LENZ et al., 2020); 27. (RAFF; WENTZEL; OBWEGESER, 2020); 28. (PARDO;

IVENS; PAGANI, 2020); 29. (HUNGUD; ARUNACHALAM, 2020); 30. (YI et al., 2021); 31. (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021); 32. (RUHUL AMIN et al., 2021); 33. (RATHEE et al., 2021); 34. (LIN et al., 2021); 35. (THÜRER et al., 2021); 36. (IMAD et al., 2022); 37. (LIU; ZHENG; XU, 2023); 38. (OLUYISOLA et al., 2022); 39. (ANTONS; ARLINGHAUS, 2022a); 40. (ANTONS; ARLINGHAUS, 2022b); 41. (TRAN et al., 2022); 42. (ATTAJER et al., 2022); 43. (LEI et al., 2022); 44. (TURNER et al., 2022).

2.4.2.3 Smart-Enhanced Organisational Functions: Characteristics and Evolution

The smart-enhanced organisational function term may comprise more than one level within the function, given that several authors (e.g., Porter; Heppelmann (2015); Romsdal et al. (2021); Tomiyama et al. (2019)) have classified SIPs according to pre-defined categories that are impacted by specific capabilities. In this step, the identified examples were fundamental to classifying the capabilities. Figure 2.6 presents the proposed framework showing the relationship between capabilities, barriers, and organisational functions. The relationship between these three categories of variables provides an evolutional path for organisational functions. This framework identifies the necessary capabilities for each organisational function according to the SIP level and the barriers that must be overcome.

Fig. 2.6 Smart-enhanced organisational functions: Relationship and evolutional path



Source: Elaborated by the author (2024)

Concerning accounting management, this function is essential to control organisations' net worth. Traditional assets management is the context where it is currently most straightforward to develop practically relevant means-ends propositions, at least regarding RFID technology. It transforms data into strategic actions that drive decision-making, analysing losses and profits (MEYER; FRÄMLING; HOLMSTRÖM, 2009). Hence, to make improved decisions, data quality and temporal aspects are essential. A SIP may contribute to making this function a smart enhanced organisational function, providing data about itself regarding, e.g., production rate, machine utilisation, capacity, and load. This enables improvements in the decision-making process, e.g. when to substitute a machine, which capacity the new machine needs to have, and optimising asset investment by maximising the return on investment (ROI) and shortening the payback (AM1). In addition, by introducing intelligence in SIPs, it becomes easier to share the status of the machine, including the condition of its main parts, and also facilitate the economic viability of the asset (MEYER; FRÄMLING; HOLMSTRÖM, 2009; YI et al., 2021). The highest level found in the literature on accounting management is the connected level. However, based on knowledge from previous levels, the potential evolution of technology, and the accounting function itself, we can infer that when the function reaches the transparent level, it will provide an even more detailed and transparent view of the organisational financial information. This includes automatically identifying positively correlated variables to support managers in making profitable decisions. At the autonomous decision-making level, the accounting function can evolve to play an even more strategic role within the company.

Concerning sustainability, this organisational function aims to reduce the organisation's environmental impact, migrating current operations to a more sustainable one. This migration has the social, economic, and environmental pillars as drivers. When this organisational function evolves to a connected level, data are automatically collected, and humans may make decisions with limited analytical capability (TOMIYAMA et al., 2019; VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021). Afterwards, in the transparent sustainability function by real-time data integration, staff can identify new patterns in millions of pieces of data through analytics solutions (SUS1) and using embedded technology that allows information storage of the entire life cycle of the machine (MEYER; FRÄMLING; HOLMSTRÖM, 2009). This new pattern may be converted into actions that reduce the entire organisation's environmental impact, such as reducing the amount of scrap and defects and improving energy management and other parameters that are not easy to identify without data integration. In addition, these capabilities only may be achieved by SIPs at a transparent level, that is, by SIPs that already have a connectivity level, which means that the organisations surpassed all structural barriers that hinder the advancement of the level of autonomy of an SIP. Although the transparent level is the highest level found in the literature, we can predict the autonomous decision-making level based on previous knowledge and characteristics of the level. Yet, SIPs can identify opportunities to expedite or delay a production order, to make production possible when renewable energy is available (ANTONS; ARLINGHAUS, 2022b; TOMIYAMA et al., 2019; TURNER et al., 2022). In summary, at this level, the SIP continuously learns from past events improving present and future decision-making, achieving a circular economy.

The traditional maintenance management function is responsible for ensuring the proper functioning of all the assets used by the process to transform raw materials into finished goods and services or to support this process. This function may, in practice, use different approaches to perform maintenance of the assets, according to the moment, to the machine status, and to a myriad of other situations that may occur unpredictably in daily operations. Now, considering the many situations and scenarios that can arise in practice and the simultaneity and interrelationship between events, maintenance management becomes a function that hardly operates at its optimum point. Moreover, implementing, evaluating, and managing indicators becomes very difficult for humans. In practice, the impact of an SIP on maintenance management may occur in different ways, according to the autonomy level of an SIP. Thus, a SIP that finds itself at a connected level may contribute to the maintenance management function by using data collected during its life-cycle (MM3) to facilitate several services and also to feed big data and analytic tools (TOMIYAMA et al., 2019), including a better end-of-life approach as before stated, achieving a circular economy. In sequence, by using a SIP at a transparent level, operations may use integrated real-time information of the machine's use, anticipating breakdown probability, and improving maintenance planning (MM1), for example, prescriptive maintenance (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021; YI et al., 2021). Besides, SIPs allow remote repair services (MM2) (when integrated with organisational systems). This integration is achieved through digital twin technology and is the last stage before the autonomous maintenance level. With this capability, maintenance staff can monitor the machine's status in real-time, and some defects may be repaired at a distance, changing only any parameter in the machine's configuration. Although in this function we found capability in levels connected and transparent, future perspectives may comprise the use of collected data concerning the entire lifecycle of a machine to autonomously improve maintenance indicators, allowing a prescriptive maintenance approach and remote repairing services. At this level, the maintenance function uses integrated historical data not only to prescribe maintenance necessities but also to schedule the replacement of the part at the last possible moment before the component fails and the machine breaks down. The spare parts purchase requisition is also made considering lead time data versus the scheduled replacement, plus the safety stock period, optimising the capital expenditure on slow-moving spare parts inventory to the maximum extent.

The PPC function comprises a series of decision-making processes to define what, how much, and when to produce and buy and the resources to be used (VOLLMANN et al., 2005). In the enhanced PPC function, connected SIP improves the organisation's data collection capability (PPC10), facilitating day-to-day management of complexities associated with the combined offer of products and services (PPC12). These capabilities allow the acquisition of other more advanced capabilities, such as the one acquired with transparent and autonomous decision-making SIPs. Besides, according to Vendrell-Herrero; Bustinza; and Vaillant (2021), organisations can better understand causal complexities regarding equifinality (different combinations of variables can be associated with the same outcome). This benefit helps organisations to solve problems and identify the relationship between variables that the limited human capacity to threat data cannot solve or identify. The only problem associated with this benefit is the computational power's necessity to threaten the data (RUHUL AMIN et al., 2021). Therefore, firms that acquire a SIP connected level have an improvement in data collection but not necessarily in solving problems. Afterwards, regarding capabilities acquired at a transparent level, integration of sensing technologies into passive RFID tags (PPC2) (ATZORI; IERA; MORABITO, 2010) allows organisations to acquire a series of other capabilities, such as remote process control (PPC7) (SOROURI; VYATKIN, 2018; YI et al., 2021) and the optimisation of products' performance by the reuse of experience, enhancing decisional performance (PPC8). The transparency acquired in achieving this level presents both an opportunity and a challenge (OLUYISOLA; SGARBOSSA; STRANDHAGEN, 2020). If, on the one hand, interoperability among various autonomous intelligent resources (MM1) and data collected may represent a source to feed analytics, enabling high precision of simulation models of production systems, on the other hand, standard data processing technologies are not capable of deriving insights from such big data (LENZ et al., 2020; OLUYISOLA; SGARBOSSA; STRANDHAGEN, 2020). Furthermore, the dynamic reconfiguration of teams' resources within production processes enables organisations to respond quickly to some unexpected changes in the operational environment, such as fault tolerance to resource breakdown and adaptability to material flow variations (PPC5) (BORANGIU et al., 2012), sometimes remotely controlling the production processes (PPC7) (IMAD et al., 2022; PORTER; HEPPELMANN, 2015; SOROURI; VYATKIN, 2018; YI et al., 2021). Finally, the autonomous decision-making level encompasses four pivotal capabilities (PPC4, PPC6, PPC8, and PPC11). These capabilities represent the most critical, encompassing autonomy across the production system, horizontally (from supplier to customer) and vertically (from shop floor control to enterprise resource planning). This heightened autonomy offers opportunities to enhance operations by leveraging past experiences for future decision-making, facilitating fully autonomous PPC (CENA et al., 2019; MEYER; FRÄMLING; HOLMSTRÖM, 2009; MEYER; HANS WORTMANN; SZIRBIK, 2011).

The traditional quality management function aims to continuously improve the product, processes, people, and the work environment's standards. When enhanced by connected SIPs, the quality management function increases the visibility of ongoing operations (QM2) (TAKAHARA; YASAKI, 2013), providing real-time information on ongoing operations. This allows organisations to control the quality of the product and production parameters in real-time, preventing defective products from arriving in the next operations (MEYER et al., 2014; YI et al., 2021). Consequently, the production rate of faulty products is severely reduced due to the real-time identification of the first product that is not inside the specifications. In the next level, the quality management function enhanced by SIPs at a transparent level ensures excellence in production control, providing high-value aggregation (QM4) (IMAD et al., 2022; PORTER; HEPPELMANN, 2015), identifying new patterns in thousands of readings from many products over time, and managing information about the process (QM5) (LENZ et al., 2020; VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021), such as identifying failures that can cause future severe damage. At this level, the capabilities enabled by SIPs configure themselves as bases for a completely autonomous decision-making quality function. However, although the function threat data provides insights into the process, the SIPs are passive and do not react to improve parameters. A SIP may identify failure probability that tests do not identify and also anticipate any breaking likelihood that can negatively impact the PPC (HUNGUD; ARUNACHALAM, 2020; LENZ et al., 2020; VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021). Thus, transparent quality management functions positively impact all other processes and organisational functions. At the highest level, the quality management function improves products' performance (QM1) (BOUAZZA et al., 2015) using the information handling capability to improve machine and process parameters, aggregating value (QM3) (PARDO; IVENS; PAGANI, 2020; PORTER; HEPPELMANN, 2015) through manufacturing servitisation. Once a SIP becomes an integrating part of a more extensive system, the value proposition broadens (PARDO; IVENS; PAGANI, 2020; PORTER; HEPPELMANN, 2015). In the metallurgical industry, for example, real-time monitoring can identify the wear rate of a Computer Numerical Control (CNC) lathe tool insert, which increases the piece's dimensions, going beyond the specified parameters and deteriorating its surface roughness. Recognising this dimensional increase, the SIP self-corrects by advancing the tool a few hundredths of a millimetre to compensate for the wear. When the insert can no longer be advanced, the machine retracts the advancement due to the insert wear and rotates it to another side (a triangular insert typically has three cutting edges for machining parts). The energy consumption of the machine, also monitored in real-time, can be compared with different rates of tool wear, machine speed, and the type of coolant fluid. Having this data, the efficiency of the SIP can be maximised, adding value to the organisation.

Table 2.6 summarises the current features of each managerial function according to the stage in which it is classified. The cells in *italics* represent future perspectives for each function. These future perspectives may be achieved soon due not only to the technological advancement of the leading disruptive technologies but also to future technologies still in development, which, when applied to SIPs, can lead to improved operational planning and control in the main organisational functions.

Table 2.6 - Features and perspectives of different stages of smart-enhanced organisational functions

Management function	**Characteristics**			
	Traditional	**Connected**	**Transparent**	**Autonomous decision-making**
Accounting Management (AM)	Asset management with a high period of inertia and a limited time horizon of the data	Real-time data gathering allows organisations to know the machines' status regarding workload, demand forecasting, and other variables that influence and serve as a basis for new investments	*Data are integrated through the Internet of Things, and positively correlated variables may be automatically identified*	*Through analytics, big data are analysed, and prescriptions for decision-making on new asset investments are significantly improved*
Sustainability (SUS)	Plan actions to reduce the environmental impact of the organisation	Real-time data gathering allows humans to identify new patterns based on a limited analytics capability	Real-time data integration allows staff to identify new parameters among data using analytics solutions. These new patterns can be converted into actions that reduce the environmental impact of the entire organisation, such as reducing the amount of scrap and defects and improving energy management and other parameters that are not easy to identify without data integration	*SIPs provide innovative solutions to improve the general sustainability of the entire process, including autonomous decision-making if any possible improvement is identified*
Maintenance Management (MM)	The most common maintenance approaches comprise the use of preventive and predictive maintenance. The use of active approaches as prescriptive maintenance is limited because of the lack of data concerning the behavioural parameters of the entire production system	Connected products collect data about machines' status. Maintenance staff must maintain them, create schedules, and sometimes react to unexpected machine failures and breakdowns	Through connectivity, the transparent MM function may execute remote repair services in case of unexpected failures. Other reactive maintenance approaches, such as preventive and predictive, are also improved through better data visualisation and the ongoing monitoring of machines' status	*Enhanced MM can use the collected data concerning the entire lifecycle of a machine to autonomously improve maintenance indicators, allowing a prescriptive maintenance approach and remote repair services*
Production Planning and Control	The traditional PPC function aims to reconcile production resources and customer demand. Some actions are taken according to particularities that evolve in each production system, specifically regarding the volume and variety of products produced	The connected PPC function takes decisions based on real-time data gathering, which improves accuracy and builds a solid base for planners to consider future scenarios	The network-integrated PPC function allows information interchange among different SIPs, resources, and systems, and the team may be dynamically reconfigured to meet PPC objectives	PPC has complete integration among physical, cyber, and social environments, using data to improve SIPs' work parameters and reusing its experience to enhance its decisional performance
Quality Management (QM)	The traditional QM function improves the most diverse parameters of production, including the goods that are being produced. Based on data, sometimes collected through production sheets, the quality team plans actions to mitigate identified problems	The connected QM function uses real-time data gathering to perform operational control	The transparent QM function may identify and address problems that tests failed to expose and manage information about the process, such as ways to identify failures that can cause future severe damage	The autonomous QM function can decide based on gathered data, identifying new patterns in thousands of readings from many products over time, reacting in many different ways, such as improving machines' status, product configuration, and other decisions that directly facilitate quality control

Source: Elaborated by the author (2024)

Notes: Cells in *italics* represent organisational functions' future perspectives. Cells in regular font represent organisational functions' current perspectives.

Regarding barriers to the adoption of SIPs, it was found that they can be classified into three main categories: (0) traditional function; (1) connected; (2) transparent; (3) autonomous decision-making. The first group impacts functions at their lowest smartness level, the traditional level (before the SIP implementation). This group contains eight barriers (BA6, BA7, BA9, BA10, BA13, BA14, BA21, and BA23) that the traditional function should overcome to achieve the later levels. For example, lack of technological maturity (BA6) impacts the function at its lowest level, because without technical feasibility, it is not possible to start the SIP implementation (LIU; ZHENG; XU, 2023; MCFARLANE et al., 2013).

The second group contains barriers (BA1, BA2, BA5, BA8, BA11, and BA15), which the connected or the transparent functions must overcome to achieve the level of autonomous decision-making. For example, at this level, communication difficulties (BA1) may hamper the integration between the SIP and other systems, not only within organisations but also in the whole supply chain (IMAD et al., 2022; LIU; ZHENG; XU, 2023). These difficulties can evolve vertical communications between ordering coordination systems and other organisational systems, such as manufacturing execution systems (MESs), Enterprise Resource Planning (ERP) systems, and other systems and horizontal communications (between SIPs).

Finally, in the third group, there are related barriers associated with autonomous decision-making (BA3, BA4, BA12, BA16, BA17, BA18, BA19, BA20, and BA22). These barriers impact organisations after they surpass the first and second stages. As they are associated with decision-making issues, difficulties in integrating many different SIPs (BA4), for example, points to the challenges of having systems with many components working together and their respective self-adaptation to real-world physical changes (IMAD et al., 2022; LIU; ZHENG; XU, 2023).

2.5 CONCLUSIONS

2.5.1 Main Results and Contributions

Using SIPs is essential to enhance operational efficiency. However, a knowledge gap remains, particularly concerning the terminological consensus on the evolution of SIPs and the capabilities and barriers linked to adopting this technology within organisations. The current literature fails to comprehensively address these aspects, mainly concerning the understanding of the capabilities enabled by SIPs and the barriers to using such technologies. In this regard, a framework was proposed to bridge this gap that identified an evolutional path for the main organisational function to become completely autonomous. Any research with this aim was found to the best of our knowledge.

A multi-method approach was conducted to develop this framework, comprising three basic research steps, including SLR, followed by expert interviews and content analysis. In the first stage, we identified 20 capabilities categorised into three levels: connected, transparent, and autonomous decision-making. Additionally, we identified 23 barriers and categorised them into three groups: pre-implementation, during implementation, and post-implementation, considering their impact on various stages of SIP adoption. Thus, we proposed a framework that offers an evolutional path for traditional organisational functions, which provides a clear trajectory for SIP adoption, both within and holistically.

This paper's main novel scientific contributions can be summarised in four key aspects. Firstly, through an extensive review of the main definitions found in the literature, our research provides a new definition for smart products directly related to the organisational context. Secondly, the capabilities provided and barriers faced by organisations are systematically analysed. Thirdly, the capabilities and barriers identified were validated by experts and classified through content analysis. The results revealed that these capabilities directly impact six different organisational functions, categorised into three levels of autonomy: connected, transparent, and autonomous decision-making. Additionally, the structural barriers were classified based on three temporal moments of SIP adoption: before, during, and after implementation. Finally, our framework presents an evolutional pathway for the main organisational functions, outlining the barriers that organisations must overcome to progress from one level to the next, eventually achieving autonomous decision-making.

In addition to the scientific contributions, this research also holds meaningful practical implications. Firstly, the evolutional pathway presented in our framework could assist organisations in gaining an in-depth understanding of the barriers they will face at each stage of SIP adoption. This understanding allows for more effective planning and adequate preparation to overcome these obstacles, which can reduce the time and resources required to implement these systems successfully.

Furthermore, our framework offers a clear vision of the capabilities that organisations will acquire as they overcome the barriers associated with each level of autonomy in organisational functions. This visualisation helps managers identify the tangible benefits that can be expected at each SIP adoption stage, facilitating the justification for ongoing investments in SIP technology. By categorising capabilities into three levels – connected, transparent, and autonomous decision-making – we provide a structure that allows organisations to evaluate their progress and set clear goals to advance towards full autonomy. This model offers a strategic roadmap and serves as a diagnostic tool to identify areas that need specific attention to reach the next level of maturity.

Additionally, identifying and categorising barriers into pre-implementation, during-implementation, and post-implementation provide a detailed perspective of the specific challenges that may arise at different stages. With this information, organisations can develop targeted mitigation strategies for each phase, increasing the likelihood of a smooth and successful transition to more advanced systems.

In summary, our framework facilitates understanding the necessary steps for SIP implementation and provides a practical guide to overcoming associated barriers and maximising organisational capabilities. Therefore, our research innovates, offering valuable insights for managers and business leaders seeking to transform their operations by adopting advanced system integration technologies.

2.5.2 Limitations and Future Research

It is worth mentioning that, similar to any other research, this study has limitations. Some limitations are associated with the SLR method. These limitations can be attributed to the subjectivity involved in defining the search string and selecting the literature based on inclusion and exclusion criteria. As a result, the authors' interpretation may have been influenced by the barriers and capabilities presented in the final sample. Furthermore, although the literature search was conducted using a predetermined search string, it was limited to three databases. This means that papers indexed only in other databases were not included in the study.

Despite these limitations, this article makes valuable contributions to the field of SIPs, opening up a range of research opportunities related to the identified capabilities and barriers. It provides insights into organisations' benefits and challenges when adopting SIPs, thereby establishing a foundation for future SLRs that will contribute to a cumulative body of knowledge.

Considering the next steps, future studies have the potential to enhance the understanding of the operational aspects of capabilities that directly impact the PPC function through a multi-method approach. This approach could involve a SLR, expert interviews, ISM, and *MICMAC* analysis. By employing this methodology, a comprehensive framework could be developed, highlighting the inter-functional relationships and the driving and dependence power of different capabilities.

Furthermore, studies involving specialists can be conducted to identify the driving and dependence power among all the identified capabilities. This research would delve deeper into the relationship between organisational functions and adopting SIPs. It would provide valuable insights into how the capabilities acquired by one organisational function can drive or enhance the capabilities acquired by other functions.

Regarding barriers, future studies can employ a combination of ISM and *MICMAC* approaches to identify a roadmap for SIP adoption. This would involve mitigating the main barriers faced by the main organisational functions, proposing effective policies to overcome them, and facilitating the transition towards an autonomous decision-making level across all functions more rapidly.

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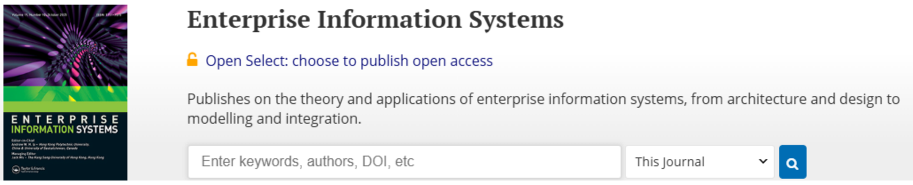
Declaration of Interest

None.

3 EXPLORING CAPABILITIES ENABLED BY SMART INDUSTRIAL PRODUCTS ADOPTION: A FRAMEWORK FOR FULLY AUTONOMOUS PRODUCTION PLANNING AND CONTROL

This chapter is composed of the second paper of the thesis and was submitted to the Enterprise Information Systems Journal. **Impact Factor Ranking:** 3,90 (Q1 – Scopus). **Current State:** R3



Purpose

This study aims to structure and understand the capabilities enabled by SIPs within the PPC function. It seeks to provide a hierarchical framework that supports the strategic integration of SIPs to achieve full autonomy in PPC.

Design/methodology/approach

A mixed-method approach was applied, combining a SLR, expert validation, ISM, and Fuzzy *MICMAC* analysis. Twelve SIP-enabled capabilities were identified, validated, and analysed to reveal their interrelationships and hierarchical structure.

Findings

The study presents a four-level framework: Connected, Transparent, Autonomous Decision-Making I and II, showing the sequential development of capabilities needed for PPC autonomy. Foundational capabilities drive the development of more advanced ones, offering organisations a roadmap to prioritise investments and enhance operational performance.

Originality

This is the first study to propose a structured, hierarchical model of SIP-enabled capabilities in PPC. It contributes to both theory and practice by clarifying capability dependencies and offering a roadmap for achieving autonomous PPC through targeted SIP adoption.

Keywords: Smart Industrial Products; Production Planning and Control; Capabilities; Interpretive Structural Modelling; Fuzzy *MICMAC*;

3.1 INTRODUCTION

Industry 4.0 has transformed industrial systems through the integration of digital technologies (ALI; ESSIEN, 2023; NORTH; ARAMBURU; LORENZO, 2020), and SIPs have become a central component of this shift. Once theoretical, SIPs now drive efficiency, automation, and data-based decision-making in operations. Their adoption is crucial in addressing challenges such as shorter product lifecycles, shifting demand, and market disruptions. However, despite growing attention, a clear definition of SIPs remains lacking (RAFF; WENTZEL; OBWEGESER, 2020), underscoring the need for further investigation into their role in enabling autonomous PPC.

This research defines the SIPs as physical, connected, and smart dimensions. Together, these dimensions facilitate the seamless integration of physical and digital components. Besides, SIPs are characterised by embedded systems enabling intelligence to recognise, analyse, and autonomously exchange data related to the customer, the manufactured goods, the production process, and the overall environment in an integrated and real-time manner (PISSARDINI et al., 2024a).

SIPs strongly reshape the way organisations deal with PPC challenges (BOUAZZA et al., 2015; MCFARLANE et al., 2013; MEYER; FRÄMLING; HOLMSTRÖM, 2009; PORTER; HEPPELMANN, 2015; PUTNIK et al., 2015) by enabling a range of diverse smart capabilities. Reaching a more advanced level of intelligence is not solely dependent on this particular acquisition. In other words, the acquisition of only one or another capability individually does not allow the PPC function to fully develop toward a complete autonomous function. Furthermore, a structured integration among capabilities is required to achieve the highest level of autonomy. This is the primary objective of this research, which is to establish a structural relationship hierarchy framework that defines a sequence of capability dependencies, providing a structured pathway for organisations to achieve a fully autonomous PPC function.

In this study, following Oluyisola et al. (2020), we understand that such autonomy in PPC is not achieved suddenly; rather, it entails steps from connected to transparent thought, ultimately leading to autonomous decision-making. More specifically, in this research, we investigate three questions:

- (RQ1) Which capabilities are enabled by adopting SIPs in the PPC function?
- (RQ2) How are these capabilities interrelated within the context of the PPC function?

- (RQ3) Which path should organisations follow to develop SIP-enabled capabilities and achieve autonomous decision-making on PPC?

To address the proposed research questions, we adopt a multi-method approach. Initially, a SLR with content analysis was conducted to identify SIP-enabled capabilities in the PPC function (RQ1). Then, ISM and fuzzy *MICMAC* analysis were applied to examine the interrelationships among these capabilities and assess their respective driving and dependence powers (RQ2), enabling the construction of a hierarchical framework that guides the progression toward autonomous decision-making in PPC (RQ3).

Although previous studies have discussed the capabilities associated with SIPs in PPC (BUENO; GODINHO FILHO; FRANK, 2020; OLUYISOLA et al., 2022; OLUYISOLA; SGARBOSSA; STRANDHAGEN, 2020), few have addressed their integration into a coherent developmental trajectory toward autonomy. Existing research tends to focus on isolated aspects, such as production monitoring (BORANGIU et al., 2012; MEYER, 2011), smart manufacturing optimisation (LENZ et al., 2020; PARDO; IVENS; PAGANI, 2020), or material flow (THÜRER et al., 2021). Others, like Raff et al. (2020), concentrate on the intrinsic characteristics that qualify a product as "smart" rather than capabilities relevant to PPC. Broader studies (e.g., MCFARLANE et al. 2013; PISSARDINI et al. 2024) offer valuable insights but lack a structured roadmap for capability development within PPC.

This study addresses this gap by proposing a hierarchical relationship framework articulating how SIP-enabled capabilities can be progressively developed to support autonomous decision-making in PPC. To the best of our knowledge, this is the first study to provide such a comprehensive and structured model, integrating theoretical foundations with empirical insights to support academic analysis and practical implementation.

The structure of this paper is as follows: Section 2 presents a literature review, positioning this paper in the SIPs field of study. Section 3 details the methodology sequence followed in this research. Sections 4 and 5 present the results and discuss the framework developed as the main output of our research. Finally, Section 6 presents the study conclusions, theoretical and managerial impacts, and directions for future studies.

3.2 LITERATURE REVIEW AND RESEARCH GAP

This section initially discusses smart products' literature, positioning this paper in the SIP field of study. In sequence, we present the research gaps based on the current literature analysis, explaining the motivations to perform this research.

3.2.1 State-of-the-art Concerning Smart Industrial Products in PPC

SIPs have emerged as a transformative force in manufacturing, reshaping how industrial operations are managed and optimised. Their integration enables greater efficiency, data-driven decision-making, and enhanced productivity. Understanding their impact on PPC is critical for competitiveness in a rapidly evolving industrial landscape. Various frameworks, often rooted in holonic manufacturing, have been proposed to harness the full potential of SIPs. Although many of these models, such as ADACOR (LEITÃO; COLOMBO; RESTIVO, 2006), PROSA (BRUSSEL et al., 1998; VALCKENAERS et al., 1999), and MASCADA (VALCKENAERS et al., 1999), predate the rise of modern SIPs, their foundational principles remain relevant today. For instance, Borangiu et al. (2012) explored distributed control through the Contract Network Protocol, contributing to early understandings of intelligent coordination in manufacturing.

Meyer, Främling, and Holmström (2009) revisited the concept of Intelligent Products, offering a structured classification based on orthogonal dimensions. Other scholars have emphasised how SIPs, supported by technologies such as Big Data, Digital Twins, and IoT systems (e.g., BORANGIU et al. 2020; PISSARDINI et al. 2024), are now integrated into day-to-day industrial operations.

Given PPC's strategic role in orchestrating resources and operations, it is a natural focal point for SIP integration. While numerous studies investigate SIPs in specific contexts, such as reliability (SONG et al., 2023a, 2023b), prototyping (WANG; RANSCOMBE; EISENBART, 2023), or smart product-service systems (KURTZ et al., 2025), their contributions are often dispersed. Prior work has addressed SIPs about quality (HUNGUD; ARUNACHALAM, 2020; YI et al., 2021), and sustainability (ANTONS; ARLINGHAUS 2022b), including their role in life-cycle management (DUFFY; WHITFIELD, 2016; NAVAS; SANCHO; CARPIO, 2020).

Research designs in the field vary widely, ranging from the development of specific intelligent devices (CARDIN et al., 2018; THÜRER et al., 2021) to studies connecting SIPs to customer interaction (LOPEZ; GARZA, 2023) and circular economy strategies (EVERTSEN; RASMUSSEN; NENADIC, 2022). Several works, such as Kim; Lim; Hsuan (2023); Liu; Ming (2019), have also proposed architectures for SIP-based product-service systems.

Despite this broad coverage, the literature lacks a consolidated analysis of how SIP-enabled capabilities relate to and depend on each other, particularly in the PPC context. Our

SLR, based on 86 studies from 1990 to 2024, highlights this gap. While individual capabilities are well documented, their interrelations remain insufficiently explored.

3.2.2 Research Gap and Motivations

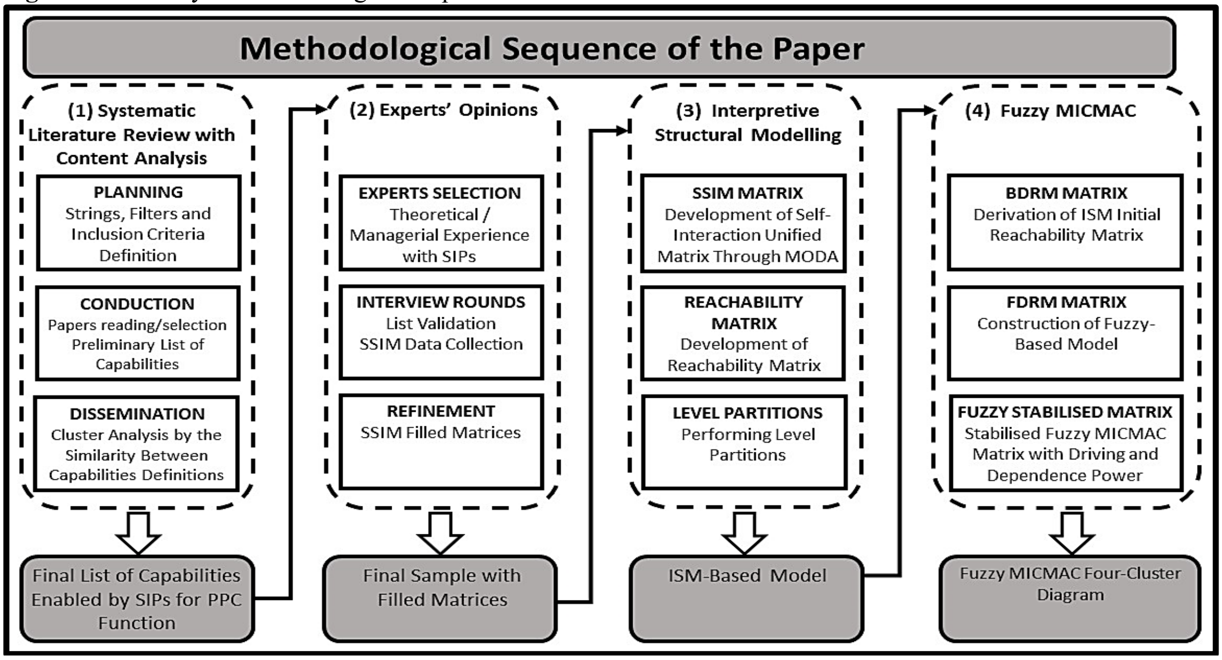
Exploring how SIP-enabled capabilities interact within PPC is the primary motivation for this study. As industrial environments become increasingly dynamic, organisations must identify these capabilities and comprehend the structural relationships among them to fully unlock the potential of SIPs. This research addresses the absence of a cohesive framework by consolidating scattered insights and examining how SIPs facilitate improved demand forecasting, resource allocation, production scheduling, and real-time decision-making. It utilises a rigorous methodology that combines SLR, expert validation, and fuzzy *MICMAC* to map the interdependencies among capabilities.

By doing so, we offer both theoretical and practical contributions. Theoretically, we clarify the hierarchical structure of SIP-enabled capabilities related to PPC. Practically, we guide organisations aiming to progress toward fully autonomous PPC systems. To our knowledge, this is the first study to develop a framework that explicitly defines the capability dependency structure for SIPs in industrial PPC contexts, highlighting the relevance and novelty of this research.

3.3 RESEARCH METHODS

This research employs a mixed-methods framework consisting of four sequential and complementary stages (Figure 3.1), combining qualitative and quantitative techniques to achieve a thorough understanding of the capabilities facilitated by SIPs in the PPC function. The integration of methods was crucial due to the exploratory nature of the topic and the necessity to organise interrelationships among complex constructs.

Fig. 3.1: Summary of methodological sequence



Source: Elaborated by the author (2025)

A SLR with content analysis was conducted in the initial stage to identify and categorise the capabilities related to PPC enabled by SIPs. This qualitative step established a solid theoretical foundation for the subsequent analysis. The second stage included expert validation from both academic and industry professionals to refine and confirm the practical relevance of the identified capabilities. In the third stage, ISM was utilised to examine the contextual relationships among the validated capabilities, facilitating the creation of a hierarchical framework. The fourth stage employed fuzzy *MICMAC* analysis to assess the driving and dependence power of each capability, providing a dynamic and quantifiable view of the system's structure. The combination of ISM and fuzzy *MICMAC* was selected over conventional multi-criteria decision-making (MCDM) methods due to its effectiveness in managing complex interdependencies without the need for extensive pairwise comparisons among all elements. Bianco et al. (2023) demonstrate that this combination offers a robust framework for modeling hierarchical relationships and evaluating the influence and dependence of elements under uncertainty, particularly in emerging and partially structured domains such as SIP-enabled PPC.

3.3.1 Systematic Literature Review with Content Analysis

To perform the SLR, we followed the three steps that Denyer and Tranfield (2009) proposed: planning, conducting, and disseminating. In the planning phase, the main parameters of our research are selected, such as the research questions, period of analysis, and idiom of the papers. Next, the conduction phase applied the objective filters previously defined in the research protocol, followed by reading titles and abstracts, to select articles that address the research objective. After reading the titles and abstracts, the remaining papers were thoroughly read, and the final sample was selected. Finally, in the dissemination step, the article was classified and analysed. The content analysis was conducted using NVivo 13 Software. In this step, we tabulated the capabilities and created a code for each, along with a brief definition. Thus, the codes and definitions were inserted into the NVivo 13 software to identify semantic similarities among descriptions, allowing for the unification of similar capabilities.

The literature review was conducted to identify which capabilities are enabled by adopting SIPs in the PPC function. A research question guided the identification of the main keywords, which, in turn, informed the construction of the research string. After that, the search was done using three databases: Web of Science, Engineering Village, and Scopus. The research protocol developed to guide our SLR is presented in Table 3.1.

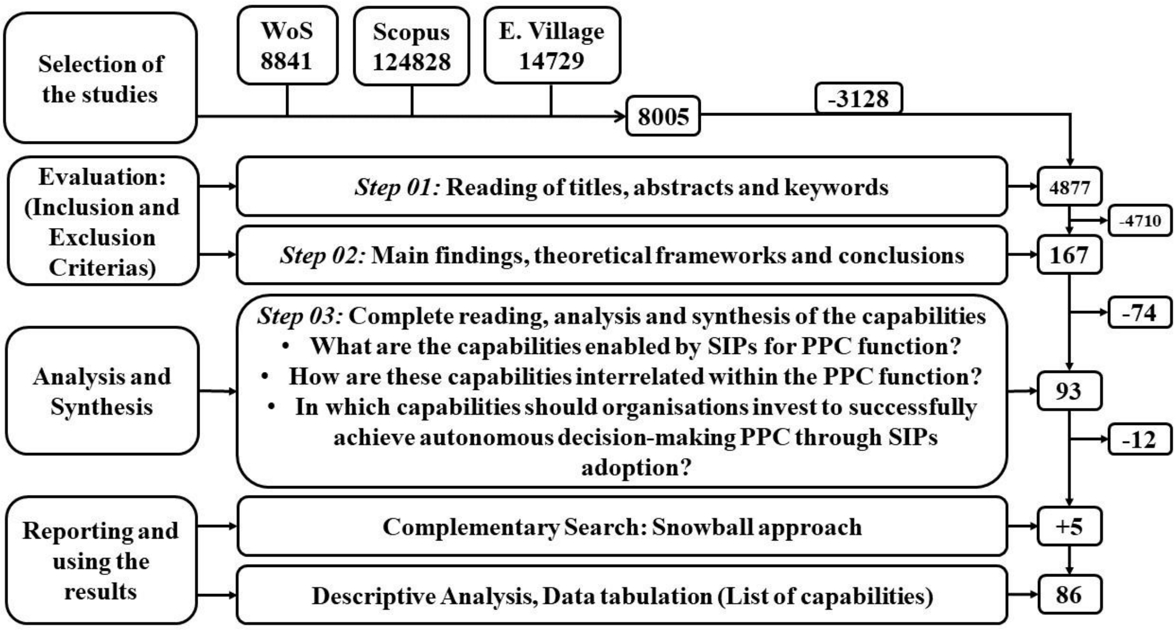
Table 3.1 - Research Protocol

Research protocol	
Objective	To identify Capabilities provided by SIPs for PPC function
Guiding Questions	What capabilities are enabled by the adoption of SIPs in the PPC function? How are these capabilities interrelated within the context of the PPC function? Which path should organisations follow to develop SIP-enabled capabilities and achieve autonomous decision-making on PPC?
Databases	Engineering Village, Scopus, Web of Science
Publication years	From 1990 to 2024
Document type	Articles, Articles in Press, Reviews
Language	English
Strings	((Smart AND Product) OR (Connected AND Product) OR (Smart AND Connected AND Product) OR (Intelligent AND Product) OR (Autonomous AND Product) OR (Autonomous AND Device) OR (Holonic AND Manufacturing))

Source: Elaborated by the author (2025)

The initial search using the string presented in Table 3.1 returned 148,398 papers. By applying objective filters, 8,005 papers were selected. After removing duplicated papers, the titles and abstracts of 4,877 papers were read. From this step, 167 papers were selected. After that, we read the introductions, main findings, theoretical frameworks, and conclusions of the remaining 93 papers. Finally, by reading thoroughly the 93 papers, 81 cited any capability enabled by SIPs adoption in the PPC function. We added five more papers through the snowball approach, having a final sample of 86 papers classified. Figure 3.2 summarises the screening process, while Table 3.2 shows the inclusion and exclusion criteria.

Fig. 3.2 Screening process



Source: Elaborated by the author (2025)

Table 3.2 - Inclusion and exclusion criteria

Filter	Criteria	Inclusion	Exclusion
1	Access	The paper should be available for access	The paper is not available for access
2	Focus	The Paper focuses on Smart Products in the industrial context.	The paper addresses Smart Products in other contexts.
3	SIPs capabilities	The paper comprises SIP capabilities in Industrial contexts, pointing out examples of how the capability impacts the PPC function	The paper comprises SIPs' capabilities in supply chain or other organisational functions
4	Quality	Articles, Articles in Press, Review Articles	Conference Papers and Books
5	Thematic Positioning	The paper focuses on one or more capabilities enabled by SIPs in the PPC function and their relationship with enhancing the smartness and autonomy of the PPC function	The paper considers Smart Product-Service Systems, not related to the organisational environment

Source: Elaborated by the author (2025)

The NVivo 13 Software was utilised for coding and data analysis of the papers. From reviewing the selected papers, it was possible to identify 23 capabilities enabled by adopting SIPs in the PPC function. With the aid of NVivo 13, we realised a cluster analysis. From this analysis and the expert's validation, the 23 capabilities were reduced to 12 due to the high semantic similarity between some of them. The semantic similarity analysis enables us to unify capabilities that may be cited differently by different researchers but have the same conceptual meaning, thereby eliminating data redundancy. The similarity between the 23 capabilities identified in the literature was calculated through Pearson's correlation coefficient. Excerpts from papers that illustrated the significance of specific competencies were incorporated into the codes, facilitating the semantic analysis of each of the 23 capabilities.

3.3.2 Experts' Opinions

The research method chosen included expert interviews to consolidate and refine the capabilities list identified in the SLR. Experts are the observers of and mechanics behind what social scientists call "causal mechanisms" (LAZEGA et al., 1999). Therefore, four academic experts with broad experience in Industry 4.0, Smart Industrial Products, and Operations Management were consulted. The experience should include more than ten years in the academic field, and the experts should have published papers in journals with a selective editorial policy. Table 3.3 shows the detailed experts' profiles.

The meetings in the interview rounds lasted an average of 50 minutes. The collected data was registered, and the list was consolidated after each meeting. During the interview, the experts were questioned about the validity of the capabilities and their following descriptions.

After each interview, the capabilities were refined based on their feedback. This iterative process resulted in a final list comprising 12 capabilities facilitated by SIPs adoption in the PPC function. To enhance the precision of this capabilities list, we follow two steps: i) the judicious selection of experienced experts; and ii) the systematic procedure for gathering, analysing, and synthesising data derived from the SLR. Consequently, we followed a four-step cycle, as suggested by Callefi et al. (2022); Saunders; Lewis; Thornhill (2012), to validate the final list:

1. The initial list was presented to the expert for their input.
2. The list, with capabilities clustered together, was presented to the experts.
3. Suggestions were diligently collected and incorporated into the final list.
4. The final list was subsequently presented to the expert for validation or the inclusion of any additional suggestions.

3.3.3 Interpretive Structural Modeling

The ISM approach was used to establish the relationship between the capabilities enabled by the adoption of SIPs in the PPC function. The ISM approach offers a structured and interactive learning process, encapsulating specialised knowledge about a set of elements that describe a system and how those elements are aggregated (GODINHO FILHO et al., 2025). It transforms unclear and poorly articulated knowledge, mental systems models, into visual and well-defined systems (RUIZ-BENITEZ; LÓPEZ; REAL, 2017). The ISM approach comprises 4 steps, proposed by Farris; Sage (1975); Warfield (1974), detailed below.

3.3.3.1 Structural Self-Interaction Matrix

The ISM model was developed based on input from 15 experts with diverse academic and professional backgrounds. According to Saunders, Lewis, and Thornhill (2012), complex topics typically require fewer interviewees. To qualify, experts should have at least 10 years of experience in operations management within highly automated organisations or, for academics, a decade of research experience with publications in reputable journals on Industry 4.0, operations management, digitalisation, or SIPs. Among the participants, 10 were researchers with extensive academic expertise, and 5 were practitioners working directly with SIPs. Table 3.3 presents their profiles.

Table 3.3 - Experts' profile

Position		**Academic background**		**SIP's / OM Experience**	
Researcher	11	PhD Industrial / Mechanical Engineering	11	< 10 years	0
Director of Operations	1	Postgraduate Degree	1	10 – 20 years	15
Operations Manager	3	Bachelor of Engineering	3	> 20 years	0

Source: Elaborated by the author (2025)

In sequence, experts filled a matrix with one of the 4 symbols: V, A, X, O, according to the following rules:

a) If variable *i* influences variable *j*, the cell is filled with V;

b) If variable *j* influences variable *i*, the cell is filled with A;

c) If variable *i* and variable *j* mutually influence each other, the cell is filled with X;

d) If there is no influence between both pairs of variables, the cell is filled with O.

The relationship between the 12 capabilities identified in the SLR is essential in this phase since the main goal of our research is to identify which variables are dependent and which affect others. Therefore, every influence direction was considered and directly impacted the final results, as a consequence, being considered in the SSIM matrix development.

3.3.3.2 Development of the Initial and Final Reachability Matrix

In this second step, we calculated the "mode" of the filled matrices to unify all the answers. After that, the SSIM matrix was converted into an Initial Reachability Matrix (IRM). To perform the conversion, we replace the V, A, X and O variables into 0s and 1s according to the following rules proposed by Attri; Dev; Sharma (2013):

a) If entry (*i*,*j*) in the SSIM is V, then entry (*i*,*j*) in the IRM becomes 1 and entry (*j*,*i*) becomes 0;
b) If entry (*i*,*j*) in the SSIM is A, then entry (*i*,*j*) in the IRM becomes 0 and entry (*j*,*i*) becomes 1;
c) If entry (*i*,*j*) in the SSIM is X, then entry (*i*,*j*) in the IRM becomes 1 and entry (*j*,*i*) becomes 1;
d) If entry (*i*,*j*) in the SSIM is O, then entry (*i*,*j*) in the IRM becomes 0 and entry (*j*,*i*) becomes 0.

The transitivity property was applied in sequence to address the Final Reachability Matrix (FRM). A transitivity relationship is one in which if S_i influences S_j and S_j influences S_k. Then, it can be inferred that S_i influences S_k. Following Ruiz-benitez et al. (2017), the transitivity property allows us to fill some cells in the matrix by inference. However, all the inference cases are filled in the FRM with a "1*" symbol. The final digraph, including the transitivity links, was obtained from the conical shape of the reachability matrix. After the indirect links had been removed, the final digraph was developed. According to the dependence and the level between the variables, they were organised in different levels where the variables in the framework's base are the most important or the driving force to achieve other capabilities.

3.3.3.3 Performing Level Partition

Through the FRM, the sets "reachability" and "antecedents" have been derived for all system variables. The reachability set consists of the variable itself and the factor that will impact it. The intersection of these sets was determined for all the variables. On the other hand, the antecedent set is composed of the variable itself and the factors that will influence the variable. In sequence, we derived the intersection of these sets for all variables, determining the different levels. The reachability set and intersection variables are R(Si) = I(Si), occupying the same superior level in the ISM hierarchy.

This level partition is used to develop the ISM model because the ISM hierarchy is built by placing the capabilities with the same level of reachability and intersection at the same matrix level. Hence, superior-level variables are the ones that do not take other variables above themselves in the hierarchy.

Finally, after identifying a superior-level variable, it is removed from consideration. The exact process was used in sequence to discover the factors at the next level. This process was repeated to find all the levels. This iterative loop helped to build the final ISM model.

The equations used in this step were:

$$R\ (S_i) = \{S_j \in S / e_{ij} = 1\} \cup \{S_i \in S\} \tag{1}$$

$$A\ (S_i) = \{S_j \in S / e_{ij} = 1\} \cup \{S_i \in S\} \tag{2}$$

The classification between the elements is represented by the equation 3:

$$I\ (S_i) = R\ (S_i) \cap A\ (Si) \tag{3}$$

3.3.3.4 ISM-Based Model Derivation

The ISM model, containing the structural relationship between the 12 capabilities enabled by SIP adoption in the PPC function, was created as a natural representation of the FRM. In the structural model, when there is a relationship between capabilities *"i"* and "*j*", this relationship is represented by an arrow from *"i"* to "*j*". Variables in the highest level were placed at the top of the digraph. The second-level variable was positioned in the second position, and so on, until all the variables had been placed. The ISM model was built after all the transitive links had been eliminated.

3.3.4 Fuzzy *MICMAC*

Although ISM model binarily evaluates each pair of capabilities, the influence of one over another can have different intensities (MOTA et al., 2021). To perform the fuzzy *MICMAC* analysis, we followed a sequence of 4 steps, detailed in the next subsection.

3.3.4.1 Performing Binary Direct Reachability Matrix (BDRM)

To determine the BDRM matrix we should replace all the entries in the diagonal of the IRM with zeros. This process is done to identify the relationships between the capabilities evaluated by fuzzified values in the Fuzzy Direct Reachability Matrix (FDRM).

3.3.4.2 Building Fuzzy Direct Reachability Matrix (FDRM)

To address the FDRM we should fuzzify the number of experts who agree with the influence of capability i on capability j. We perform this step using five linguistic terms according to Table 3.4 and the assignment rule used for establishing the fuzzyfied matrix. The second column of Table 3.4 presents the characteristic values of each linguistic term. These values will be used in the next step of our research to stabilise the *MICMAC* matrix. The FDRM is then obtained by replacing the non-zero values in the BDRM with the respective values characteristic of the relationship between the two capabilities.

Table 3.4 - Fuzzy scale and assignment rule for defining the strength of the antecedents

Strength	Value Assigned	Number of experts agreed that factor *i* drives factor *j*
No	0	None
Weak	0,25	1-4
Medium	0,50	5-8
Strong	0,75	9-12
Very Strong	1	13 or above

Source: Elaborated by the author (2025)

3.3.4.3 Calculating the Fuzzy *MICMAC* Stabilised Matrix

To stabilise the fuzzy *MICMAC* matrix, a multiplication process was performed from the initial matrices until the sum values of its rows (driving power) and columns (dependence power) did not change. According to Mota et al. (2021), different types of fuzzy compositions could be used to determine the strength of the fuzzy indirect relation from element i to j (e.g., max-min, max-product and max-average). In our research, the max-min composition is the most suitable once the minimum strength must be the maximum of all possible minimal impacts from variable i to j.

Matrix multiplication was then calculated using the rule described below to achieve the fuzzy *MICMAC* stabilised matrix:

$$Z = X \, . \, Y = max_k \left[\min\left(X_{ik} \, , Y_{kj} \right) \right] \quad (1)$$

Where X = $[X_{ik}]$ and Y = $[Y_{kj}]$

To perform the multiplication of the fuzzy matrices using this operator we use the MATLAB® software, having the Fuzzy *MICMAC* stabilised matrix as output.

3.3.4.4 Four-Cluster Diagram

From the fuzzy *MICMAC* stabilised matrix, the driving power of each capability is calculated by summing the values in its respective row, indicating how much it influences other variables. Conversely, the dependence power is derived from the sum of the values in each column, representing how much a capability is influenced by others. Capabilities with high driving power tend to trigger changes in other elements, while those with high dependence power are primarily reactive within the system.

To illustrate these relationships, we developed a four-cluster diagram that categorises capabilities into four types. Autonomous capabilities exert minimal influence and are minimally influenced, playing an isolated role in the system. Others highly influence dependent capabilities but have little impact themselves. Linkage capabilities are influential and dependent, often serving as intermediaries within the system. Finally, driving capabilities show high influence and dependence, actively shaping and being shaped by the system's complexity.

3.4 RESULTS

Each method from our previously described multi-method approach is presented with specific but complementary results. The following subsections detail the results of each methodological step.

3.4.1 Systematic Literature Review

The initial phase of this research involved a SLR, which laid the foundation for subsequent steps. The outcomes of this phase are also the input for the next phase.

By analysing the 86 papers, it was possible to derive an initial list containing the capabilities enabled by adopting SIPs in the PPC function. From the literature, 23 PPC-enabled capabilities were found. To refine the list, we perform a cluster analysis through word similarity in our content analysis. In addition, the definitions drawn for each capability were linked with a code representing a specific capability. This step reduced the list to 12 capabilities, therefore unifying 11 capabilities that, although pointed out differently in literature, had the same conceptual meaning. Finally, four academic experts analysed the final list, validating the clusterisation process performed. The final list with the identified capabilities, their codes, definitions, and the authors that cited each one is presented in Table 3.5.

Table 3.5 - Final list of capabilities

Capability	Code	Description	Citation
Sensing integration via RFID	PPC1	Ability to use sensors to detect physical, chemical, or biological properties/quantities, converting them into readable signals through the use of sensors, integrating data with the system	35, 37, 44, 53, 74
Interoperability of smart resources	PPC2	Ability to communicate among different SIPs that work under different protocols, self-managing information to meet the PPC objectives	2, 10, 11, 15, 20, 23, 26, 29, 37, 39, 43, 48, 49, 53, 61, 74, 81, 82, 83, 84, 85, 86
SIP/Production line auto-reconfiguration	PPC3	Ability to improve/upgrade SIPs during the use phase according to the production process requirements, reacting to data collected to self-adapt to the new current scenarios, reducing set-up times for different variants of standard goods, increasing speed, reducing errors, and improving change-over time	1, 2, 6, 7, 10, 14, 24, 28, 31, 34, 44, 51, 62, 63, 67, 69, 74
Workforce reconfiguration	PPC4	Ability to reconfigure the team's resources to provide agility to frequent changes in production, fault-tolerance to resource breakdowns, and adaptability to material flow variations through information integration	1, 8, 10, 15, 18, 20, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 36, 39, 42, 46, 47, 48, 49, 50, 52, 53, 54, 62, 68, 74, 78, 86
Full cyber-physical-social integration	PPC5	Ability of the SIP to autonomously make decisions acting in coordination with other SIPs, systems, and customers, improving information systems accuracy through automatic monitoring and context awareness	3, 8, 22, 23, 24, 26, 29, 35, 39, 41, 45, 48, 54, 57, 59, 62, 65, 67, 71, 72, 73, 74, 78, 82, 86
Remote process control	PPC6	Ability to control the product through integration between the SIP and remote commands/algorithms that are built into the device or reside in the product cloud	2, 57, 66, 75, 79
Self-Optimising Decision Performance	PPC7	Ability to apply algorithms and analytics to both in-use or historical data, enabling a remarkable enhancement in output, utilisation, and efficiency. Through the expertise gained from past decision-making, SIPs make optimal choices that align production parameters with customer requirements, continuously feedbacking and improving it by applying self-* methods	2, 6, 7, 9, 10, 11, 18, 22, 33, 39, 46, 48, 49, 53, 57, 58, 60, 67, 68, 73, 74, 79, 84
Machine-to-Machine integration	PPC8	Ability of networked machines to fully automate and optimise production	2, 8, 9, 10, 17, 18, 22, 46, 48, 61, 62, 66, 68, 74, 80, 81, 84
Enhanced data collection	PPC9	Ability to collect and communicate data throughout the manufacturing process to continuously update the process plan	15, 22, 36, 49, 68, 70, 75, 78, 80, 81
Adaptive and resilient production	PPC10	Ability to react to changes such as demand and production scheduling, and also to share information among SIPs as a way to bring robustness to the production process	1, 2, 4, 6, 7, 9, 10, 11, 13, 14, 15, 16, 17, 19, 20, 21, 22, 23, 29, 30, 32, 33, 34, 35, 36, 38, 39, 42, 43, 46, 48, 49, 50, 51, 53, 54, 62, 68, 75, 79, 80
Complexity management for product-service systems	PPC11	Ability of a SIP to join and facilitate the complexity management of daily tasks associated with the provision of products and services of the goods produced	37, 40, 74, 76, 77, 84
Real-Time operational visibility	PPC12	Ability to have real-time information about ongoing operations, performing operational control	1, 8, 15, 17, 18, 36, 37, 41, 55, 56, 73, 75, 81, 84

Source: Elaborated by the author (2025)

Notes: 1. (NAKANE; HALL, 1991); 2. (MATHEWS, 1995); 3. (BENGOA et al., 1996); 4. (MÁRKUS; KIS VÁNCZA; MONOSTORI, 1996); 5. (TSENG; LEI; SU, 1997); 6. (VAN LEEUWEN; NORRIE, 1997); 7. (TANAYA; DETAND; KRUTH, 1997); 8. (GOU; LUH; KYOYA, 1998); 9. (NORIYASU et al., 1998); 10. (VALCKENAERS et al., 1999); 11. (WYNS; VAN BRUSSEL; VALCKENAERS, 1999); 12. (ULIERU; NORRIE, 2000); 13. (BONGAERTS et al., 2000); 14. (LUN; CHEN, 2000); 15. (ZHANG et al., 2000); 16. (FLETCHER; DEEN, 2001); 17. (HERAGU et al., 2002); 18. (CHAN; ZHANG, 2002); 19. (JARVIS; JARVIS; MCFARLANE, 2003); 20. (SUGI et al., 2003); 21. (TAMURA; YANASE; NISHI, 2005); 22. (LEITÃO; COLOMBO; RESTIVO, 2005); 23. (LEITÃO; RESTIVO, 2006); 24. (SIMÃO; STADZISZ; MOREL, 2006); 25. (LEITÃO; COLOMBO; RESTIVO, 2006); 26. (ZHANG; ANOSIKE; LIM, 2007); 27. (COLOMBO; HARRISON, 2008); 28. (LEITÃO; RESTIVO, 2008a); 29. (LEITÃO, 2008); 30. (BLANC; DEMONGODIN; CASTAGNA, 2008); 31. (LEITÃO; RESTIVO, 2008b); 32. (CHOKSHI; MCFARLANE, 2008); 33. (SIMAO; STADZISZ, 2009); 34. (COVANICH; MCFARLANE, 2009); 35. (PANNEQUIN; MOREL; THOMAS, 2009); 36. (WANG; LIN, 2009); 37. (VALCKENAERS et al., 2009); 38. (GOCH; DIJKMAN, 2009); 39. (MEKID; PRUSCHEK; HERNANDEZ, 2009); 40. (YANG; MOORE; CHONG, 2009); 41. (BABICEANU; CHEN, 2009); 42. (HSIEH, 2009); 43. (MEYER; FRÄMLING; HOLMSTRÖM, 2009); 44. (ATZORI; IERA; MORABITO, 2010); 45. (CHEUNG et al., 2010); 46. (MCFARLANE; BUSSMANN, 2010); 47. (HSIEH, 2010); 48. (SALLEZ et al., 2010); 49. (BAL; HASHEMIPOUR, 2010); 50. (LEITÃO, 2011); 51. (MEYER; HANS WORTMANN; SZIRBIK, 2011); 52. (BORANGIU et al., 2012); 53. (LEITÃO; MAŘÍK; VRBA, 2013); 54. (MCFARLANE et al., 2013); 55. (TAKAHARA; YASAKI, 2013); 56. (MEYER et al., 2014); 57. (PORTER; HEPPELMANN, 2015); 58. (BOUAZZA et al., 2015); 59. (PUTNIK et al., 2015); 60. (LEITÃO et al., 2015); 61. (PORTER; HEPPELMANN, 2015); 62. (BARBOSA et al., 2015); 63. (ABRAMOVICI; GÖBEL; SAVARINO, 2017); 64. (TORRES-PALACIO, 2017); 65. (DING; JIANG, 2018); 66. (SOROURI; VYATKIN, 2018); 67. (CENA et al., 2019); 68. (SHIN; KIM; MEILANITASARI, 2019); 69. (ZHANG et al., 2020); 70. (LENZ et al., 2020); 71. (RAFF; WENTZEL; OBWEGESER, 2020); 72. (PARDO; IVENS; PAGANI, 2020); 73. (HUNGUD; ARUNACHALAM, 2020); 74. (DERIGENT; CARDIN; TRENTESAUX, 2021); 75. (YI et al., 2021); 76. (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021); 77. (RUHUL AMIN et al., 2021); 78. (LIU; ZHENG; XU, 2023); 79. (IMAD et al., 2022); 80. (ANTONS; ARLINGHAUS, 2022a); 81. (ANTONS; ARLINGHAUS, 2022b); 82. (TRAN et al., 2022); 83. (ATTAJER et al., 2022); 84. (LEI et al., 2022); 85. (TURNER et al., 2022); 86. (TURNER; OYEKAN, 2023);

3.4.2 ISM Results

This phase presents the steps and outcomes of the ISM analysis, defining the structural hierarchy among the PPC-enabled capabilities. The matrix was constructed based on expert responses, with the most frequent answer (Moda) selected for each pair of capabilities, as shown in Table 3.6. This matrix was then converted into a binary form (Table 3.7) and, following applying the transitivity rule, into a final version (Table 3.8). Table 3.9 displays the reachability, antecedent, and intersection sets used to establish the levels in the model. Based on this structure, a graphical representation of the ISM model was developed and is presented in Figure 3.3. The twelve PPC-enabled capabilities were organised into five hierarchical levels, discussed in the following section.

Table 3.6 - Final Structural Self-Interaction Matrix (MODA)

MODA	PPC12	PPC11	PPC10	PPC9	PPC8	PPC7	PPC6	PPC5	PPC4	PPC3	PPC2	PPC1
PPC1	V	V	V	V	V	O	V	V	V	V	V	
PPC2	V	V	V	X	V	V	V	X	V	V		
PPC3	A	V	V	A	A	A	X	X	X			
PPC4	A	V	X	A	A	A	O	A				
PPC5	V	V	V	V	X	V	V					
PPC6	V	V	O	A	A	V						
PPC7	A	A	V	A	A							
PPC8	V	V	V	V								
PPC9	X	V	V									
PPC10	A	A										
PPC11	A											
PPC12												

Source: Elaborated by the author (2025)

Table 3.7 - Initial Reachability Matrix

	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12
PPC1	1	1	1	1	1	1	0	1	1	1	1	1
PPC2	0	1	1	1	1	1	1	1	1	1	1	1
PPC3	0	0	1	1	1	1	0	0	0	1	1	0
PPC4	0	0	1	1	0	0	0	0	0	1	1	0
PPC5	0	1	1	1	1	1	1	1	1	1	1	1
PPC6	0	0	1	0	0	1	1	0	0	0	1	1
PPC7	0	0	1	1	0	0	1	0	0	1	0	0
PPC8	0	0	1	1	1	1	1	1	1	1	1	1
PPC9	0	1	1	1	0	1	1	0	1	1	1	1
PPC10	0	0	0	1	0	0	0	0	0	1	0	0
PPC11	0	0	0	0	0	0	1	0	0	1	1	0
PPC12	0	0	1	1	0	0	1	0	1	1	1	1

Source: Elaborated by the author (2025)

Table 3.8 - Final Reachability Matrix

	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12
PPC1	1	1	1	1	1	1	1*	1	1	1	1	1
PPC2	0	1	1	1	1	1	1	1	1	1	1	1
PPC3	0	1*	1	1	1	1	1*	1*	1*	1	1	1*
PPC4	0	0	0	1	0	0	1*	0	1*	1	1	0
PPC5	0	1	1	1	1	1	1	1	1	1	1	1
PPC6	0	0	1	1*	1*	1	1	0	1*	1*	1	1
PPC7	0	0	1	1	1*	1*	1	0	0	1	1*	0
PPC8	0	1*	1	1	1	1	1	1	1	1	1	1
PPC9	0	1	1	1	1*	1	1	1*	1	1	1	1
PPC10	0	0	0	1	0	0	0	0	0	1	1*	0
PPC11	0	0	1*	1*	0	0	1	0	0	1	1	0
PPC12	0	1*	1	1	1*	1*	1	0	1	1	1	1

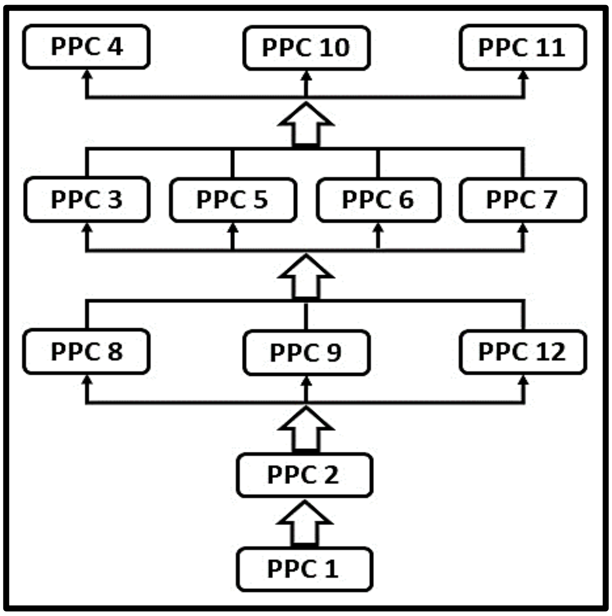
Source: Elaborated by the author (2025)

Table 3.9 - Level partition matrix

Capability	Reachability Set	Antecedent Set	Intersection Set	Level
PPC 1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1	1	V
PPC 2	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 5, 8, 9, 12	2, 3, 5, 8, 9, 12	III
PPC 3	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 5, 6, 7, 8, 9, 11, 12	2, 3, 5, 6, 7, 8, 9, 11, 12	II
PPC 4	4, 7, 9, 10, 11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	4, 7, 9, 10, 11	I
PPC 5	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 5, 6, 7, 8, 9, 12	2, 3, 5, 6, 7, 8, 9, 12	II
PPC 6	3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 5, 6, 7, 8, 9, 12	3, 5, 6, 7, 9, 12	II
PPC 7	3, 4, 5, 6, 7, 10, 11	1, 2, 3, 5, 6, 7, 8, 9, 11, 12	3, 5, 6, 7, 11	II
PPC 8	4, 5, 6, 7, 8, 11, 12, 13, 14	1, 2, 3, 5, 8, 9	2, 3, 5, 8, 9	IV
PPC 9	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 8, 9, 12	2, 3, 4, 5, 6, 8, 9, 12	III
PPC 10	4, 10, 11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	4, 10, 11	I
PPC 11	3, 4, 7, 10, 11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 7, 10, 11	I
PPC 12	2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 5, 6, 8, 9, 12	2, 3, 5, 6, 9, 12	III

Source: Elaborated by the author (2025)

Fig. 3.3 ISM-Based model



Source: Elaborated by the author (2025)

3.4.3 Fuzzy *MICMAC* Results

The following subsections present the results of the Fuzzy *MICMAC* analysis, following the previously described methodological steps.

The process begins with constructing the BDRM matrix (Table 3.10), which is obtained by replacing all diagonal entries of the IRM with zeros. The FDRM matrix (Table 3.11) was then generated using the characteristic values associated with the number of experts that assigned V, A, X, or O ratings in the SSIM matrix (Table 3.6). The stabilised matrix was calculated through matrix multiplication, as detailed in the methodology (Section 3.3.5.1 – step 3), and is presented in Table 3.12. Based on the stabilised matrix, a four-cluster diagram was developed to illustrate the driving forces and interdependencies among the identified capabilities. The resulting classification is shown in Figure 3.4.

Table 3.10 - Binary Direct Reachability Matrix

	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12
PPC1	0	1	1	1	1	1	0	1	1	1	1	1
PPC2	0	0	1	1	1	1	1	1	1	1	1	1
PPC3	0	0	0	1	1	1	0	0	0	1	1	0
PPC4	0	0	1	0	0	0	0	0	0	1	1	0
PPC5	0	1	1	1	0	1	1	1	1	1	1	1
PPC6	0	0	1	0	0	0	1	0	0	0	1	1
PPC7	0	0	1	1	0	0	0	0	0	1	0	0
PPC8	0	0	1	1	1	1	1	0	1	1	1	1
PPC9	0	1	1	1	0	1	1	0	0	1	1	1
PPC10	0	0	0	1	0	0	0	0	0	0	0	0
PPC11	0	0	0	0	0	0	1	0	0	1	0	0
PPC12	0	0	1	1	0	0	1	0	1	1	1	0

Source: Elaborated by the author (2025)

Table 3.11 - Fuzzy Direct Reachability Matrix

	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12
PPC1	0	0,50	0,75	0,50	0,50	0,75	0	0,50	1	0,50	0,75	0,75
PPC2	0	0	0,75	0,75	0,75	0,75	0,50	1	0,50	0,75	0,75	1
PPC3	0	0	0	0,75	0,75	0,75	0	0	0	0,75	0,50	0
PPC4	0	0	0,75	0	0	0	0	0	0	0,75	0,75	0
PPC5	0	0,75	0,75	0,75	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC6	0	0	0,50	0	0	0	0,50	0	0	0	0,50	0,50
PPC7	0	0	0,75	0,75	0	0	0	0	0	0,50	0	0
PPC8	0	0	0,75	0,75	0,75	0,75	0,50	0	0,75	0,75	0,75	0,75
PPC9	0	0,50	0,50	0,75	0	0,50	0,75	0	0	0,75	0,75	0,75
PPC10	0	0	0	0,50	0	0	0	0	0	0	0	0
PPC11	0	0	0	0	0	0	0,50	0	0	0,75	0	0
PPC12	0	0	0,75	0,75	0	0	0,75	0	0,75	0,50	0,75	0

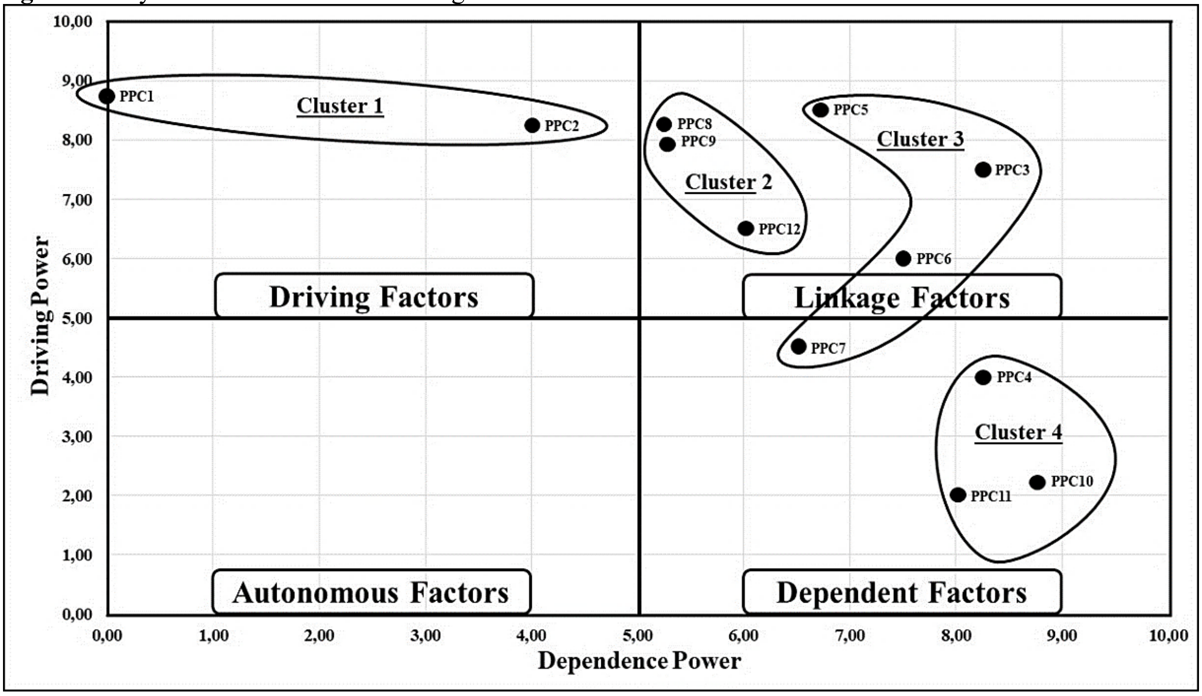
Source: Elaborated by the author (2025)

Table 3.12 - Fuzzy Stabilised Matrix

	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12
PPC1	0	0,75	0,75	0,75	0,75	0,75	0,75	1	0,75	0,75	0,75	1
PPC2	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC3	0	0,75	0,75	0,75	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC4	0	0	0	0,75	0,75	0,75	0,50	0	0	0,75	0,50	0
PPC5	0	0,50	0,75	0,75	0,75	0,75	0,75	1	0,75	0,75	0,75	1
PPC6	0	0	0,50	0,75	0,75	0,75	0,75	0	0,75	0,75	0,75	0
PPC7	0	0	0,75	0,75	0,75	0,75	0	0	0	0,75	0,75	0
PPC8	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC9	0	0	0,50	0,75	0,75	0,75	0,75	1	0,75	0,75	0,75	1
PPC10	0	0	0	0	0	0	0	0	0	0,75	0,75	0
PPC11	0	0	0	0,75	0	0	0	0	0	0,50	0	0
PPC12	0	0,50	0,75	0,75	0,75	0,75	0,75	0	0	0,75	0,75	0,75

Source: Elaborated by the author (2025)

Fig. 3.4 Fuzzy *MICMAC* Four-Cluster Diagram



Source: Elaborated by the author (2025)

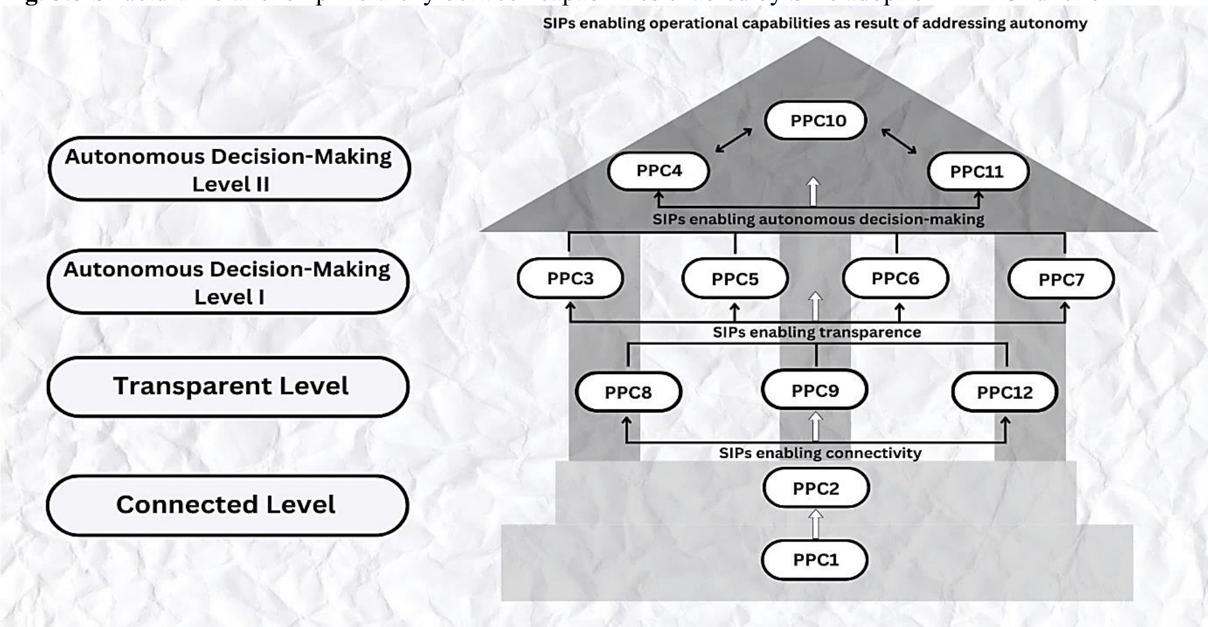
Figure 3.4 displays the 12 capabilities distributed across four clusters according to their driving and dependence power. Cluster 1 includes PPC1 and PPC2, which exhibit high driving power and low dependence, indicating their foundational role in the model. These capabilities primarily handle data acquisition and transmission, enabling subsequent technologies to function effectively. Cluster 2 contains PPC8, PPC9, and PPC12, all with high driving and dependence power. These are positioned at an intermediate level, critical enablers that interact extensively with other capabilities. Cluster 3 comprises PPC3, PPC5, PPC6, and PPC7. Although they maintain high driving power, their greater dependence suggests a placement at a higher level in the framework. These capabilities contribute to increased system transparency and enable more advanced forms of monitoring and analysis, while PPC remains largely passive. Finally, cluster 4 includes PPC4, PPC10, and PPC11. These capabilities show low driving power but are strongly influenced by others, placing them at the top of the structural model. Their development depends on the prior implementation of several other capabilities.

Notably, none of the capabilities belong to the autonomous cluster, which is defined by minimal influence and dependence. This absence reinforces the internal consistency and integration of the identified capabilities, thus supporting the robustness of the proposed framework.

3.5 STRUCTURAL RELATIONSHIP HIERARCHY BETWEEN CAPABILITIES ENABLED BY SIPs' ADOPTION IN PPC FUNCTION

Based on the results presented in the previous sections, Fig. 3.5 illustrates our proposed framework, demonstrating the structural hierarchy between capabilities enabled by SIPs adoption in PPC function. The framework encompasses four structural levels: Connected, Transparent, and Autonomous Decision-Making I and II, which are discussed in detail next.

Fig. 3.5 Structural relationship hierarchy between capabilities enabled by SIPs adoption in PPC function



Source: Elaborated by the author (2025)

3.5.1 Connected Level

The connected level is the lowest level in a PPC system. It allows connectivity among each resource with a bigger Internet of Things network. Analysing the framework (Figure 3.5), it is possible to observe that capabilities PPC 1 (Sensing integration via RFID) and PPC 2 (Interoperability of smart resources) are at the connected level. This is because both capabilities are at the bottom levels of the ISM model (Figure 3.3), and they are also grouped into cluster 1 (driving factors corner) of the fuzzy *MICMAC* (Figure 3.4).

The hierarchy of interactions reflects the essential role of these capabilities in enabling the other capabilities when adopting SIP for the PPC function once any other capabilities do not influence them. PPC 1 plays a central role in capturing and sharing real-time information throughout the production process. In addition, integrating sensing technologies into passive RFID is the first step to enable data-driven decision-making, positively impacting operational efficiency and the quality of the goods that are being manufactured.

Concerning PPC 2, this capability is addressed by achieving interoperability between different manufacturing resources inside/outside the process, allowing organisations, through analytics, to identify new patterns in data not before identified by the managers and/or PPC planners due the difficulty to threat the high amount of data that is uploaded in real-time. By addressing this capability, organisations may reduce the bullwhip effect due to the centralised coordination of the internal supply chain (MEYER; WORTMANN, 2010). Besides, by integrating different SIPs, organisations should develop plug-and-play technologies, facilitating the integration of future new resources (LEITÃO et al., 2015; MEYER; WORTMANN, 2010). In addition, PPC 2 can significantly impact operational efficiency and support decision-making processes once it provides insights from the integrated use of Big Data and Analytics, and other cutting edge technologies CARDIN et al. (2018); DERIGENT; CARDIN; TRENTESAUX (2021) establishing a cohesive ecosystem of intelligent (albeit passive) resources. Hence, by achieving this capability, organisations can face challenges related to the integration of new and old resources that may coexist inside the manufacturing environment (ABRAMOVICI; GÖBEL; SAVARINO, 2017; KAHLE et al., 2020; OLUYISOLA et al., 2022; PORTER; HEPPELMANN, 2015).

Given that the connected level is a pre-requisite for a company achieving upper levels, organisations should strategically allocate their investments to prioritise acquiring these 2 critical capabilities. This prioritisation is essential once enhancing these capabilities will have a significant and positive impact on the overall performance and adaptability of the organisation to deal with the next level of the PPC function’s autonomy.

3.5.2 Transparent Level

The second level of the framework refers to the integration of SIPs that are already connected. At this stage, organisations begin to achieve machine-to-machine (M2M) communication, enabling greater visibility across the manufacturing system. This level comprises three interrelated capabilities: PPC8 (Machine-to-Machine integration), PPC9 (Enhanced data collection), and PPC12 (Real-time operational visibility). These capabilities are positioned at a lower-intermediate level in the structural hierarchy (Figure 3.5), consistent with their placement in the ISM model (Figure 3.3) and classification in cluster 2 of the Fuzzy

MICMAC analysis (Figure 3.4), where they exhibit both strong driving and high dependence power.

The capability related to PPC8 is frequently cited in the literature as a fundamental step toward autonomous decision-making in PPC (ANTONS; ARLINGHAUS, 2022a, 2022b; LEI et al., 2022; PORTER; HEPPELMANN, 2015; SOROURI; VYATKIN, 2018). In addition to enabling system-level coordination, it facilitates the integration of foundational elements such as sensing technologies (PPC1) and interoperability (PPC2). This connectivity enhances operational visibility, allowing organisations to track machine status in real-time, including maintenance conditions and workload (IMAD et al., 2022; WRIGHT; DORNFELD; OTA, 2008). Such transparency contributes to agile responses to disruptions and supports refined coordination of production activities (BUENO et al., 2022; OLUYISOLA; SGARBOSSA; STRANDHAGEN, 2020). However, maintaining this level of integration poses challenges, particularly the need for continuous investment in connectivity infrastructure and interoperability solutions (ABRAMOVICI; GÖBEL; SAVARINO, 2017; MCFARLANE et al., 2013).

PPC9 refers to the capability to collect and communicate process data across the manufacturing system. This enables centralised production planning with decentralised, robust control (KESHAVARZI; VAN DEN HOEK, 2019; LENZ et al., 2020; PARDO; IVENS; PAGANI, 2020). Improved data quality allows for better monitoring, analysis, and adaptation to dynamic production requirements. While it supports proactive adjustments and data-driven decision-making, the passive nature of this capability demands staff with specialised expertise to interpret large volumes of data effectively (KESHAVARZI; VAN DEN HOEK, 2019; ZHANG et al., 2020). As discussed in the holonic literature, staff holons complement fundamental holons by providing contextual intelligence, thereby supporting higher autonomy and system flexibility (BRUSSEL et al., 1998, 1999). PPC12 enables real-time visibility of operational status, improving control and responsiveness. Enhancing process transparency allows prompt responses to disruptions, such as quality issues or machine failures, and supports proactive maintenance strategies (ANTONS; ARLINGHAUS, 2022b; LEI et al., 2022).

Findings related to this level align with existing studies, which identify PPC8, PPC9, and PPC12 as critical enablers of transparency in PPC (e.g., Liu, Zheng, and Xu (2023); Antons and Arlinghaus (2022b); Antons and Arlinghaus (2022a); Lei et al. (2023); Hungud and Arunachalam (2020)). It is important to note that these capabilities are contingent upon successfully implementing the foundational connected level.

3.5.3 Autonomous Decision-Making Level I

At this stage, within the proposed framework, the SIP autonomy directly affects the PPC function, without directly affecting the human operators on the shop floor. This third level of the framework comprises four capabilities: PPC3 (SIP/Production line auto-reconfiguration), PPC5 (Full cyber-physical-social integration), PPC6 (Remote process control), and PPC7 (Self-optimising decision performance). These capabilities are positioned at an upper-intermediate level in the structural hierarchy (Figure 4.5), aligned with their classification in the ISM model (Figure 3.3) and in cluster 3 of the fuzzy *MICMAC* diagram (Figure 3.4). Although they share the linkage characteristics of cluster 2, their greater dependence power places them higher in the framework, acting as a bridge between the intermediate and upper levels.

PPC3 requires a solid technological infrastructure comprising sensing technologies, big data analytics, and digital twins. Once established, this capability enables SIPs to identify data correlations and autonomously reconfigure machinery in response to deviations affecting production performance. As Zhang et al. (2020) noted, smart production lines can self-adjust based on real-time requirements, interacting with engineers to optimise time, cost, and quality parameters.

PPC5 entails the integration of physical, cyber, and social dimensions, allowing SIPs to make autonomous decisions, coordinate with other systems and stakeholders, and enhance information accuracy through contextual awareness. While this integration can significantly improve PPC performance, it also demands multidisciplinary expertise, potentially exposing gaps in workforce skills. Addressing this complexity often requires sustained investment in training and recruiting technically proficient staff (KAHLE *et al.*, 2020; MCFARLANE *et al.*, 2013; TOMIYAMA *et al.,* 2019).

PPC6 enables remote control over the production process, including configuration adjustments and maintenance operations without requiring disassembly or system shutdown (PORTER; HEPPELMANN, 2015). Despite its advantages, such as improved safety in hazardous environments, maintaining operational awareness remotely poses challenges, particularly in dynamic settings. Remote operators must achieve the same situational understanding as those physically present, and not all tasks can be executed without human intervention on site.

PPC7, in turn, leverages past experiences to enhance decision quality. By learning from historical data, SIPs can autonomously anticipate and solve specific problems, reducing external dependency (PORTER; HEPPELMANN, 2015). This capability is closely associated with adaptive planning through pheromone-based communication, as proposed in the ADACOR architecture. Inspired by ant foraging behaviour, this approach enables the dynamic reallocation of tasks in response to disruptions, allowing the system to rapidly identify alternative routes and execute revised plans (LEITÃO *et al.*, 2005; VALCKENAERS *et al.,* 1999). Such decentralised decision-making contributes to operational continuity and system resilience (DERIGENT *et al.*, 2021).

The combination of these four capabilities constitutes the main enablers of autonomy in PPC. Their high dependence power reflects their reliance on foundational elements from the connected and transparent levels. Among them, PPC7 is particularly strategic; although located in the dependent corner of the *MICMAC* diagram, it displays higher driving power than PPC4, PPC10, and PPC11. It also exhibits the lowest dependence within its cluster, suggesting it should be prioritised in the development sequence. Only by achieving self-optimising decision performance (PPC7) can the system evolve toward full cyber-physical-social integration (PPC5), automated reconfiguration (PPC3), and ultimately, remote control (PPC6).

3.5.4 Autonomous Decision-Making Level II

The highest level of the framework encompasses three capabilities. At this stage, the decisions generated by SIPs are directly applied to shop floor control, closing the loop of continuous improvement by feeding operational outcomes back into the PPC system. The capabilities involved are PPC4 (Workforce reconfiguration), PPC10 (Adaptive and resilient production), and PPC11 (Complexity management across product-service offerings). These capabilities represent the most advanced stage of autonomy, being influenced by all others in the system while exerting no influence themselves.

Their implementation depends on the maturity attained through previous levels, particularly the successful integration of Autonomous Decision-Making Level I capabilities. These final-stage capabilities operationalise decisions in the physical environment and promote the dissemination of SIP-enabled benefits across the entire organisation and its extended network.

In the structural hierarchy (Figure 3.5), these capabilities appear at the top, which corresponds to their placement in the ISM model (Figure 3.3) and in cluster 4 (dependent factors) of the four-cluster diagram (Figure 3.4). Their high dependence power and lack of downstream influence reinforce their position at the apex of the framework.

PPC4 is often interpreted as the final step toward achieving operational autonomy in PPC. Its implementation enables organisations to respond swiftly to disruptions, such as production changes, resource breakdowns, or fluctuations in material flow (BORANGIU *et al.*, 2012). Paradoxically, the issues it is designed to mitigate are already reduced by lower-level capabilities, especially those related to predictive and prescriptive control. PPC4 also enables decentralised real-time scheduling and sequencing through intelligent embedded devices that negotiate plans autonomously, replacing traditional centralised control structures. Realising this capability typically requires investments in edge computing technologies that support heterarchical control architectures (MCFARLANE *et al.*, 2013). When implemented effectively, PPC4 enhances organisational agility and reinforces the conditions needed to achieve PPC10.

PPC10 reflects the resilience and adaptability of a production system that fully incorporates autonomous decision-making. The literature indicates that SIP-enabled environments are more robust in the face of disturbances, particularly in decentralised settings (MCFARLANE *et al.*, 2013; MEYER, 2011; MEYER *et al.*, 2009). This resilience facilitates scalability, seamlessly integrating new SIPs into the existing intelligent infrastructure.

PPC11 involves managing the complexities of offering integrated product-service systems across and within organisational units. This capability is exemplified by platforms such as Siemens MindSphere (PETRIK; HERZWURM, 2019; YORSTON, 2023), which offers services that connect machines, plants, and systems while supporting third-party asset integration. These ecosystems enhance connectivity and enable better use of operational data, improving efficiency and reducing downtime. However, organisations must have already implemented the foundational capabilities from earlier levels to fully benefit from such solutions. The case of SKF illustrates this point: by using MindSphere, the company implemented performance-based contracts in which customers pay based on equipment uptime, an approach only viable when supported by high-quality data collection, analysis, and integration (SIEMENS, 2023).

3.6 CONCLUSIONS

Recently, SIPs are increasingly being adopted, supporting organisations to revolutionise how to produce goods and services. At the same time, organisations are required to acquire capabilities that directly and positively impact the PPC objectives. Therefore, this research identified 12 capabilities enabled by SIPs adoption in PPC function. This study established a structural hierarchy between these capabilities through an integrated multimethod approach, composed of an SLR, expert's interview, ISM and Fuzzy *MICMAC* approaches. The following subsections present the theoretical and practical contributions of this research, as well as the limitations and suggestions for future studies.

3.6.1 Theoretical Contributions

Firstly, our study significantly enriches the literature on SIPs by delineating a comprehensive list of 12 capabilities that SIPs enable within the PPC function, complete with definitions for each. Although research has explored the capabilities enabled by SIPs for the PPC function over the past four decades, ours is the inaugural study to comprehensively consolidate and define all these capabilities in a single publication.

Second, we introduce a framework that illustrates the hierarchical structural relationships among these 12 capabilities. This represents the main contribution of our paper to the SIPs literature, for being the first to offer a roadmap for enhancing SIPs adoption in organisations while delineating which capabilities should be prioritised to enhance and amplify others. This valuable roadmap assists organisations in efficiently allocating resources for SIPs adoption.

Third, by clustering the capabilities of the ISM model, the *MICMAC* analysis contributes to the SIPs literature by highlighting the synergy between PPC-enabled capabilities. These results demonstrate the existence of a path for optimising SIPs adoption, first achieving connectivity and then transparency, followed by autonomous decision-making I and finally autonomous decision-making II, where the PPC function becomes a fully autonomous function.

Subsequently, researchers can use this model as a foundation for conducting further investigations into each capability, their interdependencies, and their impact on PPC within the context of SIPs. This offers a roadmap for prospective empirical studies and theoretical refinements. Moreover, the model may have implications for interdisciplinary research, promoting discussions and collaborations among experts in fields such as IoT, automation, and supply chain management.

3.6.2 Managerial Contributions

Our proposed framework not only contributes theoretically but also offers substantial managerial benefits. It equips managers with a profound understanding of the structural relationship hierarchy of capabilities enabled by adopting SIPs in the PPC function. This understanding includes insights into these capabilities' driving forces and dependencies, significantly enhancing decision-making processes by aligning strategic choices with the organisation’s goals.

Additionally, the framework serves as a practical tool, guiding practitioners in prioritising capabilities based on their organisations' current SIP implementation stage. It also acts as a strategic roadmap for investing in capabilities hierarchically, preventing efforts to develop a capability dependent on others that are not yet fully mature, thereby maximising the outcomes of SIP adoption.

Furthermore, the framework aids practitioners in aligning their strategies and investments toward achieving autonomous PPC, ensuring that strategic investments translate directly into enhanced operational efficiencies. By detailing how the framework can be utilised for performance improvement, managers can track progress in capability development and gauge the impact of SIPs on the PPC function, fostering ongoing improvement and strategic coherence in organisational practices.

Finally, our framework enhances risk management by identifying and mitigating potential challenges associated with new technologies. By understanding capability dependencies and hierarchies, organisations can proactively address risks before they escalate, ensuring a smoother integration of SIPs. Therefore, our framework serves as a tool for future-proofing organisations. It allows companies to stay ahead of technological advancements and maintain competitiveness in a rapidly evolving industrial landscape. The systematic prioritisation of capabilities ensures that investments are made strategically, enhancing long-term resilience and adaptability.

3.6.3 Limitations and Future Research Directions

This study identified 12 capabilities enabled by SIPs adoption in the PPC function. As the capabilities were raised through an SLR, even seeking to minimise subjectivity utilising double researchers evaluating the papers during the screening process, it’s impossible to fully mitigate this variable from our research. The SLR has some limitations, such as the databases used to raise the papers, the period and type of materials selected, and other variables that may have excluded any relevant article that pointed out a capability not identified in this research. Notwithstanding the limitations inherent to the SLR method, the ISM approach also has limitations, including subjectivity and bias in expert opinions collected from their perspective and field of expertise. Besides, the output of ISM is an input for the fuzzy *MICMAC* approach; subjectivity and bias in expert opinions may have been replicated in *MICMAC*.

Future research could explore the applicability of the developed model across a diverse range of industries, including but not limited to automotive, electronics, and pharmaceuticals, and identify specifics across sectors and types of production systems. This comparative analysis could shed light on sector-specific variations in SIPs' impact on PPC capabilities and provide valuable insights for industry-specific strategies, empirically validating or challenging the framework presented here. Besides, conducting longitudinal studies over an extended period could help assess the evolution of SIP-enabled capabilities in the PPC function. Researchers could track changes in capabilities (including identifying new ones), adoption rates, performance outcomes over time, and the challenges associated with each SIP level, providing a dynamic perspective on the influence of SIPs on PPC. Finally, future studies could investigate the integration of emerging technologies such as artificial intelligence, machine learning, and blockchain with SIPs in the context of PPC, assessing how these technologies enhance or complement the identified capabilities, potentially opening new avenues for research and practical implementation in the field of SIPs.

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Declaration of Interest

None.

4 ORGANISATIONAL FUNCTIONS SYNERGY THROUGH CAPABILITIES-ENABLED BY SMART INDUSTRIAL PRODUCTS ADOPTION: A MULTI-METHOD STUDY

This chapter is composed of the third paper of the thesis and was published to the Management Decision Journal. **DOI:**10.1108/MD-12-2024-2887 - **Impact Factor Ranking:** 5.90 (Q1 – Web of Science).

Purpose: This study examines the potential of SIPs to enhance inter-functional synergy within industrial organizations, focusing on their role in optimizing cross-functional collaboration and addressing the challenges posed by dynamic business environments.

Design/methodology/approach: A mixed-method approach was employed, integrating a SLR, expert interviews, ISM, and Fuzzy *MICMAC* analysis. This methodology enabled the identification of capabilities facilitated by SIP adoption and their impact on organizational functions, fostering synergy among production planning, maintenance, quality, and sustainability.

Findings: The results indicated that SIPs significantly influence organizational integration by enabling capabilities such as real-time data sharing, predictive analytics, and enhanced decision-making. The study presents a hierarchical framework that demonstrates how SIPs facilitate the sequential development of capabilities, thereby enhancing inter-functional collaboration and promoting strategic alignment with Industry 4.0 principles.

Originality: This research presents a unique viewpoint by emphasizing the inter-functional synergy enabled by SIP capabilities. The article presents a complete framework that integrates theoretical models with empirical insights to utilize SIPs for enhancing organizational efficiency, sustainability, and creativity. This method lays the groundwork for subsequent research on the long-term effects of SIP-driven integration across various industrial environments.

Keywords: Smart Industrial Products, Inter-Functional Integration, Capabilities; Fuzzy *MICMAC*; Interpretive Structural Modelling

4.1 INTRODUCTION

Inter-functional integration is defined as the alignment of various interdependent management functions through mutual coordination, knowledge exchange, and collaborative decision-making (PAGELL, 2004). Also referred to as cross-functional, inter-functional, or inter-departmental collaboration (PELLATHY et al., 2019), this integration plays a critical role in industrial organisations by enhancing process efficiency, reducing uncertainty, and improving asset productivity (SWINK; SCHOENHERR, 2015). Furthermore, inter-functional integration enhances communication and collaboration between departments, fostering a shared understanding that improves operational decision-making and strategic alignment. This integration is particularly relevant in dynamic industrial environments, where coordinated decision-making is essential for achieving efficiency and innovation (CHEN; MATTIODA; DAUGHERTY, 2007; LEE et al., 2024; PATELI; LIOUKAS, 2017; SWINK; SCHOENHERR, 2015).

Despite its recognised importance, many companies continue to struggle with internal integration while prioritising external supply chain coordination (POIRIER; SWINK; QUINN, 2008; RUIZ; BRION; PARMENTIER, 2020). We argue that technology-enabled capabilities can significantly contribute to bridging these inter-functional gaps (KOCK; GEMÜNDEN, 2021). Specifically, we propose that SIPs play a key role in fostering inter-functional synergy by embedding intelligence into industrial processes. These smart products have gained increasing attention from industry practitioners, scholars, and policymakers (PISSARDINI et al., 2024a; RAFF; WENTZEL; OBWEGESER, 2020) due to their ability to integrate real-time data, automate processes, and enhance decision-making across multiple organisational functions. By enabling seamless connectivity and enhancing cross-functional coordination, SIPs facilitate a more structured and efficient integration of key organisational processes.

Within this context, the focus of this study is to unveil how SIP-enabled capabilities contribute to inter-functional synergy, defined as the alignment and reinforcement of organisational functions through the strategic prioritisation of capabilities that enhance cross-functional collaboration. Rather than analysing the specific mechanisms of synergy, this study focuses on how organisations can effectively prioritise SIP-enabled capabilities to foster integration across main functions. In light of this research context, the study seeks to address three main research questions:

- RQ1: What capabilities are enabled by SIP adoption for main organisational functions?
- RQ2: How can SIP-enabled capabilities be prioritised to enhance synergy among main organisational functions?
- RQ3: How does the sequential development of SIP-enabled capabilities facilitate the integration of diverse management functions, enhancing organisational synergy and efficiency?

To answer these questions, we employed a mixed-method approach. First, a SLR, expert interviews, and content analysis were conducted to identify and validate SIP-enabled capabilities, directly addressing RQ1. Next, to answer RQ2, we examined how these capabilities should be prioritised to maximise synergy between organisational functions, using ISM and Fuzzy *MICMAC*. These methods enabled us to identify the hierarchical relationships between SIP-enabled capabilities, illustrating which capabilities serve as foundational elements and which contribute to higher levels of organisational synergy. Finally, RQ3 was explored by developing a framework that provides a structured approach to the sequential prioritisation of SIP-enabled capabilities, offering companies a practical roadmap to achieving inter-functional integration through SIP adoption.

Despite the comprehensive exploration of capabilities enabled by SIPs across main organisational functions, existing studies—ranging from accounting management (YI et al., 2021) to sustainability (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021), maintenance (ANTONS; ARLINGHAUS, 2022a), PPC (TURNER et al., 2022), and quality management (ANTONS; ARLINGHAUS, 2022b)—face two significant limitations. First, these studies often treat SIP-enabled capabilities as isolated outcomes rather than as interconnected strategic enablers of inter-functional synergy. Second, they tend to focus on specific functions without considering how SIPs facilitate cross-functional interactions, thereby limiting their understanding of the full integrative potential.

This study addresses both gaps. Theoretically, we build on the Resource-Based View (RBV), which posits that firms gain sustained advantage by mobilising valuable, rare, inimitable, and non-substitutable resources (AMIT; SCHOEMAKER, 1993; JAY BARNEY, 1991). From this perspective, SIPs are not valuable merely by their presence, but through the capabilities they enable and how those capabilities are configured and combined across the organisation. This configurational view links SIP adoption to strategic capability development, making the prioritisation of capabilities a central concern in achieving functional synergy. In addition to RBV, the study also draws upon complementary theoretical perspectives, such as Dynamic Capabilities Theory (DCT) and Sociotechnical Systems Theory (STS), to deepen the analysis of how these capabilities interact, adapt, and evolve within complex organisational settings. This broader foundation supports a more integrative and explanatory understanding of how SIPs contribute to cross-functional alignment.

By shifting the analytical focus from technologies to capability flows, this study proposes a framework that structures how SIP-enabled capabilities evolve and influence one another, thereby fostering integration. Through the use of the ISM and Fuzzy *MICMAC* methods, we provide a hierarchical map of capability interactions and an explanation of their sequence, thereby contributing both conceptual clarity and an operational roadmap for integration strategies.

The structure of this paper is as follows: Section 2 provides an overview of the existing literature, situating this study within the broader field of SIPs research. Section 3 outlines the research methodology employed in this study. Section 4 presents the findings, examining how SIP-enabled capabilities should be prioritised to achieve inter-functional synergy. Section 5 introduces and discusses the proposed framework, demonstrating how organisations can strategically prioritise SIPs to optimise inter-functional integration. Section 6 concludes the paper by summarising the study's theoretical and managerial contributions and outlining avenues for future research.

4.2 LITERATURE REVIEW

This section establishes the theoretical framework through which this study examines the role of SIPs in facilitating inter-functional integration. We draw upon the RBV theory, DCT, and STS to provide a comprehensive lens for understanding how SIPs contribute to organisational synergy. Building on this theoretical groundwork, we then identify and critically analyse the key research gaps that this study addresses.

4.2.1 SIPs, Organisational Capability Development, and Inter-Functional Synergy

Modern technologies are fundamentally transforming industrial organisations, driving innovation and disrupting established work practices (AKBARI, 2023; RIALTI et al., 2019; ZHU; ZHANG; YU, 2024). SIPs play a central role in this transformation. While a SIP might seem like a straightforward technical asset, its true strategic worth and the competitive advantage it provides become apparent when an organisation effectively utilises and leverages its built-in capabilities for inter-functional synergy. This vital difference highlights a significant gap in current research, which often focuses on the technology itself rather than the organisation's ability to benefit from it truly.

The strategic worth of SIPs can be understood through the RBV. From an RBV perspective, SIPs act as essential resources because their ability to adapt independently to changing conditions and help achieve complex organisational goals (HOLMSTRÖM et al., 2009; LÜNNEMANN; MIN WANG; LINDOW, 2019) makes them inherently valuable. This value is not just evident in their presence but also in the distinct capabilities they enable, such as real-time analysis, big data handling, and Internet of Things (IoT) connections, which significantly enhance internal information exchange and the organisation's ability to react quickly (VISHWAKARMA; SINGH; SHARMA, 2019). The skilled arrangement of these SIP-enabled capabilities across different departments is often rare, creating unique setups that are hard for competitors to copy. Furthermore, when these capabilities are combined in a way that creates synergy within organisational processes, they become challenging to imitate. This uniqueness comes from the unclear causes and social complexity involved in truly connecting advanced technical features with human processes and collaboration between departments. New digital tools, such as cyber-physical systems and blockchain (NOTTBROCK; VAN LOOY; DE HAES, 2023), offer full functional integration, creating an overall benefit that is non-substitutable without a significant loss in performance. The competitive advantage, then, comes not just from having SIPs but from knowing how to use their capabilities to build unified, adaptable organisational systems that produce synergistic results. This study examines how SIPs, through their integrated capabilities, enhance the valuable, rare, inimitable, and non-substitutable qualities of an organisation’s resources, shifting attention from isolated technology adoption to strategic resource management.

Building on the RBV, the continuous integration of organisational functions, widely recognised in many areas (KANG et al., 2022; PELLATHY et al., 2019), directly relates to the concept of dynamic capabilities. While some studies focus on overall company output (LIU; YUXIAO, 2024), this research explicitly examines the small-scale connections that SIPs enable. This detailed focus helps explain the fundamental elements of an organisation's ability to recognise, act on, and change (FELIN et al., 2012; TEECE, 2007). SIPs serve as practical sensing tools, allowing for widespread data collection and communication, which helps organisations identify small changes and opportunities in their operating environment. This real-time data will then enable organisations to act on opportunities through informed choices and automated steps, making it easier to assign resources and adjust processes quickly. Ultimately, SIPs enable organisations to adjust and reorganise their resources, allowing them to adapt to changes in their environment and maintain a competitive edge. These dynamic capabilities, which rely on SIPs, are essential for promoting ongoing inter-functional synergy by allowing organisations to adjust their operations in response to constant changes. The approach demonstrates how specific SIP-enabled capabilities serve as the daily routines that support these higher-level, dynamic capabilities, transitioning from abstract ideas to practical technical enablers.

While SIPs offer inherent technical capabilities and support flexible organisational processes, their full potential for creating inter-functional synergy in practical settings is often discussed in relation to the sociotechnical system (STS). STS suggests that optimal organisational performance occurs when the technical and human aspects of a system are optimised together (PASMORE, 1988; TRIST; BAMFORTH, 1951). Current trends, such as dynamic structures based on IoT (SHEN et al., 2018), encourage quick organisational adjustments and better collaboration between departments. Still, significant hurdles remain in fully integrating SIPs across functions (ANICESKI et al., 2024), including insufficient IT systems, limited digital skills, and financial restrictions. These challenges highlight the critical interaction within the sociotechnical system. However, while acknowledging the broader relevance of STS for understanding barriers to implementation, this study's primary focus is on the structural interdependencies and capability architecture enabled by SIPs. It does not delve into the detailed human and social aspects of STS, such as organisational culture, individual learning processes, or workforce management, which fall outside the scope of this research. Instead, this study highlights how the technical capabilities of SIPs facilitate structural integration between functions, recognising that the complete realisation of these synergies in practice would depend on addressing socio-human factors.

Taken together, these theoretical perspectives shape our understanding of inter-functional synergy. The concept of "synergy" is central to this study's goal of understanding how SIPs contribute to greater organisational unity and performance. For this study, inter-functional synergy is defined as the mutual alignment and strengthening of organisational functions through mutual coordination, knowledge exchange, and collaborative decision-making, driven by the strategic prioritisation of SIP-enabled capabilities (PAGELL, 2004; PELLATHY et al., 2019). This definition emphasizes the active nature of synergy, which is achieved through the purposeful management of capabilities, resulting in outcomes that are greater than the sum of individual efforts (ORDANINI; RUBERA, 2008). Such synergy appears through various specific results across different functional areas, including: enhanced process efficiency and asset productivity (SWINK; SCHOENHERR, 2015), improved internal information exchange and organisational responsiveness (VISHWAKARMA; SINGH; SHARMA, 2019), effective handling of complexity (LENZ et al., 2020; THÜRER et al., 2021), and stronger sustainability outcomes, often linked to green industrial IoT and operational practices (XU; FAN; HU, 2022). These results are not isolated but interconnected, demonstrating how SIP-enabled capabilities create a networked effect where improvements in one area positively impact others, ultimately leading to an overall enhancement in the organisation's performance sustainability (ANICESKI et al., 2024; ANTONS; ARLINGHAUS, 2022b).

4.2.2 Research Gaps

Earlier studies have examined how SIPs impact individual organisational functions, such as quality management (YI et al., 2021), maintenance (LIU; ZHENG; XU, 2023), sustainability (ANTONS; ARLINGHAUS, 2022b; EVERTSEN; RASMUSSEN; NENADIC, 2022), accounting (YI et al., 2021), and PPC (ZHANG et al., 2020). While (PISSARDINI et al., 2024a) thoroughly identified various capabilities related to multiple organisational functions, they did not discuss how these capabilities interact or what that means for inter-functional integration. Existing research often treats capabilities derived from SIPs as separate outcomes rather than key strategic enablers (WANG; RANSCOMBE; EISENBART, 2023; YI et al., 2021), resulting in a partial understanding of how they work together to create synergy across organisational functions.

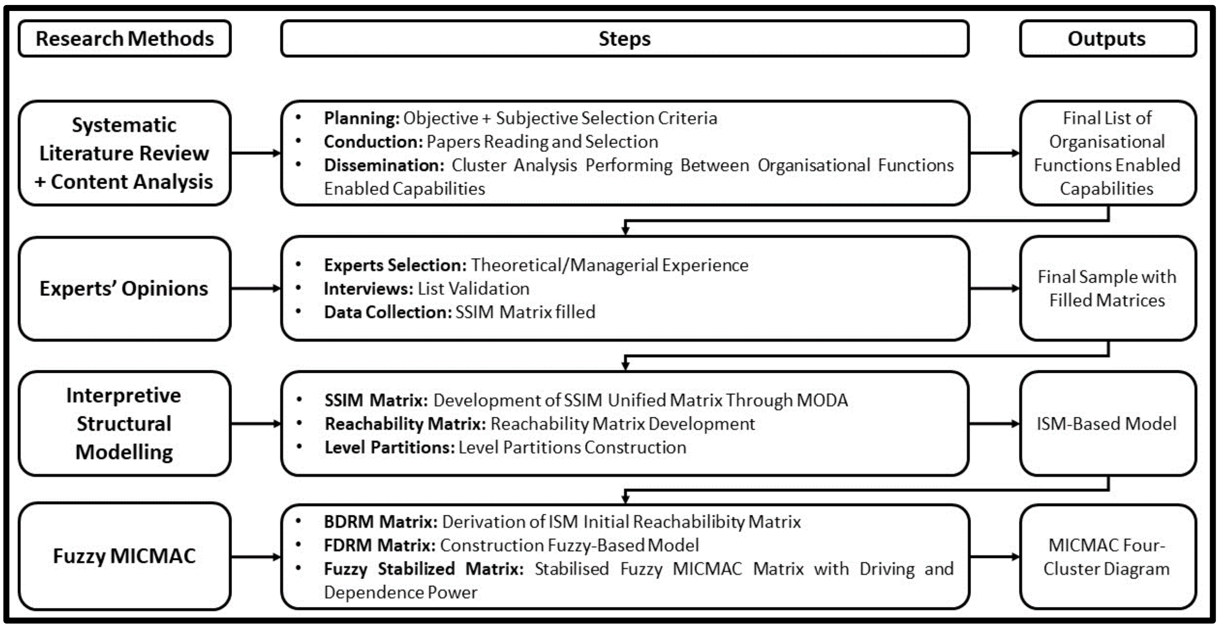
To address this critical gap, this study employs a comprehensive theoretical approach to examine SIPs as interconnected strategic assets that can generate significant inter-functional synergies. By investigating the integrating capabilities SIPs enable through the perspectives of RBV, Dynamic Capabilities, and a focused consideration of STS's contextual role, this research shifts from simply focusing on individual functional improvements to a complete view of organisational capabilities. It highlights their combined impact on operational performance, adaptability, and sustainability, emphasising that a competitive advantage stems from an organisation's unique ability to utilise SIP-enabled capabilities to foster thorough inter-functional integration. This study thus offers theoretical and practical insights into how strategically aligned SIP-enabled capabilities can significantly boost organisational efficiency, adaptability, and competitiveness by supporting a structured and synergistic capability design.

4.3 RESEARCH METHODS

Our study utilises a four-step, sequential methodology. Initially, we conducted an SLR combined with content analysis to identify the capabilities that SIPs enable across key organisational functions. This list of capabilities was then refined and validated through feedback from both academic and industry experts. Next, we applied the ISM to define the relationships among these capabilities. Finally, we employed fuzzy *MICMAC* to assess the driving and dependent influences between the capabilities. By examining how each capability affects specific organisational functions, this methodological framework enables us to uncover the synergies among the primary organisational functions.

To ensure research rigour, our methodological framework integrates a complementary sequence of techniques transitioning from qualitative to quantitative analyses. This integration enables triangulation, addressing both theoretical and practical aspects of the problem and thereby strengthening the validity of our findings. Triangulation enhances methodological robustness by combining insights from multiple sources and mitigates biases that might arise from relying on a single method. The summary of the methodological sequence is presented in Figure 4.1.

Fig 4.1 Summary of methodological sequence



Source: Elaborated by the author (2025)

4.3.1 Rationale for the conduction of a mixed-method approach in this study

Our study adopts a mixed-method approach to effectively address the complex problem of leveraging SIPs for enhancing inter-functional synergies. Although each method employed serves a distinct purpose, they complement each other. The sequential alignment of methods reinforces the robustness of our findings. Each method was chosen to contribute unique strengths while addressing the limitations of the preceding phase. For instance, while the SLR establishes a comprehensive theoretical base, the expert interviews ground this theoretical foundation in real-world perspectives. Subsequently, the ISM method ensures a structured visualisation of relationships, and the fuzzy *MICMAC* analysis quantitatively validates these relationships, adding precision and robustness to our insights.

The first approach, the SLR, establishes a comprehensive theoretical foundation by identifying existing gaps and trends in the literature on SIPs. In addition, Denyer; and Tranfield (2009) emphasise that an SLR is more than just a summary of existing research; it is a crucial process that identifies, evaluates, and synthesises relevant studies to address specific research questions. This approach ultimately facilitates drawing well-supported, transparent conclusions regarding what is known and remains unclear in the field (SAUNDERS; LEWIS; THORNHILL, 2012). Thus, the SLR allows us to contextualise our research within the broader academic discourse, identifying the state-of-the-art concerning inter-functional synergy. Based on these statements, we argue that empirical research that does not begin with an SLR may result in a lack of understanding of existing gaps in the literature. Without this foundation, the research may be decontextualised and less relevant to the field.

In sequence, we choose the experts' interview method. Interviewing industry experts enhances our findings by providing practical insights and real-world perspectives. It is the most effective way to understand decision-making processes and institutional behavior (VON SOEST, 2023). Additionally, Meuser; Nagel (2009) describe expert knowledge production as a dynamic and evolving process, oriented toward uncertain futures and incorporating unforeseen possibilities and developments. Furthermore, regarding the explicit nature of knowledge, experts have a distinctive awareness of their specialised knowledge (MEUSER; NAGEL, 2009).

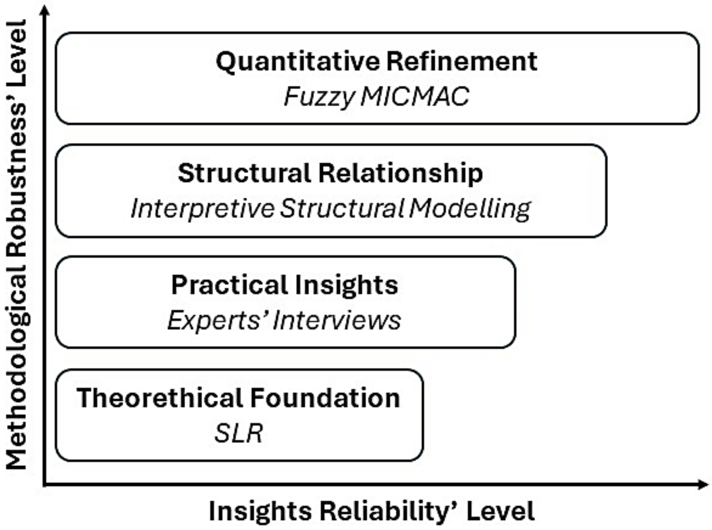
In the third phase, with the theoretical and practical insights established, we employed the ISM method to map, analyse, and structure the hierarchical relationships between the identified variables. This approach is particularly valuable at this research stage, as it focuses on capturing the complex functional synergies among different organisational functions. The

ISM approach utilizes experts' practical experience and knowledge to decompose a complex system into several subsystems, allowing for the construction of a multilevel structure model (MATHIYAZHAGAN et al., 2013). In addition, it identifies the influence and explains the direction amongst the attributes of the system (LIM et al., 2017), establishing their relationships to define a problem/issue using their dependency and driving power (MANGLA; KUMAR; BARUA, 2014). Such an analysis is crucial for understanding the role of SIPs in identifying and achieving synergistic effects in inter-functional integration. Starting with ISM before applying more quantitative techniques ensures a solid conceptual foundation for the analysis. Notwithstanding the advantages of the ISM approach, it also has weaknesses. According to Bianco et al. (2023), one of the limitations is related to the low mathematical complexity required for the ISM approach, which undermines mathematical validity and prevents assigning varying strengths to the relationships between such variables. Addressing this weakness is the primary role of our fourth methodological approach.

The fuzzy *MICMAC* model is employed to refine the relationships established in the third phase quantitatively. By incorporating fuzzy logic, the model effectively addresses the uncertainty and vagueness present in expert opinions, which are inherent in complex decision-making processes, such as the binariness property of ISM. The quantitative assessment provided by the *MICMAC* model enhances our understanding of the driving and dependent variables, thereby strengthening the decision-making framework of the study. This methodological sequence has been meticulously crafted to facilitate a progression from theory to practice, enabling the identification and refinement of structural relationships and ultimately improving the reliability of the insights obtained.

Figure 4.2 depicts how each adopted method specifically contributes to enhancing methodological robustness and the reliability of insights. The process begins with the SLR, which, while establishing a solid theoretical foundation, offers limited robustness and reliability on its own. By incorporating Expert Interviews, there is a significant increase in both methodological robustness and the reliability of insights, as these interviews provide directly applicable, practical perspectives to the research. The subsequent use of ISM enriches the analysis by allowing for the identification and visualisation of structural relationships among organisational functions. This further enhances the method's robustness through clear and precise modelling of interdependencies. Finally, the application of Fuzzy *MICMAC* delivers quantitative refinement of these structural relationships. This solidifies methodological robustness by quantifying dependencies and influences among variables, significantly improving the reliability of insights and providing a detailed, quantified view of dynamics within the organisation. This sequence of methods, therefore, builds upon the theoretical base and enhances the practicality and precision of the outcomes, maximising both the methodological robustness and the reliability of the insights obtained.

Figure 4.2: Methodological robustness and insights reliability level of our research



Source: Elaborated by the author (2025)

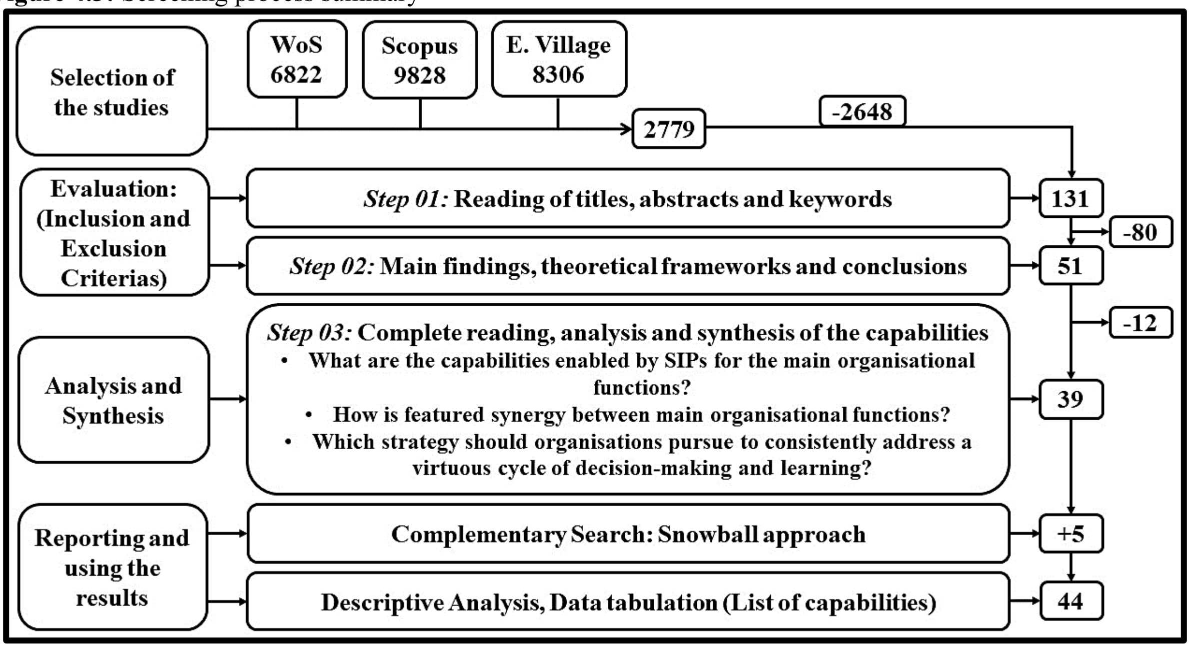
In this methodological design, we carefully considered the weaknesses of each technique. For example, despite its qualitative strength in identifying hierarchies, the ISM approach lacks the ability to quantify the intensity of relationships. This limitation is directly addressed by the fuzzy *MICMAC* method, which introduces quantitative rigour. By adopting this progression, we ensure that each method complements the others, culminating in a theoretically grounded and practically relevant framework.

4.3.2 SLR with Content Analysis

The SLR conducted by Pissardini et al. (2024) was considered as a foundation for this methodological phase. Their study identified 20 capabilities enabled by SIPs within the industrial context. To explore the possibility of additional capabilities, ensure that any potential new capabilities were considered, and investigate their relationship with organisational function synergy, the research protocol proposed by Pissardini et al. (2024) was followed. This approach was chosen to enhance the reliability of the data collected.

The string presented by Pissardini et al. (2024) was inserted into three databases (Scopus, Web of Science, and Engineering Village), yielding 24,956 papers. Applying objective filters such as language, temporal period, and paper types and removing duplicates, the final sample consisted of 2,779 papers. The titles and abstracts of these papers were reviewed to assess their alignment with the objectives of this research, guided by the subjective criteria outlined by Pissardini et al. (2024). From this initial phase, 131 papers were selected. Subsequently, the introductions, main findings, theoretical frameworks, and conclusions of the remaining papers were examined, resulting in a narrowed selection of 51 papers that were comprehensively analysed. This process led to a final sample of 39 papers citing capabilities enabled by adopting SIPs in organisational functions. Through the snowball approach, five papers were added, resulting in a final sample of 44 papers. Figure 4.3 summarises the screening process.

Figure 4.3: Screening process summary



Source: Elaborated by the author (2025)

After reviewing all 44 selected papers, the same 20 capabilities identified by Pissardini et al. (2024) were found. The next step involved adapting these capabilities and their respective descriptions to the context of synergy between the main organisational functions. In this regard, it was ensured that the capabilities accurately represented the context addressed in this study.

4.3.3 Expert's Opinion

The expert interview approach was selected to ensure the reliability of the identified capabilities by consolidating, refining, and aligning them with practical insights. While

Cronbach's alpha is commonly used to assess internal consistency, it is unsuitable for this study due to the heterogeneous nature of the identified capabilities. Since the objective is to validate each capability individually—assessing its relevance and ensuring its alignment with the study's context—an alternative validation method was required. To address this, and following previous studies Bianco et al. (2023); Callefi et al. (2022), a qualitative validation strategy was adopted, involving a panel of five academic experts with substantial experience in Operations Management and Industry 4.0. This step was critical to ensuring the robustness and reliability of the final list of capabilities. Expert selection criteria followed the guidelines proposed by Bokrantz et al. (2017); Callefi et al. (2022), prioritising a combination of expertise in Operations Management and Industry 4.0. The selection criteria required experts to have a minimum of 10 years of experience in the field. The sampling process followed a non-probabilistic, purposive sampling approach, a widely adopted strategy in expert panel research (BIANCO et al., 2023; CALLEFI et al., 2022; PISSARDINI et al., 2024a). Table 4.1 provides detailed information regarding the experts' profiles.

Table 4.1: Summary of Experts' profile of validation phase

Expert	Position	Academic education	Experience in operations management
1	Researcher	PhD in Production Engineering	24 years
2	Researcher	PhD in Production Engineering	17 years
3	Researcher	PhD in Production Engineering	17 years
4	Researcher	PhD in Production Engineering	15 years
5	Researcher	PhD in Production Engineering	19 years

Source: Elaborated by the author (2025)

We adopted an iterative consensus-building approach to ensure the validity of the qualitative data and address concerns regarding inter-rater reliability. Experts independently evaluated the relevance of each capability, and any disagreements were resolved through structured feedback cycles and moderated discussions, following best practices in qualitative validation (MEUSER; NAGEL, 2009; VON SOEST, 2023). Unlike studies that rely on predefined categorical coding for quantitative reliability measures, such as Krippendorff's Alpha (MARZI; BALZANO; MARCHIORI, 2024), the validation process in this study was qualitative and iterative. Experts did not assign fixed ratings or classifications to the capabilities but rather engaged in a dynamic process of discussion and refinement. Therefore, Krippendorff's Alpha, which assumes independent coding by multiple raters, is not applicable here, as the expert evaluations were structured to build consensus rather than quantify agreement.

To refine the precision of this capabilities list, we followed a four-step cycle proposed by Saunders; Lewis; Thornhill (2012): (i) the initial list was presented to each expert for their evaluation; (ii) the list, with capabilities clustered, was presented to each expert; (iii) suggestions were gathered and integrated into the final list; (iv) the final list was newly presented to the expert for validation or inclusion of any further suggestions. The process would return to the third step if any suggestions were incorporated.

The four interviews averaged 50 minutes each, during which we queried the experts about the validity of the capabilities, their descriptions, and their alignment with practical applications. The opinions were recorded, and the list was consolidated. Following each interview, the capabilities underwent refinement based on the experts' feedback. This iterative process culminated in a final list of 20 capabilities enabled by the adoption of SIPs in organisational functions.

The iterative nature of the expert validation process is a cornerstone of this study's robustness. By continuously refining and aligning the capabilities with expert feedback, we ensured that the results were both practically relevant and academically rigorous. This iterative feedback loop improved the accuracy of the identified capabilities and enhanced the reliability of the insights derived.

4.3.4 Interpretive Structural Modelling

To perform the ISM approach, the four steps proposed by Callefi et al. (2024); Farris; Sage (1975); Wang et al. (2024); Warfield (1974) were followed. Each step is shown in the following four subsections.

4.3.4.1 Structural Self-Interaction Matrix

In the first phase of the ISM approach, the experts' opinions lay the groundwork for addressing the unified SSIM through "Mode" (The most frequently assigned value by the experts for each pair of variables). Touching on the number of experts, Saunders; Lewis; Thornhill (2012) point out that the more complex the subject matter, the fewer interviewees. The summary of the characteristics of the experts chosen to contribute to filling the ISM matrix is presented in Table 4.2. Agreeing with Von Soest (2023), who points out the importance of having both practical and managerial experts compose the final sample of participants. Our research team comprised 11 researchers with broad academic knowledge, and five of them were involved with SIPs daily in leading companies within their respective fields.

Table 4.2 Summary of Experts' profile of ISM questionaire

Position		**Academic background**		**SIP's / OM Experience**	
Researcher	11	PhD Industrial / Mechanical Engineering	11	< 10 years	0
Director of Operations	1	Postgraduate Degree	1	10 – 20 years	16
Operations Manager	4	Bachelor of Engineering	4	> 20 years	0

Source: Elaborated by the author (2025)

Following the principles of ISM theory, each of the 16 experts completed a matrix using the four symbols:

a) When variable *i* influences variable *j*, the cell is assigned the symbol V;

b) When variable *j* influences variable *i*, the cell is assigned with A;

c) When both variable *i* and variable *j* influence each other, the cell is assigned with X;

d) When there is no influence between the two variables, the cell is assigned with O.

4.3.4.2 Development of Initial and Final Reachability Matrix

We combined all matrices by inserting, for each variable pair, the most frequently used symbol (V, A, X, O) as determined by the experts into the "mode" matrix. Subsequently, the SSIM matrix was transformed into an IRM. To carry out this transformation, we replaced the variables V, A, X, and O with 0s and 1s according to the following rules:

a) When the value at position (i,j) in the SSIM is V, the corresponding entry at (i,j) in the IRM is set to 1, and the entry at (j,i) is set to 0;

b) When the value at position (i,j) in the SSIM is A, the entry at (i,j) in the IRM is set to 0, and the entry at (j,i) is set to 1;

c) When the value at position (i,j) in the SSIM is X, both the entries at (i,j) and (j,i) in the IRM are set to 1;

d) When the value at position (i,j) in the SSIM is O, both the entries at (i,j) and (j,i) in the IRM are set to 0;

We considered the transitivity property in sequence to define the FRM. Transitivity in relationships implies that if S_i influences S_j and S_j influences S_k, then it follows that S_i also influences S_k. The final directional digraph, encompassing the transitivity links, was derived from the triangular structure of the reachability matrix.

4.3.4.3 Performing Level Partitions

From the FRM, we extracted the "reachability" and "antecedents" sets for all system variables. Subsequently, we computed the intersection of these sets for all variables, identifying the different levels of each. The partition into levels paves the way for constructing the ISM model once their hierarchy is built by placing the capabilities with similar levels of reachability and intersection at corresponding levels within the matrix. In sequence, once a superior-level variable is identified, it is removed from consideration. Besides, the same iterative process is applied to determine the factors at the next level. This iterative loop was repeated until all levels were identified, culminating in the construction of the final ISM model.

4.3.4.4 ISM-Based Model Derivation

The ISM model was developed based on the FRM. The variables at the top level were positioned at the upper part of the digraph, with subsequent levels arranged below in order, until all variables were appropriately placed. After removing any transitive connections, the ISM model was completed.

Throughout the ISM process, we employed robust validation techniques to ensure reliability. For example, using a panel of experts with diverse backgrounds ensures a comprehensive evaluation of relationships. Moreover, the structured process of deriving the reachability matrix and hierarchical levels adheres to established ISM practices, further reinforcing methodological rigour.

4.3.5 Fuzzy *MICMAC*

The fuzzy *MICMAC* analysis consisted of four steps, which are outlined in the following subsections.

4.3.5.1 Binary Direct Reachability Matrix (BDRM)

To compute the BDRM matrix, all diagonal entries of the IRM must be replaced with zeros. This step is designed to highlight the interactions between the capabilities, which are represented by fuzzy values in the Fuzzy Direct Reachability Matrix (FDRM).

4.3.5.2 Fuzzy Direct Reachability Matrix

To build the FDRM, we apply fuzzification to assess the degree of consensus among experts on the influence of capability i on capability j. This process uses five linguistic terms, as defined in Table 4.3, along with the corresponding assignment rules to establish the fuzzy relationships.

Table 4.3 Fuzzy scale and assignment criteria for assessing the strength of relationships

Relationship Strength	Value Assigned	Number of Experts Agreeing that the capablity i Impacts the capability j
No	0	No experts agree
Weak	0,25	1 to 4 experts agree
Medium	0,50	5 to 8 experts agree
Strong	0,75	9 to 12 experts agree
Very Strong	1	13 13 or more experts agree

Source: Elaborated by the author (2025)

4.3.5.3 Fuzzy *MICMAC* Stabilised Matrix

An iterative multiplication procedure is applied to the initial matrices to stabilise the fuzzy *MICMAC* until the row sums (driving power) and column sums (dependence power) converge to constant values. As highlighted by Mota et al. (2021), several fuzzy composition methods can be employed to assess the strength of the indirect fuzzy relationship between variables i and j.

This research selected the max-min composition as the most appropriate method because the minimum value reflects the strongest of all possible minimal influences from variable i to variable j. The matrix multiplication process followed the rule outlined below, resulting in the stabilised fuzzy *MICMAC* matrix:

$$Z = X\,.\,Y = max_k\left[\min\left(X_{ik}\,,Y_{kj}\right)\right] \qquad (1)$$

Where X = $[X_{ik}]$ and Y = $\left[Y_{kj}\right]$

To realise the multiplication of the fuzzy matrices using this operator, we employed the MATLAB®, which resulted in the output of the uzzy *MICMAC* stabilised matrix.

4.3.5.4 Four-Cluster Diagram

To visually represent the fuzzy *MICMAC* results, we generated a four-cluster diagram illustrating the composition of each type of power: autonomous, dependent, linkage, and driving.

The fuzzy *MICMAC* approach's reliance on expert-driven data necessitated strict quality control measures to mitigate potential biases. For instance, we employed linguistic scales and fuzzification techniques to capture uncertainty and variability in expert opinions systematically. Additionally, the stabilisation process and subsequent clustering into four categories ensured that the results were both mathematically rigorous and practically interpretable.

4.4 RESULTS

4.4.1 Capabilities Enabled by SIPs Adoption for Main Organisational Functions

Our final list comprises 20 capabilities related to quality, maintenance, accounting, sustainability, and production planning and control. Moreover, Table 4.4 answers our RQ1.

Table 4.4 Capabilities enabled by SIP's adoption for organisational functions

Capabilities	**Code**	**Description**	**Main functions impacted**
Improved efficiency in asset investment across functions	ACC 1	The ability to enhance the efficiency of asset investment decisions by integrating data from different organisational functions (e.g., production, maintenance, and finance). This enables better decision-making regarding the use, frequency, and lifecycle of assets, aligning the investment strategy with the overall organisational goals	AM
Sustainable operational practices	SUS 1	The ability to utilise integrated data for environmentally sustainable production without compromising operational efficiency across different organisational functions	SUS
Maintenance coordination and accuracy	MA 1	The ability to leverage real-time, integrated data from maintenance and production systems to improve cross-functional collaboration in maintenance planning, preventive actions, and predictive decision-making	MM
Remote repair services	MA 2	The ability to integrate SIPs with organisational systems, enabling remote collaboration for repairs, and allowing maintenance and production teams to interact seamlessly	MM
Lifecycle data sharing for optimised services	MA 3	The ability for SIPs to gather and share operational data across different departments (e.g., production, maintenance, quality control) to improve the efficiency and effectiveness of services throughout their lifecycle	MM
Sensing technology integration	PPC 1	The ability to implement sensors and RFID technologies that communicate physical, chemical, or biological data between various production units and organisational systems to enable real-time decision-making	PPC
Interoperability of autonomous SIPs	PPC 2	The ability for different SIPs to communicate and collaborate across various functions, ensuring smooth data flow, information exchange, and resource optimisation across the organisation	PPC
Automatic reconfiguration of production systems	PPC 3	The ability to dynamically adapt production lines and team resources based on real-time data, enhancing flexibility and efficiency in meeting varying production demands across function	PPC
Agility in resource allocation	PPC 4	The ability to adjust organisational resources across functions (e.g., production, maintenance, quality control) quickly in response to production changes or issues, enhancing the overall production process	PPC
Autonomous decision-making	PPC 5	The capability of SIPs to autonomously make cross-functional decisions, improving coordination and performance across organisational functions by leveraging data analytics and context-aware systems	PPC
Remote process control	PPC 6	The ability to remotely monitor and control production and maintenance processes, integrating control functions across departments and enabling real-time decision-making	PPC

Data-driven performance optimisation	PPC 7	The ability to apply data analytics from both current and historical processes across different functions to optimise decisions, enhance production performance and support inter-departmental collaborations	PPC
Machine network optimization	PPC 8	The ability for SIPs within different organisational functions to communicate and synchronise operations, automating and optimising production processes across functions.	PPC
Real-time data collection and communication	PPC 9	The ability to continuously collect and share data between departments, such as production and quality control, enabling continuous process improvement and collaboration across functions	PPC
Adaptable production systems	PPC 10	The ability of SIPs to respond flexibly to changes in demand and resource availability, ensuring a stable and collaborative production environment across multiple functions	PPC
Simplification of complexity in service delivery	PPC 11	The ability to manage complexity by integrating production, service, and quality control functions, making it easier to address multi-faceted tasks and service requirements	PPC
Real-time visibility of operations	PPC 12	The ability to provide real-time visibility into cross-functional operations, improving decision-making and fostering collaboration across different organisational departments	PPC
Strategic decision-making based on data	QM 1	The ability to use data insights to drive decisions that improve the synergy between organisational functions by identifying trends, patterns, and areas for improvement	QM
Proactive quality management	QM 2	The ability to address issues across departments (e.g., production, quality control) by using data-driven insights to improve product quality and operational processes	QM
Process security management	QM 3	The ability to manage information about the process, such as readily identifying failures that can cause future severe damage	QM

Source: Elaborated by the author (2025)

Notes: 1. (ATZORI; IERA; MORABITO, 2010); 2. (MEYER; FRÄMLING; HOLMSTRÖM, 2009); 3. (MEYER; HANS WORTMANN; SZIRBIK, 2011); 4. (BORANGIU et al., 2012); 5. (MCFARLANE et al., 2013); 6. (TAKAHARA; YASAKI, 2013); 7. (MEYER et al., 2014); 8. (PORTER; HEPPELMANN, 2014); 9. (HERNÁNDEZ; REIFF-MARGANIEC, 2014); 10. (BOUAZZA et al., 2015); 11. (PUTNIK et al., 2015); 12. (LEITÃO et al., 2015); 13. (PORTER; HEPPELMANN, 2015); 14. (DUFFY et al., 2016); 15. (DAWID et al., 2017); 16. (ABRAMOVICI; GÖBEL; SAVARINO, 2017); 17. (DING; JIANG, 2018); 18. (CENA et al., 2019); 19. (SILVERIO-FERNÁNDEZ; RENUKAPPA; SURESH, 2018); 20. (SOROURI; VYATKIN, 2018); 21. (JURIC; LINDENMEIER, 2019); 22. (KESHAVARZI; VAN DEN HOEK, 2019); 23. (TOMIYAMA et al., 2019); 24. (ZHANG et al., 2020); 25. (KAHLE et al., 2020); 26. (LENZ et al., 2020); 27. (RAFF; WENTZEL; OBWEGESER, 2020); 28. (PARDO; IVENS; PAGANI, 2020); 30. (YI et al., 2021); 31. (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021); 32. (RUHUL AMIN et al., 2021); 33. (RATHEE et al., 2021); 34. (LIN et al., 2021); 35. (THÜRER et al., 2021); 36. (IMAD et al., 2022); 37. (LIU; ZHENG; XU, 2023); 38. (OLUYISOLA et al., 2022); 39. (ANTONS; ARLINGHAUS, 2022a); 40. (ANTONS; ARLINGHAUS, 2022b); 41. (TRAN et al., 2022); 42. (ATTAJER et al., 2022); 43. (LEI et al., 2022); 44. (TURNER et al., 2022).

4.4.2 ISM Results

Table 4.5 illustrates the Mode of expert opinions for each pair of capabilities. The SSIM matrix underwent conversion, culminating in an initial binary matrix from which the IRM was derived, as demonstrated in Table 4.6. Transitioning from the IRM to the FRM involved considering the transitivity property, resulting in Tables 4.7. Additionally, Table 4.8 presents the reachability, antecedent, and intersection sets for each capability identified in the SLR, which were used as input for developing the ISM-based model. Finally, the resulting structural model, illustrated in Figure 4.4, displays the hierarchical arrangement of the 20 capabilities related to organisational functions across six levels, setting the stage for the subsequent discussion.

Table 4.5 Final Structural Self-Interaction Matrix (MODE)

MODE	QM3	QM2	QM1	PPC12	PPC11	PPC10	PPC9	PPC8	PPC7	PPC6	PPC5	PPC4	PPC3	PPC2	PPC1	MA3	MA2	MA1	SUS1	ACC1
ACC1	X	A	V	A	A	A	A	A	A	V	A	O	A	A	A	A	O	A	O	
SUS1	A	A	A	A	A	A	A	A	A	A	A	A	A	O	A	A	A	A		
MA1	V	O	V	A	V	V	A	V	O	A	A	V	O	A	A	A	V			
MA2	V	V	V	V	V	V	V	A	O	X	A	V	V	V	V	A				
MA3	V	V	V	V	V	V	X	V	V	V	V	V	V	A	A					
PPC1	V	V	V	V	V	V	V	V	O	V	V	V	V	V						
PPC2	V	V	V	V	V	V	X	V	V	V	X	V	V							
PPC3	V	V	X	A	V	V	A	A	A	X	X	X								
PPC4	O	V	A	A	V	V	A	O	A	O	A									
PPC5	V	V	V	V	V	V	V	X	V	V										
PPC6	V	V	V	V	V	O	A	A	V											
PPC7	V	A	V	A	A	V	A	O												
PPC8	O	V	V	V	V	V	V													
PPC9	V	V	V	V	V	V														
PPC10	V	V	V	A	A															
PPC11	O	A	V	A																
PPC12	V	V	V																	
QM1	A	X																		
QM2	V																			
QM3																				

Source: Elaborated by the author (2025)

Table 4.6 Initial Reachability Matrix

MODE	ACC1	SUS1	MA1	MA2	MA3	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12	QM1	QM2	QM3
ACC1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
SUS1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA1	1	1	1	1	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	1
MA2	0	1	0	1	0	1	1	1	1	0	1	0	0	1	1	1	1	1	1	1
MA3	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1
PPC2	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC3	1	1	0	0	0	0	0	1	1	1	1	0	0	0	1	1	0	1	1	1
PPC4	0	1	0	0	0	0	0	1	1	0	0	0	0	0	1	1	0	0	1	0
PPC5	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC6	0	1	1	1	0	0	0	1	0	0	1	1	0	0	0	1	1	1	1	1
PPC7	1	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	0	1	0	1
PPC8	1	1	0	1	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	0
PPC9	1	1	1	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	1
PPC10	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
PPC11	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0
PPC12	1	1	1	0	0	0	0	1	1	0	0	1	0	0	1	1	1	1	1	1
QM1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	0
QM2	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	1
QM3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1

Source: Elaborated by the author (2025)

Table 4.7 Final Reachability Matrix

MODE	ACC1	SUS1	MA1	MA2	MA3	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12	QM1	QM2	QM3
ACC1	1	1*	1*	1*	0	0	0	1*	1*	0	1	1*	0	0	0	1*	1*	1	1*	1
SUS1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA1	1	1	1	1	0	1*	1*	1*	1	1*	1*	1*	1	1*	1	1	1*	1	1*	1
MA2	1*	1	1*	1	1*	1	1	1	1	1*	1	1*	1*	1	1	1	1	1	1	1
MA3	1	1	1	1	1	1*	1*	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC1	1	1	1	1*	1	1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1
PPC2	1	1*	1	1*	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC3	1	1	1*	1*	0	0	1*	1	1	1	1	1*	1*	1*	1	1	1*	1	1	1
PPC4	1*	1	0	0	0	0	0	1	1	1*	1*	1*	0	0	1	1	0	1*	1	1*
PPC5	1	1	1	1	1*	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC6	1*	1	1	1	0	1*	1*	1	1*	1*	1	1	1*	1*	1*	1	1	1	1	1
PPC7	1	1	0	0	0	0	0	1	1	1*	1*	1	0	0	1	1*	0	1	1*	1
PPC8	1	1	1*	1	1*	1*	1*	1	1*	1	1	1*	1	1	1	1	1	1	1	1*
PPC9	1	1	1	1*	1	0	1	1	1	1*	1	1	1*	1	1	1	1	1	1	1
PPC10	1	1	0	0	0	0	0	1*	1*	0	1*	1*	0	0	1	1*	0	1	1	1
PPC11	1	1	0	0	0	0	0	1*	1*	0	1*	1	0	0	1	1	0	1	1*	1*
PPC12	1	1	1	1*	0	0	0	1	1	1*	1*	1	1*	0	1	1	1	1	1	1
QM1	1*	1	0	0	0	0	0	1	1	1*	1*	1*	0	0	1*	1*	0	1	1	1*
QM2	1	1	0	0	0	0	0	1*	1*	0	1*	1	0	0	1*	1	0	1	1	1
QM3	1	1	0	0	0	0	0	1*	1*	0	1*	0	0	0	0	0	0	1	1*	1

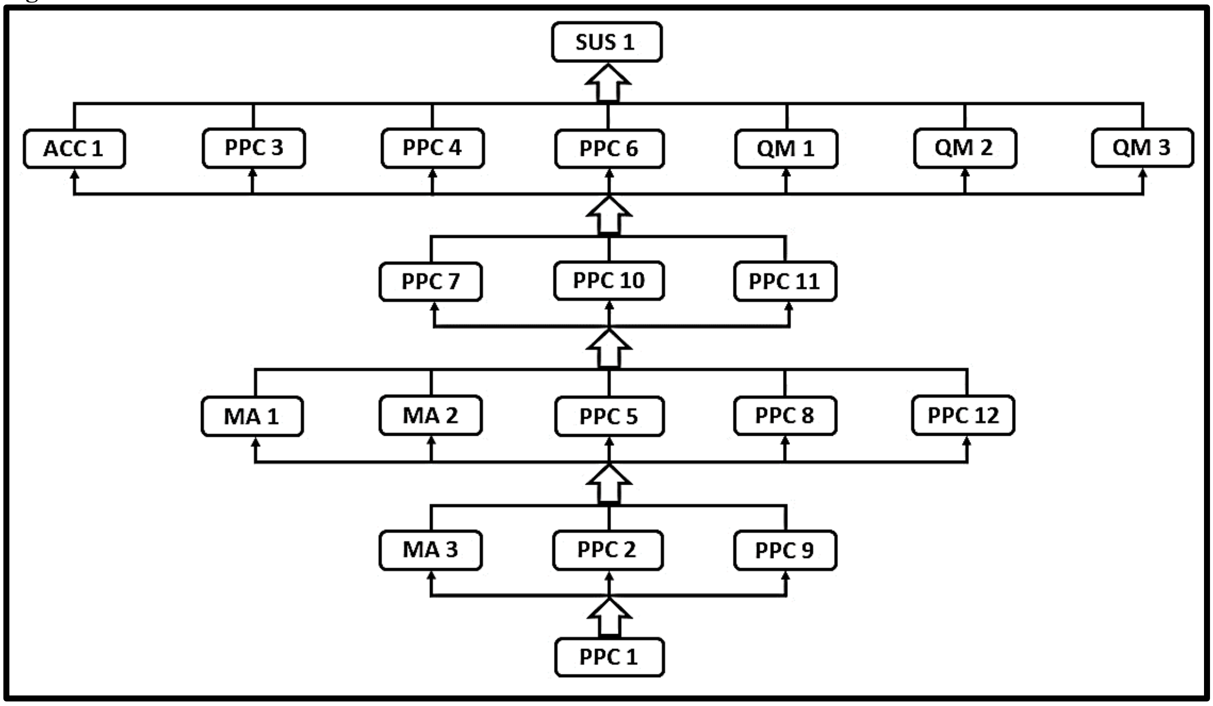
Source: Elaborated by the author (2025)

Table 4.8 Level Partition Matrix

Capability	Reachability Set	Antecedent Set	Intersection Set	Level
ACC1	1, 3, 4, 8, 9, 11, 12, 16, 17, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 3, 4, 8, 9, 11, 12, 16, 17, 18, 19, 20	II
SUS1	2	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	2	I
MA1	3, 4, 5, 6, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 10, 13, 14, 17	IV
MA2	3, 4, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 6, 7, 10, 13, 14, 17	IV
MA3	5, 6, 7, 14	5, 6, 7, 14	5, 6, 7, 14	V
PPC 1	6	6	6	VI
PPC 2	5, 7, 14	5, 6, 7, 14	5, 7, 14	V
PPC 3	1, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	II
PPC 4	1, 8, 9, 10, 11, 12, 15, 16, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 8, 9, 10, 11, 12, 15, 16, 18, 19, 20	II
PPC 5	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	IV
PPC 6	1, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	II
PPC 7	10, 12, 15	3, 4, 5, 6, 7, 10, 12, 13, 14, 15, 17	10, 12, 15	III
PPC 8	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	3, 4, 5, 6, 7, 10, 13, 14, 17	IV
PPC 9	5, 7, 14	5, 6, 7, 14	5, 7, 14	V
PPC 10	12, 14, 15	3, 4, 5, 6, 7, 10, 12, 13, 14, 15, 17	12, 14, 15	III
PPC 11	12, 14, 15	3, 4, 5, 6, 7, 10, 12, 13, 14, 15, 17	12, 14, 15	III
PPC 12	3, 4, 10, 13, 17	3, 4, 5, 6, 7, 10, 13, 17	3, 4, 10, 13, 17	IV
QM 1	1, 8, 9, 10, 11, 12, 15, 16, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 19	1, 8, 9, 10, 11, 12, 15, 16, 18, 19, 20	II
QM 2	1, 8, 9, 11, 12, 15, 16, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 8, 9, 11, 12, 15, 16, 18, 19, 20	II
QM 3	1, 8, 9, 11, 18, 19, 20	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	1, 8, 9, 11, 18, 19, 20	II

Source: Elaborated by the author (2025)

Figure 4.4: ISM-Based Model



Source: Elaborated by the author (2025)

4.4.3 Fuzzy *MICMAC* Results

The initial step of the fuzzy *MICMAC* analysis begins with the BDRM matrix, as presented in Table 4.10. To obtain the FDRM matrix (Table 4.11), we used the characteristic values based on the number of experts (Table 4.3) who assigned values V, A, X, or O in the SSIM matrix (Table 4.6). Following this, we derived the fuzzy *MICMAC* stabilised matrix, which is displayed in Table 4.12. The four-cluster diagram, shown in Figure 4.5, illustrates the driving and dependent relationships among the capabilities identified in the literature.

Table 4.9 Binary Direct Reachability Matrix

MODE	ACC1	SUS1	MA1	MA2	MA3	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12	QM1	QM2	QM3
ACC1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
SUS1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA1	1	1	0	1	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	1
MA2	0	1	0	0	0	1	1	1	1	0	1	0	0	1	1	1	1	1	1	1
MA3	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC1	1	1	1	0	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1
PPC2	1	0	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
PPC3	1	1	0	0	0	0	0	0	1	1	1	0	0	0	1	1	0	1	1	1
PPC4	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0
PPC5	1	1	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1
PPC6	0	1	1	1	0	0	0	1	0	0	0	1	0	0	0	1	1	1	1	1
PPC7	1	1	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0	1
PPC8	1	1	0	1	0	0	0	1	0	1	1	0	0	1	1	1	1	1	1	0
PPC9	1	1	1	0	1	0	1	1	1	0	1	1	0	0	1	1	1	1	1	1
PPC10	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
PPC11	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0
PPC12	1	1	1	0	0	0	0	1	1	0	0	1	0	0	1	1	0	1	1	1
QM1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0
QM2	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	1
QM3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Source: Elaborated by the author (2025)

Table 4.10 Fuzzy Direct Reachability Matrix

MODE	ACC1	SUS1	MA1	MA2	MA3	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12	QM1	QM2	QM3
ACC1	0	0	0	0	0	0	0	0	0	0	0,5	0	0	0	0	0	0	0,75	0	0,5
SUS1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA1	0,5	0,75	0	0,75	0	0	0	0	0,5	0	0	0	0,5	0	0,75	0,75	0	0,75	0	0,75
MA2	0	0,75	0	0	0	0,5	0,75	0,75	0,75	0,5	0,5	0	0	0,5	0,5	0,75	0,5	0,5	0,5	0,5
MA3	0,75	0,75	0,75	0,5	0	0	0	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,75	0,75	0,75	0,75
PPC1	0,5	0,5	0,75	0	0,75	0	0,5	0,75	0,5	0,5	0,75	0	0,5	0,75	0,5	0,75	0,75	0,75	0,75	0,75
PPC2	0,5	0	0,75	0	0,5	0	0	0,75	0,75	0,75	0,75	0,5	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75
PPC3	0,5	0,5	0	0	0	0	0	0	0,75	0,75	0,75	0	0	0	0,75	0,5	0	0,75	0,5	0,5
PPC4	0	0,5	0	0	0	0	0	0,75	0	0	0	0	0	0	0,75	0,75	0	0	0,5	0
PPC5	0,5	0,75	0,5	0,5	0	0	0,5	0,75	0,5	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC6	0	0,5	0,5	0,75	0	0	0	0,5	0	0	0	0,5	0	0	0	0,5	0,5	0,75	0,75	0,5
PPC7	0,5	0,75	0	0	0	0	0	0,75	0,5	0	0	0	0	0	0,5	0	0	0,75	0	0,5
PPC8	0,5	0,75	0	0,5	0	0	0	0,75	0	0,75	0,75	0	0	0,75	0,75	0,75	0,75	0,75	0,5	0
PPC9	0,5	0,75	0,75	0	0,75	0	0,5	0,5	0,75	0	0,5	0,5	0	0	0,75	0,75	0,75	0,75	0,75	0,75
PPC10	0,5	0,75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,75	0,5	0,5
PPC11	0,75	0,5	0	0	0	0	0	0	0	0	0	0,5	0	0	0,75	0	0	0,75	0	0
PPC12	0,75	0,75	0,75	0	0	0	0	0,5	0,5	0	0	0,5	0	0	0,5	0,75	0	0,75	0,75	0,75
QM1	0	0,75	0	0	0	0	0	0,5	0,5	0	0	0	0	0	0	0	0	0	0,75	0
QM2	0,75	0,75	0	0	0	0	0	0	0	0	0	0,5	0	0	0	0,75	0	0,75	0	0,75
QM3	0,75	0,75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,75	0	0

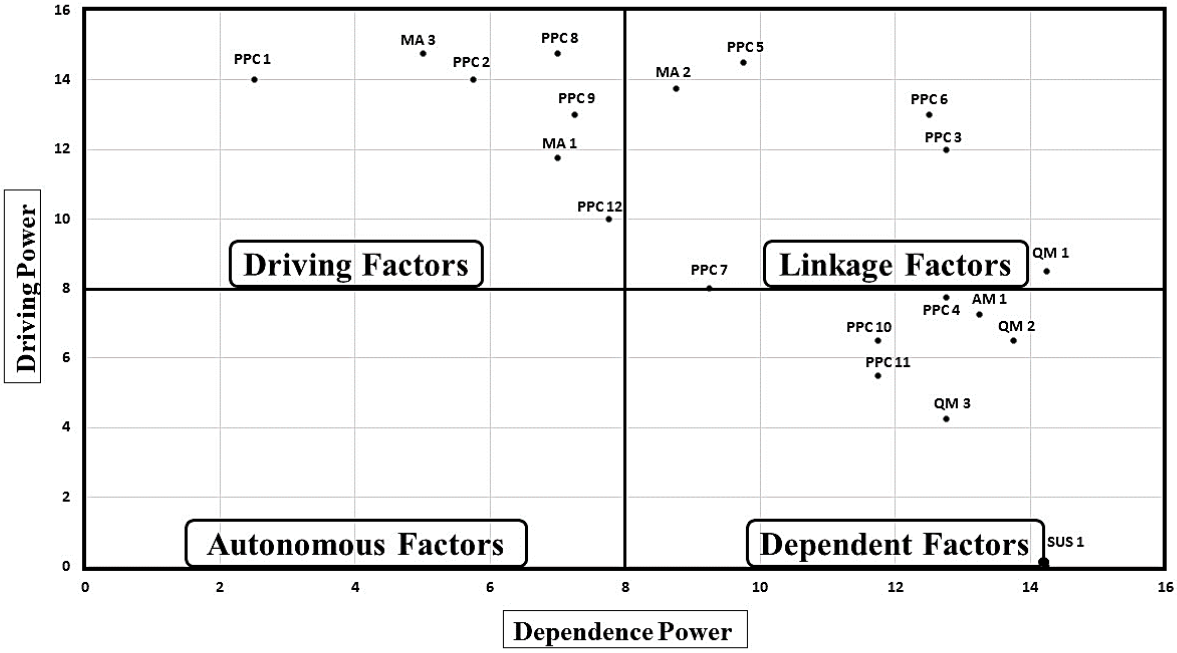
Source: Elaborated by the author (2025)

Table 4.11 Fuzzy Stabilised Matrix

MODE	ACC1	SUS1	MA1	MA2	MA3	PPC1	PPC2	PPC3	PPC4	PPC5	PPC6	PPC7	PPC8	PPC9	PPC10	PPC11	PPC12	QM1	QM2	QM3
ACC1	0,75	0,75	0,5	0,75	0	0	0	0,5	0,5	0	0	0,5	0	0	0	0,5	0,5	0,75	0,75	0,5
SUS1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA1	0,75	0,75	0	0,5	0	0,5	0,75	0,75	0,75	0,75	0,75	0,5	0	0,75	0,75	0,75	0,75	0,75	0,75	0,5
MA2	0,75	0,75	0,75	0,75	0,75	0	0,5	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
MA3	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC1	0,75	0,75	0,75	0,75	0,75	0	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC2	0,75	0,75	0,75	0,75	0,75	0	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC3	0,75	0,75	0,5	0,75	0	0	0,5	0,75	0,5	0	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC4	0,75	0,75	0	0	0	0	0	0	0,75	0,75	0,75	0,5	0	0	0,75	0,75	0	0,75	0,5	0,75
PPC5	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC6	0,75	0,75	0,75	0,75	0	0,5	0,75	0,75	0,75	0,75	0,75	0,5	0,5	0,5	0,75	0,75	0,5	0,75	0,75	0,75
PPC7	0,75	0,75	0	0	0	0	0	0,75	0,75	0,75	0,75	0	0	0	0,75	0,75	0	0,75	0,75	0,5
PPC8	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC9	0,75	0,75	0,75	0,75	0,5	0	0	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
PPC10	0,75	0,75	0	0	0	0	0	0,5	0,5	0	0,5	0,5	0	0	0	0,75	0	0,75	0,75	0,75
PPC11	0,5	0,75	0	0	0	0	0	0,75	0,5	0	0,5	0	0	0	0,5	0	0	0,75	0,75	0,5
PPC12	0,75	0,75	0	0,75	0	0	0	0,75	0,75	0,75	0,75	0,5	0,5	0	0,75	0,75	0	0,75	0,75	0,75
QM1	0,75	0,75	0	0	0	0	0	0,75	0,75	0,75	0,75	0,5	0	0	0,75	0,75	0	0,75	0,5	0,75
QM2	0,75	0,75	0	0	0	0	0	0,75	0,5	0	0,5	0,5	0	0	0,75	0	0	0,75	0,75	0,5
QM3	0	0,75	0	0	0	0	0	0,5	0,5	0	0,5	0	0	0	0	0	0	0,75	0,75	0,5

Source: Elaborated by the author (2025)

Figure 4.5 Fuzzy *MICMAC* Four-Cluster Diagram



Source: Elaborated by the author (2025)

Figure 4.4 presents the 20 capabilities enabled by the adoption of SIPs in the main organisational functions, clustered into 4 corners based on their Driving and Dependence power. In the autonomous corner, there are 7 capabilities (MA 1, MA 2, MA 3, PPC 1, PPC 2, PPC 8, PPC 9, and PPC 12), which are associated with 2 organisational functions (PPC and Maintenance function). These capabilities possess high driving power and lower dependence power. This indicates that these capabilities strongly influence others, yet, simultaneously, are not influenced by the other capabilities. In practical terms, it is possible to observe synergy between PPC and the Maintenance function at the foundational level. Continuing, the second corner (Linkage) is comprised of 6 capabilities (MA 2, PPC 3, PPC 5, PPC 6, PPC 7, and QM 1), indicating the existence of synergy between three organisational functions (PPC, Maintenance, and Quality function). This group of capabilities possesses both high driving and high dependence power. Finally, corner three (Dependent) is composed of 7 capabilities (AM1, PPC 4, PPC 10, PPC 11, QM 2, QM 3, and SUS 1). This group of capabilities has a combination of weak driving power on one hand and high dependence power on the other hand. Additionally, these capabilities demonstrate synergy between PPC, Quality, Accounting, and Sustainability functions. These capabilities are strongly dependent on others, thus occupying the highest position in the model.

4.5 DISCUSSION: A FRAMEWORK FOR SEQUENTIAL INTEGRATION AND SYNERGISTIC ENHANCEMENT OF ORGANISATIONAL FUNCTIONS THROUGH SMART INDUSTRIAL PRODUCTS

This section synthesises the results of the ISM and Fuzzy *MICMAC* analyses to articulate a framework that explains how SIPs enable a structured sequence of capability development, fostering synergies across organisational functions. Grounded in the RBV, DCT, and STS, the discussion explores how each step of the framework contributes to strategic integration and cross-functional reinforcement.

4.5.1 Step 1: Synchronising Maintenance and PPC

Analysing the results of the ISM and *MICMAC* models together, we observe that nine capabilities (PPC1, PPC2, PPC5, PPC8, PPC9, PPC12, MA1, MA2, and MA3) occupy the first three levels of the ISM model and exhibit the lowest dependence power in the *MICMAC* matrix. This highlights a strong relationship between PPC and Maintenance functions. These findings are consistent with the existing literature, which underscores the role of sensing technologies in SIPs in enhancing predictive maintenance and PPC.

From the RBV perspective, SIPs function as strategic resources that organisations can leverage to achieve long-term operational efficiencies. Their selection, however, should align with the specific capabilities the firm aims to develop, transforming them into valuable, rare, inimitable, and non-substitutable assets. For example, firms seeking to strengthen predictive maintenance and planning must adopt SIPs with integrated sensing capabilities (PPC1) that enable real-time collection of lifecycle data and support autonomous coordination between functional areas. This capability, at its core, represents a microfoundation for the firm's dynamic capabilities, allowing the organisation to 'sense' operational changes and opportunities. Cerquitelli et al. (2021) emphasise that embedded sensors enable continuous operational data collection, facilitating remote diagnostics and condition-based maintenance. Prashar (2023) further demonstrates that interoperability among smart resources improves coordination between Maintenance and PPC, establishing critical routines for cross-functional interaction. This initial synchronisation also builds a robust technical component of the Sociotechnical System, providing the infrastructure for seamless data flow and process control.

This is exemplified by Siemens' MindSphere, a cloud-based IoT platform that enables real-time machine monitoring and predictive maintenance across production facilities, improving visibility and optimising workflows (SIEMENS, 2017). Beyond enabling condition-based maintenance, Siemens' implementation of MindSphere illustrates how SIPs can actively orchestrate inter-functional synergy. The platform collects and analyses machine-level data to inform both maintenance scheduling and production planning decisions, enabling bidirectional feedback between these functions. For instance, predictive insights from real-time operational data allow planners to reschedule tasks proactively, minimising downtime and increasing asset utilisation. From a capability perspective, MindSphere activates SIP-enabled functions such as real-time data sharing (PPC9), lifecycle data integration (MA3), and predictive diagnostics (MA1), which are foundational in the lower tiers of our ISM model. This orchestration reinforces the role of SIPs as more than technical enablers—they become strategic assets embedded in cross-functional decision-making, enabling the 'sensing' and 'seizing' aspects of Dynamic Capabilities by transforming raw data into actionable insights for rapid response. Thus, according to the RBV, the adoption of systems like MindSphere should be driven by the organisation's capability requirements, such as predictive analytics, asset tracking, or autonomous decision-making, so that SIPs act as true enablers of competitive differentiation. Siemens' case reflects this logic: the deployment of MindSphere is aligned with technological feasibility and the firm's strategic objective to embed operational agility into its production systems (SIEMENS, 2017). At the ISM's first level, only PPC1 (Integration of sensing technologies into passive RFID tags) is present, directly associated with PPC, highlighting its role as a fundamental building block for SIP-enabled operations. The second level includes MA3 (Lifecycle data sharing for optimised services), PPC2 (Interoperability of autonomous SIPs), and PPC9 (Real-time data collection and communication), all grouped in the same *MICMAC* category. This configuration marks the emergence of the first synergy between PPC and Maintenance, demonstrating the development of essential 'microfoundations' for broader organisational adaptation. The integration of RFID-based sensing technologies enables SIPs to collect and transmit lifecycle data, empowering maintenance with real-time insights. This capability streamlines decision-making and enhances the autonomy of maintenance operations (ANSARI; GLAWAR; NEMETH, 2019; LUFT; LUFT; ARNTZ, 2023), further strengthening the technical component of the socio-technical system.

From an RBV lens, adopting SIPs in maintenance should consider technological feasibility and strategic goals. If the priority is minimising unplanned downtime, SIPs with predictive diagnostics and anomaly detection should be prioritised. If service efficiency is the target, remote diagnostics and digital twins become essential, as these contribute to creating unique bundles of resources. Remote diagnostics, particularly during the mid-life phase of assets, have emerged as one of the most promising services enabled by SIPs. They facilitate functions such as accurate fault detection, condition-based interventions, personnel scheduling, spare parts sourcing, and even design feedback (ANSARI; GLAWAR; NEMETH, 2019; OLUYISOLA et al., 2022). In line with our ISM model, a bidirectional synergy unfolds between PPC and Maintenance across levels 2 and 3. MA3's lifecycle data sharing facilitates the integration of the physical, social, and cyber domains (e.g., PPC5), thereby enhancing advanced planning capabilities and representing a crucial step in optimising the Sociotechnical System. For instance, when a factory uses SIPs to gather data throughout a machine's lifecycle, including technical parameters, user interactions, and system logs, this integrated information enables more accurate production planning (e.g., PPC12). SIPs carrying contextual data also enable system-level coordination (PPC8), facilitating prompt and synchronised responses across assets. Such integration prevents unplanned disruptions and boosts workflow efficiency (ANSARI; GLAWAR; NEMETH, 2019; LUFT; LUFT; ARNTZ, 2023; TSAI; LAI, 2018), embodying the ability to 'transform' existing processes within the framework of Dynamic Capabilities. Specifically, when SIPs implement MA3, by storing and sharing lifecycle data, real-time operational visibility is enhanced, allowing PPC teams to make timely production adjustments. Early signs of wear or failure can be anticipated, enabling proactive rescheduling and sustained productivity. Regarding reverse synergy, from PPC to Maintenance, enhanced data collection and communication capabilities (PPC9), along with interoperability among heterogeneous SIPs (PPC2), contribute to intelligent, self-managed information flows that align with PPC priorities. These flows, in turn, improve the precision of predictive (MA1), prescriptive, and remote maintenance services (MA2), expanding the autonomy of the maintenance function and strengthening the adaptive routines of the socio-technical system.

4.5.2 Advancing PPC through Analytics, Responsiveness, and Complexity Management

Our second level of integration concerns the relationship between integrated maintenance and more advanced PPC capabilities (PPC7, PPC10, and PPC11), located in the fourth layer of the ISM model. Maintenance coordination and accuracy (MA1) serve as a foundational input for enhancing self-performance optimisation (PPC7), enabling more precise and data-driven decisions within PPC (BORANGIU et al., 2020). Insights derived from maintenance activities contribute directly to the refinement of PPC strategies (ANSARI; GLAWAR; NEMETH, 2019).

In developing robust and adaptable production systems, both MA1 and remote repair capabilities (MA2) play a vital role in fostering flexibility and resilience. These represent key enablers of competitive advantage through SIP adoption (BORANGIU et al., 2020; TSAI; LAI, 2018), consistent with the RBV by forming a unique and inimitable bundle of capabilities. Predictive and prescriptive maintenance, supported by remote diagnostics, ensures that operations remain stable and responsive to changing demands, embodying advanced 'transforming' abilities under Dynamic Capabilities. These maintenance-related capabilities also support complexity management through PPC11. Precision in maintenance facilitates a deeper understanding of machine conditions and operational intricacies (THÜRER et al., 2021), which is crucial for simplifying service delivery in complex production environments. The integration of real-time maintenance data enables PPC to adjust production parameters and streamline operations, proactively reducing inefficiencies and thereby optimising the interdependencies within the Sociotechnical System.

In summary, this synergy, spanning levels 3 to 4 of the ISM model, demonstrates how MA1 and MA2 enhance PPC decision-making, system responsiveness, and complexity handling, particularly through advanced capabilities like PPC7, PPC10, and PPC11. This forms what we define as transparent PPC: a configuration where decision processes are informed, agile, and continuously optimised through cross-functional integration. From an industrial standpoint, companies like Siemens have successfully implemented smart industrial systems that enable real-time data sharing and operational coordination (Siemens, 2023). Similarly, GE’s Predix platform extends beyond the provision of predictive analytics, acting as a digital backbone for cross-functional coordination, particularly between Maintenance and PPC. Predix collects, analyses, and operationalises sensor-based and historical machine data across the production network, enabling early fault detection and automatic adjustment of production schedules. According to internal reports, GE achieved a 20% reduction in unplanned downtime and significant gains in operational responsiveness through this architecture (BRITTINGHAM, 2024; WEBER, 2017). What distinguishes GE’s implementation is its modular and adaptive approach, unlike Siemens' system-wide deployments. Predix allows individual sites to deploy, scale, and refine SIP-enabled capabilities based on local operational goals. This modularity facilitates localised optimisation while preserving enterprise-wide coherence. From a capability perspective, Predix supports the integration of MA1 (predictive maintenance), MA2 (remote diagnostics), and PPC10 (data-informed production planning), fostering a dynamic loop of feedback and adjustment that mirrors the layered progression of our ISM model. Our framework builds on these practices by highlighting that the true advantage lies not merely in technological deployment but in enabling synergy, where maintenance precision (e.g., MA1) directly supports the robustness and adaptability of PPC systems (e.g., PPC10). The GE case demonstrates how SIPs, when tied to capability-driven goals, enable the transformation of maintenance data into actionable insights for real-time planning, thus operationalising resource-based advantages in volatile production environments. This underscores how the technical capabilities of SIPs facilitate robust and adaptive socio-technical interactions, even when human factors are not the primary focus of measurement.

4.5.3 Step 3: Spreading Inter-functional Collaboration to Quality Control, Adaptability and Adaptive PPC

This third level of integration encompasses the accounting and quality functions, aligned with the fifth layer of our ISM model and associated with high dependence capabilities in the *MICMAC* analysis. The synergy between PPC and accounting emerges primarily through PPC7, where performance optimisation based on iterative learning contributes to more efficient asset management (ACC1). Additionally, PPC10 supports more effective resource allocation, helping Accounting ensure that investments align with evolving production (BORANGIU et al., 2020). By reducing unplanned downtime and enhancing system resilience, PPC10 reinforces long-term asset value and strengthens financial planning. PPC11 further contributes to accounting through complexity management, especially when dealing with combined product–service systems. These capabilities enhance strategic asset decisions and mitigate risk by anticipating variability and facilitating robust investment planning (ACC1). This interconnected structure reveals a layered support system from PPC to Accounting, grounded in both performance and adaptability. This expansion of integration aligns with the RBV, as it represents a broader bundling of resources and capabilities across multiple functions, making the firm's overall resource configuration more comprehensive and more challenging to replicate.

Regarding quality, PPC7 fosters collaboration by integrating lessons learned into decision-making processes. This enriches QM1 through value aggregation, enabling a more proactive and informed quality strategy (VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021). PPC10, in turn, strengthens this partnership by creating robust and flexible systems that embed quality from the design stage. It also positively influences QM2 and QM3, ensuring real-time adjustments and reducing vulnerabilities that may compromise standards. PPC11 plays a crucial role in simplifying the complexity inherent in integrated offerings, enabling Quality Management to sustain consistent performance while responding to evolving requirements (LENZ et al., 2020). These interactions also enhance PPC's internal capabilities. First, performance optimisation through PPC7 supplies actionable data for automatic reconfiguration (PPC3) and adaptive workforce deployment (PPC4) (BORANGIU et al., 2012). This enables firms to strategically assign skilled personnel, particularly during peak periods, thereby supporting both responsiveness and service quality. Second, PPC10 provides the infrastructure for such reconfiguration, facilitating both PPC3 and PPC4.

PPC11’s complexity management drives further synergy by enabling seamless production shifts (PPC3) and efficient remote control (PPC6). These capabilities foster agility and resilience, helping industrial systems adapt dynamically with minimal disruption (ABRAMOVICI; GÖBEL; SAVARINO, 2017; CENA et al., 2019; RUHUL AMIN et al., 2021; VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021). Streamlined workflows and real-time insights generated from this architecture reinforce PPC’s role as an integrative function, demonstrating the continuous 'transforming' and 'reconfiguring' aspects of Dynamic Capabilities across the organisation. From an STS perspective, SIPs at this level bridge the technical and social systems across a broader organisational scope. By providing integrated data streams (e.g., from PPC to Accounting and Quality), SIPs technically facilitate the necessary coordination for synergistic outcomes. The technical architecture supports automated reconfigurations (PPC3) and remote controls (PPC6), reducing human intervention in routine tasks and allowing human resources to focus on higher-value activities. Empirical examples support these interactions. Cerquitelli et al. (2021) emphasise how iterative performance optimisation enhances asset strategies (ACC1), while Bosch’s use of SIPs to integrate quality and accounting demonstrates how cross-functional alignment improves both operational efficiency and financial planning (BOSH, 2019). Specifically, Bosch employs its Nexeed Industrial Application System to collect, process, and visualise machine and production data in near real-time across its manufacturing network. These data streams are converted into predefined events and alerts, which are then routed to relevant stakeholders, including maintenance operators, quality control personnel, and financial analysts, thereby fostering a shared operational picture. This architecture supports capabilities such as PPC10 (data-informed planning), ACC2 (financial process integration), and QM2 (automated defect tracking), allowing cross-functional teams to make synchronised decisions. For example, insights from quality deviations can trigger updates in maintenance schedules and financial forecasts, demonstrating how SIPs enable visibility and coordinated action across traditionally siloed departments. These cases validate that SIP-enabled synergies can break down silos, enabling a cohesive, capability-driven operational strategy where the interplay between technical systems and human processes is continuously optimised.

4.5.4 Step 4: Cultivating Environmental Stewardship through Data-Driven Sustainability

The final level of our framework highlights the relationship between support functions, autonomous PPC, and sustainability (SUS1). The synergy between ACC1 (efficiency in asset investment) and SUS1 (sustainability of processes) is evident in how financial optimisation aligns with long-term environmental and social goals. This reflects the economic pillar of the Triple Bottom Line (TBL), demonstrating that asset management, when guided by sustainable practices, promotes broader process-level sustainability. This comprehensive approach to sustainability, enabled by SIPs, represents a highly strategic and often inimitable competitive advantage within the RBV, as it bundles diverse organisational capabilities towards a unique strategic outcome.

A second synergy emerges between PPC and sustainability. PPC3 (automatic reconfiguration of SIPs) enables efficient adjustments via logic or algorithms, optimising resource use, reducing waste, and improving performance (YAVUZ et al., 2023). In sequence, PPC4 supports agile workforce allocation, improving operational efficiency and social equity, which is directly linked to the social pillar of the TBL (ZHANG et al., 2020). Additionally, PPC6 (remote process control) offers real-time intervention capabilities, reducing failures, environmental impacts, and setup costs. These capabilities reflect the highest level of organisational transformation within Dynamic Capabilities, where the firm continuously adapts its processes for sustainable value creation, 'reconfiguring' its operations in response to environmental demands. From an STS perspective, this level emphasises the deep integration required across technical and social systems to achieve comprehensive sustainability outcomes. While SIPs provide the technical means for optimising resource use (PPC3, PPC6) and monitoring environmental impact (e.g., via QM1, QM2), their effective deployment for sustainability relies heavily on the alignment of human values, organisational culture, and management practices (TRIST; BAMFORTH, 1951). Rolls-Royce exemplifies this synergy through its use of digital twin technology to integrate sustainability targets into operational processes. By modelling asset performance and simulating scenarios before implementation, Rolls-Royce identifies optimal configurations that minimise energy consumption and emissions without compromising throughput. This approach has yielded measurable results, including a 15% reduction in energy use across selected facilities (WINTERHOLLER, 2024).

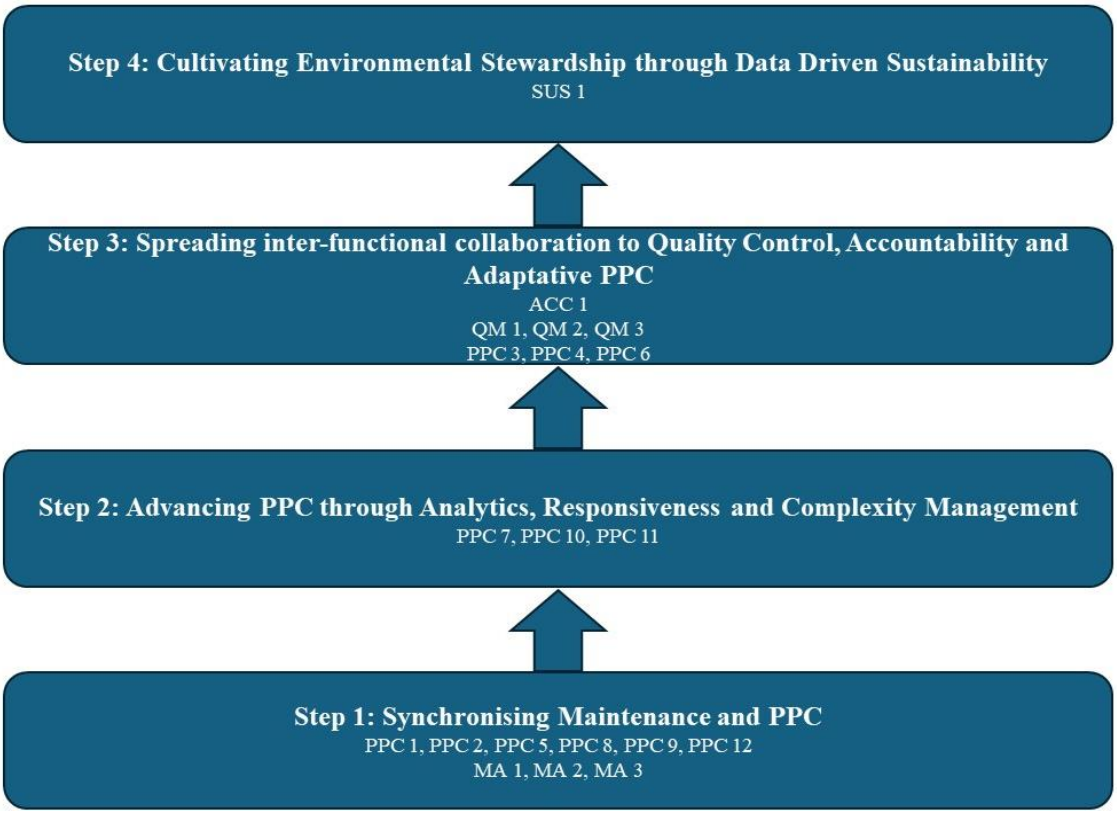
Notably, these digital twins are not isolated tools; they operate as part of a coordinated system that connects engineering, ESG compliance, and production planning. This enables the alignment of PPC3 (automatic configuration), PPC6 (remote control), and ACC1 (strategic asset allocation), forming a capability-based infrastructure for sustainable operations. These findings reinforce those of Cerquitelli et al. (2021), showing that sustainability outcomes enabled by SIPs are not isolated but are intrinsically connected to inter-functional synergies. For example, linking PPC3 and ACC1 helps organisations achieve environmental and financial objectives simultaneously, redefining sustainability as a strategic capability rather than an isolated initiative. Another critical synergy occurs between quality management and sustainability. QM1 (value aggregation) enhances sustainability by improving resource utilisation and productivity (ANTONS; ARLINGHAUS, 2022b; IMAD et al., 2022). Ongoing quality management (QM2) supports adaptability to changing customer needs, a key enabler of sustainable operations. By proactively identifying deviations before they result in waste or defects, firms enhance both quality and environmental performance. As Yi et al. (2021) note, this approach also builds market competitiveness and customer trust. Finally, QM3 (process security) safeguards organisational assets, reputation, and stakeholder confidence—foundations of sustainable growth. Measures against cyber threats, operational failures, and safety risks are essential to ensure continuity in increasingly complex industrial environments. This comprehensive approach ensures that SIP-enabled capabilities are embedded across all functions, creating value across all pillars of the TBL and truly optimising the socio-technical system for enduring performance.

4.5.5 Propositions for a capability-driven roadmap

The sequential integration framework derived from our ISM and Fuzzy *MICMAC* analyses reveals a hierarchical architecture of SIP-enabled capabilities that drive inter-functional synergy. Building upon these empirically derived interdependencies, and drawing interpretive insights from the theoretical lenses discussed throughout this section, we propose a set of testable propositions. These propositions aim to clarify the underlying mechanisms of

SIP-enabled synergy and guide future empirical research, shifting the contribution from documentation to explanation and theory-building. Figure 4.6 illustrates this sequential integration, beginning with the synchronisation of Maintenance and PPC, followed by the advancement of analytics and complexity management, the expansion toward Quality and Accounting, and concluding with sustainability integration. This progression visually reinforces how SIP-enabled capabilities are embedded across functions, creating value across all pillars of the TBL, and provides the visual roadmap that these propositions build upon.

Figure 4.6: A Framework for Sequential Integration and Synergistic Enhancement of Organisational Functions through Smart Industrial Products



Source: Elaborated by the author (2025)

Our analysis indicates that foundational capabilities act as enablers of more advanced inter-functional routines. This finding is consistent with the concept of capability layering, where operational-level routines must be in place before more complex configurations can emerge (ETHIRAJ et al., 2005). From an RBV, early-stage SIP-enabled capabilities, such as sensing technologies (PPC1), real-time data collection (PPC9), and lifecycle data sharing (MA3), represent core resources that are valuable, rare, and difficult to imitate (SIRMON et al., 2007). These capabilities form the microfoundations (FELIN et al., 2012) of a firm's ability to sense and seize opportunities, as outlined in the DCT (TEECE, 2007). In parallel, they lay the technical groundwork for optimising the STS, ensuring robustness in human-machine collaboration and cross-functional coordination (PASMORE, 1988). Based on this logic, we propose the following:

- **Proposition 1a (RBV, DCT, STS):** The successful implementation of foundational SIP-enabled capabilities—specifically sensing technologies (PPC1), real-time data collection (PPC9), and lifecycle data sharing (MA3)—is a necessary condition for the emergence of advanced predictive maintenance (MA1) and autonomous coordination (PPC2) capabilities.
- **Proposition 1b (DCT):** These foundational capabilities positively moderate the relationship between initial SIP adoption and the speed of inter-functional synchronisation between Maintenance and PPC, as evidenced by increased coordination efficiency and responsiveness.

As integration evolves, our model reveals that advanced maintenance capabilities are instrumental in enhancing PPC maturity. Predictive maintenance (MA1) and remote repair (MA2), when combined with analytics (PPC7), adaptive systems (PPC10), and complexity management (PPC11), create dynamic and difficult-to-replicate resource bundles (BORANGIU et al., 2020). This pattern reflects continuous capability reconfiguration, a central concern of DCT, while also reinforcing the logic of bundling in RBV. Furthermore, the interaction between technical coordination and decision autonomy echoes key assumptions of STS. Accordingly, we propose:

- **Proposition 2a (RBV, DCT):** The maturity of SIP-enabled predictive maintenance (MA1) and remote repair (MA2) significantly predicts a firm's ability to achieve higher levels of performance optimisation (PPC7), production system adaptability (PPC10), and complexity management (PPC11).
- **Proposition 2b (DCT, STS):** The synergistic interaction between maintenance (MA1, MA2) and advanced PPC capabilities (PPC7, PPC10, PPC11) is positively associated with increased operational agility and reduced unplanned downtime, mediated by enhanced data-driven decision-making.

The next phase in the integration sequence involves the expansion toward Quality and Accounting, enabled by the capabilities developed within PPC. This reflects a cascading effect, where earlier stages lay the foundation for broader functional inclusion. SIPs facilitate this through integrated data streams and decision-making structures (PPC3, PPC4, PPC6), allowing functions traditionally treated as silos to be orchestrated as part of a cohesive system.

This logic aligns with STS in emphasising the interaction between technical infrastructure and organisational coordination mechanisms, and with RBV in recognising the uniqueness of capability configurations. Building upon this logic, we propose:

- **Proposition 3a (STS, RBV):** Achieving transparency in PPC (enabled by PPC7, PPC10, PPC11) is a critical enabler for the SIP-driven integration of Accounting (ACC1) and proactive Quality Management (QM1, QM2, QM3).
- **Proposition 3b (RBV, DCT):** The extent of inter-functional synergy between Quality (QM1–QM3) and Accounting (ACC1) is positively moderated by the firm's level of digital maturity in PPC, resulting in enhanced financial optimisation and process security.

Finally, the framework reveals that sustainability integration emerges as the most advanced form of inter-functional synergy, closely tied to prior developments in PPC and Accounting. At this level, SIPs enable the firm to bundle and reconfigure capabilities in pursuit of sustainable value creation, a source of strategic and often inimitable competitive advantage (XU; FAN; HU, 2022; YAVUZ et al., 2023). This transformation requires deep sociotechnical integration, where technological infrastructures and organisational values align to support TBL outcomes (TRIST; BAMFORTH, 1951). In light of these findings, we propose:

- **Proposition 4a (RBV, STS):** SIP-enabled synergies in asset investment efficiency (ACC1) and adaptive PPC (PPC3, PPC4, PPC6) are positively associated with the integration of sustainable operational practices (SUS1).
- **Proposition 4b (DCT, STS):** The cumulative inter-functional synergy enabled by SIPs across Maintenance, PPC, Quality, and Accounting contributes to superior TBL performance and enhanced long-term organisational resilience.

These propositions are grounded in complementary theoretical lenses, each offering a specific interpretive lens to understand how SIP-enabled capabilities evolve and interact. RBV emphasises the value and configurational uniqueness of capabilities, DCT explains how they adapt over time, and STS highlights how technology integrates with human systems. Together, these perspectives strengthen the explanatory power of the proposed framework. By synthesising hierarchical dependencies with theoretical insights, the propositions consolidate a systemic architecture of SIP-enabled capability flows. This structure reveals how foundational routines activate and reinforce higher-order synergies across functions. Grounded in the ISM and Fuzzy *MICMAC* logic, the framework offers a practical and conceptual reference for understanding how SIP capabilities stabilise and scale within complex industrial environments.

4.6 CONCLUSIONS

The growing adoption of SIPs is transforming how organisations coordinate functions, make decisions, and organize operational routines. This study identified 20 SIP-enabled capabilities spread across five key organisational functions and examined how these capabilities relate hierarchically to promote integration. Using a sequential and mixed-methods approach, which included an SLR, expert interviews, ISM, and Fuzzy *MICMAC*, we developed a framework that illustrates the progression of capability interactions leading to cross-functional synergy.

4.6.1 Theoretical Implications

While inter-functional integration has been widely explored as a managerial or process-based challenge (PAGELL, 2004; PELLATHY et al., 2019), our study positions SIPs as key organisational resources that extend beyond enabling operational efficiency. When aligned with capability development priorities, SIPs become strategic elements within the logic of the RBV. Rather than focusing solely on the presence of technology, we demonstrate that competitive advantage stems from how firms purposefully and cohesively orchestrate and combine capabilities across functions.

The ISM–Fuzzy *MICMAC* model reveals a layered structure of capability interactions. Foundational elements—such as sensing technologies (PPC1), real-time data integration (PPC9), and lifecycle data sharing (MA3)—act as enablers for higher-level routines, including complexity management (PPC11) and sustainability-oriented practices (SUS1). This layered dynamic reflects the concept of capability modularity and supports the notion that interdependencies among capabilities influence system-level performance (ETHIRAJ et al., 2005). Our findings also extend the theory of dynamic capabilities (TEECE, 2007) by identifying concrete routines that support sensing, adapting, and reconfiguring behaviors across functions. Moreover, the study contributes to the literature on capability bundling by emphasising the emergence of horisontal capability structures. These do not develop in isolation within departments, but rather through interaction and mutual reinforcement, particularly between maintenance, production planning, quality, and sustainability. By shifting attention from isolated functions to cross-functional interactions, we offer a more integrative perspective that is better suited to the complexity of modern industrial environments.

Importantly, the framework we propose challenges linear and technology-first narratives in digital transformation. Instead, it emphasises the strategic sequencing of capabilities as a critical path to sustained performance, aligning with the idea of dynamic alignment (HELFAT; MARTIN, 2015). From this perspective, SIPs are not merely operational tools but elements that activate routines and build adaptive capacity at multiple levels within the organisation. This layered orchestration of technical and organisational routines also reflects core principles of STS, as it demonstrates how technical capabilities embedded in SIPs can reshape structures of collaboration and coordination across interdependent functions.

4.6.2 Managerial Implications

For practitioners, the framework serves as a structured decision-making tool to guide capability development, enhance collaboration, reduce inefficiencies, and strengthen inter-functional alignment. By distinguishing foundational capabilities from dependent ones, managers can establish clear priorities and sequence investments more effectively, avoiding fragmented initiatives or premature deployments.

To operationalise the framework, firms can begin with a capability diagnostic, mapping their current maturity across the 20 SIP-enabled capabilities identified in this study. This mapping helps identify which foundational elements, such as sensing technologies (PPC1) or real-time data integration (PPC9), are already in place and which require development. Next, organisations can assess the interdependencies indicated in the ISM-*MICMAC* structure to determine how current capabilities can be leveraged to enable higher-level goals, such as predictive coordination, adaptive planning, or sustainability integration. For example, organisations aiming to improve planning and scheduling must first ensure that sensing and communication mechanisms are fully functional before progressing to advanced analytics or performance optimisation. In more complex settings, such as hybrid product–service environments, investing in lifecycle data visibility (MA3) can unlock synergies between production, maintenance, quality, and accounting, ultimately enabling more cohesive and agile operations.

The framework also encourages a phased deployment model, in which capability building follows an integrated progression aligned with operational maturity and strategic priorities. This approach is exemplified by leading firms such as Siemens, GE, Rolls-Royce, and Bosch, which have structured their implementation of connected systems, diagnostics, and coordination tools according to the maturity of their internal processes and the desired business outcomes. Rather than adopting SIP technologies in isolation, these companies exemplify how capability sequencing can serve as a roadmap, first securing enabling infrastructure, then expanding toward inter-functional reinforcement, and finally integrating strategic objectives such as sustainability or resilience. By adopting this structured logic, firms can better align strategic intent with operational capability, fostering more consistent performance, faster responsiveness, and long-term competitiveness.

4.6.3 Limitations and Future Research Directions

Like any research, this study presents limitations that open avenues for further investigation. In the literature review stage, decisions regarding database selection, time frame, and relevance criteria inevitably involve a degree of subjectivity, even when protocols are standardised. Although expert interviews added contextual depth to the identification of capabilities, the ISM method still relies on individual judgment, which may be shaped by each expert's background and experience. As a result, potential inconsistencies in the early stages may influence the structure and outcomes of the final model, including the results from the Fuzzy *MICMAC* analysis.

A key limitation is the lack of empirical validation. Although the framework was developed using theoretical and expert reasoning, it has not yet been tested with real-world data. Future research could address this by employing survey methods or Structural Equation Modeling (SEM) to assess how specific capabilities impact performance. For instance, Proposition 1b, which suggests that sensing technologies (PPC1) and real-time data collection (PPC9) speed up synchronisation between maintenance and planning, could be tested through indicators such as coordination lead time, downtime reduction, or decision accuracy. Similarly, Proposition 4b, which connects the buildup of inter-functional synergies to better sustainability outcomes, could be evaluated using composite indices of operational resilience, resource efficiency, and ESG metrics.

These propositions can be theoretically anchored in frameworks such as Contingency Theory, which helps assess how environmental and organisational conditions influence the effectiveness of capabilities. STS also provides a valuable lens for examining how technical routines interact with people, structures, and processes during the deployment of capabilities. Additionally, Complexity Theory in operations management offers insights into how bundled capabilities contribute to adaptive behavior and responsiveness in dynamic environments. Another promising direction is examining how the structure and sequencing of capabilities vary across industries. Cross-sectional studies could help test the generalisability of the proposed hierarchy and reveal sector-specific patterns or deviations.

Ultimately, the set of propositions introduced in this study provides a foundation for structured hypothesis-building. Future research should refine and test these propositions using diverse analytical approaches and empirical settings to validate their findings further. This will help clarify the mechanisms through which SIP-enabled capabilities shape integration, performance, and resilience, and further consolidate the framework as a practical and conceptual tool for operations and technology management.

5 BARRIERS TO THE IMPLEMENTATION OF SMART INDUSTRIAL PRODUCTS IN ORGANISATIONS: CONCEPTUALISATION AND RELATIONSHIPS

This chapter is composed of the fourth paper of the thesis and will be submitted to before to finishe the final version of this thesis.

Abstract

The growing diffusion of Smart Industrial Products (SIPs) is reshaping how industrial organisations integrate digital technologies into their operational and strategic routines. Despite their transformative potential, SIPs adoption remains constrained by a complex web of interrelated barriers that hinder institutionalisation and systemic stability. This study aims to identify, classify, and model the relationships among these barriers to provide a structured understanding of their hierarchical influence within organisations. A sequential mixed-methods design was applied, combining a Systematic Literature Review, Experts Interview, Interpretive Structural Modelling (ISM), and Fuzzy *MICMAC* analysis. The results reveal twenty-three barriers grouped into four distinct but strongly interrelated clusters, hierarchically arranged according to their driving and dependence powers. These clusters (Structural Sociotechnical Integration, Technological Resilience, Organisational Readiness and Maturity, and Dynamic Stability through Complex Barriers Mitigation) represent a progressive configuration of institutional and technical constraints that shape organisational trajectory in adopting SIPs. Drawing on Neo-Institutional Theory, the findings demonstrate how coercive, normative, and mimetic pressures reinforce organisational inertia, producing path-dependent resistance to change and fragmented digital transformation. The study advances theory by bridging structural and institutional perspectives, offering a multi-layered framework that conceptualises how barriers interact to constrain or enable institutional evolution in digital contexts. Managerially, the framework functions as a diagnostic and strategic tool to guide prioritisation of interventions, aligning technological, organisational, and institutional dimensions for effective SIPs adoption.

Keywords: Smart Industrial Products; Barriers; Interpretive Structural Modelling; Fuzzy *MICMAC*; Neo Institutional Theory

5.1 INTRODUCTION

In the last decade, the increasing integration of Smart Industrial Products (SIPs) within manufacturing systems represents a cornerstone of digital transformation in contemporary production environments. This category of intelligent, connected products are designed not only to enhance operational efficiency but also to enable greater responsiveness, adaptability, data-driven decision-making as well as cost reduction (DING; JIANG, 2018; KESHAVARZI; VAN DEN HOEK, 2019; LEITÃO et al., 2015; MCFARLANE et al., 2013).

The exploration of barriers to the implementation of SIPs in organisations has shed light on significant challenges hindering the adoption of advanced technologies within industrial settings. Even though substantial progress has been made in understanding these barriers through the works of Atzori; Iera; Morabito (2010); Dawid et al. (2017); Ding; Jiang (2018); Juric; Lindenmeier (2019); Leitão et al. (2015); Mcfarlane et al. (2013); Meyer et al. (2014); Meyer; Hans Wortmann; Szirbik (2011); Oluyisola et al. (2022); Yi et al. (2021); Zhang et al. (2020), there remains a compelling need to delve deeper into this complex landscape. In addition, despite their promising potential, the adoption of SIPs in industrial contexts remains uneven — both among similar sectors and across different ones — often hindered by a complex interplay of technical and organisational factors, as well as by a limited understanding of the relationships between structural barriers faced to deploy them. Moreover, understanding these barriers is therefore critical for both scholars and practitioners seeking to harness the full benefits of SIPs in advanced manufacturing environments. Yet, adopting SIPs without a clear strategy, results in isolated solutions that do not directly contribute to enhance organisational functions (PISSARDINI et al., 2024). Furthermore, according to Pissardini et al. (2024) if an organisation does not surpass all barriers in one determined temporal moment, it can not enhance smartness level of their main functions. In addition, according to the authors, barriers manifest a cumulative and regressive dynamic whereby, notwithstanding the successful surpassing of those inherent to the pre-implementation phase, the recurrence of any such barrier possesses the potential to vitiate antecedent progress and compel an organisational relapse to a prior locus within the adoption continuum. Finally, although some authors studied SIPs pointing barriers to deploy it in manufacturing, these are theoretically studied or pointed out as secondary results of the study of SIPs adoption in specific contexts. Thus, the tendency industrial products evolution towards smart products has entailed the necessity for further studies to deeply understand these products' impacts on the manufacturing environment since this new industrial stage is affecting competition rules, industry structure, and customer demands (BARTODZIEJ, 2017).

In this regard, the main objective of this research is to propose a roadmap for organisations to mitigate barriers to SIPs adoption in manufacturing environments. The proposed roadmap provides a structured and actionable path to support organisations in prioritising, addressing, and overcoming the key structural challenges associated with SIPs' adoption. Given the conceptual ambiguity surrounding SIPs, as highlighted by Raff et al. (2020), in our research we adopt the definition proposed by Pissardini et al. (2024) for whom SIPs are "Products incorporating elements of the physical, connected, and smart dimensions, featuring embedded systems enabling smart functionalities, including recognition, analysis, and autonomous exchange of data about the customer, goods in production, processes, and the environment in real time, offering innovative integrated services through self-improvement of their configurations to optimise performance and maximise organisational value." It is important to highlight that both topics (Barriers and SIPs) have been the subject of leading research efforts worldwide such as Liu et al. (2023); McFarlane et al. (2013); Takahara & Yasaki (2013), among others.

In our study, as above presented, we believe that such structural barriers are not suddenly surpassed; rather, it should be done in steps, according to the structural relationship hierarchy between them. Thus, in this research, we investigated three questions:

- (RQ1) What barriers do organisations face to adopt a SIP?
- (RQ2) How are these structural barriers interrelated?
- (RQ3) Is there a logical roadmap that organisations should follow to make the process of implementing a SIP more secure, sustainable, and efficient?

By identifying and critically analysing the structural barriers organisations face in adopting SIPs, this study proposes a structured roadmap designed to strategically overcome these challenges. This contribution supports organisations in navigating the complexities of SIPs adoption, while enriching academic discourses on digital transformation, operational resilience, and technology-enabled organisational change. Although some research has been conducted on SIPs, there exists a gap in the field concerning this topic. As stated by Porter & Heppelmann (2015), the deployment of SIPs requires an entirely new 'technology stack'. In other words, a cutting-edge technological infrastructure that serves as a conduit for data exchange between the product and the user (including itself in the higher levels of autonomy), integrating information from various internal business systems, entities, and external sources.

Researchers such as Bueno et al. (2022) and Pardo et al. (2020) have emphasised the transformative potential of embedded technologies in creating and capturing value. This technology stack serves as a multifunctional platform within SIPs, facilitating data storage, analytics, application execution, and ensuring secure access to products and the associated data flow (Porter & Heppelmann, 2015). While it is evident that enabling technologies empower SIPs to function effectively, the specific impact of these barriers on various organisational functions remains a subject that requires further investigation.

This study addresses this gap by proposing a roadmap for managers in practice and organisations to strategically direct efforts in articulating how barriers to SIPs adoptions can be progressively overcome them. To our knowledge, no prior study has proposed such an integrative and systematically developed model that bridges theory and empirical data to inform both academic inquiry and practical use.

Thus, the remainder of this research is organised as follows: Section 2 presents the literature review and the research gap we seek to fill. Section 3 outlines the methodological approach. Section 4 reports the results. Section 5 introduces the final framework discussing it in relation to leading scholarship in the field. Finally, Section 6 offers concluding remarks and avenues for future research.

5.2 LITERATURE REVIEW AND RESEARCH GAP

This section offers a literature review on the challenges surrounding the adoption of SIPs, thereby contextualising this study within the wider academic discourse on industrial digitalisation. Subsequently, the analysis highlights key gaps in existing literature, laying the foundation to explain our motivations behind performing this research, highlighting its relevance and thematic positioning.

5.2.1 State-of-the-art Concerning Barriers to SIPs Adoption: A Neo-Institutional Perspective

This section analyses the state-of-the-art regarding barriers to SIPs adoption within organisations from a Neo-Institutional perspective. Accordingly, Neo-Institutional Theory was adopted to interpret how institutional mechanisms (e.g., legitimacy pressures, isomorphic forces, institutional logics, institutionalisation processes, decoupling, and institutional change) contribute to the persistence and reinforcement of the barriers identified in literature. By framing these barriers as outcomes of coercive, normative, and mimetic pressures, the theory provides an analytical basis for understanding why organisations often reproduce rather than overcome institutionalised constraints that hinder SIP assimilation. Building on this groundwork, the section delineates the theoretical assumptions and analytical basis that guide the subsequent empirical investigation.

In the last decade, researches on SIPs has evolved from a primarily technological focus to a more socio-organisational and institutional orientation, revealing the existence of different categories of barriers that hinder their full assimilation into industrial practice. Although SIPs promise superior integration, adaptability, and data-driven decision-making, empirical evidence suggests that organisational, cultural, and infrastructural conditions often prevent these potentials from being materialised. Consequently, studies on SIP adoption have progressively moved beyond purely technical assessments, adopting diverse methodological approaches that expose the multi-layered nature of these barriers.

In industrial contexts, qualitative investigations demonstrate that barriers to SIP adoption are frequently embedded in legacy infrastructures and institutional routines. Kahle et al. (2020) identified barriers as, for example, misalignment between SIPs and ageing production technologies, lack of connectivity, cooperation barriers (low trust, fear of data leakage), and financial barriers (uncertain ROI) in SMEs developing SIPs. Besides, Mcfarlane et al., (2013) similarly emphasised organisational resistance, risk concerns, and cultural acceptability constraints when intelligent product architectures introduce new decision-making autonomy into factory operations. Further, Meyer (2011) showed that integration gaps between SIPs and incumbent IT structures lead organisations to resist transitions away from centralised control. Overall, these qualitative findings reveal that SIP adoption is constrained by persistent institutional practices and inter-organisational dynamics, not merely by technology readiness. Such persistence can be theoretically understood as a consequence of institutional inertia, in which established routines and norms gain legitimacy through repetition and are therefore maintained even when technically inefficient (DIMAGGIO; POWELL, 1983; MEYER; ROWAN, 1977). The coercive influence of supply-chain partners and regulatory agencies reinforces standardised practices that discourage experimentation with autonomous SIP architectures, while normative expectations within professional and managerial communities reproduce traditional coordination logics (GREENWOOD; HININGS; WHETTEN, 2014; SCOTT, 1995). As a result, organisations may adopt SIPs symbolically to signal conformity, (without effectively integrating them into operational routines) illustrating the classic decoupling effect described in Neo-Institutional Theory.

Quantitative assessments reinforce these insights by showing that infrastructural constraints produce statistically measurable adoption risks. Experiments conducted in logistics and production settings reveal that SIP architectures still exhibit limited autonomous performance and inferior efficiency to centralised systems under normal conditions, reducing business justification for adoption (BORANGIU et al., 2012; MEYER; WORTMANN, 2010; PANNEQUIN; MOREL; THOMAS, 2009). System-level evaluations further demonstrate that the lack of interoperability between intelligent products and existing information systems causes decision delays and operational instability (HOLMSTRÖM et al., 2009; KIRITSIS, 2011). Additionally, industry surveys quantify that technological capability readiness remains restricted to a minority of firms, leaving most organisations structurally unprepared for SIP deployment (KAHLE et al., 2020). These quantitative results show that SIP adoption failure is driven by measurable performance gaps, not only by behavioural resistance. From a Neo-Institutional standpoint, such measurable inefficiencies also act as reinforcing feedback loops that legitimise the continuation of conventional control systems (HININGS; GEGENHUBER; GREENWOOD, 2018). When early adopters face performance setbacks, mimetic pressures lead others to emulate conservative strategies, further institutionalising non-adoption behaviours across the industrial field.

In addition, technical-analytical contributions, often grounded in testbeds, engineering methods, or technological capability analysis, also expose barriers as secondary phenomena. These studies typically highlight deficits in interoperability standards (MCFARLANE et al., 2013), digital infrastructure (KAHLE et al., 2020), engineering tools (TOMIYAMA et al., 2019), and cybersecurity readiness (RUHUL AMIN et al., 2021) that hinder SIP implementation in practice. Notable examples include research on development capabilities for smart products (e.g., interoperability and model-integration limitations) and the challenges associated with data connectivity and high technical configuration requirements in industrial environments. In this regard, (PISSARDINI et al., 2025) analysed the SIPs role in shaping inter functional synergy. This advancement showed us that some negative factors and institutional pressures contributes to perpetuate structural barriers to SIPs adoption within organisational environments.

Taken together, existing theoretical perspectives indicate that the intended organisational gains from SIP adoption are frequently symbolic rather than enacted, because institutional mechanisms shape how technology-enabled practices become legitimised internally. Rather than enabling new coordination structures and cross-functional decision-making, SIPs are often incorporated into pre-existing hierarchical routines, thereby limiting their transformative potential (BROMLEY; POWELL, 2012). As such, improvements in efficiency, information visibility or responsiveness rarely materialise uniformly, since their realisation depends on the degree of coupling between SIP capabilities and institutional expectations governing accountability, authority and professional identity (GREENWOOD et al., 2011). Moreover, industrial actors tend to emulate “accepted” digitalisation practices within their field not due to proven effectiveness, but to preserve external legitimacy under mimetic pressures (DIMAGGIO; POWELL, 1991; HININGS; GEGENHUBER; GREENWOOD, 2018). Consequently, the organisational benefits typically associated with SIP implementation remain contingent outcomes, realised only when institutional environments allow — or actively support — the reconfiguration of established structures and meanings surrounding work and coordination.

Building upon this theoretical gap, this study addresses how institutional mechanisms interact with the structural and technological dimensions of SIP adoption. While prior research has conceptually acknowledged institutional barriers, few have empirically examined their interrelations and hierarchical influence within industrial settings. By combining the Neo-Institutional perspective with the Interpretive ISM and Fuzzy MICMAC methods, this research identifies how specific coercive, normative, and mimetic pressures materialise as structural barriers that restrict SIP diffusion. Through this integrative approach, institutional theory is operationalised into an analytical framework that explains not only what barriers exist, but why they persist within organisational systems. Accordingly, this study contributes to bridging the gap between institutional theory and digital manufacturing research, translating abstract concepts such as legitimacy, isomorphism, and decoupling into observable mechanisms within the adoption process of SIPs. This connection provides a structured theoretical foundation to guide empirical analysis and to clarify how institutional stability and organisational transformation can coexist during digital transitions. By doing so, the research expands the understanding of institutional complexity in industrial digitalisation and establishes a conceptual foundation for the hierarchical modelling presented in the following sections.

5.2.2 Research Gaps and Motivations

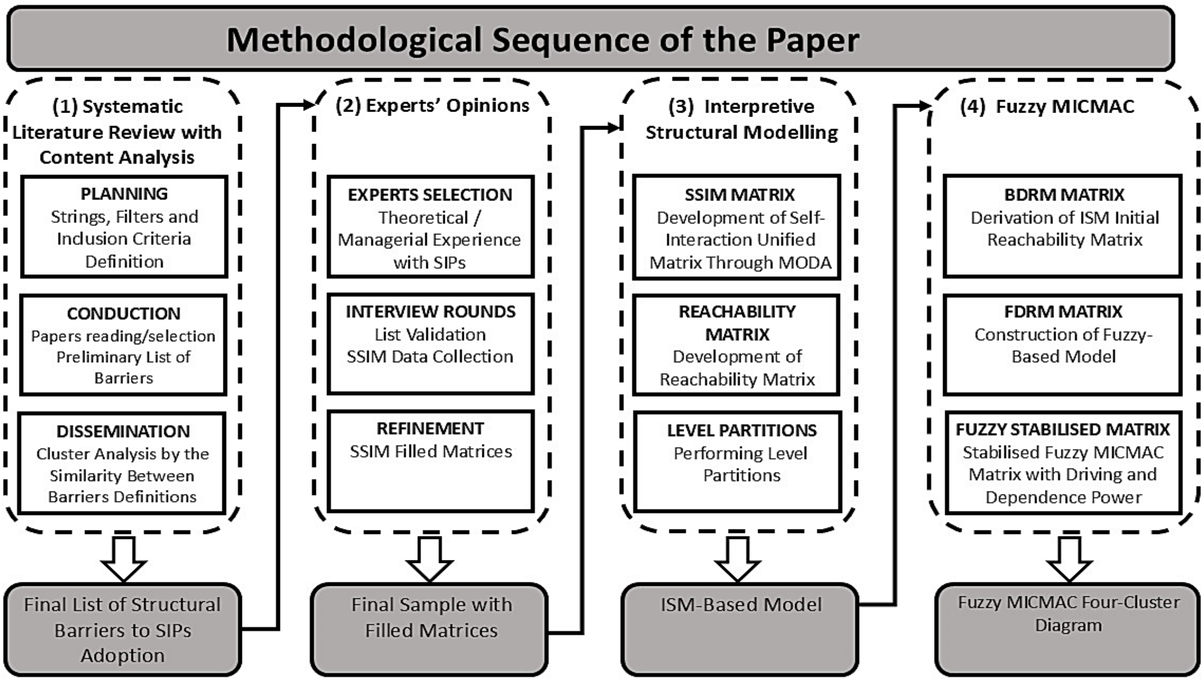
From a Neo-Institutional perspective, the adoption of SIPs is constrained not only by technical limitations but also by institutionalised organisational arrangements that inhibit socio-technical alignment. Although SIPs provide the technological means for distributed coordination and cross-functional dataflows, their effective use depends on the compatibility of institutional logics, workforce routines, and managerial control systems with such distributed forms of decision-making (GREENWOOD et al., 2011; HININGS; GEGENHUBER; GREENWOOD, 2018). Institutional pressures (coercive mechanism) demands from regulatory frameworks, normative expectations arising from professional standards, and mimetic tendencies to reproduce established competitors' practices often lead firms to reproduce existing operational models rather than embrace SIP-enabled transformation (DIMAGGIO; POWELL, 1991; SCOTT, 1995). Even when IoT-enabled models promise greater agility and closer interaction among organisational units, misalignments between established professional norms and SIP-mediated routines generate organisational resistance, slowing implementation and reinforcing path-dependent practices (BROMLEY; POWELL, 2012; DIMAGGIO; POWELL, 1983; FUENFSCHILLING; TRUFFER, 2014). As a result, SIP-enabled change may be symbolically adopted to signalise modernisation while decoupling persists at the operational level (BROMLEY; POWELL, 2012). Lastly, SIP-related barriers arise not only from capability deficits but from institutional inertia, which systematically prioritises conventional socio-technical configurations over transformative integration.

Taken together, existing theoretical perspectives indicate that the intended organisational gains from SIP adoption are frequently symbolic rather than enacted, because institutional mechanisms shape how technology-enabled practices become legitimised internally. Rather than enabling new coordination structures and cross-functional decision-making, SIPs are often incorporated into pre-existing hierarchical routines, thereby limiting their transformative potential (BROMLEY; POWELL, 2012). As such, improvements in efficiency, information visibility or responsiveness rarely materialise uniformly, since their realisation depends on the degree of coupling between SIP capabilities and institutional expectations governing accountability, authority and professional identity (GREENWOOD et al., 2011). Moreover, industrial actors tend to emulate "accepted" digitalisation practices within their field not due to proven effectiveness, but to preserve external legitimacy under mimetic pressures (DIMAGGIO; POWELL, 1991; HININGS; GEGENHUBER; GREENWOOD, 2018). Consequently, the organisational benefits typically associated with SIP implementation remain contingent outcomes, realised only when institutional environments allow — or actively support — the reconfiguration of established structures and meanings surrounding work and coordination.

5.3 RESEARCH METHOD

This research employs a mixed-methods framework consisting of four sequential and complementary stages (Figure 5.1), combining qualitative and quantitative techniques to achieve a thorough understanding of the barriers faced by organisations to adopt SIPs. The use of integrated methods proved fundamental, once the topic's exploratory nature demanded a systematic arrangement of the structural relationship between each of the barriers, organisations face to adopt SIPs. Furthermore, although each method has specifics output, they serve a distinct and particular purpose, complementing each other. To complement, the sequential alignment of methods reinforces the robustness of our findings. Beyond these reasons, each method contributes with specific strengths, while addressing the limitations of the preceding phase. While SLR establishes a comprehensive theoretical foundation, expert interviews ground this theoretical foundation in real-world perspectives. Subsequently, the ISM method ensures a structured visualisation of relationships, and the fuzzy *MICMAC* analysis quantitatively validates these relationships, not only refining, but also adding precision and robustness to our insights.

Figure 5.1: Methodological sequence of the paper



Source: Elaborated by the author (2025)

5.3.1 Reasoning Behind Choosing Mixed-Method Approach

The first phase of our research comprised a SLR. This approach was strategically adopted to raise the barriers faced by the organisations deploying SIPs. This qualitative methodology allows us to pave a robust theoretical foundation for the next phases. According to Denyer; Tranfield (2009) a SLR is more than just a summary of existing research; it is a crucial process of identifying, evaluating and synthesising relevant studies to address specific research questions. Moreover, it allows achieving reasonable conclusions about what is and what is not known in a determined field of knowledge (SAUNDERS; LEWIS; THORNHILL, 2012). Therefore, the SLR positions our research within the broader field of knowledge by identifying the current state of knowledge on barriers faced by organisations to adopt SIPs. We contend that empirical studies not grounded in a prior SLR risk overlooking existing gaps in literature. So, without such a foundation, research may become decontextualised and less meaningful to the academic field (PISSARDINI et al., 2025).

The second phase of our research was composed of the expert's validation, with broad academic and managerial experience, to refine the constructs raised, confirming the practical relevance of the identified barriers. In this phase, the experts were intentionally chosen, incorporating real-world view, based in their managerial and academical backgrounds. According to Von Soest (2023), it is the most effective way to externalize the implicit knowledge, aligning it with practical contexts of the day to day. Furthermore, Meuser; Nagel (2009) state that experts have unique awareness of their specialised knowledge, helping us to unlock the relationship between barriers without loosing fidelity with practical context.

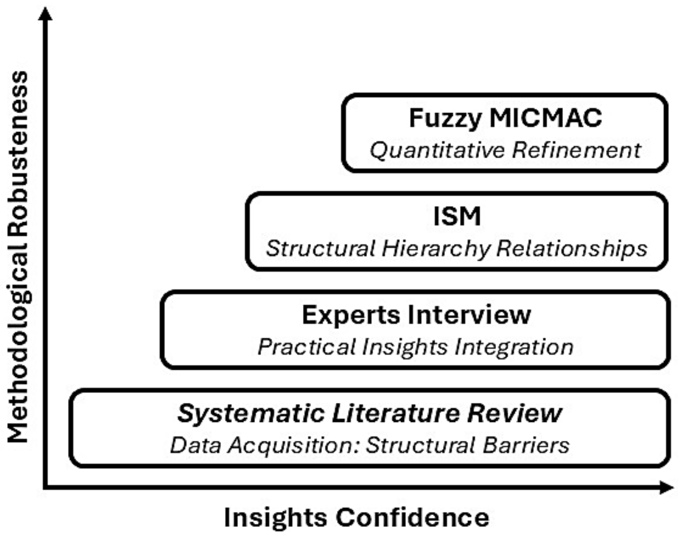
Having consolidated the theoretical and managerial insights on our research, we employed ISM approach to evaluate the hierarchical relationship between barriers. In this phase, the ISM is pivotal as it sheds light in capturing the complex interrelationship among barriers faced by organisations/managers to adopt SIPs. As detailed by Mathiyazhagan et al. (2013), the ISM decompose a complex system into several subsystems. These subsystems allow us to build an initial framework, containing the structural hierarchy relationship. This structural relationship is not only the output of the ISM phase, but also the input to stablish their driving and dependence power in the next phase (MANGLA; KUMAR; BARUA, 2014). This sequential analysis paves the way to analysing the relationship between the barriers, proposing a final framework that will help organisations and managers in guiding efforts to mitigate those barriers that drive others. Although the ISM output is elementary to apply fuzzy *MICMAC*, other limitations of the method support our choice for the *MICMAC* approach. First, ISM relies heavily on expert judgement to establish the relationships among variables, which introduces subjectivity and potential inconsistency in the model. Second, the

ISM approach lacks a quantitative assessment of the degree of influence and dependence between variables, providing only a binary representation of relationships. This weaknesses is also pointed by Bianco et al. (2023). Third, ISM does not allow for testing the stability or robustness of the resulting structural model. The *MICMAC* analysis, in turn, overcomes these limitations by quantifying the strength of interrelationships, verifying the internal consistency of the model, and classifying variables according to their levels of influence and dependence—thus enhancing the overall reliability of the findings.

Finally, the fuzzy *MICMAC* approach is applied to mitigate the weaknesses of the ISM, refining (quantifying) the relationship stablished in the third phase. By using fuzzy logic, the framework addresses uncertainty present in the experts' judgement, due to the binary nature regarding ISM. In addition, the quantitative assessment achieved through the *MICMAC* approach enhances our understanding of the driving, dependent, and linkage factors, thereby strengthening the final strategic framework that will guide managers in directing their efforts towards the implementation of SIPs within organisations. This methodological sequence was strategically adopted to facilitate the transition, from theory towards practice, allowing us to identify, refine, structure and, finally, improve reliability of the final framework, bringing fidelity with the real-world organisational environment.

Figure 5.2 illustrates how each method contributes to enhancing both methodological robustness and the reliability of insights. The process begins with the SLR, which establishes a solid theoretical foundation but offers limited robustness and reliability on its own. The integration of expert interviews substantially strengthens both aspects by grounding the research in practical, directly applicable perspectives. The subsequent application of ISM further enriches the analysis by enabling the identification and visualisation of structural relationships among barriers faced by organisations to adopt SIPs, thereby improving robustness through clear and systematic modelling of interdependencies. Finally, the use of fuzzy *MICMAC* provides quantitative refinement by measuring the degrees of influence and dependence among variables. This step ensures methodological robustness and significantly enhances the reliability of insights, offering a detailed and quantified understanding of the structural barriers' dynamics. Collectively, this methodological sequence builds upon the theoretical foundation while increasing the practical relevance and analytical precision of the results, thereby maximising both robustness and reliability.

Figure 5.2: Methodological robustness and insights confidence of the research



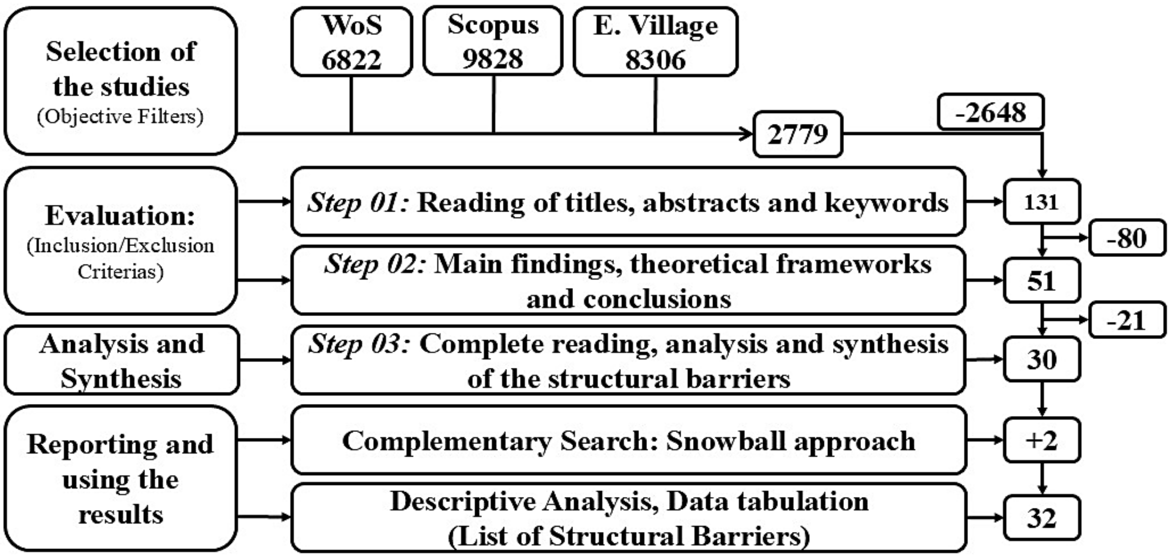
Source: Elaborated by the author (2025)

5.3.2 Systematic Literature Review and Content Analysis

The structural barriers, raised as the output of the first phase (SLR), we adopt the work of Pissardini et al. (2024). In their study, it was presented 23 structural barriers, faced by organisations to adopt SIPs within industrial context. In this regard, we reapply the criterias presented in the research protocol of the above presented authors, to verify if any new structural barriers were identified. This approach was chosen to enhance the reliability concerning structural barriers.

The string presented by Pissardini et al. (2024) was inserted into three databases (Scopus, Web of Science, and Engineering Village), yielding 24,956 papers. Applying objective filters such as language, period, type of papers and, removing duplicates, the final sample consisted of 2,779 papers. Following, guided by the subjective criteria outlined by Pissardini et al. (2024), the titles and abstracts of these papers were read, assessing their alignment with the main objective of our research. From this phase, 131 papers were selected. Subsequently, the introductions, main findings, theoretical frameworks, and conclusions of the remaining papers were examined, resulting in a narrowed selection of 51 papers that were comprehensively analysed. This process led to a final sample of 30 papers citing any structural barriers. Through the snowball approach, two papers were added, resulting in a final sample of 32 papers. After reviewing all 32 selected papers, the same 23 barriers identified by Pissardini et al. (2024) were found. In this regard, it was ensured that the barriers accurately represented the context addressed in this study. Figure 5.3 summarises the screening process.

Figure 5.3: Summary of the screening process



Source: Elaborated by the author (2025)

5.3.3 Experts' Interview

Seeking to ensure reliability, we chose the experts' interview to refine and align the identified barriers with practical insights. Regarding internal consistency, some approaches are commonly used to achieve it such as Cronbach's or even Kkrippendorf's alpha. In our study, however, this index is unsuitable due to the heterogeneous nature of the barriers. Once our target is to individually validate each barrier, we adopt an alternative method also used by Bianco et al. (2023) and Pissardini et al. (2025). In the alternative validation method, the strategy utilised was qualitative. To perform this phase, four academic experts with substantial experience in Operations Management and Industry 4.0 were consulted. This step was critical to ensuring the robustness and reliability of the final list of barriers. The experts were selected following the criteria outlined by Bokrantz et al. (2017), emphasising a balanced combination of expertise in Operations Management and Industry 4.0. Eligibility required participants to have a minimum of ten years of professional experience in the field. A non-probabilistic, purposive sampling strategy was employed, which is a well-established approach in expert panel research Bianco et al. (2023); Pissardini et al. (2025). Detailed information regarding the experts' profiles is presented in Table 5.1.

Table 5.1: Summary of experts' profile of validation phase

Expert	Position	Academic education	Experience in operations management context
1	Researcher	PhD in Production Engineering	24 years
2	Researcher	PhD in Production Engineering	17 years
3	Researcher	PhD in Production Engineering	15 years
4	Researcher	PhD in Production Engineering	19 years

Source: Elaborated by the author (2025)

To enhance the validity of the qualitative data and mitigate potential issues of inter-rater reliability, a consensus-oriented, iterative procedure was implemented. Each expert initially reviewed the relevance of the identified barriers independently, after which any divergent opinions were reconciled through structured rounds of feedback and discussions, in line with recognised qualitative validation practices (MEUSER; NAGEL, 2009; VON SOEST, 2023). In contrast to studies that employ predefined coding frameworks and quantitative reliability indicators, such as Krippendorff's Alpha (MARZI; BALZANO; MARCHIORI, 2024), the validation process we adopted was qualitative and iterative in nature. Rather than providing fixed scores or categorical assessments, experts participated in a dynamic exchange aimed at refining and clarifying the barriers. Consequently, the use of Krippendorff's alpha was deemed inappropriate, as this metric presupposes independent coding, whereas the present approach was designed to achieve collective agreement rather than to measure statistical consistency. In summary, the four-step cycle, adapted from Saunders; Lewis; Thornhill (2012), consisted of: (i) presenting the initial list to each expert for evaluation; (ii) presenting the clustered list of barriers; (iii) collecting and integrating suggestions into the final list; and (iv) presenting the revised list again for validation or further input. If new suggestions were incorporated, the process returned to step three.

Four semi-structured interviews were conducted, each lasting approximately 50 minutes, during which experts were asked to assess the validity and clarity of the identified barriers, as well as their relevance to real manufacturing contexts. The discussions were recorded, and the feedback was consolidated for further analysis. After each interview, the list of barriers was refined according to the experts' suggestions. This iterative process resulted in a final set of 23 structural barriers hindering the adoption of SIPs in manufacturing. The cyclical nature of the expert validation process underpins the methodological robustness of this study. Through continuous refinement and alignment with expert insights, the findings were ensured to be both practically grounded and academically sound, thereby enhancing the precision of the identified barriers and the reliability of the conclusions drawn.

5.3.4 Interpretive Structural Modelling

To perform the ISM approach, we follow the four steps proposed by Farris; Sage (1975); Wang et al. (2024); Warfield (1974). Each step is detailed in the following four subsections.

5.3.4.1 Structural Self Interaction Matrix

The first phase of the ISM approach comprised the construction of the SSIM matrix. To perform SSIM, the opinions of each expert was accounted, serving as a basis to calculate the “Mode” (Most frequently assigned value for each pair of variables). Concerning the number of experts, according to Saunders; Lewis; Thornhill (2012) the more complex the subject matter, the fewer interviewees. The main characteristics of the experts chosen to contribute to filling the ISM matrix are presented in Table 5.2. In agreement with Von Soest (2023), the final sample was composed of experts from both theory and practice. The research team consulted comprised 10 researchers with broad academic knowledge, and 4 of them were involved with SIPs daily in leading companies within their respective fields.

Table 5.2: Summary of experts’ profile of ISM questionnaire

Position		**Academic background**		**SIP’s / OM Experience**	
Researcher	10	PhD Industrial / Mechanical Engineering	10	< 10 years	0
Operations Manager	4	Postgraduate Degree	1	10 – 20 years	14
		Bachelor of Engineering	3	> 20 years	0

Source: Elaborated by the author (2025)

Following the ISM theory, each expert completed a matrix using the four symbols:

a) When variable *i* influences variable *j*, the cell is assigned the symbol V;

b) When variable *j* influences variable *i*, the cell is assigned with A;

c) When both variables (*i* and *j*) influence each other, the cell is assigned with X;

d) When there is no influence between the two variables, the cell is assigned with O.

5.3.4.2 Developing Initial and Final Reachability Matrix

In the second step of the ISM approach, we developed the IRM and FRM. To transform the SSIM into the IRM, we just replaced the four variables with 0s and 1s, according to the following rules:

a) If the value at position (*i*,*j*) in the SSIM is V, the entry at (*i*,*j*) in the IRM is set to 1, and the entry at (*j*,*i*) is set to 0;

b) If the value at position (*i*,*j*) in the SSIM is A, the entry at (*i*,*j*) in the IRM is set to 0, and the entry at (*j*,*i*) is set to 1;

c) If the value at position (*i*,*j*) in the SSIM is X, both the entries at (*i*,*j*) and (*j*,*i*) in the IRM are set to 1;

d) If the value at position (*i*,*j*) in the SSIM is O, both the entries at (*i*,*j*) and (*j*,*i*) in the IRM are set to 0;

After binarising the IRM matrix, we considered the transitivity to define the Final Reachability Matrix (FRM). Transitivity in relationships implies that if S_i influences S_j and S_j influences S_k, then it follows that S_i also influences S_k. Thus, we derived final directional digraph, with the transitivity links, from the triangular structure of the reachability matrix. In practice, to perform this step, we fill all the (*i, j*) cells that contain value “1” in the IRM with “1” in the FRM. Thus, we identify all (*i, j*) cells in the IRM matrix that contain the value "0". For each of these cells, we examine the corresponding row and column in which the "0" appears. If a given column cell contains the value "1" (e.g., cell 5), and the same position in the corresponding row (i.e., position 5) also contains a "1", we replace the "0" with "1*" (directly in the FRM matrix), indicating that transitivity is assumed at that position. This procedure is repeated for every "0" found in the matrix.

5.3.4.3 Performing Level Partition

To perform level partitions, we consider the FRM data as input. Thus, we build a table with 5 columns (“Variable”, “Reachability”, “Antecedent” “Intersection” “Level”. Initially, all variables (BA1 to BA23) are listed in the first column. In the second column (Reachability), only the row associated with the variable under analysis is examined. All positions (*i*,*j*) in which the corresponding cell contains the value “1 or 1*” are recorded, indicating the elements that are directly reachable from the variable in question. The third column (Antecedent) is constructed using an analogous procedure; however, in this case, the focus is on the column associated with the variable. All positions where the column contains the value “1” are registered, representing variables that have a direct influence on the variable under analysis. The fourth column (Intersection) captures the common elements between the Reachability and Antecedent sets. That is, it contains all positions that simultaneously appear in both the second and third columns. Finally, to define the fifth column (Level), a comparison is made between the Reachability and Intersection sets for each variable. When both sets are identical, it indicates that the variable does not facilitate the reachability of any other variable beyond those that influence it. As a result, such variables are assigned to Level I and subsequently removed from the matrix. This process is then iteratively repeated for the remaining variables. In each iteration, variables whose Reachability and Intersection sets remain equal are assigned to the next hierarchical level (e.g., Level II, Level III, etc.) and removed accordingly. The iteration continues until all variables have been assigned a level and the system is completely decomposed. Therefore, the level partition serves as a foundation for constructing the ISM model, as it enables the organisation of barriers with equivalent reachability and intersection levels into corresponding tiers within the matrix, thereby establishing the basis for the structural hierarchy.

5.3.4.4 ISM-Based Matrix

The ISM model was constructed based on the initial FRM framework. Variables identified at the highest hierarchical level were positioned at the top of the digraph, followed sequentially by the remaining levels, ensuring a structured placement of all variables. Upon the elimination of transitive links, the final ISM model was established.

The ISM model was developed based on the FRM. The variables at the top level were positioned at the upper part of the digraph, with subsequent levels arranged below in order, until all variables were appropriately placed. After removing any transitive connections, the ISM model was completed.

Throughout the ISM process, we employed robust validation techniques to ensure reliability. For example, using a panel of experts with diverse backgrounds ensures a comprehensive evaluation of relationships. Moreover, the structured process of deriving the reachability matrix and hierarchical levels adheres to established ISM practices, further reinforcing methodological rigour.

5.3.5 Fuzzy *MICMAC*

As ISM, the *MICMAC* approach is also composed of 4 steps, which will be detailed in the next subsections.

5.3.5.1 Performing Binary Direct Reachability Matrix

To build the BDRM matrix, we should replace all diagonal entries of the IRM with “0s”. This procedure is designed to reinforce the interactions between barriers, which will be represented by fuzzy values in the next step.

5.3.5.2 ISM-Based Matrix

After replacing all entries in the main diagonal with “0s”, the BDRM is used as input to perform the FDRM. In this step, we apply fuzzification (replacing all cells filled with value “1” in the FDRM by a value that is associated with the number of experts that agreed that barrier i influences barrier j. This process uses five linguistic terms, as defined in Table 5.3, along with the corresponding assignment rules to establish the fuzzy relationships.

Table 5.3: Fuzzy scale and assignment criteria for assessing the strength of relationships

Relationship Strength	Assigned Value	Number of Experts Agreeing that Barrier *i* Impacts Barrier *j*
No	0	0 to 2 experts agree
Weak	0,25	3 to 5 experts agree
Medium	0,50	6 to 8 experts agree
Strong	0,75	9 to 11 experts agree
Very Strong	1	12 or above experts agree

Source: Elaborated by the author (2025)

5.3.5.3 Calculating the Fuzzy *MICMAC* Stabilised Matrix

To realise the third step, we applied an iterative procedure to the initial matrices, seeking to stabilise it. Stabilisation is achieved by multiplying the FDRM by itself until the row sums (driving power) and column sums (dependence power) no longer change. According to Mota et al. (2021) several fuzzy composition methods can be employed to assess the strength of the indirect fuzzy relationship between variables i and j. In our study, we chose the max-min operator as the most appropriate method because the minimum value reflects the strongest of all possible minimal influences from variable i to variable j. The matrix multiplication process followed the rule outlined below, resulting in the stabilised fuzzy *MICMAC* matrix:

$$Z = X \,.\, Y = max_k \left[\min\left(X_{ik}\,, Y_{kj}\right)\right] \tag{4}$$

Where X = $[X_{ik}]$ and Y = $[Y_{kj}]$

To realise the stabilisation, given a matrix Z_{ij}, the element $Z_{1,1}$ of the resulting matrix, can be calculated using the following expression $Z_{ij} = Max_k \left[Min\left(X_{ik}, Y_{kj}\right)\right]$. Therefore, for each Z_{ij} cell the process involves two steps: Identify the minimum of each pair of corresponding elements, across row i and column j (e.g.: $Z_{1,2}$ e $Z_{2,1}$). After selecting the minima value between each pair of variables, the maximum among these minimum values is chosen. The resulting value is then assigned to the respective cell of the matrix. This process is iteratively applied, crossing each row with all columns. If the resulting matrix differs from the previous one, the iteration continues. Stabilisation is achieved when two successive iterations yield identical matrices.

5.3.5.4 The Four-Cluster Diagram: A Necessary Step to Refine the Model

In the fourth and last phase, we built a visual representation of the variables in 4 categories: autonomous, dependent, linkage, and driving. The input for this phase was the fuzzy stabilised matriz. To visually represent the fuzzy *MICMAC* results, we sum all the values of a row for each variable. The total is the position of the variable in the Driving axis. Executing the same process for each cell that composes a column, for each variable, the total value is the position of the variable in the Dependence axis.

Although fuzzy *MICMAC* analysis relies on expert-derived judgements, strict methodological procedures were implemented to minimise potential bias and enhance data reliability. Specifically, linguistic scales and fuzzification techniques were applied to systematically represent the uncertainty and variability inherent in expert evaluations. Furthermore, the iterative stabilisation of the fuzzy matrix and the subsequent four-cluster classification ensured that the final results were both mathematically robust and practically meaningful. Moreover, the “autonomous” category also contributes to methodological robustness. When a variable is positioned within this category, it exhibits weak causal linkages within the system. Their presence may indicate either an external factor that can be excluded from the model or a potential issue requiring further evaluation.

5.4 RESULTS

5.4.1 Conceptualising Structural Barriers to SIPs Adoption

Table 5.4 shows the outcome of the SLR and expert opinion steps. Our final list comprises 23 structural barriers faced by organisations to adopt SIPs, answering RQ1.

5.4.2 ISM Results

Continuing with the presentation of results, the following subsections outline the outcomes of each stage described in the methodology (Sections 5.3.4.1 to 5.3.4.4). Table 5.5 presents the mode of expert assessments for each pair of structural barriers. The SSIM was subsequently transformed into an initial binary matrix (Table 5.6), from which the FRM was derived. The transition from the IRM to the FRM incorporated the transitivity principle, resulting in the matrix displayed in Table 5.7. Furthermore, Tables 5.8a to 5.8c provides the reachability, antecedent, and intersection sets corresponding to each barrier identified in the SLR, serving as inputs for constructing the ISM-based model. Finally, the structural model produced (Figure 5.4), illustrates the structural relationship hierarchy of the 23 structural barriers across three levels, laying the groundwork for the ensuing discussion and *MICMAC* analysis.

Table 5.4 - Barriers faced by organisations in implementing SIPs

Barriers	Code	Description	References
Communication difficulties	BA1	Refers to communication difficulties at vertical levels (between organisational tiers, from control to planning), and horizontal levels (across the supply chain, from suppliers to customers)	1, 2, 3, 4, 5, 9, 11, 12, 17, 18, 20, 21, 22, 29, 32
Vulnerability in data security	BA2	Refers to the high vulnerability in the evolving IoT landscape, where data collected, its sharing, and potential manipulation across all levels (horizontal and vertical) are crucial factors for organisations adopting an SIP	1, 3, 5, 7, 8, 9, 10, 12, 13, 16, 17, 18, 20, 21, 27
Decreased planning efficiency when control is decentralised	BA3	Decentralising production control improves system robustness but reduces efficiency, as decentralised systems respond slower to unexpected events like machine failures or disruptions	2, 15, 31
Difficulties in integrating many different SIP	BA4	Refers to the way to operationalise IoT, allowing many systems with many components, built under different protocols, to work harmonically, adapting to the world's physical changes	3, 23, 29, 32
Difficulties in aligning old industrial technologies with the implementation of a new SIP	BA5	Refers to the coexistence of new and old technologies, mainly in areas where transformation processes are evolutionary and not revolutionary (e.g. medicine)	4, 10, 12, 18, 20, 30
Lack of technological maturity	BA6	Many building blocks for supporting product intelligence are either in place or under development. Deployment on an industrial scale can also be considered within this barrier	4, 32
Full adoption difficulties/lack of system stability (operational practicality and decision execution)	BA7	Initial deployments are likely to be partial rather than full deployments. In the case of full deployment, the complete stability of the entire system also needs to be considered	4
Contractual and revenue-sharing challenges	BA8	Most companies fear having their ideas/confidential information leaked, prefering to compete individually	4, 10, 14, 19, 20
Social, psychological, and cultural individualistic behaviour barriers	BA9	Refers to resistance to process change, especially if the process is deeply rooted in the organisation, including fears around sharing knowledge and ideas	4, 18, 19, 20
Lack of technical and economic feasibility in the early stage of utilisation	BA10	Feasibility refers to the likelihood of success or reasonableness of a project and, in early SIP data use, measures its technical and economic viability	4, 17, 19, 21, 29, 32
Complicated system introduction or even its affinity with already existing business systems	BA11	Integrating an SIP with business systems requires procurement and deployment, with potential failures due to OS and browser differences	5, 9, 29
Tracking technology is a key challenge in turning abundant operational data into accurate, timely control decisions	BA12	The belief that tracking technology alone improves operational control can be misleading; without tools like big data and analytics, managing and identifying patterns in large data volumes is impossible	6, 32
Lack of infrastructure (networks or low latency), in some industrial regions where	BA13	Refers to the lack of network and multi-layer infrastructure required for new entrants in the market or not being available in the region where an organisation is set up	7, 12, 16, 19, 20, 27, 29, 30

industries are based			
Uncertainty about ROI, payback, high costs and investments to (internally) develop an SIP	BA14	Uncertainty about ROI and payback is critical; investment is justified only if returns exceed the short product life cycle, considering costs like time and specialised labour	4, 8, 16, 17, 18, 20, 21
Self-adaptation difficulties among the SIP and its environment (plug-and-play technologies)	BA15	Refers to a product's inability to recognise process standards or usage patterns and self-adapt, which technologies like Big Data and Analytics can enable. SIPs must work seamlessly with various technologies without installation or upgrades	9, 29
High energy consumption	BA16	The energy consumption of the SIP is proportional to the complexity of the operation it performs, and not all the products can store energy, requiring other technologies to capture it	1, 9, 22, 27, 29
Risk of bad event propagation	BA17	The product can replicate learning from both positive and negative events	9, 27
High complexity of management	BA18	The complexity of the product/service can directly influence the management tasks, the way it interacts with the good being produced, with the other agents of the process, and with its ecosystem	9, 22, 24
Lack of security and trust in using data	BA19	Refers to the trustworthiness of the SIP's decisions, including cloud usage and confidence in data from competitor's products inaccessible to the organisation	9
High complexity of system management due to the increase in the number of agents used	BA20	Refers to difficulties related to the infrastructure robustness required when the number of agents (e.g. tags RFID, sensors) acting in a determined environment (and even outside it) significantly increases	12, 23, 24, 30
Cost strategy is not aligned to innovative SIP solutions	BA21	High focus on cost reduction and not on aggregate value for itself and its customers	20, 29, 30
Cyber-attack vulnerability	BA22	The high level of network connectivity dependence can bring new cyber-attack threats	25, 26
Lack of adequate computational resources	BA23	Refers to insufficient computational power, battery, storage, and I/O bandwidth to host and manage IoT applications and services	22, 27, 28, 29

Source: Elaborated by the author (2025)

Notes: 1. Atzori et al. (2010); 2. Meyer et al. (2009); 3. Meyer et al. (2011); 4. McFarlane et al. (2013); 5. Takahara & Yasaki (2013); 6. Meyer et al. (2014); 7. Porter & Heppelmann (2014); 8. Hernández & Reiff-Marganiec (2014); 9. Leitão et al. (2015); 10. Porter & Heppelmann (2015); 11. Dawid et al. (2017); 12. Abramovici et al. (2017); 13. Ding & Jiang (2018); 14. Silverio-Fernández et al. (2018); 15. Sorouri & Vyatkin (2018); 16. Juric & Lindenmeier (2019); 17. Keshavarzi & Van Den Hoek (2019); 18. Tomiyama et al. (2019); 19. Zhang et al. (2020); 20. Kahle et al. (2020); 21. Lenz et al. (2020); 22. Hungud & Arunachalam (2020); 23. Yi et al. (2021); 24. Vendrell-Herrero et al. (2021); 25. Ruhul Amin et al. (2021); 26. Rathee et al. (2021); 27. Lin et al. (2021); 28. Thürer et al. (2021); 29. Imad et al. (2022); 30. Oluyisola et al. (2022); 31. Antons & Arlinghaus (2022); 32. (LIU; ZHENG; XU, 2023);

5.4.2.1 Structural Self-Interaction Matrix

Table 5.5 – Structural Self-Interaction Matrix

	B23	B22	B21	B20	B19	B18	B17	B16	B15	B14	B13	B12	B11	B10	B09	B08	B07	B06	B05	B04	B03	B02	B01
B01	A	V	A	A	V	A	A	O	V	V	A	V	A	O	A	O	A	A	A	X	X	O	
B02	A	X	O	A	X	A	V	V	A	O	A	V	V	A	A	X	O	A	A	X	A		
B03	A	A	V	A	A	A	O	O	A	V	A	V	A	A	V	O	V	V	V	A			
B04	A	V	A	X	X	A	V	V	X	V	A	V	X	A	V	A	V	A	A				
B05	A	X	A	X	X	A	V	V	X	V	A	V	V	O	O	V	X	A					
B06	A	V	A	V	V	V	V	V	V	V	X	V	V	V	V	O	V						
B07	A	V	A	A	V	X	V	V	A	V	A	V	V	A	A	O							
B08	O	A	O	O	A	A	O	O	O	A	A	A	O	A	O								
B09	O	O	O	A	A	X	O	O	V	V	O	O	V	A									
B10	V	V	X	A	X	A	V	A	X	V	V	V	V										
B11	A	V	O	X	X	X	V	A	X	V	A	V											
B12	O	O	O	O	A	A	O	O	X	V	A												
B13	V	V	A	A	V	V	V	V	V	V													
B14	V	A	X	O	O	A	A	A	O														
B15	A	V	O	A	O	X	V	O															
B16	A	O	V	A	O	O	O																
B17	A	X	A	V	A	A																	
B18	V	X	A	X	V																		
B19	A	X	A	O																			
B20	A	V	O																				
B21	V	O																					
B22	A																						
B23																							

Source: Elaborated by the author (2025)

5.4.2.2 Initial Reachability Matrix

Table 5.6 – Initial Reachability Matrix

	B01	B02	B03	B04	B05	B06	B07	B08	B09	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23
B01	1	0	1	1	0	0	0	0	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0
B02	1	1	0	1	0	0	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	1	0
B03	0	1	1	0	1	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0
B04	0	0	1	1	0	0	1	0	1	0	1	1	0	1	1	1	1	0	1	1	0	1	0
B05	1	1	0	1	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	0	1	0
B06	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
B07	1	1	0	0	0	0	1	0	0	0	1	1	0	1	0	1	1	1	1	0	0	1	0
B08	1	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B09	1	1	0	0	1	0	1	1	1	0	1	0	0	1	1	0	0	1	0	0	0	0	0
B10	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1
B11	1	0	1	0	0	0	0	1	0	0	1	1	0	1	1	0	1	1	1	1	0	1	0
B12	0	0	0	0	0	0	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0
B13	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1	1
B14	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
B15	0	1	1	0	0	0	1	1	0	0	0	0	0	1	1	0	1	1	0	0	0	1	0
B16	1	0	1	0	0	0	0	1	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0
B17	1	0	1	0	0	0	0	1	1	0	0	1	0	1	0	1	1	0	0	1	0	1	0
B18	1	1	1	1	1	0	0	1	0	1	0	1	0	1	0	1	1	1	1	1	0	1	1
B19	0	0	1	0	0	0	0	1	1	0	0	1	0	1	1	1	1	0	1	0	0	1	0
B20	1	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	1	0
B21	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1	0	1	1	1	1	1	0	1
B22	0	0	1	0	0	0	0	1	1	0	0	1	0	1	0	1	0	0	0	0	1	1	0
B23	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	0	1	1

Source: Elaborated by the author (2025)

5.4.2.3 Final Reachability Matrix

Table 5.7 – Final Reachability Matrix

	B01	B02	B03	B04	B05	B06	B07	B08	B09	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23
B01	1	1*	1	1	1*	1*	1*	1*	1*	0	1*	1	0	1	1	1*	1*	1*	1	1*	1*	1	1*
B02	1	1	1*	1	0	1*	1*	1	1*	1*	1	1	0	1*	1*	1	1	1*	1	1*	1*	1	0
B03	1*	1	1	1*	1	1	1	1*	1	1*	1*	1	1*	1	1*	1*	1*	1*	1*	1*	1	1*	1*
B04	1*	1*	1	1	1*	1*	1	1*	1	1*	1	1	1*	1	1	1	1	1*	1	1	1*	1	1*
B05	1	1	1*	1	1	1*	1	1	1*	1*	1	1	1*	1	1	1	1	1*	1	1	1*	1	1*
B06	1	1	1*	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1*
B07	1	1	1*	1*	1*	0	1	1*	1*	1*	1	1	0	1	1*	1	1	1	1	1*	1*	1	1*
B08	1	1*	1	1	1*	1	1	1	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	0
B09	1	1	1*	1*	1	1*	1	1	1	1*	1	1*	0	1	1	1*	1*	1	1*	1*	1*	1*	1*
B10	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1*	1	1*	1	1*	1	1	1
B11	1	1*	1	1*	1*	1*	1*	1	1*	1*	1	1	1*	1	1	1*	1	1	1	1	1*	1	1*
B12	1*	1*	1*	1*	1*	1*	1*	1	1	0	1	1	0	1	1	0	1*	1*	0	0	1*	1*	1*
B13	1	1	1	1	1	1*	1	1	1	1*	1	1	1	1	1	1	1	1	1	1*	1*	1	1
B14	1*	1	1*	1*	1*	1*	1*	1	1*	0	1*	1*	1*	1	1*	1*	1*	1*	1*	1*	1	1*	1
B15	1*	1	1	1*	1*	1*	1	1	1*	1*	1*	1*	0	1	1	1*	1	1	1*	1*	1*	1	1*
B16	1	1*	1	1*	1*	1*	1*	1	1	1	1	1	1*	1	1	1	1*	1*	1*	1*	1	1*	1*
B17	1	1*	1	1*	1*	1*	1*	1	1	1*	1*	1	1*	1	1*	1	1	1*	1*	1	1*	1	1*
B18	1	1	1	1	1	1*	1*	1	1*	1	1*	1	1*	1	1*	1	1	1	1	1	1*	1	1
B19	1*	1*	1	1*	1*	1*	1*	1	1	1*	1*	1	0	1	1	1	1	1*	1	1*	1*	1	1*
B20	1	1	1	1*	1*	1*	1	1	1	1	1*	1	1	1	1	1	1*	1*	1	1	1*	1	1*
B21	1	1	1*	1	1	1	1	1	1	1*	1	1	1	1*	1	1*	1	1	1	1	1	1*	1
B22	1*	1*	1	1*	1*	1*	1*	1	1	1*	1*	1	1*	1	1*	1	1*	1*	1*	1*	1	1	1*
B23	1	1	1	1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1*	1	1	1*	1	1

Source: Elaborated by the author (2025)

5.4.2.4 Level Partition Matrix

Table 5.8a – Level-Partition Matrix (First Partition)

Barrier	Reachability Set	Antecedent Set	Intersection Set	Level
BA1	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA2	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 20, 21, 22	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22	I
BA3	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA4	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA5	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA6	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA7	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA8	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22	I
BA9	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15, 16, 17, 18, 19, 20, 21, 22, 23	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA12	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 17, 18, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 17, 18, 21, 22, 23	I
BA13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	3, 4, 5, 6, 8, 10, 11, 13, 14, 16, 17, 18, 20, 21, 22, 23	3, 4, 5, 6, 8, 10, 11, 13, 14, 16, 17, 18, 20, 21, 22, 23	-
BA14	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA16	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA17	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA18	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA19	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA20	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-
BA21	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA22	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	I
BA23	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	1, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	-

Source: Elaborated by the author (2025)

Table 5.8b – Level-Partition Matrix (Second Partition)

Barrier	Reachability Set	Antecedent Set	Intersection Set	Level
BA5	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II
BA6	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II
BA10	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II
BA13	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 20, 23	5, 6, 10, 13, 16, 20, 23	-
BA16	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II
BA19	5, 6, 10, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 16, 19, 20, 23	II
BA20	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II
BA23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 19, 20, 23	II

Source: Elaborated by the author (2025)

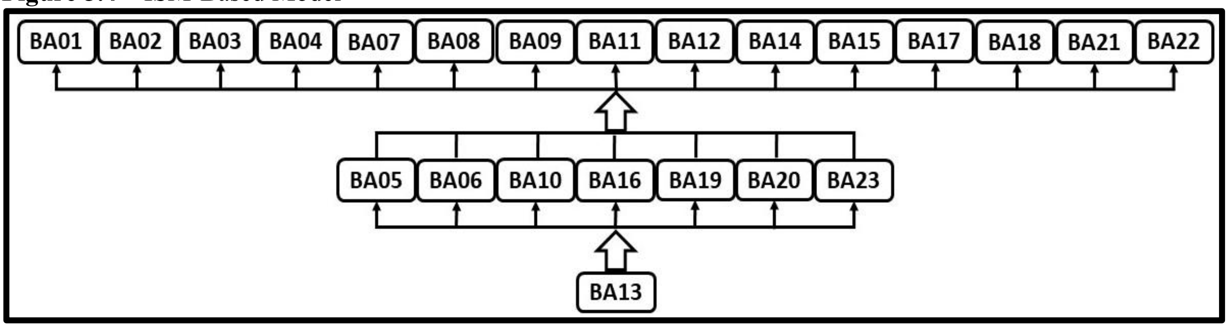
Table 5.8c – Level-Partition Matrix (Third Partition)

Barrier	Reachability Set	Antecedent Set	Intersection Set	Level
BA13	5, 6, 10, 13, 16, 19, 20, 23	5, 6, 10, 13, 16, 20, 23	5, 6, 10, 13, 16, 20, 23	III

Source: Elaborated by the author (2025)

5.4.2.5 ISM-Based Model Derivation

Figure 5.4 – ISM-Based Model



Source: Elaborated by the author (2025)

5.4.3 Fuzzy *MICMAC* Results

The last step of our analysis comprises the presentation of results related to the fuzzy *MICMAC*. The following subsections (5.4.3.1 to 5.4.3.4) outline the outputs of each step of the *MICMAC* approach, described in the methodology (Sections 5.3.5.1 to 5.3.5.4).

The Fuzzy *MICMAC* analysis begins with the BDRM matrix, as outlined in Table 5.9. In the following, to construct the FDRM matrix (Table 5.10), we utilised the characteristic values determined by the number of experts (Table 5.3) who assigned the symbols V, A, X, or O in the SSIM matrix (Table 5.5). Subsequently, this process led to the development of the stabilised Fuzzy *MICMAC* matrix, presented in Table 5.11. The four-cluster diagram in Figure 5.5 illustrates the interrelationships between the structural barriers identified in the literature, highlighting both their driving and dependent characteristics.

5.4.3.1 Binary Direct Reachability Matrix (BDRM)

Table 5.9 – Binary Direct Reachability Matrix

	B01	B02	B03	B04	B05	B06	B07	B08	B09	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23
B01	0	0	1	1	0	0	0	0	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0
B02	1	0	0	1	0	0	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	1	0
B03	0	1	0	0	1	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0
B04	0	0	1	0	0	0	1	0	1	0	1	1	0	1	1	1	1	0	1	1	0	1	0
B05	1	1	0	1	0	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	0	1	0
B06	1	1	0	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
B07	1	1	0	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	0	0	1	0
B08	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B09	1	1	0	0	1	0	1	1	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0
B10	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1
B11	1	0	1	0	0	0	0	1	0	0	0	1	0	1	1	0	1	1	1	1	0	1	0
B12	0	0	0	0	0	0	0	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0
B13	1	1	1	1	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	0	1	1
B14	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
B15	0	1	1	0	0	0	1	1	0	0	0	0	0	1	0	0	1	1	0	0	0	1	0
B16	1	0	1	0	0	0	0	1	1	1	1	1	0	1	1	0	0	0	0	0	1	0	0
B17	1	0	1	0	0	0	0	1	1	0	0	1	0	1	0	1	0	0	0	1	0	1	0
B18	1	1	1	1	1	0	0	1	0	1	0	1	0	1	0	1	1	0	1	1	0	1	1
B19	0	0	1	0	0	0	0	1	1	0	0	1	0	1	1	1	1	0	0	0	0	1	0
B20	1	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0	1	0
B21	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1	0	1	1	1	1	0	0	1
B22	0	0	1	0	0	0	0	1	1	0	0	1	0	1	0	1	0	0	0	0	1	0	0
B23	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	0	1	0

Source: Elaborated by the author (2025)

5.4.3.2 Fuzzy Direct Reachability Matrix (FDRM)

Table 5.10 – Fuzzy Direct Reachability Matrix

	B01	B02	B03	B04	B05	B06	B07	B08	B09	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23
B01	0	0	0,5	0,5	0	0	0	0	0	0	0	0,25	0	0,5	0,25	0	0	0	0,25	0	0	0,5	0
B02	0,5	0	0	0,5	0	0	0	0,5	0	0	0,5	0,25	0	0	0	0,5	0,5	0	0,75	0	0	1	0
B03	0	0,5	0	0	0,75	0,5	0,5	0	0,5	0	0	0,75	0	0,5	0	0	0	0	0	0	0,25	0	0
B04	0	0	0,25	0	0	0	0,5	0	0,5	0	0,25	0,5	0	0,5	0,25	0,5	0,75	0	0,5	0,5	0	0,5	0
B05	0,5	0,5	0	0,5	0	0	0,5	0,5	0	0	0,5	0,5	0	0,5	0,75	0,5	0,5	0	0,25	0,5	0	0,5	0
B06	0,5	0,75	0	0,5	0,5	0	0,5	0	0,5	0,5	1	0,75	0,5	0,5	0,75	0,75	0,75	0,75	0,75	0,5	0	0,75	0
B07	0,5	0,25	0	0	0	0	0	0	0	0	0,75	0,5	0	0,5	0	0,5	0,5	0,5	0,25	0	0	0,5	0
B08	0,5	0	0,5	0,5	0	0,5	0,75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B09	0,75	0,25	0	0	0,5	0	0,5	0,5	0	0	0,25	0	0	0,75	0,5	0	0	0	0	0	0	0	0
B10	0,5	0,5	0,5	0,75	0,5	0	0,5	0,5	0,5	0	0,75	0,5	0,75	0,5	0,25	0	0,25	0	0,5	0	0,5	0,75	0,5
B11	0,75	0	0,5	0	0	0	0	0,5	0	0	0	0,5	0	0,5	0,5	0	0,75	0,5	0,25	0,5	0	0,75	0
B12	0	0	0	0	0	0	0	0,75	0,75	0	0	0	0	0,5	0,25	0	0	0	0	0	0	0	0
B13	0,75	0,75	0,75	0,75	0,75	0	0,75	0,75	0,5	0	0,75	0,75	0	0,5	0,5	0,5	0,75	0,5	0,25	0	0	0,75	0,5
B14	0	0,5	0	0	0	0	0	0,5	0	0	0	0	0	0	0	0	0	0	0	0	0,5	0	0,5
B15	0	0,5	0,5	0	0	0	0,5	0,75	0	0	0	0	0	0,5	0	0	0,5	0,25	0	0	0	0,5	0
B16	0,75	0	0,75	0	0	0	0	0,75	0,75	0,75	0,5	0,5	0	0,75	0,75	0	0	0	0	0	0,25	0	0
B17	0,25	0	0,5	0	0	0	0	0,5	0,5	0	0	0,5	0	0,5	0	0,5	0	0	0	0,5	0	0,5	0
B18	0,5	0,5	0,5	0,5	0,5	0	0	0,5	0	0,75	0	0,75	0	0,75	0	0,5	0,5	0	0,5	0,5	0	0,25	0,5
B19	0	0	0,5	0	0	0	0	0,75	0,25	0	0	0,5	0	0,5	0,5	0,75	0,5	0	0	0	0	0,5	0
B20	0,5	0,5	0,5	0	0	0	0,5	0,5	0,5	0,5	0	0,5	0,5	0,5	0,5	0,5	0	0	0,5	0	0	0,5	0
B21	0,25	0,5	0	0,5	0,75	0,5	0,5	0,5	0,5	0	0,5	0,5	0,75	0	0,25	0	0,5	0,5	0,5	0,5	0	0	0,75
B22	0	0	0,5	0	0	0	0	0,5	0,5	0	0	0,5	0	0,75	0	0,75	0	0	0	0	0,5	0	0
B23	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,75	0,5	0	0,5	0,5	0	0	0,5	0,5	0,75	0	0,75	0,5	0	0,75	0

Source: Elaborated by the author (2025)

5.4.3.3 Fuzzy Stabilised Matrix

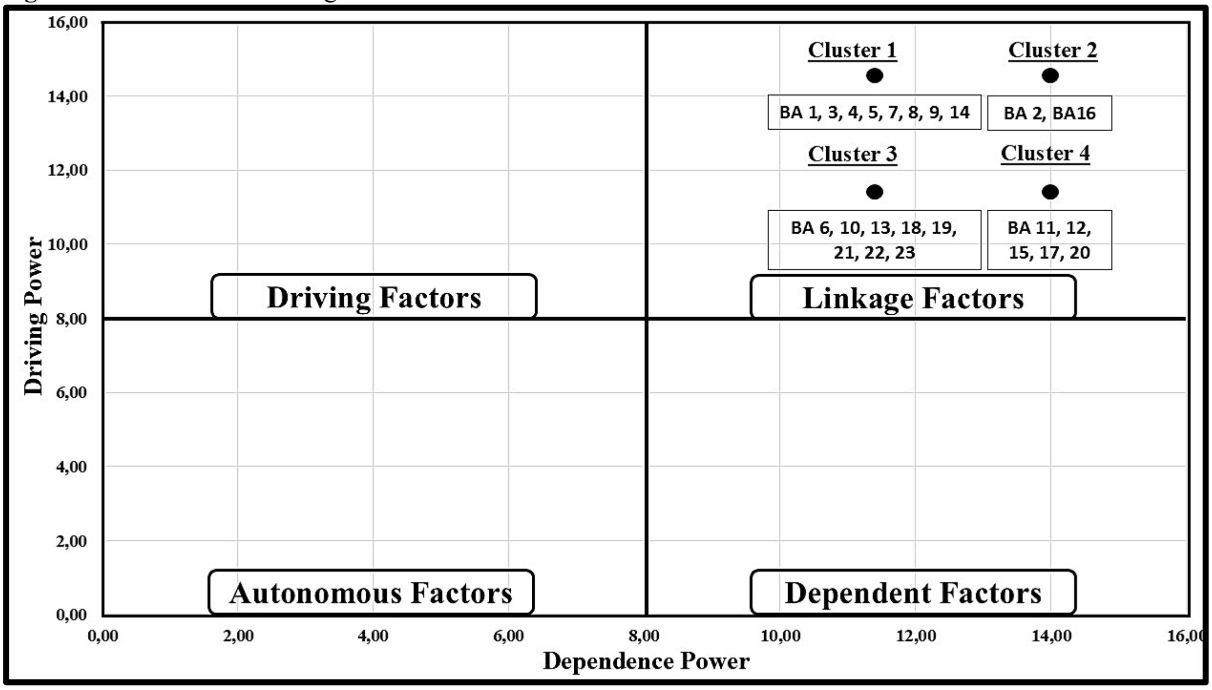
Table 5.11 – Fuzzy Stabilised Matrix

	B01	B02	B03	B04	B05	B06	B07	B08	B09	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23
B01	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B02	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B03	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B04	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B05	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B06	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B07	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B08	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B09	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B10	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B11	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B12	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B13	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B14	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B15	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B16	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B17	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B18	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B19	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B20	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B21	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B22	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5
B23	0,75	0,75	0,75	0,75	0,75	0,5	0,75	0,75	0,75	0,5	0,5	0,5	0,5	0,75	0,5	0,75	0,5	0,5	0,5	0,5	0,5	0,5	0,5

Source: Elaborated by the author (2025)

5.4.3.4 Four-Cluster Diagram

Figure 5.5 – Four-Cluster Diagram



Source: Elaborated by the author (2025)

Figure 5.5 summarises the twenty-three barriers faced by organisations in adopting SIPs, grouped into four clusters within the linkage quadrant. The concentration of all barriers in this quadrant indicates a non-stabilised system, a condition typically observed in complex organisational innovation contexts such as SIP adoption. Although the interrelationships among the barriers are intricate, the emergence of four subgroups reveals the presence of relatively cohesive internal substructures. These substructures act as compensatory mechanisms of local stability, where certain barriers become self-reinforcing while simultaneously maintaining external dependencies. Together, the ISM and Fuzzy *MICMAC* analyses provide a comprehensive understanding of these interdependencies, contributing to the explanation of RQ2.

5.5 INFLUENCED-BASED HIERARCHY OF BARRIERS TO SIPs' ADOPTION

The integrated analysis of the four clusters provides a systemic understanding of how barriers to the adoption of SIPs interact, evolve, and reinforce one another within organisational contexts. The hierarchical configuration derived from the ISM and Fuzzy *MICMAC* analyses reveals a strongly interconnected and non-stabilised system, with cohesive internal structure, here organised in cascading structure, where influence flows from foundational to dependent layers. Therefore, at the base of this structure, Cluster 1 (Structural Sociotechnical Integration Barriers) represents the principal driving layer, capturing the technological and organisational misalignments that originate systemic instability. Above it, Cluster 2 (Technological Resilience Barriers) reflects the dual constraint of cybersecurity and energy efficiency that sustains operational reliability. The third layer, Cluster 3 (Organisational Readiness and Maturity Barriers) highlights the institutional and infrastructural conditions required to consolidate SIP implementation, revealing a maturity gap between strategic intent and operational capability. Finally, at the most dependent level, Cluster 4 (Complex System Barriers to Dynamic Stability) embodies the emergent consequences of systemic interdependence and adaptive rigidity, where complexity and overembeddedness challenge managerial control and learning dynamics.

Together, these four clusters form an interconnected framework that illustrates how structural, technological, organisational, and adaptive dimensions coalesce to shape the institutionalisation of SIPs. Besides, from the discussions, we present four propositions (Section 5.5.5) comprising the challenges to adopt (institutionalise) SIPs in organisational manufacturing environment. Thus, the derived propositions (P1–P4) encapsulate this multi-layered configuration: from the foundational misalignments driving systemic fragmentation (P1), through the resilience trade-offs that constrain sustainable scaling (P2), to the maturity gap that limits consolidation (P3) and the complexity feedbacks that destabilise dynamic equilibrium (P4). This integrated perspective provides a theoretically grounded basis for interpreting SIPs adoption as a path-dependent, institutionally embedded process shaped by sociotechnical co-evolution across multiple systemic layers.

5.5.1 Structural Sociotechnical Integration Barriers

Analysing the refined results from the *MICMAC* approach, Cluster 1 represents the foundational set of barriers that exert the strongest driving influence across the system. It integrates both technological and social obstacles that collectively hinder the effective institutionalisation of SIPs. The barriers grouped here, ranging from communication inefficiencies (BA1) and interoperability challenges (BA3, BA4, BA5, BA7) to contractual, behavioural, and economic uncertainties (BA8, BA9, BA14), reflect the dual nature of the problem: While the technological infrastructure struggles to achieve stability and integration, organisational and relational structures remain fragmented. Regarding communication difficulties barrier (BA1), it directly decreases planning efficiency when control is decentralised (BA3) (MEYER; HANS WORTMANN; SZIRBIK, 2011), due to the own challenges regarding, not only many SIPs integration (BA5) (ABRAMOVICI; GÖBEL; SAVARINO, 2017; KAHLE et al., 2020a; MCFARLANE et al., 2013; TOMIYAMA et al., 2019) but also, integrating new SIPs that work under different protocols (industrial technologies) (BA4) (ANTONS; ARLINGHAUS, 2022a; IMAD et al., 2022). Besides, at the early stages of implementation, organisations face difficulties regarding full adoption due to the lack of systems stability, mainly regarding decision execution when the problems are complex or faced for the first time by SIPs, making the adoption only partial or even unsuccessful (MCFARLANE et al., 2013). In addition, social, psychological and cultural individualistic behaviours also negatively impact the early stage of the SIPs implementation because, once employees fear losing their jobs as a consequence of SIP adoption, they may be reluctant to share key information that would facilitate the effective implementation and configuration of SIP systems (KAHLE et al., 2020; MCFARLANE et al., 2013). Last but not least, contractual and revenue-sharing challenges (BA8), together with financial uncertainty regarding return on investment (ROI), payback periods, and the high costs associated with internally developing SIPs (BA14), substantially hinder their adoption (KAHLE et al., 2020; MCFARLANE et al., 2013). For many organisations, internal development of SIPs may mean developing internal capabilities that are not even part of their core activities. The lack of transparent governance mechanisms for intellectual property and revenue distribution discourages collaborative ventures, restricting knowledge exchange across the entire value chain. Simultaneously, unclear or delayed economic returns weaken managerial commitment to long-term innovation strategies, particularly in firms operating under cost-driven business models. This combination of contractual ambiguity and financial insecurity reinforces organisational risk aversion, leading to fragmented development efforts, underinvestment in digital capabilities, and ultimately, a slower institutionalisation of SIP technologies within industrial ecosystems.

Mitigating these foundational barriers requires coordinated managerial actions aimed at reducing fragmentation and enabling stable SIP deployment from the outset. Prioritising interoperability through modular architectures and supplier-agnostic communication standards helps avoid technological lock-in and accelerates integration across manufacturing assets. Transparent governance agreements for data ownership and revenue distribution strengthen trust with partners and lower resistance to collaboration. Simultaneously, structured digital training and internal communication programmes are necessary to reduce employee uncertainty, encourage information sharing, and support changes in operational routines. Finally, incremental implementation through pilot projects with clear performance indicators reduces perceived financial risk and improves decision reliability when transitioning from partial deployments to broader organisational adoption.

5.5.2 Technological Resilience Barriers

Cluster 2 encompasses two interrelated barriers, vulnerability in data security (BA2) and high energy consumption (BA16), that jointly constrain the technological resilience of SIP ecosystems. Despite their apparent thematic divergence, both represent fundamental limitations in the operational sustainability of digital infrastructures, inclusive pointed in an integrated way by Atzori; Iera; Morabito (2010); Lin et al. (2021), for whom Digital Twin should contribute to optimise SIPs by balancing performance, efficiency, and reliability. Data security concerns highlight the fragility of interconnected networks and the institutional pressures for compliance with regulatory and ethical standards, while energy consumption reveals the technological inefficiencies inherent in complex, sensor-intensive systems. Positioned above Cluster 1 in the influence–dependence hierarchy, this cluster represents a more dependent layer within the system. While it relies on the foundational sociotechnical alignment established in Cluster 1, it primarily reflects the outcomes of those structural conditions. In other words, technological resilience emerges as a consequence of how effectively organisations manage the integration and stability barriers identified in the preceding level.

Mitigating technological resilience barriers requires early integration of cybersecurity-by-design principles and energy-efficient architectural choices during SIP development and deployment. Implementing encryption standards, continuous vulnerability monitoring, and secure data governance policies reduces exposure to cyber threats while maintaining trust in distributed decision-making. Likewise, optimising hardware specifications, using low-power communication protocols, and adopting edge-processing strategies minimise unnecessary energy demand and prevent operational bottlenecks as system complexity scales. Pilot validation under real operating conditions, supported by continuous performance tracking, allows organisations to correct vulnerabilities before wide rollout and ensures that technological reliability does not degrade as adoption progresses.

5.5.3 Organisational Readness and Maturity Barriers

Cluster 3 comprises organisational and infrastructural barriers that define a firm's readiness and maturity for adopting SIPs. The barriers grouped here, ranging from the lack of technological maturity (BA6) and insufficient infrastructure (BA13, BA23) to technical and economic infeasibility in early utilisation (BA10), managerial and strategic misalignments (BA18, BA21), and vulnerabilities in data security and cyber-protection (BA19, BA22), expose structural weaknesses in both organisational capability and digital foundations. These limitations indicate that many firms remain institutionally unprepared to progress from experimental to consolidated SIPs implementation stages, even after mitigating lower-level barriers related to structural integration (Cluster 1) and technological resilience (Cluster 2). Regarding BA6, the lack of technological maturity constitutes the central constraining force within this cluster, shaping how the other organisational and infrastructural barriers manifest. Its interdependence with the lack of infrastructure (BA13) is particularly strong, as immature technological systems depend on stable network and low-latency infrastructures, while infrastructural inadequacy, in turn, inhibits the development of advanced digital capabilities. The same circular dependency applies to the lack of adequate computational resources (BA23), since insufficient processing power, storage, and bandwidth restrict the capacity to host and manage intelligent product functionalities, reinforcing the technological immaturity of the system (ANTONS; ARLINGHAUS, 2022a; MCFARLANE et al., 2013). This condition also affects technical and economic feasibility in the early stages of SIP utilisation (BA10), as firms with low technological maturity struggle to assess the viability of implementation, often underestimating costs and overestimating the potential benefits (MCFARLANE et al., 2013). The resulting uncertainty amplifies the complexity of management (BA18), where limited technological awareness and fragmented information flows increase the cognitive and operational burden on decision-makers. Similarly, a cost strategy not aligned with innovation (BA21) reflects managerial prioritisation of short-term cost reduction rather than long-term digital competitiveness, perpetuating underinvestment in the technological base (ANTONS; ARLINGHAUS, 2022a). Moreover, the lack of technological maturity undermines the organisation's ability to ensure data security and trust (BA19), since unreliable systems and inconsistent protocols compromise confidence in the SIP's decisions and cloud-based interactions. This fragility also extends to cyber-attack vulnerability (BA22), as weak defences and outdated architectures increase exposure to cyber threats and operational disruptions. These interrelations position BA6 as both a structural cause and an amplifying mechanism for infrastructural, managerial, and informational deficiencies that constrain the institutional readiness required for effective SIPs adoption (ANTONS; ARLINGHAUS, 2022a).

The lack of technical and economic feasibility in the early stage of SIP utilisation (BA10) is a pivotal constraint in this cluster, acting as the bridge between technological maturity and managerial decision-making. Its interrelationship with the lack of infrastructure (BA13) is direct: when basic network and latency conditions are inadequate, pilot projects become technically unreliable and economically unattractive, discouraging investment in subsequent development phases. These interrelated barriers are common where a less developed region offers fiscal benefits for organisations, and the local infrastructure is poor or undeveloped. This infrastructural fragility inflates costs and reduces confidence in scalability, reinforcing the perception that SIPs remain experimental rather than industrially viable. The interdependence between BA10 and the high complexity of management (BA18) is equally evident. Limited feasibility amplifies managerial uncertainty, as decision-makers must operate without reliable performance data or even clear economic projections. This uncertainty leads to conservative planning and fragmented responsibility allocation, which, in turn, exacerbate project delays and inefficiencies. Moreover, when technological and economic feasibility are unclear, managerial complexity increases because each subsystem must be, not only analysed, but also justified individually rather than integrated into a cohesive implementation strategy. The link between BA10 and the lack of security and trust in using data (BA19) emerges from the role of data reliability in validating feasibility assessments. If the data underpinning cost, productivity, or performance projections are untrustworthy, early-stage evaluations become distorted, causing under- or overestimation of benefits. Consequently, the organisation perceives SIP adoption as economically unfeasible due to informational uncertainty rather than actual cost structure. From a strategic standpoint, BA10 closely interacts with the misalignment between cost strategy and innovation (BA21). When financial management is driven by short-term cost-reduction logic, feasibility analyses are biased against long-term technological investments (IMAD et al., 2022). The lack of an innovation-oriented budgeting approach prevents firms from capturing dynamic efficiency gains, making SIPs appear prohibitively expensive at the outset. This misalignment perpetuates a self-reinforcing cycle: low perceived feasibility leads to underinvestment, which sustains low technological maturity and further limits feasibility in future cycles. The connection with cyber-attack vulnerability (BA22) is subtler but significant. Ensuring cybersecurity compliance and resilience introduces additional costs and technical requirements, often neglected in feasibility studies. When these risks and mitigation costs are underestimated, pilot implementations fail under real-world operational conditions, leading to managerial scepticism about SIP sustainability. Thus, here, organisations face another important trade off: Mitigating security fragility means improvement in systems reliability but, not without any redundance and extra costs that, if not foreseen in advance, significantly reduces the perceived economic value and viability of the SIPs. Finally, the lack of adequate computational resources (BA23) constitutes a structural barrier to feasibility. Without sufficient processing power, memory, and communication bandwidth, SIP applications cannot operate efficiently or autonomously, inflating maintenance and integration costs. These technical deficiencies directly translate into poor feasibility evaluations, as they undermine both operational performance and scalability potential. These interactions position BA10 as a mediating mechanism that translates technical immaturity and infrastructural fragility into managerial and strategic resistance. It links the tangible constraints of the digital architecture to the cognitive and financial barriers of organisational decision-making, reinforcing the institutional perception that SIP adoption remains high-risk and low-return.

The lack of infrastructure, particularly networks and low-latency systems in certain industrial regions where firms operate (BA13), represents a geographically and institutionally embedded barrier that constrains the scalability of SIPs implementation. Beyond the technical limitations of connectivity, this barrier exposes territorial asymmetries in access to digital infrastructure, making some organisations structurally dependent on external service providers or public investment cycles (IMAD et al., 2022; KAHLE et al., 2020; LIN et al., 2021; OLUYISOLA et al., 2022). Its interrelationship with the high complexity of management (BA18) is immediate (LEITÃO et al., 2015; LIN et al., 2021). In contexts where network coverage and latency are inconsistent, managing SIP-enabled processes becomes increasingly complex, as information flows are fragmented and response times unpredictable. Managers are forced to rely on ad hoc coordination mechanisms and manual interventions, which not only increase operational burden but also undermine the systemic vision required for intelligent, decentralised control. The connection between BA13 and the lack of security and trust in using data (BA19) arises from the dependency of data integrity on stable communication environments. Weak or unstable networks amplify the risk of data loss, corruption, or unauthorised interception during transmission. Consequently, firms operating in poorly connected regions exhibit lower confidence in data-driven decision-making, perceiving SIP systems as unreliable or even unsafe for critical operations. Although Leitão et al. (2015); Porter; Heppelmann (2014) discussed both barriers in their work, these barriers were independently studied and works jointly treating both barriers remains scarce in literature. Strategically, BA13 interacts strongly with the misalignment between cost strategy and innovation (BA21). Firms situated in regions with deficient digital infrastructure often face disproportionately higher implementation costs due to the need for customised network solutions, private connectivity, or latency compensation technologies. When cost strategies prioritise short-term savings, these additional expenses are seldom justified, leading to underinvestment and reinforcing a cycle of technological marginalization (KAHLE et al., 2020). The relationship between BA13 and cyber-attack vulnerability (BA22) stems from the inherent exposure created by inadequate or outdated infrastructures. Poorly maintained networks lack the segmentation, redundancy, and security protocols necessary to isolate malicious activity. In such environments, even minor cyber incidents can propagate rapidly across systems (LIN et al., 2021), exacerbating managerial risk aversion and delaying digital transformation initiatives. Finally, the interdependence between BA13 and the lack of adequate computational resources (BA23) reflects a structural duality: limited network capability restricts access to distributed and cloud-based processing power, while insufficient local computation capacity aggravates dependency on unreliable external connections. This reciprocal constraint forms a systemic bottleneck in which infrastructure and computational limitations reinforce one another (LIN et al., 2021), ultimately defining the pace and feasibility of SIP adoption. Thus, these interrelations position BA13 as an institutionally anchored barrier that transcends organisational boundaries. It embodies the material consequences of regional digital inequality and infrastructural underdevelopment, making SIP adoption not merely a question of technological readiness, but also of territorial and institutional capability.

The high complexity of management (BA18) constitutes a central organisational barrier in SIP adoption, reflecting the managerial challenges arising from the growing number of interconnected agents, data sources, and decision nodes within intelligent systems. This complexity becomes self-reinforcing as firms attempt to coordinate multiple technological layers without sufficient structural integration or governance mechanisms. Its relationships with the other barriers in this cluster highlight the institutional and cognitive limitations that undermine digital transformation. The interconnection between BA18 and the lack of security and trust in using data (BA19) lies in the managerial dependence on reliable and interpretable information. When data accuracy and source integrity are uncertain, the management of SIP operations becomes reactive rather than analytical. Managers must continuously validate or cross-check information from heterogeneous systems, increasing cognitive load and delaying decisions (LEITÃO et al., 2015). Over time, this dynamic foster institutional mistrust towards data-driven control, as uncertainty translates into high perceived managerial risk. In strategic terms, BA18 is also strongly linked to the misalignment between cost strategy and innovation (BA21). Managerial complexity often leads to short-term decision horizons, as firms prioritise operational control and immediate cost reduction over strategic alignment and innovation-driven investment. The absence of integrated cost governance mechanisms exacerbates fragmentation: financial decisions are made in isolation from technological planning, perpetuating inefficiencies and inhibiting cross-departmental coordination. In such settings, SIP adoption is not rejected for technical reasons but rather deprioritised because managerial systems are unable to internalise its long-term benefits. The relationship between BA18 and cyber-attack vulnerability (BA22) emerges from the governance gaps that accompany complex system architectures. As management structures struggle to oversee dispersed and interdependent systems, responsibilities for cybersecurity become diffused. This lack of accountability produces inconsistent enforcement of security protocols and delayed responses to threats. Consequently, organisational complexity not only magnifies the exposure to cyber risks but also weakens the firm's institutional capacity to react effectively once incidents occur (RATHEE et al., 2021; RUHUL AMIN et al., 2021). Finally, the link between BA18 and the lack of adequate computational resources (BA23) is both operational and structural. Limited processing capacity increases the need for manual oversight and coordination, forcing managers to compensate for technological deficiencies through human intervention. This substitution amplifies managerial workload and error probability, especially in data-intensive environments (LIN et al., 2021). Conversely, the absence of management tools capable of integrating information from distributed systems prevents the efficient allocation of computational resources, creating a feedback loop where managerial and technological limitations reinforce one another. The presented interrelations illustrate how managerial complexity serves as an institutional amplifier of systemic fragility. BA18 bridges the technological deficiencies represented by BA23 and BA19 with the strategic misalignments expressed in BA21, translating technical uncertainty into organisational inertia. In this sense, the high complexity of management not only constrains the efficiency of SIPs implementation but also delays the institutional learning processes required to stabilise digital transformation at the organisational level.

The lack of security and trust in using data (BA19) represents a critical barrier to the institutionalisation of smart, connected systems. In SIP environments, the perceived unreliability of data—whether due to integrity concerns, unauthorised access, or uncertainty regarding its provenance—undermines both technological confidence and managerial decision-making. This barrier operates as a transversal constraint, shaping the organisational response to digitalisation across strategic, operational, and infrastructural domains. The relationship between BA19 and the misalignment between cost strategy and innovation (BA21) arises from the managerial trade-off between investment in data security and the pursuit of cost efficiency. When organisations adopt short-term, cost-oriented strategies, cybersecurity and data governance initiatives are often deprioritised as non-productive expenditures. This strategic underinvestment not only limits the implementation of robust protection mechanisms but also weakens the institutional culture of data trust (OLUYISOLA et al., 2022). Over time, the absence of dedicated budgets for data assurance transforms security into a discretionary rather than structural component of innovation, reinforcing organisational inertia towards full digital integration. The link between BA19 and cyber-attack vulnerability (BA22) is direct and mutually reinforcing. Low levels of data trust typically stem from repeated or perceived security breaches, while insufficient security infrastructures magnify those perceptions. As cyber threats evolve, the inability to ensure data confidentiality, availability, and integrity exacerbates scepticism among both managers and employees (LIN et al., 2021). This cyclical interaction creates a "trust deficit" that compromises information-sharing and cross-functional collaboration, particularly in distributed SIP architectures. Consequently, even technically recoverable systems face resistance to reintegration due to persistent doubts about data reliability. The interdependence between BA19 and the lack of adequate computational resources (BA23) lies in the technical–organisational feedback loop between resource constraints and data protection capabilities. Limited computational capacity restricts the deployment of advanced encryption, monitoring, and anomaly-detection tools, while the absence of such tools reinforces concerns regarding data security. Furthermore, in systems relying heavily on cloud-based processing, inadequate local computing resources amplify exposure to external vulnerabilities, as data must transit through multiple insecure layers before reaching secure nodes. Hence, the infrastructural weakness reflected in BA23 acts as both a technical and psychological source of distrust in data-driven processes. Thus, the absence of data trust transforms technological and financial constraints into institutional barriers, eroding commitment to digital transformation (IMAD et al., 2022).

The misalignment between cost strategy and innovation (BA21) and the vulnerability to cyber-attacks (BA22) are closely intertwined through the tension between financial rationalisation and digital resilience. As before stated, in many organisations, cost-driven management philosophies prioritise short-term financial efficiency over long-term risk mitigation. This strategic orientation often results in underinvestment in cybersecurity infrastructures, workforce training, and data protection mechanisms. As Porter; Heppelmann (2014) note, smart, connected products require continuous expenditure on digital maintenance, encryption, and monitoring, with costs frequently omitted in conventional budgeting models. Consequently, when cost-control policies dominate, cybersecurity becomes reactive rather than preventive, exposing organisations to cascading vulnerabilities. Furthermore, when firms perceive security as a cost centre rather than a value enabler, they institutionalise fragility: the absence of strategic alignment between innovation and protection leads to operational disruptions, reputational damage, and managerial distrust in digital systems. Hence, the interaction between BA21 and BA22 illustrates a structural paradox: Reducing costs at the expense of security undermines the very efficiency such strategies aim to achieve. The relationship between cost strategy misalignment (BA21) and the lack of adequate computational resources (BA23) reflects a systemic imbalance between economic priorities and technological capability. Organisations that adopt cost-minimisation logics frequently underinvest in hardware, processing capacity, and storage infrastructure, perceiving such investments as peripheral to their core business. However, as Kahle et al. (2020); Porter; Heppelmann (2014) highlight, computational resources are not auxiliary assets but strategic enablers of product intelligence and data-driven value creation. When these resources are insufficient, the scalability of SIP operations is compromised, leading to performance bottlenecks, integration delays, and increased dependency on external providers. This technical constraint further reinforces cost-oriented managerial bias, as limited computational performance is mistakenly interpreted as a justification for avoiding digital expansion. The result is a self-reinforcing cycle: resource scarcity restricts technological evolution, while short-term cost strategies perpetuate that scarcity. Ultimately, the interplay between BA21 and BA23 exposes how economic conservatism constrains the digital backbone of SIPs ecosystems, weakening both organisational readiness and long-term competitiveness.

Last but not least, the interrelationship between cyber-attack vulnerability (BA22) and the lack of adequate computational resources (BA23) reflects the technical and organisational fragility of immature SIP environments. Limited processing capacity, memory, and network bandwidth weaken the ability to implement robust cybersecurity protocols such as real-time monitoring, anomaly detection, and multi-layer encryption (HUNGUD; ARUNACHALAM, 2020; RATHEE et al., 2021). In such contexts, computational scarcity is not merely a performance constraint but a direct security exposure: insufficient local processing forces firms to depend on cloud-based or third-party infrastructures, expanding the attack surface and increasing dependence on external governance. At the same time, persistent cyber-attack vulnerability further aggravates resource underutilisation. When organisations experience repeated security breaches or lack confidence in their ability to protect data, they tend to deactivate advanced computing functionalities or restrict autonomous operations, thereby reducing system efficiency. This reactive posture transforms potential computational capability into latent capacity, available but strategically underused due to perceived risk. Furthermore, the absence of adequate computing infrastructure hinders the deployment of proactive resilience measures such as distributed intrusion-detection systems or self-healing architectures. As a result, firms operate in another paradoxical equilibrium: they cannot strengthen cybersecurity without upgrading computational resources, yet budget constraints and managerial risk aversion prevent such upgrades because of ongoing security concerns. The outcome is a structural feedback loop where technological limitation and vulnerability reinforce one another, delaying the institutional stabilisation of SIP ecosystems.

Mitigating organisational readiness and maturity barriers requires strengthening the internal capabilities that sustain reliable, scalable SIP deployment. Developing structured digital transformation roadmaps with defined milestones helps align managerial priorities with long-term innovation objectives, while targeted upskilling programmes close the competence gap that hinders confident decision-making. Upgrading network and computational infrastructure through phased investments ensures that pilot projects evolve into operationally stable systems rather than isolated prototypes. Integrating cost-management tools with performance analytics increases the visibility of digital returns, helping managers shift from short-term cost control to evidence-based innovation funding. Establishing permanent governance routines for cybersecurity, data integrity, and cross-functional collaboration further enhances confidence in SIP operations, reducing uncertainty and enabling consistent organisational learning and capability consolidation.

5.5.4 Complex Systems Barriers to Dynamic Stability

Cluster 4 represents the set of barriers that emerge at the most dependent level of the system, where organisational complexity and adaptive limitations converge to constrain the attainment of dynamic stability. This group comprising tracking technology limitations (BA12), self-adaptation difficulties (BA15), risk of adverse event propagation (BA17), and the growing complexity of managing numerous system agents (BA20), captures the consequences of systemic interdependence within SIPs ecosystems. These barriers reflect how technological sophistication and increased connectivity can unintentionally amplify instability, creating feedback loops that challenge managerial control and real-time responsiveness.

The relationship between BA11 and the challenge of transforming tracking data into actionable control decisions (BA12) emerges from the dependency of data value on systemic interoperability. When SIPs are introduced without full alignment to enterprise systems, such as ERP or MES platforms, data streams generated by tracking technologies become fragmented or non-standardised. As demonstrated by Vendrell-Herrero; Bustinza; Vaillant (2021), fragmented digital architectures compromise the analytical feedback loop that enables real-time monitoring and predictive control. Hence, incomplete system integration undermines both traceability and analytical precision, limiting the capacity of SIPs to support informed decision-making. The interdependence between BA11 and self-adaptation difficulties (BA15) reflects the tension between rigid system architectures and the need for plug-and-play flexibility. As highlighted by Abramovici; Goebel; Dang (2016); Leitão et al. (2015) the absence of interoperability standards constrains the ability of intelligent products to autonomously recognise operational contexts or adapt to new environments. Without seamless system interfaces, adaptive capabilities (central to the intelligence of SIPs) remain latent or underutilised. Integration challenges thus act as a systemic inhibitor of self-configuring behaviour, creating path dependency where system rigidity perpetuates organisational inertia. The connection between BA11 and the risk of bad event propagation (BA17) stems from the instability introduced by fragmented system integration. Insufficient synchronisation across virtual and physical layers can cause learning mechanisms within SIPs to replicate erroneous responses throughout connected nodes (ABRAMOVICI; GOEBEL; DANG, 2016). These feedback inconsistencies transform isolated operational failures into system-wide vulnerabilities, thereby amplifying the potential for undesirable event propagation. Finally, the link between BA11 and the high complexity of system management (BA20) is rooted in the scalability challenges of multi-agent coordination. As Yi et al. (2021) argue, poorly integrated system architectures exponentially increase the management burden, since every additional device, sensor, or control node adds configuration overhead and communication latency. The managerial complexity of maintaining coherence across distributed agents becomes unsustainable when integration protocols are weak or inconsistent.

Self-adaptation difficulties (BA15) represent one of the most critical barriers to achieving autonomy and resilience in SIPs. In principle, SIPs are expected to recognise environmental changes, process standards, and operational patterns, adjusting their behaviour accordingly. However, when integration mechanisms are rigid or learning feedback loops are fragmented, adaptive capacity remains limited, leading to operational inefficiencies and systemic vulnerability. The relationship between BA15 and the risk of bad event propagation (BA17) is inherent to the nature of adaptive learning. As Abramovici; Goebel; Dang, (2016) observe, adaptive systems rely on iterative learning cycles in which sensor-derived feedback informs decision rules. When self-adaptation mechanisms are incomplete or inconsistent across system layers, SIPs may misinterpret environmental cues, propagating incorrect responses or faulty configurations throughout the network. This phenomenon transforms local learning errors into systemic dysfunctions, particularly in interconnected production ecosystems. Similarly, Leitão et al. (2015) highlight that in distributed manufacturing environments, insufficient coordination between adaptive agents increases the likelihood of undesirable event replication. Thus, the inability of SIPs to self-adjust effectively not only reduces operational flexibility but also amplifies risk dispersion, undermining the stability of the entire intelligent system. Moreover, the interdependence between BA15 and the high complexity of system management (BA20) derives from the scaling challenges inherent in adaptive multi-agent systems. According to Yi et al. (2021), the exponential growth of interconnected devices and sensors increases the coordination overhead required to maintain consistent system behaviour. When adaptive agents operate without synchronised standards or robust supervisory mechanisms, management complexity escalates non-linearly. Each autonomous component introduces potential divergence in response patterns, requiring continuous recalibration and monitoring. This dynamic reflects a paradox of digital transformation: as systems become more intelligent and distributed, the managerial effort to ensure coherence may increase rather than diminish, particularly when self-adaptation capabilities are immature. Taken together, these relationships reveal that limitations in self-adaptation (BA15) act as both a symptom and a cause of systemic instability. They constrain the ability of SIPs to contain the spread of erroneous behaviours (BA17) and to manage the operational complexity emerging from dense, multi-agent architectures (BA20). Therefore, overcoming BA15 is fundamental for transforming intelligent products from reactive technological artefacts into proactive, learning-oriented entities capable of sustaining reliable performance in dynamic industrial environments.

The risk of bad event propagation (BA17) represents a fundamental systemic vulnerability in intelligent production environments, where learning mechanisms allow products and systems to replicate both successful and erroneous behaviours. The interdependence between BA17 and the high complexity of system management (BA20) emerges from the escalating difficulty of maintaining coherence and stability as the number of interacting agents increases. Distributed manufacturing systems that rely on autonomous, communicating agents are highly susceptible to feedback amplification: minor deviations or learning inaccuracies in one node can rapidly spread through interconnected networks Barbosa et al. (2015). This propagation effect becomes more severe in complex, multi-agent configurations, where the synchronisation of decision-making processes depends on real-time information exchange across heterogeneous platforms. Besides, when virtual and physical layers of SIP ecosystems are poorly harmonised, erroneous data or faulty configurations can be replicated and reinforced through iterative feedback loops, magnifying operational disruptions (ABRAMOVICI; GOEBEL; DANG, 2016). Yi et al. (2021) also note that the management of such interconnected systems becomes exponentially more challenging as the number of devices, sensors, and controllers increases. Each additional component introduces a new communication interface and potential point of failure, intensifying the need for monitoring, validation, and conflict resolution. Consequently, the propagation of undesirable events (BA17) is not an isolated phenomenon but rather a structural consequence of the managerial and infrastructural complexity described in BA20. The absence of standardised coordination protocols or supervisory intelligence compounds this effect, as systems lack the meta-level governance required to identify and isolate anomalous behaviours before they cascade through the network. Collectively, these interrelations reveal a mutually reinforcing cycle: as system complexity (BA20) grows, the likelihood and impact of event propagation (BA17) increase, while recurring propagation events further complicate system management. This cyclical dependency highlights the necessity for integrated governance architectures capable of balancing local autonomy with global stability, an institutional capability that remains underdeveloped in most SIP implementations.

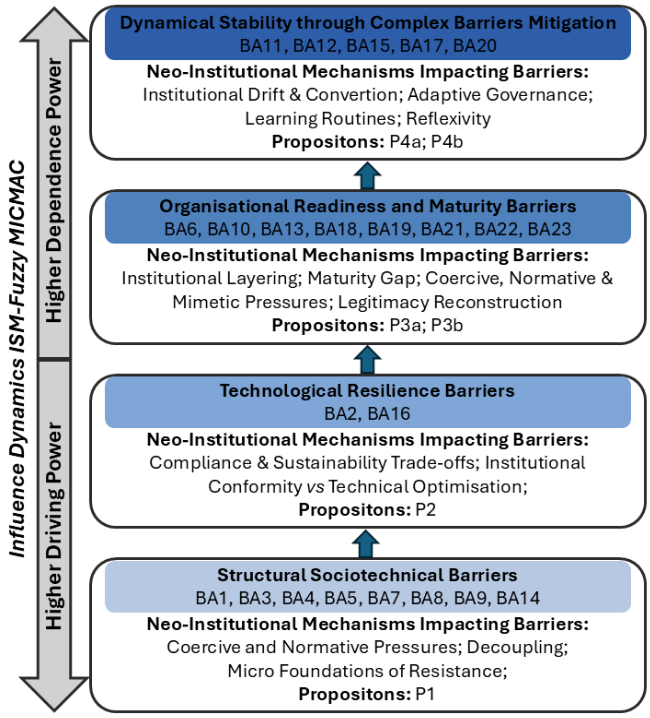
Mitigating the complex system barriers constraining Dynamic Stability demands an organisational shift toward adaptive governance and proactive risk containment. Implementing real-time monitoring architectures, anomaly-detection systems, and closed-loop feedback routines allows deviations to be identified and corrected before cascading through interconnected agents. Strengthening interoperability standards and supervisory control layers reduces coordination overhead and prevents propagation of erroneous behaviours across distributed networks. Scenario-based simulation and digital-twin environments can be employed to test adaptive responses under varying operational conditions, improving both predictive capacity and system resilience. Continuous learning cycles, supported by multidisciplinary review teams, ensure that lessons from local disruptions are institutionalised into global control strategies. Through these practices, Dynamic Stability evolves into a tangible operational capability that enables SIP ecosystems to sustain Social, Environmental, and Economic Sustainability while maintaining flexibility and control in increasingly complex industrial contexts.

5.5.5 Propositions for an Influence-Based Understanting of the SIPs Adoption Barriers

The roadmap for barriers to SIPs mitigation, derived from our ISM and Fuzzy *MICMAC* analyses reveals a highly concentrated barriers on the Linkage square. This phenomenon indicates a non-stabilised system, condition typically observed in complex organisational innovation contexts, guided by institutional pressures such as SIPs adoption. Although the interrelationships among the variables are intricate, we can perceive four subgroups, with different driving and dependence power, which reveals the presence of relatively cohesive internal substructures that act as compensatory mechanisms of local stability, where certain barriers become self-reinforcing while simultaneously maintaining external dependencies.

Building upon these empirically derived interdependencies and drawing interpretive insights from the theoretical lenses discussed throughout this section, we propose a set of testable propositions. These propositions aim to clarify the complex relationships among the barriers faced by organisations in adopting SIPs, guiding future empirical research and shifting the contribution from documentation to explanation and theory-building. Figure 5.6 illustrates this sequential integration, beginning with the synchronisation of Structural Sociotechnical Integration, followed by Technological Resilience, progressing toward Organisational Readiness and Maturity, and concluding with Complex System Barriers to Dynamic Stability. This progression visually reinforces how the barriers faced by organisations in adopting SIPs evolve from foundational integration challenges to dynamic system-level interdependencies, serving as a visual roadmap upon which these propositions are constructed.

Figure 5.6 – Theoretical roadmap of SIP adoption barriers: From integration to dynamic stability



Source: Elaborated by the author (2025)

Our analysis indicates that foundational barriers act as institutional anchors that constrain the emergence of higher-order adaptive mechanisms. This finding aligns with the concept of institutional layering, wherein lower-level structural constraints must be addressed before more dynamic organisational arrangements can stabilise (MAHONEY; THELEN, 2009). From a Neo-Institutional perspective, early-stage Structural and Sociotechnical barriers (e.g. fragmented communication, legacy system dependence, and contractual uncertainty) represent coercive (e.g., technological standards and interoperability requirements) and normative pressures (e.g., expectations for collaboration and data sharing) that contribute to perpetuate organisational inertia (DIMAGGIO; POWELL, 1991; MEYER; ROWAN, 1977). These barriers constitute the microfoundations of resistance (GREENWOOD; HININGS; WHETTEN, 2014), embedding taken-for-granted routines and legitimised practices that hinder structural change. In parallel, they shape the institutional logics that define what is considered legitimate, efficient, or acceptable within the organisation, thereby constraining technological renewal and cross-functional coordination through SIPs full adoption. Managerially, overcoming this cluster requires integrated interventions that synchronise the technical and organisational subsystems, addressing interoperability not only as a technological issue but also as an institutional and cultural one. This managerial sociotechnical integration requirement is in accordance with the study of Pissardini et al.

(2025), which presents connectivity and integration as the first level barriers that should be developed, in order to achieve cross-functional integration. Based on this logic, we propose the following:

- **P1.** *The persistence of Structural Sociotechnical Integration Barriers suggests that institutional and socio-technical misalignments are mutually reinforcing. Coercive and normative pressures institutionalise technological and organisational fragmentation, sustaining a path-dependent configuration that inhibits systemic stability and full SIP adoption.*

As the integration of SIPs advances, technological resilience emerges as a critical condition for ensuring system reliability and institutional legitimacy. Barriers related to data security vulnerability (BA2) and high energy consumption (BA16) expose the fragility of digital infrastructures and the organisational trade-offs between performance, efficiency, and sustainability. From a Neo-Institutional perspective, these barriers embody coercive pressures associated with regulatory compliance and normative expectations regarding environmental responsibility. Consequently, organisations face the paradox of technological adaptation: The need to modernise digital systems while adhering to institutional norms that constrain rapid transformation. This dynamic reflects the tension between technical optimisation and institutional conformity, where the pursuit of security and sustainability often reinforces structural rigidity and inhibits innovation. Addressing these barriers therefore requires not only technical solutions but also institutional adjustments that align resilience as a path to legitimacy. Based on this reasoning, we propose the following: In practical terms, strengthening technological resilience requires the co-evolution of security architectures and energy-efficient designs, aligning technical performance with institutionalised norms of sustainability and trust in data management.

- **P2.** *The persistence of Technological Resilience Barriers reflects the coexistence of coercive and normative pressures that constrain the co-evolution of security and sustainability. Institutional compliance demands reinforce structural rigidity, limiting technological adaptation and hindering the stabilisation of resilient SIP ecosystems.*

Beyond technological resilience, organisational maturity emerges as the next frontier in the institutionalisation of SIP adoption. While the former concerns the technical infrastructure required for stability, the latter reflects the organisation's capacity to align institutional logics, governance systems, and cultural norms with the digital transformation process. In this sense, this third layer encompasses structural misalignments that hinder the full institutionalisation of SIPs adoption, including limited technological maturity (BA6), infrastructural (BA13, BA23), and managerial and financial misalignments (BA10, BA18, BA21). These barriers collectively represent institutional inertia resulting from path-dependent structures and fragmented decision-making logics. From a Neo-Institutional perspective, they reflect institutional layering, where legacy routines and governance systems persist alongside emerging digital logics, producing organisational ambivalence and delayed adaptation. Furthermore, coercive and normative pressures for conformity (e.g., compliance with established standards, cost-control norms, and managerial risk aversion) together mimetic tendencies to imitate more advanced peers without equivalent resource endowment, reinforce this misalignment between the institutional and technological subsystems. Consequently, readiness to adopt and mature SIP integration is not merely a function of technical capability, but of institutional alignment and legitimacy reconstruction. For managers in practice, efforts to mitigating this cluster requires the simultaneous development of technical infrastructure and institutional competences, aligning structural conditions, governance mechanisms, and cultural readiness to sustain the digital transformation process. Trust in data, therefore, is not merely a technical attribute but a foundational condition for organisational readiness, influencing both the perceived legitimacy of SIP adoption and the stability of inter-organisational digital networks.

- **P3a.** *Organisational Readiness and Maturity Barriers persist due to an institutional maturity gap, where coercive, normative, and mimetic pressures reinforce the misalignment between institutional and technological subsystems, constraining organisational adaptation and delaying the institutionalisation of SIP practices.*
- **P3b.** *Bridging this institutional maturity gap requires the reconciliation of coercive, normative, and mimetic pressures with emergent digital logics, enabling alignment between legitimacy-seeking behaviours and technological advancement within organisations.*

At the top of the hierarchy, the fourth cluster represents the highest level of systemic dependence and dynamic instability, reflecting the organisation's ability (or inability) to sustain adaptation under complex and continuously changing conditions. This cluster encompasses barriers associated with systemic integration and adaptive coordination, including complicated system introduction and legacy affinity (BA11), tracking technology challenges (BA12), self-adaptation limitations (BA15), risk of bad event propagation (BA17), and the high complexity of managing multiple autonomous agents (BA20). Together, these barriers embody the tension between technological dynamism and institutional control, exposing how attempts to achieve adaptive stability can paradoxically generate new layers of organisational fragility. From a Neo-Institutional standpoint, these barriers illustrate mechanisms of institutional drift and conversion (MAHONEY; THELEN, 2009), where partial adjustments to new digital architectures occur without a corresponding transformation of underlying institutional logics. The result is a hybrid system that retains old governance routines while introducing advanced technological artefacts, which produces incoherence between technological potential and institutional capability. For example, the introduction of sophisticated tracking and autonomous decision systems (BA12, BA20) can outpace the organisation's capacity to absorb and legitimise these innovations, leading to reactive instead of proactive governance. Likewise, difficulties in SIPs' self-adaptation (BA15) and their propensity to propagate adverse events (BA17) signal a failure in institutional reflexivity, that is the ability of the system to reinterpret and update its operational logic in response to emerging feedback. Consequently, the fourth cluster captures a paradox of dynamic stability: as organisations pursue flexibility, their institutional inertia converts adaptability into vulnerability. Achieving genuine stability thus requires not simply integrating complex systems, but institutionalising adaptive governance: Mechanisms that allow learning, risk containment, and the reconfiguration of organisational routines without eroding systemic coherence. From a managerial perspective, overcoming this cluster requires embedding adaptive governance structures that balance autonomy and control. Managers must institutionalise feedback mechanisms and learning routines capable of interpreting errors as inputs for continuous improvement rather than as signals of system failure. Stability, in this sense, emerges not from the suppression of complexity but from its institutional orchestration, where technological adaptability is matched by managerial reflexivity and cross-level coordination.

P4a. *Dynamic Stability Barriers persist when institutional drift and partial conversion prevent the alignment between adaptive technological architectures and entrenched governance structures, transforming flexibility into systemic vulnerability.*

P4b. *The institutionalisation of adaptive governance and learning mechanisms mitigates the effects of dynamic instability, enabling organisations to convert complexity into resilience and sustain the long-term institutionalisation of SIP ecosystems.*

5.6 CONCLUSIONS

The growing adoption of Smart Industrial Products (SIPs) is reshaping how organisations design, govern, and sustain digital transformation processes. Rather than enabling seamless integration, this transition exposes a complex set of structural, technological, organisational, and adaptive barriers that collectively constrain the institutionalisation of SIP adoption. Through an interpretive and sequential mixed-methods design, including a systematic literature review (SLR), Experts Interview, Interpretive Structural Modelling (ISM), and Fuzzy *MICMAC* analysis, this study identified twenty-three barriers and examined their hierarchical interrelations. The resulting framework depicts a four-layer structure that reveals how these barriers interact, accumulate, and evolve across organisational levels, shaping the dynamics of SIP adoption.

5.6.1 Theorethical Contributions

While digital transformation has often been framed as a technical or managerial challenge, this study advances a theoretical understanding of the barriers to SIP adoption as an *institutionally conditioned process*. By integrating ISM and Fuzzy *MICMAC* to identify the driving and dependence power between the 23 barriers through Intitutional Theory lens, we move beyond a technology-centred perspective, explaining how coercive, normative, and mimetic pressures structure organisational behaviour and shape the persistence of barriers. SIP adoption, therefore, is not simply a matter of technological readiness, but a process embedded in institutional logics that determine what is perceived as legitimate, efficient, and feasible. The proposed framework highlights how barriers hierarchically interact and be strongly interconnected, showing that resistance emerges not only from operational deficiencies but also from institutional mechanisms that stabilise the organisational status quo.

Although the *MICMAC* results revealed that all barriers fall within the linkage quadrant (indicating high systemic interdependence) it was possible to perceive that they were organised in four cohesive substructures. These clusters form a *layered institutional architecture*, in which interdependent barriers are hierarchically organised according to their driving and dependence power. Hence, while the *MICMAC* diagram exposes the horizontal instability of the system, our conceptual framework reveals its vertical order, a structured manifestation of institutional complexity.

Foundational barriers (e.g., communication difficulties (BA1), interoperability issues (BA3–BA5), and contractual uncertainty (BA8)) act as institutional anchors that restrict higher-order adaptation. As organisations attempt to address these lower-level misalignments, more complex layers emerge, including those related to technological resilience, organisational maturity, and dynamic stability. This hierarchical dynamic aligns with the concept of institutional layering (MAHONEY; THELEN, 2009), suggesting that change occurs incrementally through the accumulation and transformation of existing structures rather than abrupt substitution. By conceptualising barriers as interconnected layers of institutional resistance, the study extends the application of the Neo-Institutional Theory to contexts of digital transformation and complex sociotechnical integration. Importantly, the framework we propose challenges linear and technology-first narratives in digital transformation. Instead, it emphasises the strategic sequencing of barriers as a critical path to sustained performance, aligning with the idea of dynamic alignment (HELFAT; MARTIN, 2015). From this perspective, SIPs are not merely operational tools but elements that require structured routines in order to building adaptive capabilities at multiple levels within the organisation, as demonstrated by (PISSARDINI et al., 2025).

5.6.2 Managerial Contributions

For managers in practice, the proposed framework works as a structured diagnostic and decision-support tool to manage the complex web of barriers constraining SIP adoption. By distinguishing foundational barriers from dependent ones, managers can get strategic insights to prioritise mitigation efforts and sequence organisational interventions more effectively, avoiding fragmented digital initiatives or standalone technology deployments. This perspective shifts managerial attention from addressing isolated obstacles to managing interrelated institutional, organisational, and technological frictions as a system of co-evolving barriers.

To mitigate the barriers according to our proposed framework, organisations should begin with a barrier mapping exercise, assessing their current exposure across the 23 barriers identified in this study. This diagnostic allows managers to identify which foundational sociotechnical misalignments (e.g., communication difficulties, interoperability failures, or contractual uncertainty) must be addressed before higher-order issues, such as organisational maturity or system complexity can be effectively mitigated. Subsequently, by analysing the interdependencies revealed through our proposed framework, firms can develop targeted strategies that address not only the technical dimension of each barrier but also its practical institutional and cultural roots.

Our framework also supports a staged intervention logic, in which mitigation actions follow an incremental yet integrated path aligned with organisational readiness. We can perceive the practical application of our proposed framework by observing leading firms such as Siemens, Bosch, and others, that are progressive and constantly establishing and adapting their sociotechnical foundations to new sceneries through standardisation, data governance, and capability-building, before advancing toward mitigation of barriers that directly affects organisational dynamic stability. Instead of tackling SIP barriers in isolation, these firms approach them as layered institutional challenges, synchronising technical improvements with governance reforms and behavioural change.

5.6.3 Limitations and Future Research Directions

Like any research, this study presents several limitations which offer valuable avenues for further investigation. In the early stages, methodological choices regarding database selection, expert recruitment, and criteria for relevance inevitably involved a degree of subjectivity, even under structured protocols. Although expert validation helped refine the identification and classification of barriers, the ISM method still relies on interpretive judgement, which may vary according to each expert's institutional background and technological exposure. Consequently, small inconsistencies in the initial relational matrices could propagate through the ISM hierarchy and, as a consequence, influence the Fuzzy *MICMAC* distribution, potentially affecting the final configuration of interdependencies.

A key limitation lies in the lack of empirical validation through quantitative or longitudinal data. While our framework offers a theoretically grounded and expert-informed view of the institutional barriers to SIPs adoption, it has not yet been tested empirically. Future studies should operationalise the propositions presented here, statistically addressing how specific barrier configurations influence the degree of SIPs adoption or even its degree of institutionalisation. For instance, the permanence of Structural Sociotechnical barriers could be examined through indicators of vertical and horizontal communication difficulties, interoperability effectiveness, or organisational legitimacy. Similarly, Organisational Readiness and Maturity barriers could be evaluated via metrics of governance adaptability, digital maturity, or alignment between technological and institutional subsystems. Notwithstanding these research opportunities, theoretical extensions may also emerge from integrating complementary perspectives by exploring how Institutional Logics interact with Dynamic Capabilities in shaping digital transformation trajectories, bridging dynamic stability. Alternatively, Contingency Theory may help reveal how institutional pressures vary across industries, regulatory regimes, or organisational sizes. Cross-sectoral comparative studies could test the reproducibility of the proposed framework, revealing whether certain barrier clusters are context-specific or structurally recurrent across distinct industrial ecosystems.

Finally, the propositions advanced in this study provide a foundation for hypothesis building and model testing. Future empirical studies could refine and validate these propositions across diverse contexts, using mixed or longitudinal approaches to capture the temporal evolution of institutional resistance configurations. Such efforts would help clarify how the coercive, normative, and mimetic pressures dynamically interact between themselves, in order to shape organisational responses to SIP adoption. By filling these gaps, the proposed framework could be further consolidated as a theoretical and managerial tool for understanding and moving efforts in strategically mitigating institutional complexity evolved in digital transformation among different organisational fields.

6 CONCLUSIONS

This section presents the conclusions of the thesis. In general, it covers an overview of the results, the final conceptual model, the contributions, presenting the discussions of the limitations and suggesting future research directions.

6.1 AN OVERVIEW OF THE THESIS RESULTS

This research is composed of four interrelated articles. Article 1 (Chapter 2) responds to specific objective SO1, (to identify capabilities and barriers associated with (Smart Industrial Products) SIPs for organisational functions, proposing a framework that delineates the Evolutional Path these functions traverse to become Smart-Enhanced ones). Article 2 (Chapter 3) answers the specific objective SO2, (to establish a Structural Relationship Hierarchy framework that defines a sequence of capability dependencies, offering a structured pathway for organisations to attain a fully autonomous PPC function). Article 3 (Chapter 4) focus on objective SO3 (to unveil inter-functional synergy between organisational functions through adoption of SIPs. Finally, Article 4 (Chapter 5), evaluates the relationship between barriers faced by organisations to implement SIPs, offering a roadmap to strategically mitigate them.

Chapter 2, was a multi-method research, composed of a SLR, experts interview and content analysis. The SLR carried out in a final sample of 35 papers to identify the evolutional path each organisational function follows when organisations adopt SIPs. It identified 20 capabilities that impact organisational functions and 23 barriers faced by organisations according to the temporal moment of the journey towards fully autonomous SIPs' adoption. These capabilities and barriers were validated by experts and classified using content analysis, culminating in a final framework that presents the evolutional path for the main organisational functions as well as the barriers faced before, during and after SIPs adoption. Besides, the results (capabilities and barriers) of this chapter served as a basis for the next chapters (chapter 3, 4 and 5) of this thesis.

Chapter 3 presented, based on the PPC-enabled capabilities (identified in Chapter 2) and through expert opinion, ISM and Fuzzy *MICMAC* approach, the structural hierarchy relationship between capabilities that directly impact PPC function, culminating in a framework with the path to achieve a fully autonomous PPC function. This path provides which capabilities are achieved according to the level of autonomy of the PPC function. As a result, it was found that the structural hierarchy relationship between PPC-enabled capabilities provides a roadmap for organisations to prioritise efforts in achieving first capabilities related to connected, passing by transparent, autonomous decision-making I and finally autonomous decision-making II level, where PPC function becomes fully autonomous.

Chapter 4 aimed to enhance the comprehension of these relationships across all organisational functions. Following the same methodological sequence as Chapter 3, this chapter presents a framework illustrating the synergy between organisational functions through the adoption of SIPs. Our framework demonstrates that a virtuous cycle should encompass four levels of interfunctional synergy. In this regard, the first level of synergy involves the synchronisation of maintenance and PPC as the foundation for production control, facilitating the collection and exportation of data for improvements in production planning. The second level focuses on advancing PPC through the basic capabilities of the Maintenance function, further enhanced by the utilisation of analytics, responsiveness, and complexity management. The third level of synergy involves the interaction of low-intermediate level PPC with Accountability and Quality, thereby enhancing the virtuous cycle. At this level, the synergistic relationship transforms the high-intermediate level of PPC function enabled capabilities into an adaptive entity, wherein all organisational functions collaborate towards shared objectives and challenges to maximise organisational efficiency. Lastly, at the fourth level of synergy, the virtuous cycle enables the organisation to foster environmental stewardship through data-driven sustainability efforts. At this stage, the adoption of SIPs becomes crucial in aiding the organisation to achieve Social, Environmental, and Economic Sustainability.

Chapter 5 helped us to conceptualise and evaluate the relationship between structural barriers faced by organisations to adopt a SIP. Following the same methodological sequence as Chapter 3 and 4, this chapter presents a structured roadmap that allowed us not only to explain barriers existence through Neo-Institutional Theory but also to guide managerial actions in strategically surpass structural barriers. Besides, our framework demonstrates that, to harness full potential of SIPs, unlocking a fully autonomous PPC and organisational sustainability through maximisation of interfunctional synergy, four levels of barriers should by surpassed. In this regard, the first level comprises the Structural Sociotechnical barriers. The second level are composed by Technological Resilience barriers. The third level of structural barriers involves the Organisational Readness and Maturity barriers. At this level, overcoming organisational readiness and maturity barriers supports the institutional legitimisation of SIP-enabled practices, reducing decoupling between technological adoption and operational execution. As legitimacy increases and resistance is progressively weakened, decision-making authority and digital coordination expand more consistently across functions, enabling organisations to shift from symbolic adoption towards fully enacted transformation. Lastly, the fourth level of structural barriers is composed by the Complex Barriers that directly impacts the Dynamical Stability level of the organisation. At this stage, Dynamic Stability enables SIP-driven gains to translate into sustained Social, Environmental, and Economic Sustainability, as resilient coordination prevents regression and reinforces long-term institutional performance. Therefore, this thesis seeks to understand SIPs' role in enhancing organisational autonomy, exploring the evolutional path of organisational functions, investigating the structural relationship hierarchy between capabilities impacting PPC function, as well as the interfunctional synergy through capabilities enabled by the adoption of SIPs in industrial operations. And, finally, understanding how strategically suspass structural barriers to SIPs adoption in organisations. So, the capabilities, the barriers and the evolutional path were raised in Chapter 2. The structural relationship hierarchy was understood and used to provide a road map for a fully autonomous PPC function in Chapter 3. The synergy between organisational functions was investigated in Chapter 4. And finally, structural barriers were analised in Chapter 5. This way, it was possible to understand SIPs role in enhancing PPC autonomy, in amplifying interfunctional synergy, and the relationship between structural barriers to adopt them, providing 3 roadmaps to guide organisations' efforts in the journey to successfully adopt SIPs in their manufacturing processes.

6.2 THESIS CONTRIBUTIONS FOR THE ORGANISATIONAL THEORY FIELD

This section complements the theoretical foundations underpinning this doctoral thesis and presents its specific contributions to each organisational theory employed throughout the research. The investigation integrates multiple theoretical perspectives to explain the organisational transformation enabled by SIPs. This thesis adopts four theorethical lens to explain the results. Paper three utilised the Resource-Based View (RBV), the Dynamic Capabilities Theory (DCT) and the Sociotechnical Systems Theory (STS). Besides, the fourth paper used Neo-Institutional Theory (NTI) mechanisms to explain the configuration of each cluster of the structural barriers to SIPs adoption.

First, the RBV served as a foundation to conceptualise SIPs as enablers of valuable, rare, inimitable, and non-substitutable capabilities that, when configured strategically, generate sustained competitive advantage. In sequence, DCT complemented this lens by framing the sequential and adaptive nature of SIP-enabled capabilities, demonstrating how they evolve and reconfigure across organisational functions to sustain inter-functional synergy. Moreover, STS provided interpretative support for understanding how SIPs reshape the balance between technical and human subsystems, fostering socio-technical alignment in capability development and integration. This alignment can be considered as base to the next trend in the organisational manufacturing environment, the Industry 5.0, which is based in three main pilars: Resilience, Human-Centricity and Sustainability. Finally, the Neo-Institutional Theory (NIT) was adopted to explain the structural and institutional barriers influencing the diffusion and legitimisation of SIP practices within industrial contexts, highlighting how organisations can strategically mitigate institutional resistance through legitimacy-building and long-term dynamic stability. Table 6.1 Summarises the theoretical contributions of this thesis to each of the organisational theory.

Table 6.1 – Theoretical contributions of the thesis for each of the organisational theory

Organisational Theory	Application within the Thesis	Theorethical Contribution
RBV	Provided the theoretical basis for conceptualising SIPs as strategic enablers of organisational resources and capabilities	Extends RBV by demonstrating that SIP-enabled capabilities are not static internal assets but dynamic, resources that foster cross-functional synergy
DCT	Explained the adaptive and evolutionary behaviour of SIP-enabled capabilities across organisational functions	Advances DCT by proposing and empirically validating a hierarchical structure (via ISM and Fuzzy MICMAC) illustrating how dynamic capabilities sequentially evolve through inter-functional integration
STS	Supported the analysis of synergy formation through the interaction	Enriches STS by evidencing how SIPs act as boundary objects that promote socio-technical alignment,

	between technical autonomy and human coordination	enhancing organisational cohesion and system responsiveness
NTI	Framed the interpretation of structural and institutional barriers affecting SIPs' adoption and legitimisation	Expands NIT by integrating an influence-based roadmap that links isomorphic pressures, legitimacy acquisition, and dynamic stability within digital transformation processes

Source: Elaborated by the author (2025)

6.3 FINAL CONCEPTUAL MODEL, PROPOSED ANALYSIS STRUCTURE AND CONTRIBUTIONS

The final conceptual model proposed in this thesis integrates the four frameworks developed across the previous chapters, representing an evolutionary, cumulative, and dynamic process of organisational transformation enabled by SIPs. The framework is structured around three interdependent levels: Functional Evolution Through Structural Hierarchy of PPC-enabled Capabilities, Inter-Functional Synergy, and Dynamic Stability through Barriers Mitigation, forming a continuous cycle of capability building, coordination, and institutional consolidation.

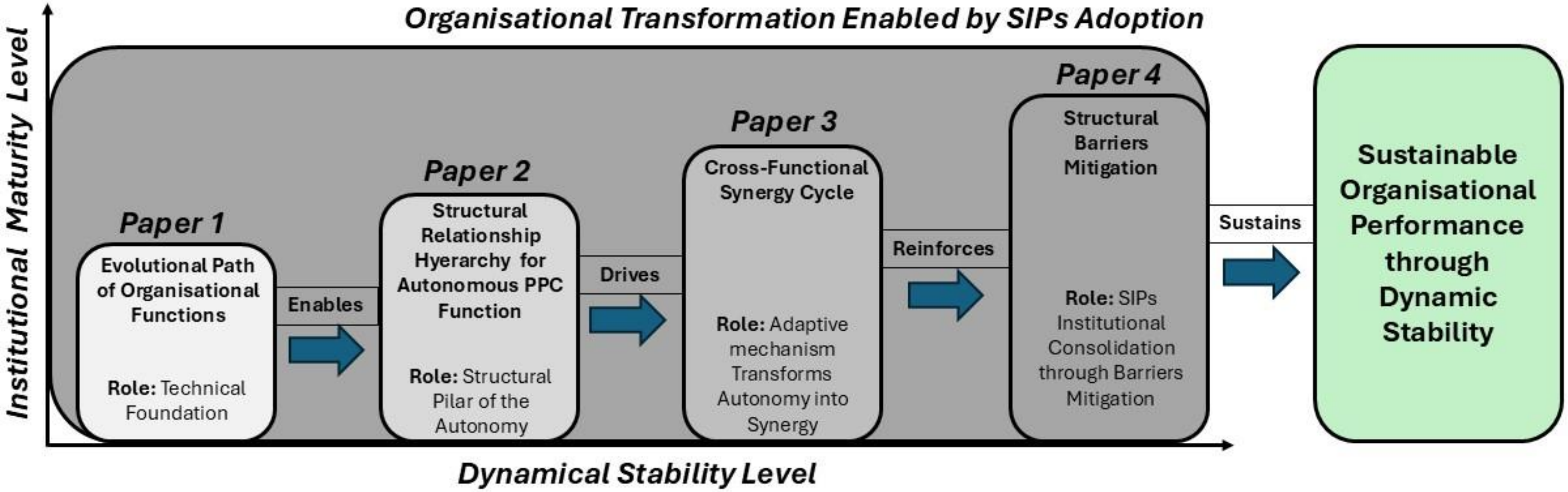
The first level stems from the integration of Models 1 and 2 (Evolutional Path and Fully Autonomous PPC Framework). It is specific to the PPC function, which operates as the structural axis of autonomy and coordination within industrial operations. The model delineates the structural hierarchy of capabilities that guide the PPC's evolution through the stages Traditional, Connected, Transparent, Autonomous Decision-Making I, and Autonomous Decision-Making II. Each stage represents an incremental enhancement of decision-making capability, data integration, and functional independence. At this level, capabilities act as the engine of transformation, providing the technical foundation that enables the PPC to orchestrate cross-functional processes and facilitate real-time, data-driven control.

The third model (Inter-Functional Synergy Framework), extends our analysis beyond the PPC to reveal how SIP-enabled capabilities stimulate synergy among main organisational functions. The integration process unfolds across four progressive stages: 1) Synchronisation between Maintenance and PPC, establishing the foundation for coordinated production control; 2) Advancement of the PPC through analytics, responsiveness, and complexity management; 3) Expansion of collaboration to Quality and Accountability, reinforcing cross-functional feedback loops; 4) Consolidation of Sustainability through data-driven decision-making that integrates economic, environmental, and social performance. At this point, inter-functional synergy operates as the adaptive mechanism that transforms technical autonomy into organisational efficiency and resilience. The organisation evolves from a mechanistic configuration into an adaptive sociotechnical system capable of dynamically respond to environmental and technological shifts.

Finally, derived from the fourth model (Barriers Mitigation Roadmap), this level acknowledges that SIP-enabled transformation is constrained by hierarchical layers of structural barriers that must be strategically mitigated. The barriers are grouped into four categories: 1) Structural Sociotechnical Integration, addressing the alignment of technological and human subsystems; 2) Technological Resilience, reflecting infrastructure robustness and cyber-physical security; 3) Organisational Readiness and Maturity, relating to digital competence and absorptive capacity; 4) Dynamic Stability through Complex Systems barriers mitigation, representing the balance between institutional legitimacy and adaptive coordination. The progressive overcoming of these barriers leads to institutional legitimacy and sustained organisational equilibrium, consolidating transformation as a technological, social, and institutional phenomenon. At this final stage, Dynamic Stability encapsulates the integration of capabilities, coordination, and legitimacy, enabling the organisation to maintain continuity while evolving through unseen change.

Together, they form an evolutionary, cumulative, and self-reinforcing architecture in which technological capabilities enhance functional smartness — first improving autonomy, which fosters cross-functional synergy, which in turn enhances stability, and ultimately secures long-term sustainable performance. In parallel, the continuous and structured mitigation of structural barriers promotes the institutionalisation of SIP-enabled practices by progressively reducing coercive, normative, and mimetic pressures, thus diminishing symbolic adoption and legacy inertia and reinforcing the legitimacy and embeddedness of digital transformation across organisational fields. Figure 6.1 presents the unified model of this thesis. Consolidating the four models developed in this thesis, and illustrating the progressive integration from SIP-enabled capabilities (Model 1) to PPC autonomy (Model 2), inter-functional synergy (Model 3), and institutional consolidation through barrier mitigation (Model 4), culminating in dynamic stability and sustainable organisational performance.

Figure 6.1 – Unified SIP-Enabled Organisational Transformation Framework



Source: Elaborated by the author (2025)

6.4 SIPs: CONCEPTUAL CLARIFICATION, LIMITATIONS AND THE “RED BOTTOM” OF THE AUTONOMY

After more than two decades of rapid digitalisation in industrial systems, the concept of SIPs has progressively moved from a theoretical promise to a practical reality in manufacturing operations. Despite the strong technical background developed throughout this thesis, it is relevant, at this final stage, to clarify in a more direct and accessible way what a SIP effectively is, what its inherent limitations are, and where the possible “red bottom” of this category of products.

In simple terms, a SIP is no longer a passive artefact that only performs mechanical functions, but a product that is capable of sensing its own condition and its environment, communicating data in real time, processing information locally or remotely, and interacting autonomously with other systems, machines, and organisational functions. Unlike traditional automation, which is strictly rule-based and limited to predefined sequences, SIPs operate within connected digital ecosystems, enabling prediction, self-adjustment, learning, and cooperative decision-making. In practice, a SIP is simultaneously a physical asset, a digital information carrier, and an active decision-support node within the production system.

From the organisational perspective, SIPs change the logic of production management. They transform data into a continuous operational flow rather than static reports, reduce informational asymmetries across functions, and allow organisational functions to operate under the same logic of real-time feedback and distributed intelligence. This capability redefines traditional managerial roles, reducing reaction time to disturbances, and enabling new forms of prescriptive and predictive decision-making.

However, SIPs are not a technological panacea. Their integration introduces structural complexities that go far beyond infrastructure investment. One of the first limitations is organisational readiness. SIPs presuppose digital maturity, data governance, cybersecurity routines, interoperable systems, and human competencies capable of interpreting and acting upon algorithmic outputs. When these elements are absent or weakly developed, SIPs tend to amplify operational noise instead of reducing it. Instead of clarity, organisations may experience information overload, misaligned priorities and decision paralysis.

Another critical limitation lies in the sociotechnical dimension. SIPs inevitably shift the locus of decision-making. Tasks previously executed by human operators based on experience and tacit knowledge become increasingly delegated to cyber-physical systems. This transition generates resistance, trust issues, and sometimes a perceived loss of professional identity. When the human factor is neglected, SIPs may be technically efficient but socially fragile, resulting in low acceptance and suboptimal utilisation.

From the economic standpoint, SIPs also follow a non-linear cost-benefit logic. Initial implementation phases demand high investment in digital infrastructure, system integration, data modelling and cybersecurity. While early gains may be significant in terms of visibility and responsiveness, the marginal returns of additional autonomy tend to decrease after a certain threshold. At advanced stages, each incremental level of autonomy requires disproportionately higher financial, organisational and cognitive effort.

This leads directly to the concept discussed as the SIPs' "Red Bottom". The red bottom represents the critical threshold beyond which further increases in autonomy no longer generate proportional strategic or operational value. It is the boundary where technical feasibility collides with organisational control, economic rationality and systemic risk.

At the red bottom of autonomy, SIPs led us to make important considerations. They negotiate production priorities, reschedule operations, trigger maintenance actions, and balance multi-objective performance indicators in real time. While this level of autonomy is technically impressive, it also represents a zone of increased vulnerability. At this point, the organisation becomes structurally dependent on algorithmic mediation. Decision logic becomes opaque for managers, traceability becomes more complex, and responsibility diffusion emerges as a critical governance issue.

Beyond the red bottom, three major risks intensify. First, control erosion: Managers progressively lose direct visibility over why certain decisions were taken by the system. Second, systemic fragility: Highly autonomous networks tend to amplify local errors into global disturbances due to high interconnectivity. Third, cognitive displacement: The organisation gradually transfers its analytical capacity to machines, weakening strategic sense-making and human judgement over time.

Therefore, we believe that the red bottom is not defined by technological limits, but by organisational, economic and ethical boundaries. It marks the point at which the question is no longer "Can we automate further?" but rather "Should we do it?". Beyond this threshold, the pursuit of full autonomy may compromise resilience, trust, accountability and strategic flexibility.

In practical terms, the red bottom varies across industries, production strategies and organisational cultures. High-volume, standardised environments tend to tolerate deeper autonomy than highly customised, safety-critical or creative production systems. The optimal level of SIP autonomy is thus contingent and must be continuously reassessed as technology, regulation and human competencies evolve.

This critical perspective does not diminish the transformative potential of SIPs. On the contrary, it reinforces the central idea of this thesis: SIPs are most powerful when embedded within balanced sociotechnical systems. Their value does not lie in replacing human intelligence, but in augmenting it, serving as a foundation for the next industrial paradigm, Industry 5.0, where human–machine coexistence will require not only the consolidation of the capabilities identified in this thesis but also the development of a new wave of capabilities grounded in human safety, resilience, and sustainability. The strategic challenge for organisations is not to maximise autonomy blindly, but to determine the precise point at which digital intelligence, human expertise, and organisational governance operate in a stable and productive equilibrium.

6.5 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This section outlines the limitations of the methods employed in this thesis, some of which are inherent to the chosen approach. Firstly, the processes involved in a SLR are naturally prone to researchers' biases. These biases can be attributed, for instance, to the selection of both objective and subjective variables during the planning phase. Our evaluation focused solely on journal articles in the English language within fields associated with engineering and operations management. Consequently, certain significant works may have been omitted from the initial sample. Furthermore, the assessment of the remaining papers was conducted using subjective filters. Initially, we reviewed the titles and abstracts of the papers to gauge their alignment with the acceptance criteria. Consequently, some papers might have been excluded at this stage despite being relevant to the inclusion criteria.

To address these limitations, a double-blind review process was implemented, involving two independent researchers who assessed the same papers, facilitating a comparison of results. Even though, the complete elimination of subjectivity in data interpretation remains unattainable. Given that Chapters 4 and 5 adhered to the same methodological sequence, their limitations are identical, stemming from the chosen approach.

Regarding ISM, this method was employed to assess the relationship between PPC-enabled capabilities. Nonetheless, the ISM approach does have several limitations. Firstly, its effectiveness heavily relies on the expertise and background of the involved experts. Secondly, it is highly sensitive to how questions are formulated. Thirdly, addressing a system that is either extensive or intricate may prove challenging and exceedingly tiresome when dealing with a particularly large matrix. Lastly, ISM cannot accommodate temporal changes.

To counter these limitations, our sample consisted of both academic and practical experts, each with over a decade of experience. The practical experts boasted diverse expertise in the realm of Smart Industrial Products, spanning countries such as Brazil, Germany, and Japan. Additionally, five academic experts actively contributed to formulating descriptions of capabilities and barriers, resulting in a consensus on the final list of both capabilities and barriers. Besides, the ISM matrices from chapters 4 and 5 consisted of 12 and 20 variables respectively, which didn't make responding so challenging and tiresome.

Concerning Fuzzy *MICMAC*, this approach also carries its limitations. Primarily, there is complexity associated with attributing fuzzy values. This complexity is linked to the sensitivity level integrated into the fuzzy model. Secondly, interpretation might be challenging due to the multitude of possible scenarios. Thirdly, precise data is required for input into the influence matrix. Lastly, similar to ISM, Fuzzy *MICMAC* encounters constraints in addressing temporal changes. To address these limitations, we employed five qualitative values, each with a different assigned value, constituting 0.25 of the range, based on the number of experts agreeing that factor "*i*" drives factor "*j*". Additionally, in relation to the approach's limitation in accommodating temporal changes, we anticipate that upon the full implementation of a SIP, changes will be more predictive. These changes are expected to be more infrastructural in nature, influencing decisions related to "what and when" to do rather than structural alterations (in levels or even in in own SIPs ecosystem). These infrastructural changes, however, may introduce new capabilities not found in the literature.

Last but not least, some gaps identified in this research have not yet been studied. First, future studies could explore the applicability of the developed model across a diverse range of organisations including, but not limited to, automotive, electronics and pharmaceuticals, identifying particularities across these industries and types of production systems. Second, researchers could track changes in capabilities (including identifying new ones), adoption rates, performance outcomes over time, and the challenges associated with the consolidation of each SIP level, providing a dynamic perspective on the influence of SIPs on production PPC. Finally, future studies could investigate the role of each emerging technologies such as artificial intelligence, machine learning, and blockchain in the ecosystem of fully autonomous SIPs in the context of PPC, assessing how these technologies enhance or complement the identified capabilities, potentially opening some new avenues for future research and practical implementation in the field of SIPs.

APPENDIX

Table A1 - Articles identified in the Systematic Literature Review

#	Source	Publication Title
01	(Atzori et al., 2010)	The Internet of Things: A survey
02	(Meyer et al., 2011)	Production monitoring and control with intelligent products
03	(Meyer, 2011)	*Intelligent Products: A Survey*
04	(Borangiu et al., 2012)	Distributed manufacturing control with extended CNP interaction of intelligent products
05	(McFarlane et al., 2013)	Product intelligence in industrial control: Theory and practice
06	(Takahara & Yasaki, 2013)	Problems with using smart devices for business and efforts to resolve them
07	(Meyer et al., 2014)	Intelligent products for enhancing the utilisation of tracking technology in transportation
08	(Porter & Heppelmann, 2014)	How smart, connected products are transforming competition
09	(Hernández & Reiff-Marganiec, 2014)	Classifying smart objects using capabilities
10	(Bouazza et al., 2015)	A model for manufacturing scheduling optimization through learning intelligent products
11	(Putnik et al., 2015)	Smart objects embedded production and quality management functions
12	(Leitão et al., 2015)	Intelligent products: The grace experience
13	(Porter & Heppelmann, 2015)	How smart, connected products are transforming companies
14	(Duffy & Whitfield, 2016)	*Smart Products through-life*
15	(Dawid et al., 2017)	Management science in the era of smart consumer products: challenges and research perspectives
16	(Abramovici et al., 2017)	Reconfiguration of smart products during their use phase based on virtual product twins
17	(Ding & Jiang, 2018)	Incorporating social sensors, cyber-physical system nodes, and smart products for personalized production in a social manufacturing environment
18	(Cena et al., 2019)	Multi-dimensional intelligence in smart physical objects
19	(Silverio-Fernández et al., 2018)	What is a smart device? - a conceptualisation within the paradigm of the internet of things
20	(Sorouri & Vyatkin, 2018)	Intelligent product and mechatronic software components enabling mass customisation in advanced production systems
21	(Juric & Lindenmeier, 2019)	An empirical analysis of consumer resistance to smart-lighting products
22	(Keshavarzi & Van Den Hoek, 2019)	Edge Intelligence-On the Challenging Road to a Trillion Smart Connected IoT Devices
23	(Tomiyama et al., 2019)	Development capabilities for smart products
24	(Zhang et al., 2020)	Environment interaction model-driven smart products through-life design framework
25	(Kahle et al., 2020)	Smart Products value creation in SMEs innovation ecosystems
26	(Lenz et al., 2020)	Optimizing smart manufacturing systems by extending the smart products paradigm to the beginning of life
27	(Raff et al., 2020)	Smart Products: Conceptual Review, Synthesis, and Research Directions

28	(Pardo et al., 2020)	Are products striking back? The rise of smart products in business markets
29	(Hungud & Arunachalam, 2020)	Digital twin: Empowering edge devices to be intelligent
30	(Yi et al., 2021)	Digital twin-based smart assembly process design and application framework for complex products and its case study
31	(Vendrell-Herrero et al., 2021)	Adoption and optimal configuration of smart products: The role of firm internationalization and offer hybridization
32	(Ruhul Amin et al., 2021)	Cyber attacks and faults discrimination in intelligent electronic device-based energy management systems
33	(Rathee et al., 2021)	Decision-Making Model for Securing IoT Devices in Smart Industries
34	(Lin et al., 2021)	Evolutionary digital twin: A new approach for intelligent industrial product development
35	(Thürer et al., 2021)	Self-Organizing Material Flow Control using Smart Products: An Assessment by Simulation
36	(Imad et al., 2022)	Intelligent machining: a review of trends, achievements and current progress
37	(Liu et al., 2021)	Digitalisation and servitisation of machine tools in the era of Industry 4.0: a review
38	(Oluyisola et al., 2022)	Designing and developing smart production planning and control systems in the industry 4.0 era: a methodology and case study
39	(Antons & Arlinghaus, 2022a)	Data-driven and autonomous manufacturing control in cyber-physical production systems
40	(Antons & Arlinghaus, 2022b)	Distributing decision-making authority in manufacturing–review and roadmap for the factory of the future
41	(Tran et al., 2022)	Retrofitting-Based Development of Brownfield Industry 4.0 and Industry 5.0 Solutions
42	(Attajer et al., 2022)	An analytic hierarchy process augmented with expert rules for product driven control in cyber-physical manufacturing systems
43	(Lei et al., 2022)	Reinforcement learning-based dynamic production-logistics-integrated tasks allocation in smart factories
44	(Turner et al., 2022)	Industry 5.0 and the Circular Economy: Utilizing LCA with Intelligent Products

Source: Elaborated by the author

Table A2 - Selected papers from the SLR of capabilities enabled by SIPs adoption in PPC function

#	Source	Publication Title
01	(ATZORI; IERA; MORABITO, 2010)	The Internet of Things: A survey
02	(MEYER; HANS WORTMANN; SZIRBIK, 2011)	Production monitoring and control with intelligent products
03	(MEYER; FRÄMLING; HOLMSTRÖM, 2009)	*Intelligent Products: A Survey*
04	(BORANGIU et al., 2012)	Distributed manufacturing control with extended CNP interaction of intelligent products
05	(MCFARLANE et al., 2013)	Product intelligence in industrial control: Theory and practice
06	(TAKAHARA; YASAKI, 2013)	Problems with using smart devices for business and efforts to resolve them
07	(MEYER et al., 2014)	Intelligent products for enhancing the utilisation of tracking technology in transportation
08	(PORTER; HEPPELMANN, 2014)	How smart, connected products are transforming competition
09	(BOUAZZA et al., 2015)	A model for manufacturing scheduling optimization through learning intelligent products
10	(PUTNIK et al., 2015)	Smart objects embedded production and quality management functions
11	(LEITÃO et al., 2015)	Intelligent products: The grace experience
12	(PORTER; HEPPELMANN, 2015)	How smart, connected products are transforming companies
13	(ABRAMOVICI; GÖBEL; SAVARINO, 2017)	Reconfiguration of smart products during their use phase based on virtual product twins
14	(DING; JIANG, 2018)	Incorporating social sensors, cyber-physical system nodes, and smart products for personalized production in a social manufacturing environment
15	(CENA et al., 2019)	Multi-dimensional intelligence in smart physical objects
16	(SOROURI; VYATKIN, 2018)	Intelligent product and mechatronic software components enabling mass customisation in advanced production systems
17	(ZHANG et al., 2020)	Environment interaction model-driven smart products through-life design framework
18	(LENZ et al., 2020)	Optimizing smart manufacturing systems by extending the smart products paradigm to the beginning of life
19	(RAFF; WENTZEL; OBWEGESER, 2020)	Smart Products: Conceptual Review, Synthesis, and Research Directions
20	(PARDO; IVENS; PAGANI, 2020)	Are products striking back? The rise of smart products in business markets
21	(HUNGUD; ARUNACHALAM, 2020)	Digital twin: Empowering edge devices to be intelligent
22	(YI et al., 2021)	Digital twin-based smart assembly process design and application framework for complex products and its case study
23	(VENDRELL-HERRERO; BUSTINZA; VAILLANT, 2021)	Adoption and optimal configuration of smart products: The role of firm internationalization and offer hybridization
24	(RUHUL AMIN et al., 2021)	Cyber-attacks and faults discrimination in intelligent electronic device-based energy management systems

25	(IMAD et al., 2022)	Intelligent machining: a review of trends, achievements, and current progress
26	(LIU; ZHENG; XU, 2023)	Digitalisation and servitisation of machine tools in the era of Industry 4.0: a review
27	(ANTONS; ARLINGHAUS, 2022a)	Data-driven and autonomous manufacturing control in cyber-physical production systems
28	(ANTONS; ARLINGHAUS, 2022b)	Distributing decision-making authority in manufacturing–review and roadmap for the factory of the future
29	(TRAN et al., 2022)	Retrofitting-Based Development of Brownfield Industry 4.0 and Industry 5.0 Solutions
30	(ATTAJER et al., 2022)	An analytic hierarchy process augmented with expert rules for product driven control in cyber-physical manufacturing systems
31	(LEI et al., 2022)	Reinforcement learning-based dynamic production-logistics-integrated tasks allocation in smart factories
32	(TURNER et al., 2022)	Industry 5.0 and the Circular Economy: Utilizing LCA with Intelligent Products

Source: Elaborated by the author

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