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Unveiling digital technology adoption in the pharmaceutical supply chain: a *macro*, *meso*, and *micro* analysis

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UNIVERSITÀ DEGLI STUDI DI SIENA

Dipartimento di Ingegneria dell'Informazione e Scienze Matematiche

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Introduction

The Pharmaceutical Supply Chain (PSC) is a critical component of the healthcare ecosystem, responsible for ensuring the timely, safe, and secure delivery of drugs and medical supplies to patients and healthcare institutions. In recent years, the digital transformation of the PSC has emerged as a strategic priority. The increasing complexity of global SC operations, the rising expectations of innovation in healthcare delivery, and major disruptions such as the COVID-19 pandemic have prompted pharmaceutical organizations to explore Digital Technologies (DT) as a means to improve operational coordination, accelerate biomedical and clinical innovation, and enhance the resilience of SC systems [1]. During the pandemic, large-scale digital transformation initiatives became widespread, shifting organizational mindsets, unlocking new funding opportunities, and fostering an enduring appetite for DTs. Nevertheless, for many firms, they remain a relatively recent and ongoing endeavor. Recent insights from a Deloitte survey [2] of 105 PSC leaders reveal the fragmented nature of digital transformation in the sector: only one-third of pharmaceutical companies are pursuing comprehensive digital transformation programs, while most focus on isolated improvements. Notably, no firm has yet achieved full-scale deployment of advanced digital capabilities. Several factors still challenge the path toward digital transformation at the SC level, and they need to be carefully systematized.

The exploration of DTs within the pharmaceutical industry, particularly from a management studies perspective, is limited [3]. Existing research is primarily located within the broader healthcare setting, focusing on patient-centered approaches, drug discovery and development, operational efficiency in care providers, knowledge management, and sustainability, with relatively little attention devoted to the PSC [4][5]. This highlights a notable gap in the literature and underscores the need for more comprehensive studies to advance academic debates on digital transformation in the PSC.

To date, research on digital transformation in the PSC has largely focused on the adoption and use of individual DTs, offering technical or application-oriented insights, while paying limited attention to managerial perspectives [3]. Although a few studies [1, 6, 7, 8] have examined multiple digital solutions, they often lack a detailed analysis of technology-specific factors influencing adoption and implementation processes. Another significant gap lies in the limited empirical understanding of how SC relationships shape DT adoption within pharma supply networks. While existing studies have primarily examined the impacts and influences of DTs on the dynamics of SC relationships (e.g., [9],[10],[11]), empirical evidence on the managerial mechanisms that support the diffusion of DTs both within and between PSC organizations remains scarce.

To fully understand the implications of digital transformation within the pharmaceutical context, it is essential to first outline the structure and operational dynamics of the PSC. The following section provides a general overview of its key processes and decision areas, which form the foundation for analyzing the impact of DTs across different stages of the SC.

Key processes and decision areas in the PSC

The PSC encompasses all techniques, methodologies, tools, and infrastructures used to manage physical drug flows and the corresponding information flows. The complexity of pharmaceutical delivery is organized through a series of interlinked processes designed to ensure a high level of efficiency, transparency, and responsiveness across healthcare operations. These processes include manufacturing, procurement, transportation, warehousing, inventory management, distribution, and reverse logistics.

Manufacturing. The PSC begins with drug production. Pharmaceutical companies manufacture a wide range of products characterized by distinct demand patterns, from widely used commercial drugs (e.g., vaccines and painkillers) to specialized clinical or specialty products (e.g., biologics and stem cells), each with unique dosage form, stability profiles, and economic values. The manufacturing process involves key activities, including drug formulation, production (after pre-clinical research and regulatory approval), clinical trials, quality control, and packaging and labeling. Ensuring consistent quality across multiple production sites, particularly under stringent regulatory frameworks such as Good Manufacturing Practices (GMP) compliance, represents a persistent challenge. Data generated during manufacturing, including batch numbers, production timestamps, and temperature requirements, are crucial for downstream logistics [12, 13, 14].

Procurement. The procurement process involves evaluating the suppliers capable of providing the required goods and selecting them, typically through competitive bidding or direct negotiation [15]. Beyond identifying cost-effective partners, procurement teams must plan and execute demand analysis and forecasting, and ensure supply reliability in volatile global markets and regulatory scrutiny. Inaccurate forecasts and unreliable or geographically concentrated suppliers can expose organizations to disruptions and shortages of essential medicines, as highlighted during recent crises [16]. In addition, the absence of a robust supplier verification system can allow substandard or counterfeit materials to enter the SC, affecting product safety [17]. Strategic decisions include the range of products and services to purchase, supplier power, and the overall capacity of the supply network.

Transportation. The transportation process involves moving pharmaceutical products from manufacturers to wholesalers, and between different warehouses (including hospital pharmacies), often through intermediate distributors [18]. The primary objectives are to reach the right customer, at the right time, with the right quantity, quality, and cost [8]. Decisions focus on optimizing routes based on time, costs, and expiration dates, encompassing routine trips and milk runs, pallets and stock-keeping unit selection, and the choice of transportation means until the last mile delivery. Maintaining product integrity during transportation—especially for temperature-sensitive drugs—poses major logistical and compliance challenges. Cold chain failures, fragmented logistics networks, and limited real-time visibility can compromise product safety and regulatory compliance.

Inventory management. The management of the inventory includes the operations used to receive, collect, and sort drugs and medical supplies. It is considered a critical operation, with several methods proposed to balance stock availability and holding costs, thereby improving the service level of PSC actors and warehousing practices [19]. More recent innovations include the personalized unit-dose system, with medicines provided to hospital pharmacies that are divided into single doses, and automated dispensing machines. However, managing pharmaceutical inventories remains challenging due to the perishable nature of many products and the risk of obsolescence. Balancing safety stock with the prevention of expiration and ensuring traceability across locations are persistent issues, particularly in multi-tier and globalized supply networks.

Warehouse management. Key decisions in warehouse management concern layout and space organization, storage operations at different tiers of the PSC (e.g., ward warehouses and hospital pharmacies), pharmacy operations within hospitals, and capacity planning. Important considerations include warehouse location, dimensions, equipment, partitioning, and operational decisions related to receiving, storage, picking, and shipping, as well as task planning to reduce ergonomic workload and balance automation with human labor [19]. These facilities must comply with strict environmental and safety regulations, such as Good Distribution Practices (GDP), while maintaining optimal temperature and humidity conditions to ensure product quality. Space limitations, manual handling errors, and the high cost of automation technologies further limit efficiency and flexibility.

Distribution. This process pertains to the micro-logistics view, encompassing the internal logistics of hospitals and patient care units, from drug prescription to administration [15]. It includes preparing and delivering doses from hospitals' pharmacies to the wards or care units, local storage, and administering or disposing of medications according to prescriptions [19]. At this stage, challenges often arise from coordination failures, information asymmetries, and potential medication errors. Ensuring accurate and timely delivery to patients, while minimizing waste, requires highly synchronized processes and digital integration between hospital departments.

Reverse logistics. Once distribution is complete, part of the PSC is dedicated to managing the reverse flow and storage of goods - including expired and recalled drugs and pharmaceutical wastes - from the point of final consumption, i.e., the care unit or the pharmacy. Proper disposal requires coordination among multiple stakeholders and consideration of inventory and production planning, alongside emerging traceability technologies [20]. Reverse logistics remains underdeveloped in many pharmaceutical systems, constrained by fragmented responsibilities, high costs, and limited digital traceability. The absence of standardized return procedures often results in inefficiencies and risks to both public safety and sustainability objectives.

Overall, all PSC operations aim to ensure a continuous, seamless flow of materials and services, supporting efficient and reliable healthcare delivery, while facing significant risks and roadblocks [21].

These complexities and inherent risks underscore the potential of digital transformation to enhance visibility, coordination, and resilience in the PSC, enabling more agile and data-driven decision-making at every stage.

Outline of the research

Building on the research gaps identified in the preceding sections, this thesis is structured around three studies that examine digital transformation in the pharmaceutical industry from a multi-level perspective, encompassing *macro*-, *meso*-, and *micro*- levels of analysis (Figure 1).

The first study aims to understand the state-of-the-art of DTs in the PSC, with a focus on the key determinants influencing their acceptance and use by PSC organizations (*macro*-level perspective). The second and third studies investigate how different managerial levers can influence the adoption of DTs. More specifically, the second study adopts an inter-organizational perspective by exploring the role of SC collaboration in supporting the diffusion of DTs across SC networks (*meso*-level perspective). The third study takes an intra-organizational perspective, examining the contextual factors and behavioral responses that shape the integration of AI technologies in the SC demand planning of a pharmaceutical manufacturing firm (*micro*-level perspective).

The research questions (RQ) guiding this thesis are the following:

RQ1) *What DTs have been investigated in the PSC from an adoption perspective?*

RQ2) *What are the major factors that prevent or favor the adoption of these DTs in the PSC?*

RQ3) *What are the avenues for future research on factors in the digital transformation of the PSC?*

RQ4) *Which actors favor the diffusion of DTs along the PSC?*

RQ5) *What support mechanisms are adopted to collaboratively foster the adoption of DTs?*

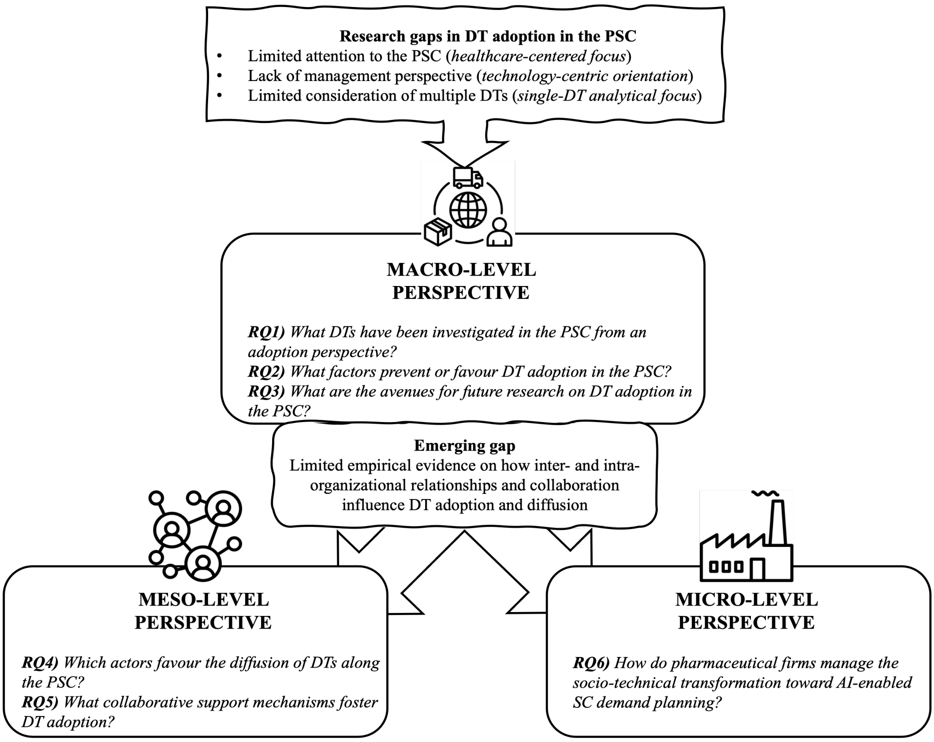
RQ6) *How do pharmaceutical firms manage the socio-technical transformation toward AI-enabled SC demand planning?*

RQ1-RQ3 were formulated to go beyond fragmented, technology-specific analyses in the PSC context by consolidating knowledge on DT adoption and related influences and identifying avenues for future research. To address RQ1-RQ3, a systematic review of the literature on DT adoption in the PSC was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [22], ensuring methodological rigor in the identification, selection, and analysis of relevant publications. The review analyzes 173 studies through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) [23]. It maps the adoption landscape of nine DTs widely discussed in the PSC research and the key UTAUT factors that either prevent or favor their acceptance and use. In addition, the study highlights major research gaps that inform future research.

RQ4 and RQ5 are motivated by the scarcity of studies examining the role of SC relationships in the adoption of DTs within pharmaceutical supply networks, in contrast to the predominant body of prior research, which has focused on the reverse relationship—namely, how the adoption of DTs affects SC relationships. To answer RQ4 and RQ5, the second study adopts a mixed-method research design to explore the role of key PSC actors in supporting the diffusion of DTs and to assess the impact of some inter-organizational collaborative mechanisms at the economic, technological, and human resource levels. Drawing on the Innovation Diffusion Theory (IDT) [24], the study combines quantitative data from a survey of 74 managers at different PSC tiers with qualitative insights from semi-structured interviews with 12 of these respondents, allowing for a deeper understanding of the mechanisms underlying the quantitative findings.

Finally, RQ6 responds to the limited empirical knowledge of how digital transformation unfolds within PSC organizations, particularly in relation to advanced and still-maturing technologies such as AI. Existing studies often emphasize technical aspects or application outcomes, while overlooking the socio-technical factors shaping the adoption process of the technology. Using a qualitative case study approach, the third study aims to generate rich, contextual insights into the behavioral and institutional dynamics of AI-driven demand planning transformation in a Spanish pharmaceutical firm. Data were collected through semi-structured interviews and were complemented by archival and public data to ensure methodological triangulation. Following the inductive approach of the Gioia methodology [25], qualitative data were coded into first-order concepts, second-order themes, and three aggregate dimensions. The resulting grounded model revealed how AI adoption unfolds from pre-adoption conditions to the realization of operational benefits and value.

The remainder of the thesis is structured as follows. After this introduction, Chapters 1, 2, and 3 present the three studies that form the core of this research. The Conclusions chapter synthesizes the findings and discusses the overall theoretical and practical contribution of the thesis.



- Limited attention to the PSC (*healthcare-centered focus*)
- Lack of management perspective (*technology-centric orientation*)
- Limited consideration of multiple DTs (*single-DT analytical focus*)

RQ1) *What DTs have been investigated in the PSC from an adoption perspective?*
RQ2) *What factors prevent or favour DT adoption in the PSC?*
RQ3) *What are the avenues for future research on DT adoption in the PSC?*

Limited empirical evidence on how inter- and intra-organizational relationships and collaboration influence DT adoption and diffusion

RQ4) *Which actors favour the diffusion of DTs along the PSC?*
RQ5) *What collaborative support mechanisms foster DT adoption?*

RQ6) *How do pharmaceutical firms manage the socio-technical transformation toward AI-enabled SC demand planning?*

Figure 1: Overview of the three analytical perspectives (*macro*, *meso*, and *micro*) adopted in the research

Chapter 1

The adoption of digital technologies in the pharmaceutical supply chain: A systematic literature review

This first chapter establishes the *macro*-level foundation of the thesis by providing an exhaustive map of the digital transformation landscape across the global Pharmaceutical Supply Chain (PSC). By synthesizing existing literature through the Unified Theory of Acceptance and Use of Technology (UTAUT), it identifies the broad technological trends and the systemic drivers and barriers that shape Digital Technology (DT) adoption and use across PSC organizations. While this chapter clarifies what technologies are being adopted and which general factors influence this process, it also reveals a critical gap: the lack of empirical evidence regarding the collaborative dynamics between PSC actors. This macro-level overview sets the stage for the subsequent chapters, which examine, at the *meso*-and *micro*-levels, respectively, how inter- and intra-organizational relationships affect the adoption and diffusion of DTs.

1.1 Introduction

Technological advancements have long been recognized as fundamental to the progress of the PSC [26], and the urge to remain at the forefront of these developments has led to the implementation of various solutions that can transform the entire logistics chain in the pharma industry [27]. DTs can be applied across many functions to make the entire PSC more efficient, traceable, and well-coordinated, bringing considerable advantages in terms of safety, precision, and innovation, as well as improving knowledge management among all the PSC participants (manufacturers, distributors, wholesalers, healthcare providers, retailers, and patients). Recent insights from a Deloitte survey [2] of 105 PSC leaders underscore the practical urgency for SC actors to embrace digital transformation, reinforcing the importance of investigating technology adoption from both the organization's and the employees' perspectives.

The growing importance of digital transformation has attracted considerable scholarly attention regarding its drivers and impacts within the PSC. The majority of papers analyzed the state of the art in the use of some specific DTs, such as blockchain [28][29][30], drones [31][32], and additive manufacturing [33]. Only a few reviews broadened their focus by considering different digital solutions. For example, [6] and [1] explored how the use of blockchain and RFID can improve the level of transparency and accountability in the PSC. [34] showed that the adoption of Industry 4.0 technologies can support the development of sustainable PSCs, even if it requires solving several related challenges. Similarly, [7] focused on track-and-trace systems based on RFID or barcodes to prevent falsified medical products from entering the PSC, emphasizing the political, economic, and social contexts that influence their implementation. To the best of current knowledge, only [8] reviewed the studies on the adoption of DTs in the PSC, but did not provide a detailed view of the specific barriers that affect the implementation of each technology. This lack prevents a full understanding of the common issues that may occur in the adoption of different DTs in the PSC.

The present study aims to review the existing studies on the adoption of different DTs in the PSC from the viewpoint of the employees and the organizations in charge of the different SC operations. While not considering the adoption perspective of patients, the goal is to uncover the current and future trends of research on DT adoption determinants by PSC personnel. As outlined in the Introduction chapter, this study addresses the following research questions (RQ):
RQ1) *What DTs have been investigated in the PSC from an adoption perspective?*
RQ2) *What are the major factors that prevent or favor the adoption of these DTs in the PSC?*
RQ3) *What are the avenues for future research on factors in the digital transformation of the PSC?*

An in-depth investigation of the factors affecting or hampering the acceptance and use of technologies in different processes and decision areas should consider if they are related to the nature of these technologies, as well as to some characteristics of the actors involved and the external environment. To this aim, this study analyzes the literature on determinants of the PSC digital transformation by adopting the UTAUT proposed by [23] as a theoretical framework. By applying the UTAUT, it offers a nuanced understanding of how to bridge the gap between technological potential and effective implementation. The findings provide valuable insights for practitioners and researchers alike, showing how a deeper understanding of acceptance and use patterns can improve operational efficiency, enhance SC resilience, and inform strategic production and distribution planning in a complex supply network like pharmaceuticals.

The remainder of this study is organized as follows. After this introduction, Section 1.2 describes the framework underpinning the review process, which allows us to define the UTAUT model. Section 1.3 describes the methodology of systematic literature review according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, followed by Section 1.4 with the results of the analysis to answer RQs 1-2. Section 1.5 critically discusses these findings and identifies the research gaps for future research avenues, answering RQ3. Finally, Section 1.6 points out the theoretical and practical contributions of the study, as well as its limitations and conclusions.

1.2 Theoretical background

The adoption of DTs by individuals, organizations, and industries has been analyzed by using several models that consider different kinds of determinants [35]. In particular, the most widely used model for the analysis of technology adoption is surely the Technology Acceptance Model (TAM) proposed by [36]. This model discusses how the intention to use a certain technology is affected by two main determinants: Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU). The former is defined as “the degree to which a person believes that using a particular system would enhance his/her job performance”, while the latter is “the degree to which a person believes that using a particular system would be free of effort”. The TAM model was developed to analyze technology adoption by individuals. Nevertheless, employees’ decision to adopt or reject a certain technology is often a social phenomenon in which employees may influence each other, as well as be affected by some characteristics of the environment and organization in which they operate [37]. For this reason, TAM has been largely employed even in the analysis of technology adoption by organizations [35], but with the inclusion of other variables, which act as either external predictors or moderators, thus leading to the development of more advanced and complex TAM versions [38].

In this sense, one of the most recent and complete models for the analysis of technology adoption is the UTAUT, proposed by [23]. Different from TAM, this model includes more potential determinants of technology adoption, thus enabling a better understanding of this phenomenon, as demonstrated by the larger variance explained by UTAUT models compared to TAM ones [39]. In particular, UTAUT models provide a clearer picture of the role played by some social and environmental factors, which could significantly affect the innovative behavior of firms operating in highly integrated SCs, such as the PSC [40]. UTAUT classifies the adoption factors into four categories: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).

PE extends the TAM's PU by including elements from other models, such as extrinsic motivation, job fit, relative advantage, and outcome expectations. The adoption of new technology can affect the PE experienced by an organization by influencing not only its economic performance but also the quality and speed of its operations, as well as the jobs of its employees [23].

The second UTAUT determinant, EE, extends the TAM's PEOU by including elements from other models, such as complexity and ease of use. EE is strongly related to the level of trialability of a technology [41], since it may favor a more correct evaluation of the effort required for its implementation, and its level of standardization [42], which can reduce the organizational effort necessary for its implementation, thanks to the provision of common guidelines.

The third UTAUT determinant, SI, is "the degree to which an individual perceives that important others believe he or she should use the new system" [23]. This construct is not related to those included in TAM, but it is also based on constructs used in other technology adoption models, such as subjective norm, social factors, and image. In the analysis of the adoption of a technology by individuals, SI is associated with the psychological pressure exerted by peers and top managers [23]. In the analysis of the adoption of technology by an organization, SI should consider not only the psychological pressure due to some internal mechanisms, such as coordination, leadership, and culture [43], but also the role played by external actors, starting from those operating in the SC [44].

Finally, FC is "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system". It is based on constructs already used in other adoption models, different from TAM, such as perceived behavioral control and compatibility. FC includes all the internal and external constraints that may affect technology adoption by an organization, from the environmental conditions to the necessary resources and competencies [23].

1.3 Methodology

Aiming at exploring current areas of discussion and enhancing a robust knowledge base [45] on the factors affecting the adoption of DTs in the PSC, this study performs a systematic literature review. The review process was conducted following the PRISMA guidelines [22, 46]. This technique guarantees the validity of the literature search, identification, selection, and reporting, and the reliability of data analysis. Moreover, this protocol has been extensively adopted in healthcare reviews, as well as in more recent publications on the healthcare SC [14, 47]. The most recent PRISMA version [46] comprehends the items of identification, screening, and inclusion, below.

Identification. A keyword search was performed in the Scopus database to identify terms reflecting the scope of the pharmaceutical industry and the SC as the unit of analysis. Accordingly, the search combined (drug OR pharma* OR medical OR healthcare OR “health care” OR “hospital”) and (“supply chain” OR logistics) in the title, abstract, and keywords. In addition, the search string included keywords (connected with ‘OR’) referring to a set of DTs identified in prior PSC-related works [8, 30, 48, 49, 50]. These technologies are Additive Manufacturing (AM), Artificial Intelligence (AI), Big Data Analytics (BDA), blockchain, drones, Electronic Health Records (EHR), Electronic Medical Records (EMR), Electronic logistics information systems (E-logistics), Internet of Things (IoT), machine learning, Radio Frequency Identification (RFID), and robots. The identification phase yielded a total of 3,467 papers after removing duplicates.

Screening. In this phase, inclusion and exclusion criteria were defined to guide the screening and selection of studies deemed relevant to the aims of the study. Only works written in English and published in peer-reviewed journals were included. Conference papers, industry reports, books, and book reviews were excluded in order to ensure a focus on quality publications. No restrictions were imposed on the time span of the publications.

The screening was conducted considering the following eligibility criteria: *Process scope*, *Application*, and *Adoption factors*.

Concerning the *Process scope*, only studies dealing with the technology adoption from the perspective of personnel involved in SC operations were selected, while studies focusing on patients as users were excluded. In addition, only applications related to processes and decision areas within PSC operations and logistics were considered. Accordingly, studies addressing technologies for processes strictly related to hospitals and healthcare facilities—such as patient data management or surgery scheduling—were excluded.

Concerning the *Application*, papers focusing on the development of DTs or on very early adoption patterns by healthcare organizations were excluded when they did not consider the implications for the users of these technologies according to adoption factors.

Concerning the *Adoption factors*, the review included papers studying implementation modes, drivers and barriers, as well as benefits and challenges of DT adoption in the PSC that are referable to one or more factors of the UTAUT model, also from an organizational perspective. Papers studying factors of DT adoption in other SCs were also included in the final set when the healthcare or pharmaceutical industry constituted one of the application contexts.

Three researchers independently scanned the title, abstract, and keywords of the publications to avoid bias by applying these criteria. After resolving any potential disagreement by discussion and consensus, a total of 1060 papers were considered eligible for full-text reading.

Included. After reading the full text of the papers, the final sample resulted in 130 papers providing an overview of the current state of research on DT adoption in the PSC context. Each of the 130 papers underwent cross-referencing, leading to the inclusion of 43 additional relevant studies, for a total of 173 papers. After presenting the descriptive findings, the themes identified in Section 1.2 – i.e., UTAUT factors – were used for conducting the thematic analysis of the publications. This analysis followed a structured approach, based on full-text examination of the papers, involving the systematic identification of keywords associated with different DT adoption and acceptance factors, and their assignment to the corresponding UTAUT dimension (Table A.1). The results on the classification and literature coverage of adoption factors according to UTAUT dimensions are reported in Table A.2.

Figure 1.1 presents the PRISMA flow diagram followed in this study for identifying, screening, and analyzing the relevant publications to the aims of the study.

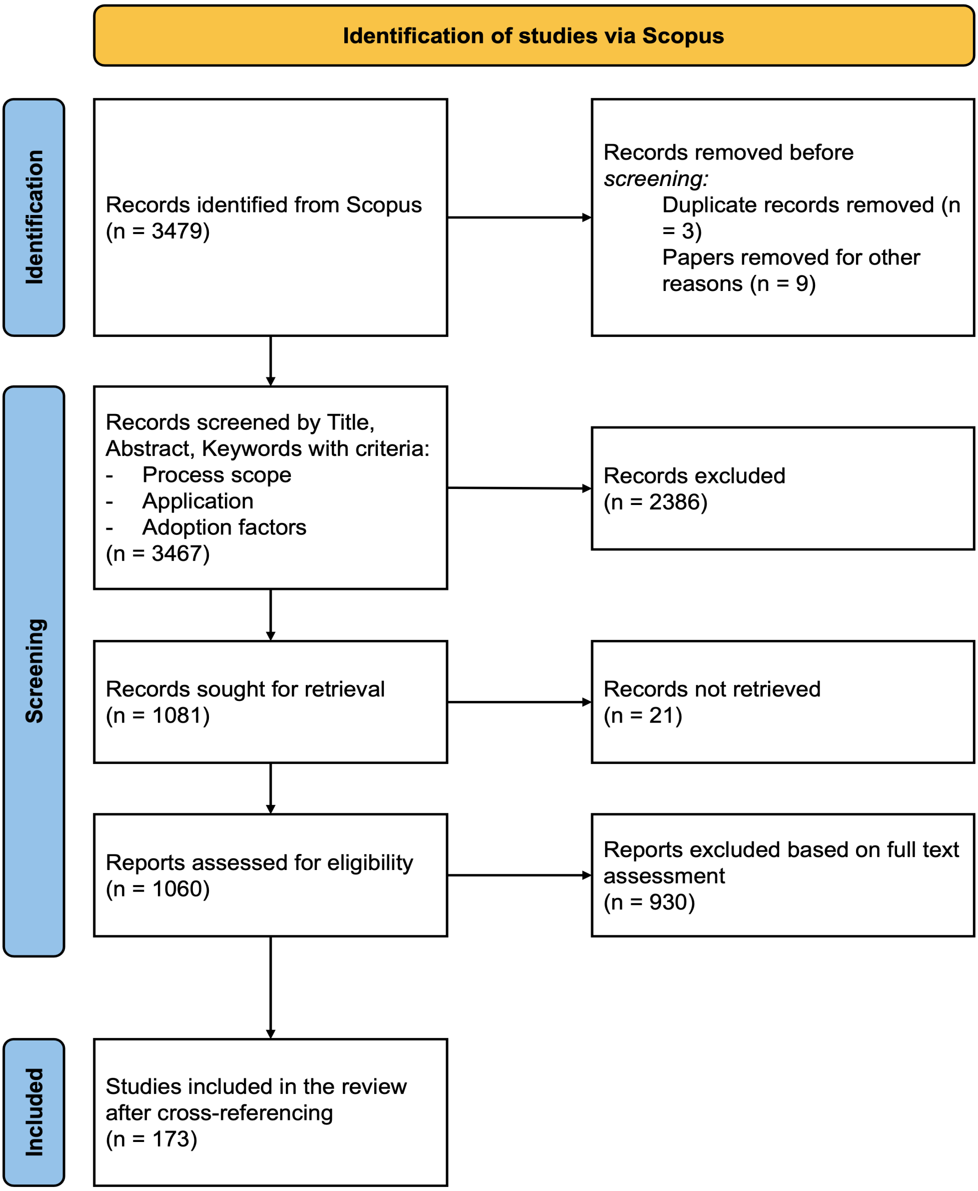


Figure 1.1: PRISMA flow diagram and results

1.4 Results

This section presents the results of the descriptive analysis and critically examines the resulting 173 papers with two lenses: the DTs adopted in the PSC, and the UTAUT dimensions driving their adoption.

1.4.1 Descriptive results

All the papers included in the review are focused on the PSC of commercial drugs, while no studies discussed the adoption of DTs in the SCs that deliver clinical drugs. Besides, most papers are focused on drugs based on small molecules, while only two papers [51, 52] discuss biologics.

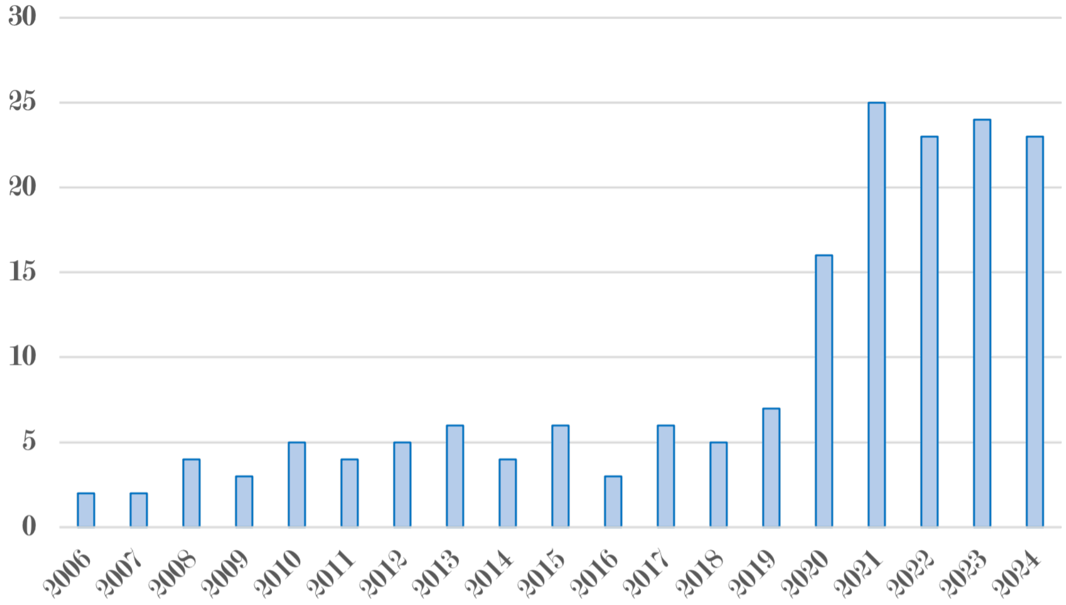


Figure 1.2: Distribution of papers over time

The distribution of papers over time (Figure 1.2) shows a growing interest of researchers in the topic of technology adoption in the PSC, with a marked increase in publications in 2020. This surge likely reflects the intensified attention on the PSC during the COVID-19 pandemic. As shown in Figure 3, these publications appeared predominantly in journals categorized under the Physical Sciences (42%), followed by those in Social Sciences (27%), Health Sciences (23%), and Life Sciences (8%), according to the All Science Journal Classification (ASJC) in Scopus. The journals with the highest number of published papers are the *Journal of Medical Systems* (7 papers), Drones (7 papers), *IEEE Transactions on Engineering Management* (6 papers), and the *International Journal of Environmental Research and Public Health* (5 papers).

The analysis of methodological approaches reflects a balanced distribution between conceptual (90 papers) and empirical research (83 papers). The most frequently used method among conceptual papers is the literature review (69 papers). Empirical papers primarily adopt surveys (27 papers) and qualitative methods (36 papers), especially case studies and secondary data analysis. Mixed-methods papers combine literature reviews or mathematical/simulation models with qualitative methods, such as interviews (6 papers), case studies (4 papers), or Delphi studies (2 papers), or with quantitative analysis, including DEMATEL (4 papers) or a survey (1 paper). Others integrate participant observations, interviews, or focus groups with other qualitative methods or surveys (both 2 papers).

Technology adoption model or theory	**References**
UTAUT	[39, 52, 53, 54]
Technology-Organization-Environment (TOE)	[55, 56, 57, 58]
TAM	[59, 60]
Task-Technology Fit (TTF)	[61, 62]
TAM + UTAUT	[63]
TAM + TOE	[64]
TAM + Innovation Diffusion Theory (IDT)	[65]
TOE + IDT	[66]
TOE + Technological Readiness Index (TRI)	[28]
TOE + Organizational Information Processing Theory (OIPT)	[67]
TOE + Human-Organization-Technology fit (HOT-fit)	[68]

Table 1.1: Technology adoption model and theories in empirical studies on DTs in the PSC

Only a few empirical studies have technology adoption models and theories underpinning their theoretical frameworks. As shown in Table 1.1, there appears to be a prevalence of theories and models that incorporate multiple contextual factors to describe the readiness and adoption behavior of DT users, such as TOE (4 papers) and UTAUT (4 papers). At the same time, the literature remains fragmented, with some studies relying on models that consider a narrower set of acceptance factors—such as the TAM (2 papers)—or, more recently, on frameworks emphasizing effective technology use—such as TTF (2 papers)—and even one-off attempts (in total 7 papers) combining multiple models and theories—such as TAM and UTAUT, TAM and TOE, or these two merged with IDT. All of these models originate from different disciplinary traditions and emphasize distinct levels of analysis, which have often limited their applicability to specific contexts or stakeholder perspectives. In this regard, UTAUT provides a more comprehensive and integrative theoretical lens by bridging individual- and organizational-level perspectives. While TAM primarily focuses on individual cognitive evaluations (PU and PEOU), UTAUT extends this view by incorporating social and environmental conditions (SI and FC). In contrast, the TOE framework [69] adopts a predominantly organizational perspective, emphasizing technological, organizational, and environmental conditions, while neglecting individual-level adoption mechanisms. This limits its ability to explain how managerial and employee perceptions mediate organizational decisions regarding DTs. Similarly, TRI [70] focuses on individual predispositions toward technology, overlooking structural and environmental constraints; TTF [71] emphasizes task–technology alignment, but provides limited insight into social and institutional dynamics; and IDT [24] concentrates on innovation characteristics and diffusion processes, rather than on actual usage behavior within complex organizational settings. Overall, UTAUT provides an internally consistent and empirically validated framework that integrates individual, social, and organizational determinants within a single model, avoiding the conceptual fragmentation and complexity associated with the ad hoc combination of multiple theories. Furthermore, empirical evidence supports its superior explanatory power in technology adoption studies [23].

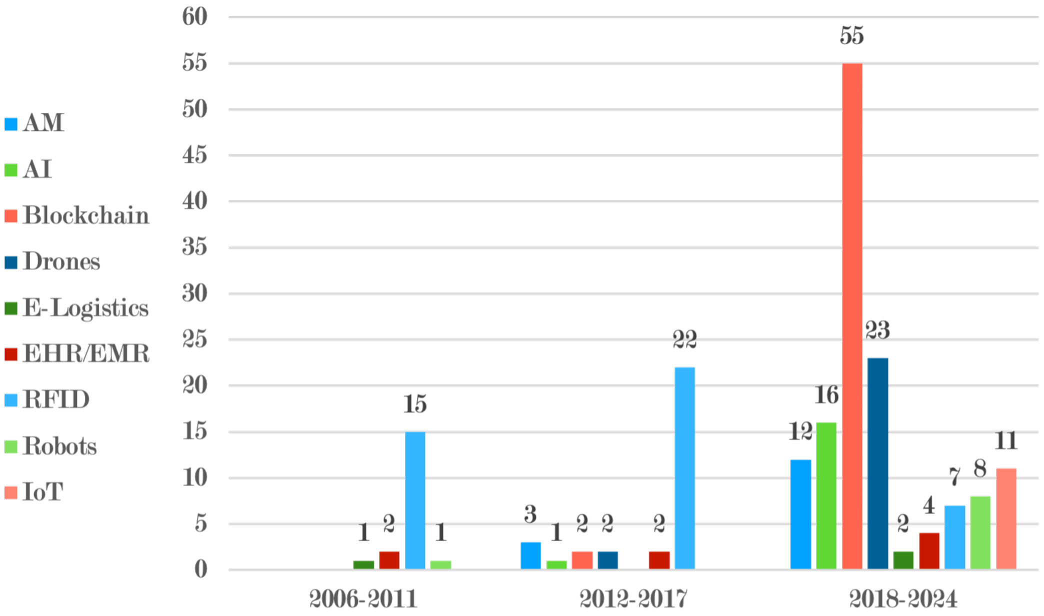


Figure 1.3: Distribution of papers at 5-year intervals by technology

Figure 1.3 shows the temporal distribution of contributions on the most investigated DTs in the PSC. Specifically, nine technologies were identified from the reviewed studies: RFID, IoT, blockchain, e-logistics, AI, robots, drones, EHR/EMR, and AM. RFID is one of the oldest and most discussed technologies, with a publication span of 19 years. The number of papers dealing with RFID adoption in the PSC has been decreasing during the last 6-year period. This trend suggests a waning interest in RFID adoption in favor of more advanced technologies such as blockchain, drones, AI, AM, IoT, and robots. Blockchain is the most discussed technology along with RFID and one of the emerging ones, as evidenced by the considerable peak in the number of publications in the last 6-year period. The same applies to drones, although the total number of publications is lower (25 versus 57 on blockchain). The least investigated technology from the point of view of organizational adoption appears to be e-logistics, which scores only 3 papers. Among the studies analyzed, 161 (93%) focus on a single DT, while the remaining 12 studies examine multiple DTs. Notably, none of these 12 studies addresses more than four technologies. Two [6, 50] out of five literature reviews specifically studied up to four DTs.

1.4.2 Major technologies and their adoption in the PSC

Radio Frequency Identification (RFID)

RFID is a technology that allows the identification and tracking of objects and individuals through electromagnetic wave propagation. In the PSC, it offers significant benefits for product authentication and anti-counterfeiting by creating an electronic pedigree that tracks the movement of each item from manufacturing to distribution [61, 72]. In warehouse operations, RFID enables seamless data collection, automated inventory tracking, and faster product retrieval, reducing labor costs and minimizing human error [63, 73]. The embedding of expiration dates into RFID tags supports the First-In, First-Out (FIFO) inventory method, helping prevent the distribution of expired pharmaceuticals [73, 74, 75]. In clinical settings, RFID integration reduces medication errors by matching patient records with prescribed drugs [76, 77, 78]. When combined with robotic dispensers or automated cabinets, it also facilitates the timely identification of expired or recalled medications [50, 73]. Despite these advantages, RFID implementation involves substantial initial costs, which may limit adoption, particularly in smaller firms or developing countries [78, 79, 80]. The interoperability between different systems and concerns about data privacy also present challenges [81]. Some researchers advocate for stakeholder-specific customization to boost adoption [74]. Others argue that alternative systems like barcodes gain more traction due to their cost-effectiveness and standardization [72, 79, 82, 83, 84].

Internet Of Things (IoT)

The IoT is a network of interconnected sensing and actuating devices capable of communicating and interacting remotely through the Internet. It enables the real-time collection, processing, and sharing of vast amounts of data, enhancing visibility, responsiveness, and decision-making. Research on IoT adoption primarily concentrates on patient care activities like collecting patient and staff data, remotely monitoring patient health indicators, and emergency alert systems. Some studies suggest that this is because SC management is perceived as a supporting function rather than a core process within the healthcare sector, which may lead to the deprioritization of investments in IoT technologies [64]. Key applications in the PSC include automating inventory management, monitoring environmental conditions (e.g., temperature, humidity, light exposure) during manufacturing and transportation, and tracking product movement to ensure quality and prevent disruptions [64, 85]. Integrating IoT may be hindered by several barriers, such as high implementation costs, technological immaturity, integration complexity, organizational misalignment, and lack of digital skills [64, 86].

Blockchain

Blockchain is a decentralized digital ledger that enables peer-to-peer transactions to be recorded immutably and executed automatically without the need for third-party intermediaries. In the PSC, blockchain enhances drug traceability by securely documenting every interaction among stakeholders using cryptographic verification, thereby preventing counterfeiting and ensuring SC integrity from manufacturing to end-user [52, 87]. When integrated with IoT, it further strengthens data security and real-time monitoring capabilities, supporting drug authentication, quality control, and transparency across the PSC [85, 88, 89]. The existing body of research indicates that the adoption of blockchain technology within the PSC is still in its nascent stages, requiring overcoming challenges related to regulatory alignment, interoperability, standardization, and initial investment costs [87, 90, 91]. Moreover, most studies on blockchain adoption in the PSC emerging from this review are conceptual (37 out of 57), primarily literature reviews (26). The lack of empirical evidence can hinder the development of large-scale and successful blockchain-based platforms tailored for the PSC [30].

E-logistics

E-logistics refers to the use of electronic methods, informatics tools, and internet-based systems to manage logistics processes. Its primary applications in the pharmaceutical industry include digitalization of procurement, material handling, and inventory management activities [53, 65]. These systems can be used by multiple PSC actors, often with the support of digital platforms and web-enabled systems [92]. While there is a growing recognition of the benefits e-logistics can offer to the PSC in terms of efficiency, traceability, anti-corruption, and compliance, widespread adoption may be hindered by the need for substantial infrastructure investment and adaptation to sector-specific regulations. Research indicates that the ability of e-logistics systems to generate cost savings is a key driver for their adoption in the PSC, while anti-corruption objectives may be secondary [92]. However, implementing anti-corruption measures can foster an efficient, trustworthy, and compliant SC environment that indirectly lowers financial risks, improves operational efficiency, and safeguards resources, leading to long-term cost savings [92].

Artificial intelligence (AI)

AI refers to computer systems designed to perform tasks typically requiring human intelligence, such as learning, reasoning, and problem-solving [93]. Within this domain, BDA plays a critical role as an enabling component, providing the large-scale data processing capabilities that fuel AI-driven insights to extract actionable patterns [94, 95]. In the PSC, AI technologies show strong potential across several critical applications, including demand forecasting, inventory optimization, counterfeit drug detection, and logistics planning [6, 96]. Machine learning algorithms can detect potential errors early in tablet manufacturing, ensuring a safer production process [14] even in the reverse flows. At the clinical level, the analysis of large volumes of patient data through AI facilitates personalized patient care, supporting healthcare professionals in making more accurate and informed decisions regarding pharmaceutical dosing [97, 98]. Despite these promising applications across the entire PSC, the widespread adoption of AI technologies remains in its early stages. Challenges, such as a lack of sufficient investment, data privacy concerns, regulatory barriers, and the need for specialized expertise, hinder their full-scale implementation [6, 99]. Some studies point out that the alignment between data usage and regulatory compliance is a significant hurdle, due to the sensitive nature of pharmaceutical data and the stringent regulations governing their handling and storage [68, 14]. The relatively low number of studies (17) on AI adoption in the PSC identified in this review may reflect these challenges, as well as the constantly evolving nature of AI technologies.

Robots

Robots are programmable machines capable of executing tasks autonomously or semi-autonomously. An emerging application of robotics is the retrieval, storage, and delivery of materials, such as medicines, medical supplies, and laboratory samples, also alongside hospital personnel [100, 101, 102]. Electronic cabinets also fall within pharmaceutical robotics and serve as secure storage units that support inventory control, drug traceability, and the removal of recalled or expired items [50]. The rise in technological capabilities and the reduction of the costs for their implementation are expected to drive increased adoption of robots in the healthcare industry. A significant push has been prompted by the COVID-19 pandemic, when they provided a feasible solution to the lack of staff and the risk of contagion in hospitals [103]. However, robot deployment still poses socio-technical challenges associated with their integration into existing systems and workflows, staff training and adaptation, and ethical considerations about the risk of job loss [100, 104]. The literature on robot adoption in the PSC remains limited and largely conceptual, with only a few empirical studies (3 out of 9 papers), indicating a need for more evidence-based research.

Drones

Drones are aerial robots that can be operated remotely via radio waves or function autonomously without onboard personnel [105]. Their deployment in healthcare has accelerated significantly due to the COVID-19 pandemic, with swift transportation of diagnostic samples to centralized laboratories, thus supporting faster clinical decisions and improving patient outcomes [106]. This rapid adoption appears to have sparked increased interest from the academic community, as reflected in Figure 1.3. On the one side, drones are increasingly explored for transporting medications to remote or underserved areas, supporting emergency response during natural disasters or humanitarian crises, and optimizing routes, also in terms of carbon footprint minimization instead of traditional transport methods [50, 107, 108, 109]. On the other side, adoption hurdles include regulatory challenges, high operational costs, technological limitations, safety concerns, and the lack of skilled manpower [109, 110, 111]. Moreover, similar to robotics, drone adoption raises ethical considerations regarding potential job displacement [32, 108].

Electronic health/medical records (EHR/EMR)

Although the terms are often used interchangeably, EHR and EMR have some differences. They both aim to digitize patient health information, but their scope varies. While EMR serves as a digital version of the paper charts used in a clinician's office, EHR focuses on the total health of the patient, extending beyond standard clinical data collected in the provider's office to provide a broader view of the patient's care [112]. Both systems offer essential functionalities for managing drugs within hospitals, including drug dosing support, pharmaceutical administration, and Computerized Physician Order Entry (CPOE), which allows direct entry for medication orders, connecting physicians to pharmacies, manufacturers, and other healthcare entities [59, 113, 114]. Results from some studies indicate higher adoption rates for functionalities associated with patient care, such as electronic clinical documentation and results viewing. In contrast, those associated with decision support, especially drug dosing support systems, have the lowest adoption rates in many hospitals. This can be attributed to the limited organizational and financial resources of hospitals, IT capabilities, and performance incentives [114, 115].

Additive Manufacturing (AM)

Also known as 3D printing, AM is a DT based on the layer-by-layer production of 3D objects from digital designs [116, 117]. In the PSC, this technology enables the on-demand fabrication of Active Pharmaceutical Ingredients (API), formulations, and oral dosage forms with tailored doses and complex release profiles, directly in pharmacies, patients' homes, or pharmaceutical plants, potentially transforming both production and distribution models [118, 119, 120]. By allowing customized medicines to be printed as needed, AM reduces reliance on centralized mass production, minimizes waste from expired drugs, and optimizes storage space and inventory levels [116, 121]. Research interest in AM adoption in the PSC has grown recently, as illustrated in Figure 1.3. The limited number of empirical studies (4 out of 15) exploring its full integration and impact confirms its relative infancy in the industry. Indeed, AM adoption comes with several challenges, including regulatory compliance hurdles, quality assurance concerns, the need for material/process standardization, high setup costs, limited scalability, and worries regarding intellectual property and counterfeiting [116, 119, 122]. A multiple case study by [120] reveals that pharmaceutical companies often perceive AM technologies as weak and insignificant.

1.4.3 Major factors driving adoption of DTs in the PSC

Based on the UTAUT model described in Section 1.2, Table 1.2 provides an overview of the UTAUT dimensions (PE, EE, SI, and FC) associated with each DT in the selected studies. The most studied factors for each dimension and the number of papers discussing them are reported.

Performance Expectancy (PE)

The analysis reveals that 148 of 173 papers included in the review describe how DTs can improve the organizational performance of actors involved in the PSC (PE dimension).

The implementation of some DTs, especially blockchain, RFID, IoT, and drones, can affect the level of security of the PSC, as they can improve the use of sensitive health data by providing more reliable and robust protocols for the management and transmission of this data [89, 123, 124]. Conversely, the PE associated with drones can be negatively affected by the insufficient regulation of data transfer, especially when drones travel between locations managed by different organizations [125]. Safety concerns are often perceived as a source of potential physical risk for patients who interact with drones, despite their proven capability to safely deliver drugs and medical devices [108]. Safety is also relevant for robots and AM, which are regulated by severe norms that try to minimize the risks associated with the use of these DTs in healthcare [106, 121].

Beyond security and safety, studies discuss the PE for the improvement of the reliability of internal operations provided by robots and AM [50] and the scalability of blockchain, which can be easily extended to different applications in the PSC [126]. These benefits are closely tied to technology trust, as insufficient confidence in system performance and output can undermine their perceived value and, ultimately, hinder adoption [60, 127]. Quite surprisingly, only a few

DT	PE	PE factors	EE	EE factors	SI	SI factors	FC	FC factors
RFID	29	security (19), economic benefits (9)	19	standardization (12), complexity (7)	20	organizational leadership (10), SC relationships (7)	40	economic constraints (31), privacy regulation (20)
IoT	10	security (9), general benefits (3), reliability (3)	5	standardization (5), complexity (2)	6	SC relationships (4), stakeholder relationships (1), internal coordination (1), organizational leadership (1), organizational culture (1)	10	other regulation (6), economic constraints (5), HR skills (5), privacy regulation (5)
Blockchain	50	security (30), scalability (28), standardization (1), reliability (1)	34	standardization (21), complexity (12)	39	SC relationships (26), stakeholder relationships (17)	46	economic constraints (30), HR skills (26), privacy regulation (25), other regulation (2), IT infrastructure (1)
E-logistics	3	general benefits (3), economic benefits (2)	2	standardization (1), complexity (1), trialability (1)	2	SC relationships (2), stakeholder relationships (1), internal coordination (1)	2	IT infrastructure (2), organizational constraints (2)
AI	14	security (6), data quality (6), general benefits (2), reliability (2)	6	standardization (3), ease of use (2), trialability (1)	12	SC relationships (6), organizational culture (3), stakeholder relationships (1), internal coordination (1)	15	HR skills (9), other regulation (8), IT infrastructure (4), economic constraints (2), privacy regulations (1)
Robots	9	reliability (6), safety (3), general benefits (3)	4	complexity (2), ease of use (2)	3	stakeholder relationships (2), SC relationships (1), internal coordination (1)	7	economic constraints (5), physical constraints (2), IT infrastructure (2), privacy regulation (2), other regulation (2), HR skills (2)
Drones	20	security (12), safety (6), scalability (1)	7	complexity (5), ease of use (1), standardization (1)	12	stakeholder relationships (10), organizational leadership (3), SC relationships (1)	22	other regulation (15), privacy regulation (8), HR skills (8), economic constraints (1), IT infrastructure (1)
EHR	4	economic benefits (2), general benefits (1), employees' job (1)	2	complexity (1), ease of use (1)	5	SC relationships (2), stakeholder relationships (1), competitor relationships (1), internal coordination (1)	6	economic constraints (6), organizational size (4)
AM	9	safety (3), reliability (3), security (2), scalability (1), general benefits (1), economic benefits (1)	6	standardization (4), ease of use (3)	5	SC relationships (4), competitor relationships (1), organizational culture (1)	14	other regulation (12), HR skills (6), economic constraints (6), other regulations (1)

Table 1.2: Literature coverage of the UTAUT dimensions in PSC DT adoption

studies emphasize the economic benefits that an organization can achieve by adopting some DTs, such as RFID, e-logistics, and EHR [56, 92, 112], which appear among the more mature technologies.

Effort Expectancy (EE)

Concerning the EE dimension of UTAUT, only 85 of 173 papers included in the review describe factors that can affect the effort spent by organizations in the PSC in the implementation of the DTs under analysis.

In particular, the level of standardization that characterizes several DTs, such as RFID, IoT, blockchain, e-logistics, AI, and AM, influences the capability of the PSC actors to correctly implement them. For example, the adoption of blockchain is often hindered by the lack of standard practices, especially for data sharing [128, 129], while the limited standardization in the coding scheme for medical products has long prevented the diffusion of RFID [79].

Another largely investigated EE factor is the level of complexity of the DTs, such as drones, whose limited usability and design increase the level of effort required by the organizations interested in their implementation in the PSC [125, 130].

Social Influence (SI)

The analysis of factors related to the SI dimension of UTAUT is carried out by 104 of 173 papers and can be classified into two main categories: those associated with a SI that occurred within the organizations, and those associated with a SI that involves external actors that participate in the PSC or the wider network of stakeholders.

In the internal environment, organizational leadership represents the most studied factor in the literature on the implementation of RFID, with decentralized leadership [40] and where top management supports digital transformation [131], to mitigate the resistance to change by the employees [57]. Similarly, the presence of leaders who are aware of the pros and cons of DTs and support organizational change is a decisive element even for the adoption of drones [111, 132]. Other factors related to the internal environment, such as organizational culture and coordination mechanisms, have a less significant impact on the promotion of the adoption of DTs in the PSC.

In the relationship with external actors, the use of blockchain in the PSC requires that all the participant actors implement this technology by guaranteeing a sufficient level of interoperability, which is a necessary prerequisite for reliable data sharing [113], especially for the blockchain for the prevention of counterfeit drugs [133]. The alignment with the other actors in the PSC is essential to the effective implementation of other DTs, such as e-logistics, which needs constant monitoring of the levels of all the inventories within the PSC [65], and AI, which can support the management of the drug inventories only if all the members of the PSC are characterized by sufficient technological sophistication [68] and limited resistance to correctly adopt this DT [96]. The only DT that is not affected by the relationships in the SC is drones, whose massive use largely depends on the acceptance by public opinion, with perceived risks for safety and privacy associated especially in urban environments [110].

Facilitating Conditions (FC)

Factors related to the last UTAUT dimension, FC, have been discussed in almost all the papers included in this review, 162 out of 173.

Many papers focused their attention on some regulatory conditions that may stimulate or hinder the adoption of some DTs. For example, privacy regulations represent a relevant incentive for the adoption of blockchain, which guarantees better protection of healthcare data by using advanced cryptography techniques [134]. Conversely, privacy concerns have slowed down the adoption of drones because of their potential capability to capture pictures or videos in private and public spaces [135]. This sums up the FC factor of regulatory issues that hinder the adoption of drones, which have to comply with several norms approved by aviation authorities, aiming at minimizing the possible safety and defense risks provoked by this DT [136]. For AM, health regulatory authorities show a scarce propensity to approve drugs developed by using 3D printers and even develop guidelines to support this drug manufacturing approach [51]. In the case of RFID and IoT, regulations had a double effect. On the one hand, regulation against counterfeit medicines stimulated the adoption of these DTs [80, 88]. On the other hand, the lack of regulation of some technical aspects, like the frequency bands used by these DTs [86], has further reduced the organization's capability to correctly implement these technologies.

In this sense, two main internal factors related to FC emerge from this review, i.e., economic constraints and competencies and skills of human resources (HR). Most studies suggest that the adoption of many DTs, such as RFID, IoT, blockchain, e-logistics, EHR, and robots, is prevented by their cost, which cannot be easily incurred by some less-funded organizations involved in the PSC [115]. The cost of these DTs is due not only to their purchase and first implementation [137], but also to their operations [84], maintenance, and long-run support [138], as well as to the training for the employees who have to use them [86]. This latter cost is strongly related to the other internal FC factor that often prevents the implementation of many DTs, which is HR competencies and skills. For example, drones have scarcely been adopted in low-income countries, even because of the insufficient technical expertise of the workers involved in the PSC [105, 139]. The need for requalification of the workforce, based on the development of digital competencies, is also a relevant critical factor for the success of the implementation of AI and AM [140, 119].

Finally, other internal FC factors include high pervasiveness, like e-logistics [92], and the need of a sufficiently large organizational size guaranteeing the availability of human, physical, and financial resources to overcome the issues in the DT implementation.

1.5 Future avenues for research on UTAUT factors affecting the digital transformation of the PSC

The findings of this review reveal that different aspects of technology adoption in the digital transformation of the PSC require further attention.

Investigating DTs in the PSC from an adoption perspective. The analysis allowed us to identify the acceptance and use patterns of the nine DTs mostly implemented in the PSC, i.e., RFID, IoT, blockchain, e-logistics, AI, robots, drones, EHR, and AM.

Beyond the identified standalone applications, the IoT and e-logistics information systems seem among the most promising to be studied in integration with other DTs. Moreover, the evidence on the temporal trends in the research opens up further considerations on newer technologies as a fad or a fashion for pharma operations and logistics. AI and blockchain seem to deserve particular attention for different reasons. AI technologies are still in the early stages of adoption, with few contributions mainly focusing on aspects of pharmaceutical data security and regulatory compliance [68, 14]. Conversely, the literature on blockchain enabling factors and barriers has grown exponentially, with still uncertainties about the potential benefits of technology, due to its relative immaturity within industry and beyond [90]. A comparison between the promising trends of these technologies in the PSC would enrich the research stream with effective and sustainable digital transformation patterns of this SC. Further studies should also consider the use of theoretical lenses and models, from UTAUT and TOE to IDT, and their combinations, to better position their results and newness.

Most of the reviewed literature focuses on the adoption of DTs within specific areas or functions of the PSC. For instance, AM is primarily investigated regarding on-demand drug production, while drones are examined in relation to transportation and distribution. Conversely, the adoption of AI is studied for its impact across many processes, but not across the entire PSC. The technologies enhancing traceability, tracking, and data security (RFID, IoT, and blockchain) are more frequently investigated across different processes and decision areas within the PSC. The analysis reveals a lack of contributions in studying the DT adoption with a holistic perspective that considers multiple tiers and decision areas, which would bring important insights into the PSC, characterized by the coexistence of multiple stakeholders and the complexity of processes and technologies. Along with this line, the outbreak of COVID-19 further highlighted the importance of facilitating the digital transformation of the whole PSC [8].

Beyond the rich literature on the factors pertaining to single processes and DT, the implications of a systematic implementation and thus adoption of bundles of technologies, with a longitudinal perspective, would benefit the research stream on PSC digital transformation. Moreover, the gaps in forward processes and upstream coordination operations of the PSC largely affect the reverse logistics flows [20], requiring further investigation of the UTAUT factors in reverse logistics that can be interlinked to an effective adoption of related DT in the forward flows.

Major factors that prevent or favor the adoption of DTs in the PSC. With the adoption of UTAUT as a theoretical lens, the analysis shows that PE in the PSC is predominantly framed in terms of improvements in SC security and the reliability of internal operations, with trust in the technology emerging as a critical underlying condition. In contrast, expected economic benefits receive comparatively limited attention and are mainly discussed in relation to more mature DTs. The EE dimension mostly prevents digital transformation due to the limited standardization and high complexity of most DTs, while SI-related factors, intended as both internal organization and external actors' influences, are mainly studied in terms of favoring DT use and acceptance by PSC personnel. The involvement of all PSC actors is required, and influencing especially technologies for tracing and tracking (blockchain and IoT), but a solid reference on the role, conditions, and behaviors of different PSC actors in the effective and efficient digitalization of pharma logistics and SC operations could be provided by further empirical studies involving different kinds of organizations. UTAUT factors for SI within global PSCs could be studied also according to different SC configurations—i.e. whether the single processes are managed in a centralized or decentralized setting—and kinds of business and PSC actors—i.e. whether the factors change or are reinforced when processes and decision areas are managed and controlled by pharma suppliers, manufacturers, distributors, and healthcare systems located in different countries.

It also emerged that most papers have focused their analysis on the factors related to the FC dimension. These primarily include economic constraints, as well as skills and competencies in the workforce. Nevertheless, the individual perspective should integrate the institutional one, with further exploration into the implications of the diversity in regulations that have been studied as an FC factor for the majority of DT analyzed. Further research could revise these factors, considering that modern PSCs span across countries and continents, in more complex and interrelated networks of actors. This aspect requires including cultural issues and behavioral attitudes of personnel that could influence the use of DTs to effectively ensure the safe, timely, and seamless delivery of drugs and medical devices to healthcare facilities and patients worldwide.

Most notably, extant research focused on the specific UTAUT dimensions in the scope of a single technology or PSC process, with the risk of overlooking the differentiation of the acceptance and use patterns between different technologies. There is a need to develop arguments, test and extend the existing models with empirical data that enhance understanding of the actual adoption patterns of more DTs.

The high complexity of the PSC and the issues exacerbated by the COVID-19 pandemic, including the urge for resilience, sustainability, and more patient-centered approaches, require more in-depth investigations of the contextual features affecting integrated DT adoption. Case studies and large-scale explorations are needed to better capture the interplay and thus cause-and-effect relationships of factors that hinder or favor the involvement of personnel in adopting multiple DTs, and thus their effective integration.

Finally, further investigation is required into the adoption factors driven by the most recent evolutions towards the Industry 5.0 paradigm, for a more sustainable, resilient, and personnel-centered (and not only patient-centered) PSC. For example, the few studies on drones and robots highlight a limited adoption due to the high introduction cost and limited capabilities, but with several opportunities for sustainable and environmental impacts [109, 110].

Additional research on reverse logistics and its digital transformation dynamics could also help overcome the difficulties in implementing it and contribute to making PSC more efficient and resilient at the same time. A thoughtful understanding of conditions pertaining to these more recent aspects would further enhance systematic DT adoption along the overall PSC.

The following Table 1.3 lists the main categories of gaps requiring further research on factors in the digital transformation of the PSC, the specific issues discussed in this section, and the corresponding research questions.

Category of gap	Gap identified	Research questions
Technology adoption scope	Studies focus on adoption of DTs in isolated or specific PSC processes, lacking integrated adoption perspectives across the whole PSC	*– How does the integrated adoption of multiple DTs affect the resilience and efficiency of the PSC?* *– What are the implications of implementing bundles of DTs along the PSC?* *– What are the advantages and disadvantages of a fragmented versus a holistic digital transformation approach in the PSC?*
AI adoption in the PSC	AI is widely studied across several PSC processes, but no study adopts a holistic perspective on its implementation throughout the full SC	*– How can AI be holistically integrated across all tiers and actors in the PSC?* *– What are the barriers and enablers for end-to-end AI adoption in the PSC?*
Stakeholder integration	Limited analysis of the roles, behaviors, and coordination among different PSC stakeholders in DT adoption	*– How does the integration of multiple stakeholder perspectives influence the adoption of DTs in the PSC?* *– What is the role of SC partnerships in driving DT adoption?*
Comparative analysis of DTs	Limited comparison of UTAUT dimensions between different DTs	*– How do UTAUT dimensions differ between emerging and mature technologies in the PSC?* *– What lessons from mature tech adoption can inform newer DTs implementation?*
Regulatory and cultural contexts	Lack of analysis on how regulatory diversity and cultural factors affect DT adoption across global PSCs	*– How does the diversity of regulations across countries influence DT adoption in the PSC?* *– What is the role of regulatory agencies (e.g., the FDA and EMA) in promoting or hindering the adoption of DTs in the PSC?* *– How do Social Influence and behavioral attitudes vary across cultural contexts and SC configurations and what is their impact on DT acceptance and usage?*
Industry 5.0 and sustainability focus	Few studies explore how Industry 5.0 technologies (e.g., drones, robots, AM) contribute to a sustainable, resilient, and human-centered PSC	*– What are the key adoption factors and barriers associated with emerging Industry 5.0 technologies?* *– How can personnel-centered innovation drive sustainable digital transformation?*

Table 1.3: Research gaps and future research questions in PSC digital transformation

Chapter 2

To be or not to be... digital! How supply chain partners can support the adoption of digital technologies

Building on the *macro*-level gaps identified in the previous chapter, this study shifts the focus to the *meso*-level of analysis by investigating the role of inter-organizational collaboration in Digital Technology (DT) adoption. It empirically examines how interactions with Pharmaceutical Supply Chain (PSC) partners influence the diffusion of three key DTs: Artificial Intelligence (AI), blockchain, and drones. These DTs were selected for both their strategic value in an integrated adoption across the PSC and their being the most debated, yet still relatively immature, in practical implementation. By uncovering the managerial mechanisms that support technology diffusion across the supply network, this study identifies AI as particularly relevant for further investigation, providing the logical transition to Chapter 3, which zooms in on a *micro*-level case study to explore how digital transformation unfolds within a pharmaceutical manufacturing firm.

2.1 Introduction

Despite the significant potential benefits in the healthcare sector, the PSC still lags in the deployment of DTs and cutting-edge practices to fully realize these impacts, especially when considering the adoption from the whole SC perspective [10, 141]. Achieving meaningful digital transformation in PSCs requires extensive interaction and collaboration across the network, involving collective effort to co-create and share value-generating processes [10], but the industry's siloed nature creates significant barriers, such as low digital maturity among partners and a lack of unified leadership [142].

Overcoming these barriers necessitates a deeper understanding of the relational dynamics and support structures that enable DT adoption. While prior research confirms that the joint use of different DTs can foster collaboration (e.g., [9], [10], [11]), distinct gaps remain. First, less attention has been paid to the specific mechanisms that support the diffusion of DTs among different PSC partners. Beyond the complexity of the pharma SC and the general difficulties in DT adoption, there is also the need to consider that each SC actor has its own characteristics and requirements, with pharma manufacturers and distributors showing the most critical ones [143]. Second, most of the literature focused on hospital-oriented initiatives and resulting performances, neglecting the perspective of leveraging upstream SC players' relationships [144, 145] and the necessity of continuity of healthcare product delivery and responses to disruptions in the upstream processes [146]. Hence, further research is required to understand the role of different PSC actors and the array of initiatives that can accelerate the digital transformation of an organization, beyond its organizational characteristics [141, 144].

This work aims to investigate how different actors foster the adoption of DTs in the PSC, and the types of collaborative mechanisms they enact at the inter-organizational level for the specific DT diffusion. As already mentioned in the Introduction chapter, the research questions we identified to achieve the outlined objective are:
RQ4) *What actors favor the diffusion of DTs along the PSC?*
RQ5) *What support mechanisms are adopted to collaboratively foster the adoption of DTs?*

We focused our investigation on three specific DTs: blockchain, drones, and AI, which have received extensive coverage in recent studies on the adoption of DTs within the PSC [14, 27, 87, 107, 108, 111, 147]. They are also recognized as disruptive technologies in both PSC management [8] and logistics management [148, 149].

Building on the Innovation Diffusion Theory (IDT) [24], we employed mixed methods research to analyse the contributions of four PSC actors—Goods Suppliers (GS), Service Providers (SP), Technology Providers (TP), and customers—and twelve distinct support actions on the effective diffusion and adoption stages of DTs along the PSC.

The analysis of this data allows us to highlight the current state of DT adoption in PSC operations, showing a higher level of diffusion of AI. Besides, the results of our regression model suggest a significant positive role played by SPs. Finally, among the support actions by the PSC partners, those related to the improvement of the competencies of human resources seem to be the most diffused in the firms with a more advanced level of DT adoption.

This study sheds further light on the mechanisms behind the digital transformation of SC, clarifying the roles of different actors and the support actions that could be adopted to favor a more integrated implementation of DTs. In this sense, the present work may also provide a valuable contribution to managers involved in the digital transformation of their organization by enabling the definition of implementation patterns that increase the effectiveness of DTs.

The structure of the study is as follows. Section 2.2 describes the theoretical background of the study, while Section 2.3 presents data and methods. Section 2.4 illustrates the results of our study, whose theoretical and practical implications are discussed in Section 2.5.

2.2 Theoretical background

This section provides the theoretical background of the study, focusing on disruptive technologies in the PSC, the IDT as the guiding theoretical lens, and the role of collaboration within the SC, as illustrated in Figure 2.1.

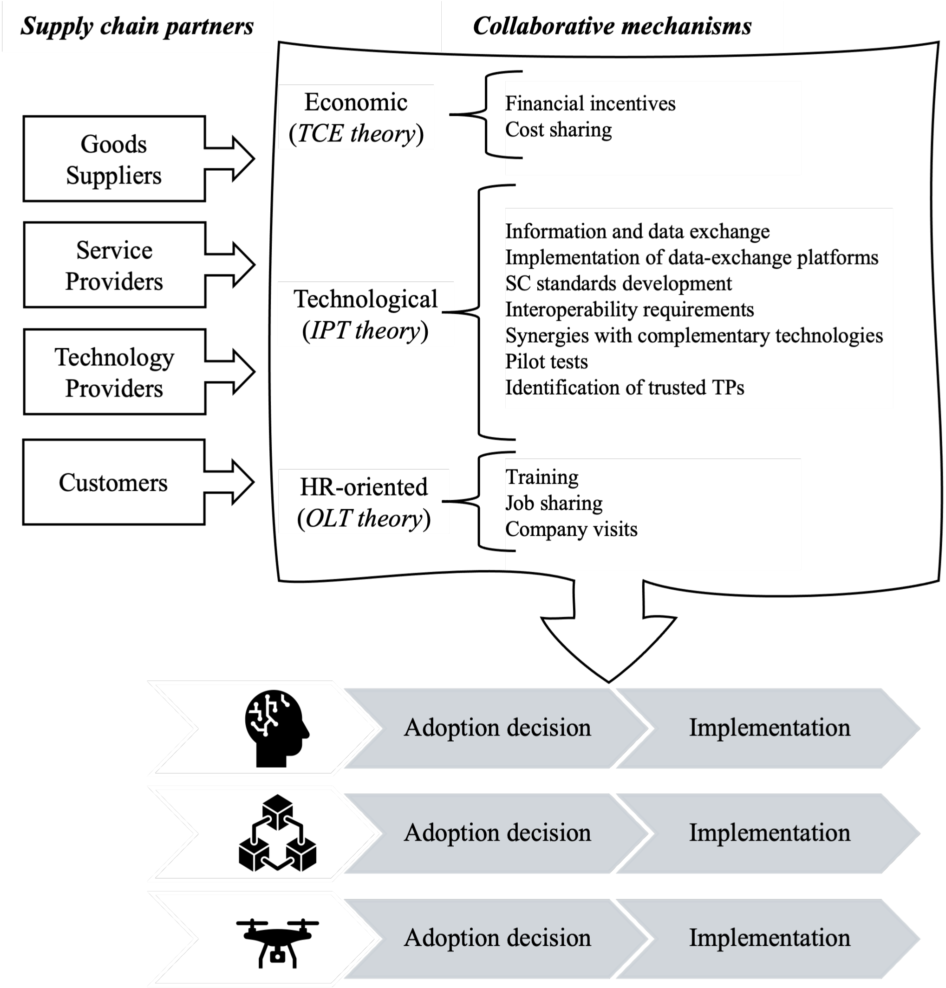


Figure 2.1: Overview of the theoretical background underpinning the research

2.2.1 Disruptive technologies in the PSC

Among the emerging disruptive DTs, AI, blockchain, and drones stand out for their potential to transform the PSC, enhancing various critical processes from sourcing to end-user consumption (Saha et al., 2022).

Studying the diffusion of these three DTs together in the PSC is interesting for PSC literature and practice, as their strategic value lies not merely in their individual capabilities but in their integrated and system-wide adoption across the SC. Both Blockchain and AI emerge as horizontal technologies, offering scalable applications across the full spectrum of SC actors—from suppliers to manufacturers, distributors, and end-users [30, 87, 150]. For blockchain, integration at every level is essential, given its nature as a distributed system that relies on multi-stakeholder validation and transparency [127]. Likewise, the adoption of AI requires system-wide integration, as its effectiveness depends on access to real-time data and coordinated decision-making across all PSC actors [140]. Although drones may appear as vertically targeted tools, their adoption must also be understood in a systemic context. When embedded into the PSC in an integrated manner, drones can function as critical enablers of real-time data flow, enhancing coordination and information exchange between upstream and downstream stakeholders. Their implementation also requires SC-level standardization, which is essential to ensure that stakeholders and technical systems operate within a unified, interoperable framework [32]. Moreover, the technical constraints related to drone payload capacity and packaging requirements introduce design implications for pharmaceutical manufacturers and suppliers, underscoring the broader impact of drone adoption across the PSC, beyond the distribution stage [151].

Over the past five years, researchers have increasingly examined the integration of these three DTs within the PSC, as they could be combined to obtain intelligent SC management systems in healthcare [152]. Nevertheless, challenges persist regarding their complete acceptance and adoption by the personnel involved across various processes and decision-making domains within the SC [14, 27, 87, 107, 108, 111, 147]. In particular, the adoption of DT to make the logistics and SC processes more dynamic and integrated requires greater efforts and collaboration with stakeholders that also go beyond the traditional scope of SC management [141].

2.2.2 DT adoption under the Innovation Diffusion Theory (IDT) lens

In the literature, the analysis of DT adoption in the SC has been carried out through different theoretical lenses, such as Technology Organization Environment (TOE) [69], Technology Acceptance Model (TAM) [36], and IDT [24]. The present study adopts the IDT framework for two main reasons.

First, IDT posits how each decision maker, either an individual or an organization, follows a structured process in the adoption of the DT under analysis. In particular, the first IDT model proposed by [24] identifies five different stages in the innovation-decision process: the "Knowledge stage", when the decision maker starts collecting information on the DT, the "Persuasion stage", when the decision maker collects sufficient knowledge to form a favourable, or unfavourable, attitude toward the DT, the "Decision stage", when the decision maker commits to the choice to adopt, or reject, the DT, the "Implementation stage", when the decision maker starts using the DT, and the "Confirmation stage", when the decision maker analyses the feedback generated by the DT use [24]. The present study adopts a simplified version of the IDT model proposed by [153], which defines three stages of innovation adoption at the organizational level: Initiation, Adoption decision, and Implementation. The Initiation stage encompasses both the "Knowledge" and "Persuasion" phases of Rogers' model, while the Implementation stage integrates the "Implementation" and "Confirmation" phases. This model has previously been applied in the SC domain by [154], who employed it to investigate and propose a strategic framework for overcoming technological barriers to the adoption of blockchain technology. Thanks to the use of this model, it is possible to analyze the diffusion of a new DT in a socio-technical system, such as a SC, where each firm may be characterized by a specific stage and speed of adoption.

Second, IDT assumes that the diffusion of a new DT is triggered by social mechanisms since all the actors, especially the so-called "innovators" that first adopt the innovation, may spread information and/or exert pressure that leads to a wider and faster diffusion of the DT. Hence, IDT offers a valuable framework for a better understanding of how the diffusion of a DT among the firms of a SC is influenced by different types of stakeholders and the specific actions made by each actor.

This social-mechanism perspective is especially critical in the PSC. Unlike standard SCs, the PSC is a highly regulated, high-stakes environment defined by stringent patient safety requirements, demands for data integrity in tracking, and complex interdependencies [90]. In this context, DT diffusion does not only concern investment decisions. It is constrained by the need for validated trust, interoperability, and collective adherence to compliance [10, 58]. Therefore, the social pressure and support from partners such as SPs or customers are not just helpful but often a prerequisite for every PSC actor to successfully navigate the Initiation, Adoption decision, and Implementation stages.

Previous studies applying IDT to the analysis of DT adoption in the SC have mainly focused on dyadic relationships. [155] analyses how the level of digital innovation of distributors can be affected by manufacturers in the same SC, which can maintain compatibility and interoperability in the whole SC by leading the other actors to adhere to their own technological standards and operational paradigms. [156] focuses on the role played by an automotive-industrial firm in the digital transformation of its suppliers, showing that they accept the adoption of DTs only in the presence of sufficient economic and operational benefits. These two studies provide a partial view of the diffusion of a DT among the firms of a SC, because they focus only on the relationships between two types of partners in the SC: manufacturer-distributors and manufacturer-suppliers, respectively. The need to extend the analysis to a larger variety of SC partners is highlighted by several studies [157, 158], which show that a successful adoption of DTs in a SC requires the participation of all partners.

2.2.3 The role of the different PSC actors in DT adoption

The collaboration and coordinated roles among multiple stakeholders play a pivotal role in the successful adoption of disruptive technologies [159, 160, 161]. Given the inherent complexity and interdependence of supply networks, no single firm can fully achieve digital transformation in isolation. Moreover, the benefits of SC collaboration materialize when all partners across the SC, spanning from suppliers to end customers, actively engage in cooperative practices [162]. SC relationships can serve as strategic assets for advancing DT, where digital demands from partners encourage firms to initiate transformation, and access to shared digital resources helps mitigate challenges such as information asymmetry and capital constraints [163].

The need for collaboration is particularly pronounced in complex supply networks such as PSCs, where siloed approaches are insufficient. This was especially evident during the COVID-19 pandemic, when an unprecedented surge in demand for medical supplies highlighted the importance of cohesive and agile SC responses [164] and also the role of cooperation in mitigating the impact of disruptions [165]. In addition, the effective integration of DTs requires alignment not only at the technical level but also in terms of governance structures, incentives, and data-sharing agreements across the network [10]. For example, the implementation of blockchain technology hinges on reaching consensus among PSC actors to establish common protocols for secure and transparent data exchange, while managing concerns over disclosing sensitive information [58, 90]. Similarly, the effective deployment of AI hinges on alignment among stakeholders in terms of technological maturity and the shared ability to support complex functions such as drug inventory management [68].

While the link between collaboration and DT adoption is established, a clearer understanding of the specific roles different SC actors play in enabling the adoption is needed. Prior research, such as [166], has examined actor roles through an Open Innovation lens, finding significant contributions from horizontal partners (e.g., competitors, R&D centers) in the electronics industry. However, the PSC, with its high demand for supply reliability, security, and velocity [167], necessitates a focus on vertical integration and the continuous involvement of direct SC partners, considering their specific requirements and constraints [142].For these reasons, the present study focuses on actual partners in the SC, classifying them into four main categories: GSs, SPs, TPs, and customers.

GSs include raw materials suppliers, pharmaceutical manufacturers producing finished pharmaceutical products, and packaging providers. These organizations operate in the upstream segment of the PSC, and their adoption of DTs is closely linked to the level of interconnectivity and information-sharing capabilities across the network [168]). While it is often the customer who initiates digital SC systems, their successful implementation heavily relies on the active integration of suppliers. This integration demands a substantial commitment of significant technological and organizational resources from suppliers to align with customers' digital infrastructures [156].

SPs encompass freight transport companies (operating via ocean, air, road, and rail), freight forwarders (3PLs or 4PLs), airlines, shipping lines, airports, seaports, ground handling providers, as well as firms engaged in research and development, or quality assurance. Customer collaboration with 3PL providers, in particular, has been shown to support digital transformation and improve both service and financial performance [169]. Moreover, outsourcing logistics to 3PLs provides pharmaceutical manufacturers with greater flexibility compared to in-house logistics, as these providers frequently update their technologies and operational practices. This enables pharmaceutical firms to focus on core activities while reducing logistics-related costs [170, 171].

TPs are organizations delivering digital solutions and IT services tailored to PSC operations. Strategic partnerships with TPs for adopting Industry 4.0 technologies have been associated with reduced implementation costs, enhanced customer loyalty, and greater innovation capacity [166]. Collaboration with TPs and healthcare SPs is often necessary to build the infrastructure and governance models required to operationalise blockchain networks [147].

The successful adoption of DTs depends not only on integration with GSs, SPs, and TPs but also on aligning with the expectations and requirements of *Customers*. Their influence shapes both the pace and direction of DT adoption, making them a central stakeholder group in the transformation process [161]. For example, suppliers adopting new technologies often seek specific support measures from customers, such as financial assistance to help cover implementation costs and targeted training programs to build the necessary skills and knowledge [156]. In the analysis of companies across various levels of the PSC, the definition of customers extends to a spectrum of actors involved in the distribution and consumption of pharmaceutical products before end consumers, i.e., patients.

2.2.4 Collaborative support in digital transformation

Beyond the general benefits of collaboration outlined above, it is important to explore the specific ways in which PSC actors can support one another in implementing DTs. These can be broadly classified into technological, economic, and human resource-oriented actions, each addressing specific challenges of the digital transformation process in the PSC [10].

The *economic* dimension includes the mechanisms to mitigate the financial risks and uncertainties that affect the PSC and arise from its interactions with the broader macro-environment. The relevance of such mechanisms for DT adoption can be effectively explained through the lens of Transaction Cost Economics (TCE) [172]. According to TCE, organizations seek to minimize transaction costs required to exchange a product or service between two entities, while maximizing transaction performance [172]. In the context of SCs, this perspective has been widely applied to explain how firms organize and govern relationships with their partners to minimize exchange and coordination costs [173, 174]. Specifically, TCE helps to understand firms' choices between market-based and hierarchical governance structures depending on the level of asset specificity, uncertainty, and frequency of transactions [172, 175]. The process of adoption of DTs typically involves significant upfront investment, information asymmetries, and complex coordination among SC partners, all factors that contribute to higher transaction costs [173, 176]. In this context, economic collaborative mechanisms such as cost-sharing and financial incentives can play a crucial role in mitigating these costs by distributing risk, reducing capital constraints, and lowering barriers to entry, particularly for smaller or less technologically mature firms [156, 177, 178, 179]. For instance, shared investments among same-tier partners (e.g., manufacturers) can reduce perceived uncertainty of DT implementation and make collaborative investment more economically viable [170]. Moreover, financial support from downstream customers has been shown to play a key role in suppliers' acceptance and integration of digital SC systems [156], reinforcing the importance of collaborative financial arrangements in overcoming transaction-cost barriers to DT adoption.

The *technological* dimension encompasses support activities aimed at addressing technological challenges arising from the increasing digitization and interdependence of SC actors. From the perspective of the Information Processing Theory (IPT) [180], organizations must develop sufficient information processing capacity to cope with rising uncertainty and achieve competitiveness [181]. In the pharmaceutical context, DTs generate vast amounts of real-time data that must be transmitted, interpreted, and acted upon across organizational boundaries [143]. This underscores the need for collaborative mechanisms that enhance technological coherence and reduce informational frictions across the SC [174]. Transparent and timely information exchange enables SC partners to identify collaboration opportunities and areas where DTs can create value [182, 183, 184, 185, 186]. Actions such as the adoption of common data-exchange platforms between customers and suppliers are particularly relevant, as they support seamless communication while reducing the burden of managing multiple, potentially incompatible systems—one of the most cited barriers to supplier acceptance of digital SC solutions [156]. Standards and interoperability protocols further enhance the information processing capacity of the SC by ensuring efficient data exchange, reducing miscommunication, and supporting timely decision-making across distributed actors [10, 187, 184]. Moreover, as recent studies suggest, early-stage efforts to explore, define use cases, and experiment through pilot tests are instrumental in supporting organizational sense-making processes, particularly for emerging technologies such as AI [188]. Another important initiative within the technological dimension includes the identification of trusted TPs who can offer domain expertise, customized solutions, and reliable support throughout the DT adoption journey. In this regard, R&D centers and customers, in this context, often function as inbound open innovation agents, supporting technology sourcing and technology scouting activities that feed into the broader innovation pipeline of the SC [166]. Finally, rather than independently developing and implementing an entire digital solution, SC partners can leverage synergies with complementary technologies as a form of collaborative support to accelerate DT adoption. Different organizations may possess distinct technological assets, specialized expertise, or proprietary digital tools that, when integrated, create a more robust and interoperable solution aligned with Industry 4.0 objectives [189].

The *human resource* dimension includes supporting actions and incentives required to overcome the lack of knowledge and experience in digital skills among managers and employees—factors that often hinder effective responses to SC challenges [143, 190]. Organizational Learning Theory (OLT) [191] provides a useful lens for understanding this need. According to OLT, such actions are essential for fostering the continuous acquisition, dissemination, and application of knowledge that supports effective DT adoption and integration [192]. Collaborative initiatives with other organizations can facilitate co-creation opportunities, enabling firms to pool resources and expertise for mutual learning and capability development [193]. For instance, structured training and skill development programs covering both technical competencies (e.g., system-specific software use) and broader digital literacy and best practices represent powerful enablers of organizational learning in SCs [194, 183]. Importantly, learning occurs not only through formal education but also through experiential mechanisms and social learning mechanisms, in which employees learn from one another through observation, interaction, and shared experiences [195]. In this context, job sharing and company visits can function as high-impact tools for enhancing external knowledge acquisition [192].

2.3 Methodology

The study adopts mixed methods research by combining a quantitative exploratory survey with qualitative semi-structured interviews. This choice is motivated by the exploratory nature of the study [196], which aims to answer the two RQs by providing a multi-faceted understanding of DT adoption in the PSC and clarifying the role played by different actors and support mechanisms. Indeed, the use of mixed methods research can offer a more comprehensive description of the phenomenon under analysis [197], enhancing and clarifying the results of the survey with the insights generated by semi-structured interviews.

For this aim, we implemented a sequential design of mixed methods research, where the survey was followed by semi-structured interviews, which involved different participants and allowed us to collect more nuanced information that complemented the survey results. The results of the survey and the insights from semi-structured interviews were finally compared and combined to synthesize a more comprehensive understanding of the phenomenon under analysis.

The survey was designed to assess the overall level of adoption of three specific DTs (blockchain, drones, and AI) and quantify the frequency of various support initiatives provided by the different PSC partners (GS, SP, TP, and customers). The semi-structured interviews were conducted to collect qualitative insights, helping to explain the underlying reasons (“why”) behind the quantitative findings.

To collect the quantitative data, a questionnaire was administered in August 2023 to participants of a professional course on pharma logistics, including managers of worldwide pharmaceutical companies, logistics providers, and healthcare SPs. We gathered a total of 74 valid answers, reaching a response rate equal to 54.8 percent.

The questionnaire was structured into five main sections.

The first section comprises demographic questions, seeking information on respondents’ job profiles and the characteristics of their organizations. The details of the sample are presented in Table 2.1.

The second section includes questions on the level of adoption of each DT under analysis, measured by using a four-level ordinal scale inspired by the adoption stages proposed by [153]. In particular, we added a preliminary stage (No Knowledge/Interest stage) for firms that are not interested in evaluating the adoption of a DT. Thus, the adoption scale consists of the following levels: “No consideration of any DT applications” (No Knowledge/Interest stage); “Preliminary discussion on DT applications, but no further action” or “Advanced analysis but no final decision to implement DT applications yet” (Initiation stage); “Decision to have DT applications made, but implementation in progress” (Adoption decision stage); “We currently use one or more DT applications” (Implementation stage). Only respondents in either the Adoption decision or Implementation stage can answer the questions in the following sections.

The third section includes questions on the extent to which these DTs are implemented in different PSC processes, including procurement, supplier selection, demand management, order processing, inventory management, transportation, and reverse logistics. The fourth section focuses on the role of the four key PSC actors in the adoption of the three DTs.

The questions in the final section explore how frequently specific support initiatives have been implemented by each of the four PSC actors to facilitate the adoption of the three DTs within the respondent’s organization. Frequency is measured using a five-level ordinal scale (Never, Rarely, Sometimes, Often, and Very Often). The support initiatives reflect the economic, technological, and human resource–oriented collaborative mechanisms identified in Section 2.2. Specifically, the questionnaire investigates the role of twelve different initiatives, including financial incentives, cost-sharing, information and data exchange, implementation of data-exchange platforms, SC standard development, interoperability requirements, synergies with complementary technologies, pilot tests, identification of trusted TPs, training, job sharing, and company visits.

The Results section presents both a descriptive analysis of this data and the results of a logistic regression. The choice of this regression model is motivated by the binary nature of the dependent variable, which is the adoption stage, coded as 1 for “Implementation” and 0 for “Adoption decision”. In our regression model, we include 4 independent variables, each representing the average frequency at which respondents make use of each of the twelve support actions listed above, as provided by each of the four SC actors.

The semi-structured interviews were conducted between October and December 2024 with 12 key stakeholders from different SC tiers, including four freight forwarding companies, three TPs, two pharmaceutical companies, two packaging providers, and one airline. Thanks to these interviews, we could collect insights from organizations classified as the four key PSC actors whose role in the adoption of the three DTs has been investigated in the survey. Further details about the interviewees can be found in Table 2.2. The interviews followed a research protocol structured around open-ended questions covering three main areas: the application of the three DTs, the role of PSC partners in DT adoption, and the corresponding support actions undertaken. They were designed to deepen qualitative aspects such as the motivations behind the adoption (or non-adoption) of DTs, perceptions of the evolution of organizations' digital maturity and the associated impacts, the nature of collaborations with external actors (including SC partners), key drivers and barriers, and insights into the data required for implementation. The interviews also examined comparisons with collaborative mechanisms employed in previous change projects, as well as expert opinions and strategic insights regarding the sector and the current state of the art in DT adoption. Each interview, lasting between 40 and 60 minutes, was recorded and transcribed verbatim. In line with the procedures suggested by [198], we associated each result of the survey with the themes emerging from the semi-structured interviews, thus reaching a more complete understanding of the mechanisms underlying the phenomenon under analysis.

Role of the company in the PSC	%
Distributor	62
Manufacturer	16
University or research center	14
Healthcare provider	5
Wholesaler	3
Size	%
Small(10 - 49 employees, €2 - €10 million turnover)	23
Medium (50 - 249 employees, €11 - €50 million turnover)	16
Big ($\geq$ 250 employees, $\geq$ €51 million turnover)	61
Location	%
Asia	22
Global	26
Europe	40
America	11
Africa	1
Customers	%
Logistics companies	74
Healthcare providers	11
Manufacturers	12

Table 2.1: Characteristics of the survey sample

Interviewee number	Role	Affiliation
1	Air Operations Manager	Freight forwarding company A
2	Regional Head of Healthcare	Freight forwarding company B
3	Solutions Sales DirectoR	Freight forwarding company C
4	Strategic Development and Pricing Manager	Ocean carrier
5	Business Development Manager	Tech company A
6	Global SME Life Sciences and Pharma Director	Tech company B
7	Chief Executive Officer	Tech company C
8	Global Delivery Strategy	Pharma company A
9	Quality consultant	Pharma company B
10	Business Development Manager	Packaging company A
11	Regional Sales Director	Packaging company B
12	Global Product Development Lead	Airline

Table 2.2: Characteristics of the interview sample

2.4 Results

The collected data have been analysed, first, to show the adoption level of the three DTs. Then, the role of the four types of PSC actors in the diffusion of these DTs will be investigated, also through a regression analysis. Finally, the use of twelve types of support actions in the implementation of these DTs will be presented.

Figure 2.2 shows the distribution of surveyed organizations across four stages of DT adoption—"No Knowledge/Interest", "Initiation", "Adoption decision", and "Implementation"—for blockchain, drones, and AI. Overall, the data indicate a generally low level of DT adoption within the surveyed organizations. Blockchain and drones are predominantly in the early stage of adoption, with most organizations either lacking knowledge/interest in these DTs (36 and 40 firms, respectively) or being in the Initiation stage (29 and 21 firms, respectively). In contrast, AI appears to be at a more advanced stage overall, with a greater proportion of firms reporting either a formal adoption decision (13 firms) or active implementation (14 firms).

The limited adoption of the DTs can be attributed to several recurring concerns identified in the interviews. These include a strong reliance on and satisfaction with existing internal systems, a perceived low benefit-cost ratio, concerns about security and technological maturity of these solutions, as well as unclear ownership and governance structures.

Regarding blockchain adoption, one interviewee noted:

"*We have our internal systems that we have to stick to; we have very robust protocols, security protocols as well. We had faced a cyber-attack a couple of years ago, so they're very restrictive in any interconnectivity there.*"

Another participant emphasized the financial constraints typical of smaller firms:

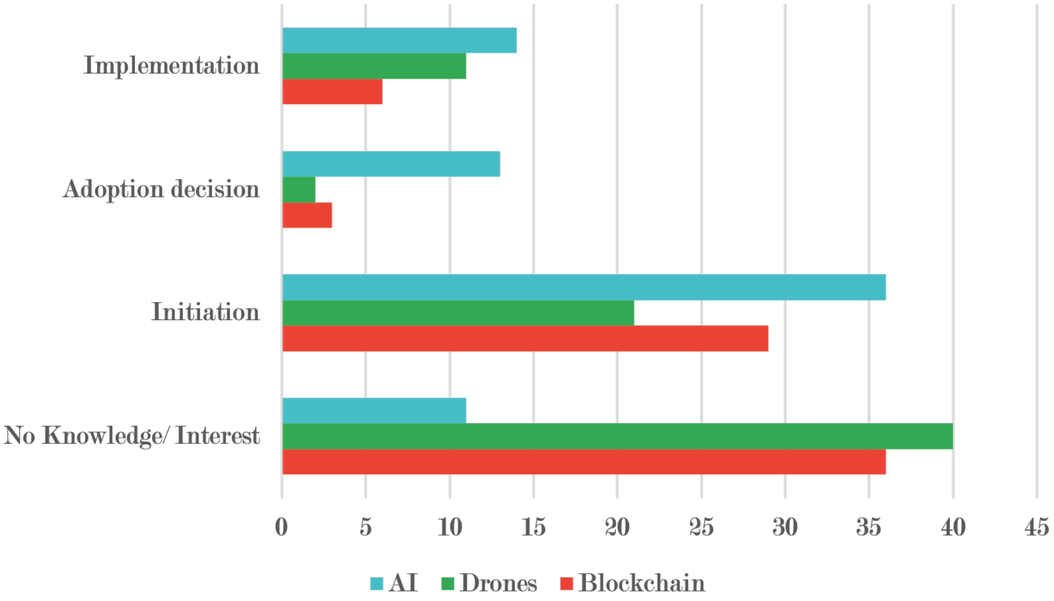


Figure 2.2: Diffusion of DTs across respondents' organizations

"We are quite a small company. So, when we've looked into the cost of investment versus the value that it would bring to our organization and our customers, blockchain is something that we are aware of and evaluating, but haven't yet implemented."

Similarly, on AI adoption, one interviewee explained:

"We have evaluated AI to try and support our solution. However, the thermal models that we use and that we have validated internally, currently, we don't necessarily see an application where AI would help us there."

Concerns over security and reliability were common across all three DTs, especially in the context of transporting sensitive pharmaceutical cargo. As one interviewee stated:

"We want to make sure that whatever we deploy for pharma, that's 100% secure, it's 100% reliable. Anything beyond or anything below that is something that we don't want to risk the integrity of the cargo. We don't want to risk the integrity of the existing process. Once that technology is completely safe for us and replicable, then it's going to come to pharma as well."

Ownership and governance emerged as critical barriers, particularly in relation to the adoption of blockchain and drone technologies. In the case of blockchain, several interviewees pointed to the absence of a clear leadership structure and investment responsibility. One participant remarked,

"There is no real owner of blockchain, and therefore, there is no clear budget holder either. Everybody is patiently waiting for somebody to own a blockchain and invest in blockchain. And that's all the pain. Nobody really wants to be the one paying for a tool that everybody can use. I guess that's the problem."

A similar issue was raised regarding drone adoption, where the lack of direct ownership and operational control limited organizational engagement. As one interviewee explained:

"*It's not organizationally widely accepted yet. If we do drone deliveries, we don't operate a fleet of drones. It's not our fleet of drones, it's not our pilot, and sometimes it's not even our product anymore, so why would we be interested in operating drones, right? It's more for us to make sure that everybody has access to our medications to help the pharma industry as a whole.*"

Moreover, several organizations questioned drones' suitability for large-volume distribution, especially for firms operating as non-asset-based entities that rely on outsourcing for logistics functions.

Concerning the areas of application of the three DT, survey respondents identified transportation as the primary area of AI application, followed by demand management, inventory management, and reverse logistics. This is corroborated by interview insights, which highlighted that freight forwarding companies widely use AI for event analysis, such as monitoring temperature deviations in drug shipments. Similarly, packaging companies reported leveraging AI for virtual testing of packaging solutions and to manage reverse logistics of boxes sent to pharmacies and hospitals. Drones were predominantly reported in the survey as being used within the transportation domain, a finding supported by interviewees who described their use primarily for last-mile deliveries in hard-to-reach areas, both in manufacturing and packaging contexts. Although blockchain adoption is still limited according to survey data, the few companies that have implemented it do so comprehensively across multiple PSC processes, indicating its potential for horizontal scalability. Interview responses reinforced this, with only three companies (two freight forwarders and one manufacturer) actively using blockchain. The manufacturer was notably the only organization to have adopted all three technologies — AI-based data analytics, blockchain for track-and-trace verification and reverse logistics, and drones for remote deliveries and data collection on behalf of partner firms.

To analyze the role of the four types of PSC partners in the adoption of the DTs, we computed a logistic regression to evaluate how each of these partners has supported the companies that are either in the Adoption decision phase or in the Implementation phase of one of the three DTs studied.

Variable	**Coefficient**
Support from Customers	1.09 (0.72)
Support from Goods Suppliers	-2.78* (1.10)
Support from Service Providers	2.44* (1.14)
Support from Technology Providers	-0.92 (0.71)
Constant	0.80 (0.58)
N	49
Pseudo R^2	0.2055
Log likelihood	-25.598282
Robust standard errors in brackets; *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; §$p \leq 0.1$	

Table 2.3: Logit regression model results

Table 2.3 shows the results of the logistic regression, which indicate that average support from SPs and average support from GSs are statistically associated with DT adoption at 5% significance level. Despite the limited sample size, the model exhibits sufficient statistical power to detect significant effects. Specifically, support from SPs is associated with higher odds of adoption (odds ratio = 11.43). This quantitative finding suggests that organizations perceiving higher levels of support from SPs show a notable tendency to be in the “Implementation” phase of DT adoption compared to the “Adoption decision” phase. This underscores the potential facilitative role that SPs are perceived to play in bridging the gap from deciding to implementing DTs. Conversely, support from GSs was identified as a statistically significant and negative predictor of DT adoption (odds ratio = 0.06). This implies that higher perceived support from GSs is associated with a lower likelihood of an organization being in the “Implementation” phase, indicating a potential inhibiting or non-contributory effect from GSs in driving the shift from the adoption decision to actual implementation.

Interviews confirm the critical role of SPs, especially freight-forwarding companies that serve as intermediaries between packaging providers and pharmaceutical companies. They share insights with packaging providers about the needs of pharma companies.

"*So, I like to think that freight forwarders, sometimes, as far as what needs are out there, technology-related, they can be in our eyes and ears to the pharma customer directly to hear, ‘What are the things that they’re missing right now? What do they need?’ And we can get that information back from them, and it provokes us to develop new technology or new processes that might align better with what the pharmaceutical companies are asking for.*"

On the other hand, they recommend specific packaging providers or solutions, helping pharma companies identify suitable suppliers.

"*As a forwarder, we see all of those potential solutions of flying by passing through our warehouse. So, try to educate our customers as well. “Okay, guys, this is all available within the market, so this might be beneficial for you to look at.*"

Additionally, as early adopters of AI and blockchain, SPs like airlines and shipping lines have encouraged their customers, such as freight forwarding companies, to adopt the DTs to meet interoperability requirements. Moreover, SPs, particularly air carriers, could play a key role in the indirect adoption of drones by asset-free companies, such as some freight forwarding companies. In this sense, one interviewee stated:

"*If, in the future, the airline Qatar Airways decides to introduce the use of specific drones for the transportation of pharmaceuticals on certain routes and incorporates it into their services, into their network, then we, as users, as freight forwarders, could use this service.*", while another manager added:

"*What will most likely happen is that we’ll form a strong partnership with someone who is already well-established, has extensive knowledge of drones, is fully aware of all the regulations, and is the best fit for us. That’s where we’ll start our partnership.*"

In the interviews, GSs were never mentioned as particularly impactful in driving the adoption of new technologies. Some interviewees described a lack of technological engagement on their part. One respondent explicitly noted the absence of interaction at the technological level with such suppliers:

"*I would say that mainly the dry ice supplier or the insulated box supplier — with them, there is maybe no interaction at a technological level.*"

Figure 2.3 provides insights into how organizations’ engagement with specific support actions

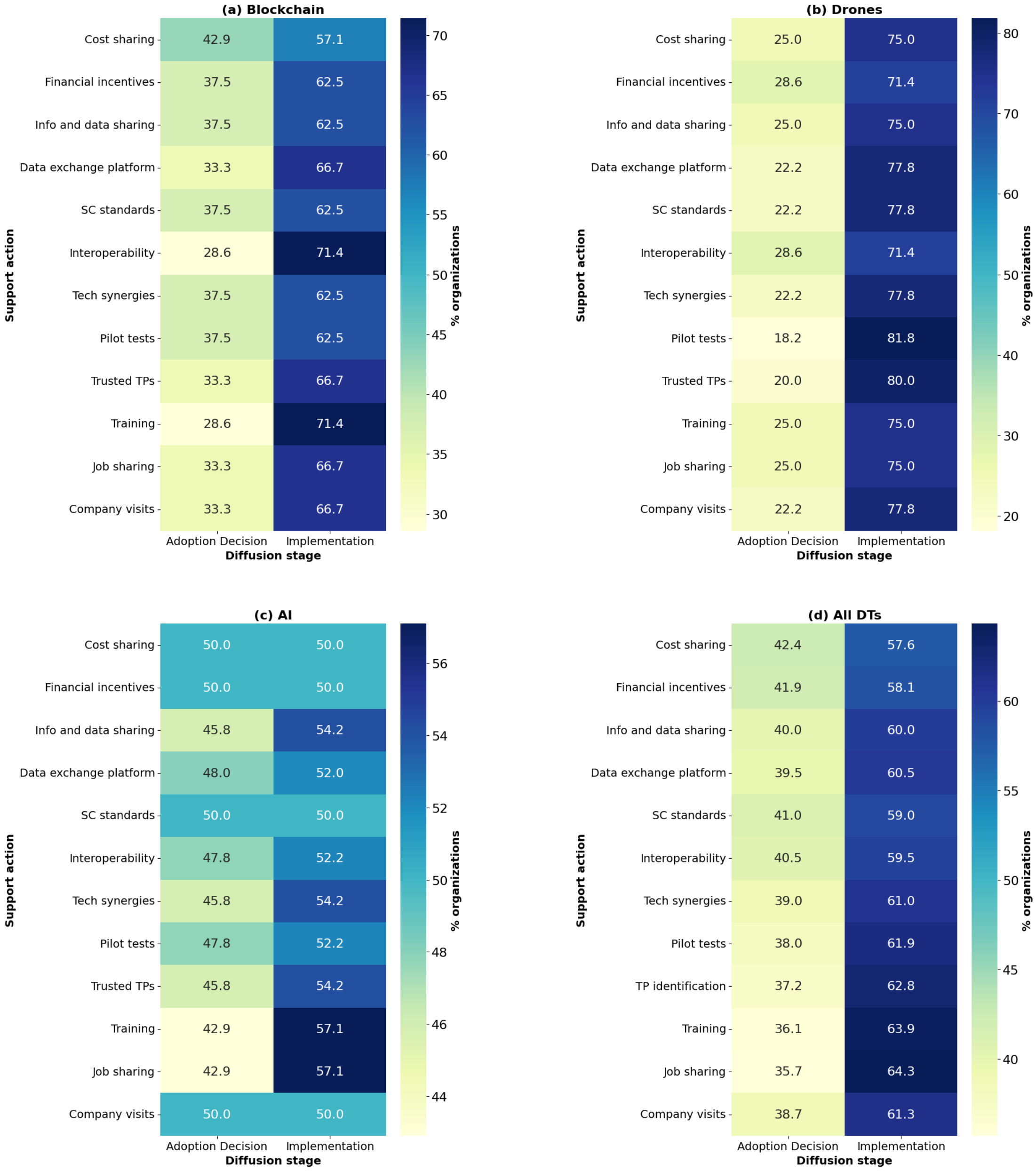


Figure 2.3: Heatmaps showing the percentage of organizations (among those engaging with each support action) in the "Adoption decision" versus "Implementation" stages for (a) blockchain, (b) drones, (c) AI, and (d) all DTs combined

correlates with their positioning in the "Adoption decision" versus "Implementation" stages for each DT.

Across all support actions, blockchain and drones consistently show a higher proportion of organizations in the implementation phase compared to the adoption decision phase. In contrast, AI exhibits a more balanced distribution, suggesting that, although many organizations are engaging in supporting actions, a significant portion (ranging from 42,9% to 50%) is still in the decision-making phase rather than moving towards active implementation.

Among the three categories, technological support actions were the most frequently used overall, especially for AI, where more than 20 organizations reported engaging in the implementation of data exchange platforms, synergies with complementary technologies, identification of trusted TPs, pilot testing, interoperability requirements, and SC-level standards. These actions were also highly effective in moving adopters from decision to implementation. For example, 81.8% (9 out of 11) of organizations that reported conducting drone pilot tests were already in the implementation stage, underscoring the critical role of hands-on experimentation. As one interviewee explained,

"*We don't want to own drones, we own pilots, but we want the industry to start using it, where there's an appropriate use case [...] We show where we want to go, what we need as the pharma industry, what patients really need, if we believe this makes the world better.*"

Another participant illustrated the visibility and trust-building effects of such efforts:

"*We did a kind of publicity thing to showcase the possibilities of utilizing our technology with drones. We partnered with a large pharmaceutical company to deliver some vaccines to a remote people group that wasn't accessible by car, by bus, or by train. So, we did represent the future, where we are ready to adapt and be innovative, designing something that can be utilized by both pharmaceutical companies and customers alike to deliver packages by drones. I think a lot of pharmaceutical companies have to trust drones first before they're gonna worry about having packaging that can be stuck on drones.*"

In addition, 77.8% of organizations that reported synergies with drones' complementary technologies were in the implementation phase. As noted by one interviewee:

"*Although we don't manufacture drones, we have worked with some logistics companies that used our thermal packaging for remote last-mile deliveries by drone. In some cases, we specially designed and customized the box sizes to fit the drone's payload capacity.*", highlighting how cross-technology collaboration can facilitate successful deployment.

Economic support actions, including cost sharing and financial incentives, were less widely adopted, particularly for blockchain and drones (used by a maximum of 8 organizations). In most cases, more than half of the organizations using these mechanisms had progressed to implementation. For instance, among those adopting cost-sharing, 75% (6 out of 8) had implemented drones, suggesting that collaborative funding approaches are particularly effective in reducing entry barriers. However, a notable share of organizations using financial incentives remained in the decision phase—especially for AI—highlighting that financial levers alone may be insufficient. This is also reflected in the interviews: "*For blockchain and drones, I really feel there's a need for more European-driven funding to build up these capabilities, so it's all easier for all pharma companies to step in. The Zipline operation in Rwanda is a good example: the government supported it, and now 90% of all blood is distributed by drones. AI is slightly different because that's more in your control environment. You have to decide what elements of AI are useful, and then invest accordingly.*"

HR-oriented actions are also less commonly used, especially for blockchain and drones (adopted by 6 to 9 organizations per DT). When aggregating data across all DTs, however, they emerge as the most effective category in supporting the transition from adoption decision to implementation. Mechanisms such as training, job sharing, and company visits were associated with the highest implementation rates (ranging between 61% and 64%), outperforming both technological and economic support actions. For example, 75% of organizations that adopted training or job sharing for drones had already implemented the DT, and similar patterns were observed for blockchain. This trend suggests that, while often overlooked, people-centric mechanisms may represent a critical but underutilized lever for enabling digital transformation in PSCs. One interviewee highlighted the role of internal capacity-building:

"*We get regularly trained on our technology. I don't have an IT degree or a technology degree. I understand data, research, and methods, but I don't understand the technology used in our industry from a systems standpoint. Being able to break it down allows everyone to understand and become comfortable with it.*"

2.5 Discussions and conclusions

This study provides an updated view of the digital transformation of the PSC, revealing a fragmented yet evolving landscape. While some actors are actively engaging with more than one advanced DT, overall adoption remains limited and primarily concentrated in transportation and distribution (including last-mile and reverse logistics) and packaging activities. Blockchain and drones remain in earlier phases, with most firms reporting either no interest or only preliminary exploration. In contrast, AI demonstrates a higher level of maturity, with more firms reaching the adoption decision and implementation stages. This uneven pattern reflects the complexity of introducing DTs in highly regulated, safety-sensitive environments, where technological uncertainty, resource constraints, and unclear governance structures continue to prevail [143].

When examining specific support actions by SC partners, technological mechanisms were the most implemented, particularly for AI. However, pilot tests and synergies with complementary technologies appeared especially effective in supporting the transition from adoption decision to implementation for drone technologies. The prominence of technological support actions reflects firms' attempts to manage rising environmental complexity by enhancing their information-processing capacity [181]. Such mechanisms directly improve organizations' ability to collect, process, and interpret information across boundaries, thereby reducing informational distortions and coordination challenges [143]. The fact that SPs—the PSC actors most strongly associated with DT implementation—mainly engaged in technological support initiatives, such as interoperability requirements, synergies with complementary technologies, and the identification of trusted partners, further suggests the strategic relevance of this category of actions.

Economic support actions, including cost-sharing and financial incentives, were less frequently adopted. However, where applied, they substantially facilitated the transition to implementation, particularly for high-uncertainty DTs such as blockchain and drones. This appeared especially relevant for smaller or resource-constrained firms, echoing interview findings where financial concerns and the lack of clear leadership for major investment emerge as key barriers [142]. Conversely, for AI, financial incentives alone appeared insufficient, as a significant share of organizations remained in the decision phase despite receiving such support. Investment decisions depend not only on financial resources but also on uncertainty surrounding returns on investment and the limited availability of clear use cases, as the interviews confirmed. This aligns with prior studies suggesting that firms often refrain from AI-related investments not simply because of costs, but because they lack understanding of potential benefits—even when public initiatives offer subsidies for digital transformation SC financing projects [199, 200].

HR-oriented actions, although less commonly employed, emerged as the most effective mechanisms for bridging the gap between the adoption decision and implementation across all DTs. Our findings confirm the central role of structured training in enabling organizational learning and facilitating DT adoption [183, 194]. However, the data also suggest that learning within PSCs extends beyond formal training. Experiential and social learning mechanisms—such as job sharing and company visits—proved particularly effective in advancing implementation. These initiatives create opportunities for employees to learn through observation, interaction, and shared experiences, fostering the transfer of tacit knowledge and best practices across organizational boundaries [192, 195]. Moreover, collaborations with SC partners, particularly SPs, may serve as co-creation platforms that promote mutual learning and capability development [193]. Such collaborative interactions cultivate a collective understanding of DTs, helping organizations internalize external expertise and transform it into actionable knowledge [201].

These empirical findings establish a clear link to theoretical perspectives. This study contributes to SC management and digital transformation literature by clarifying the role of collaborative support mechanisms in influencing the diffusion of DTs within the PSC. From the perspective of the IDT [24], the study offers empirical evidence on the current diffusion patterns of AI, blockchain, and drones, and identifies the mechanisms through which SC partners shape this process. By illustrating how inter-organizational relationships influence the transition from adoption decision to implementation, the research extends prior work that has predominantly focused on firm-level antecedents, such as top management support [141]. Technological support actions—widely adopted by SPs—underscore the importance of information processing capabilities emphasized by IPT [180], confirming the central tenet that structural and technological adaptations are needed to match information demands of the DT adoption process [174, 181]. Economic mechanisms validate the risk-reducing role predicted by TCE [172], confirming that collaborative governance structures help distribute investment risks and lower entry barriers at least for high-uncertainty technologies like blockchain and drones [173]. HR-oriented actions, which emerge as the most effective enablers for moving from adoption decision to implementation, reinforce the core assumption of OLT [191] that organizations leverage learning to innovate and adapt to changing environments [192]. However, they appeared to be an underutilized lever for developing absorptive capacity and ensuring that DT adoption efforts translate into effective implementation.

Finally, the results reveal differentiated roles among PSC actors, showing that SPs act as facilitators and knowledge brokers, while GSs may play a limited or even inhibiting role in DT adoption. This aligns with prior research on barriers to SC integration, which highlights the importance of a dominant player in the PSC that acts as a leader in promoting digital initiatives [142].

Overall, the findings offer several practical insights for managers and decision-makers within the PSC, by suggesting practical elements to be considered in their current and future strategies for the digital transformation process.

First, this study contributes to raising awareness on the actual and potential level of DT adoption across different stages of the PSC, particularly in relation to three key technologies that are identified among the most impactful yet challenging to implement, i.e., AI, blockchain, and drones. While AI is already being applied to process and analyze large volumes of data, its full potential remains untapped, especially in generative AI and decision-making. Blockchain poses challenges related to its decentralized governance, with no clear owner or budget holder. On the other hand, the adoption of drones appears inevitable, with evolving regulations and clearer frameworks paving the way for broader integration. These results reflect a heterogeneous digital maturity across DTs and PSC actors, pointing to the need for targeted support to move from exploration to execution.

Second, this study highlights the importance of fostering stakeholder collaboration, particularly with SPs, as a critical strategy to accelerate the adoption of DTs. These organizations do not merely serve logistical functions but actively facilitate the flow of technological knowledge and innovation across the SC.

Third, the analysis underscores the need for a more systematic investment in HR development. Despite being among the most effective support mechanisms, HR-oriented actions such as training, job sharing, and company visits remain underutilized. Strengthening internal capabilities through structured learning and experiential knowledge transfer can play a decisive role in moving organizations from intention to actual implementation of DTs.

Despite the valuable insights provided by this study, it is not without limitations. The sample is primarily composed of European distribution companies, potentially limiting generalizability across the full range of PSC actors (e.g., manufacturers, healthcare providers, and wholesalers). Future research should consider expanding the geographical scope, including emerging markets where DT adoption might follow different trajectories; deep-dive case studies involving underrepresented PSC actors to develop a more granular understanding of their support needs and barriers; and longitudinal studies that track how organizations evolve through different DT stages over time.

Chapter 3

Navigating Artificial Intelligence adoption in the pharmaceutical supply chain: A socio-technical perspective

Building on the *meso*-level insights from Chapter 2, this chapter shifts the focus to the *micro*-level to explore how Digital Technologies (DT) are integrated within a single pharmaceutical manufacturing firm. While Chapter 1 mapped the state-of-the-art of digital transformation across the Pharmaceutical Supply Chain (PSC) and Chapter 2 examines inter-organizational mechanisms supporting DT diffusion, Chapter 3 investigates the intra-organizational dynamics that shape the adoption and implementation of Artificial Intelligence (AI) in SC demand planning. AI was selected as the focal technology due to its relatively higher maturity compared to blockchain and drones, with more firms progressing from adoption decisions to implementation, making it particularly suitable for observing practical integration.

3.1 Introduction

The increasing recognition of AI as a transformative force in SC management has catalyzed a growing body of scholarly research aimed at understanding its diverse applications and implications [202, 203, 204, 205, 206]. AI solutions have shown significant potential in enhancing sustainability, operational efficiency, decision-making accuracy, and SC resilience across various industries [140, 207, 208].

Among the various SC management functions, demand planning has emerged as a particularly dynamic and critical domain. Since 2019, there has been a marked increase in AI-related investigations in demand planning, reflecting its evolution into a prominent research frontier [209]. This heightened focus stems from the need to overcome the limitations of traditional forecasting methods, which often fail to capture the complexity and volatility of modern markets [210]. However, current research on the application of AI in demand planning remains largely grounded in a technical perspective, focusing on the development of algorithms, predictive models, and optimization techniques, while giving considerably less attention to the behavioral dimensions of AI adoption. Critical factors such as user acceptance, trust, collaboration, and the human element in decision-making remain underexplored [211, 212]. Moreover, much of the literature relies on analytical or simulation-based approaches, with relatively few empirical case studies of early adopters to examine how AI integration unfolds in practice and provide a comprehensive understanding of the associated drivers, challenges, and success factors [209].

Building on the Technological-Organizational-Environmental (TOE) [69] framework, this study seeks to address these gaps by exploring the contextual factors that interact with human behavior in the integration of AI-based systems in the pharmaceutical sector. Characterized by complex global SCs and stringent regulatory requirements, this industry represents a particularly critical setting for demand planning, where forecasting inaccuracies may lead to overproduction, shortages, patient harm, or environmental waste [213]. Moreover, it offers a compelling and underexplored context for observing organizational changes associated with digital transformation initiatives [3]. The study also responds to recent calls to deepen understanding of AI adoption in SC management, a field in which structured knowledge and established frameworks are still emerging [203, 205].

Given that many firms are still experimenting with AI solutions, this study embraces an exploratory research approach, employing a case study methodology to generate rich, contextualized insights into the real-world dynamics of AI-driven transformation.

The chapter continues as follows. After this introduction, Section 3.2 reviews the literature on AI-driven demand planning in the pharmaceutical SC. Section 3.3 presents the theoretical background guiding the study. Section 3.4 describes the research methodology, including research design, case selection, data collection, and data analysis. Section 3.5 presents the research findings, which are discussed in Section 3.6. Finally, Section 3.7 concludes the chapter by highlighting the theoretical and practical contributions, addressing limitations, and suggesting avenues for future research.

3.2 AI-driven demand planning in the pharmaceutical SC

Demand planning is a critical function in the pharmaceutical SC, serving as the foundation for all managerial decisions that guide the planning and execution of SC activities [214]. Factors such as expiration dates of highly sensitive medications, the shelf life of active pharmaceutical ingredients, and the precise timing of clinical trial supplies require accurate forecasting, where meeting customer expectations is crucial for long-term organizational viability. Inaccurate forecasts can lead to shortages of essential medicines, resulting in harm to patients, or in overproduction, causing environmental waste, one of the major contributors to climate change [213].

AI offers a promising solution by fundamentally changing how pharmaceutical companies anticipate demand, manage inventories, and coordinate production. Through advanced predictive analytics, AI can uncover complex patterns and dependencies, significantly enhancing forecast accuracy [14, 215]. By leveraging techniques such as machine learning and deep neural networks to process large-scale datasets—including historical sales, market trends, seasonal variations, and exogenous variables—AI enables more precise and adaptive forecasts [214]. Its impact extends beyond forecast generation to inform a wide array of operational and strategic decisions [209, 216]. For instance, inventory management benefits from dynamic, real-time optimization of reorder points and safety stock levels. Such AI-enhanced systems are particularly valuable in the pharmaceutical sector, where traditional inventory models often fail to account for critical constraints, including limited storage capacity, stringent product shelf-life requirements, and complex financial arrangements, such as trade credits [217]. SC resilience is similarly enhanced through scenario simulations and predictive disruption analysis, allowing companies to proactively identify and mitigate risks [218, 219].

Despite this potential, the implementation of AI in the pharmaceutical industry faces several significant barriers. First, there is a shortage of specialized expertise necessary to develop, operate, and maintain AI systems effectively [6, 99]. This is compounded by the need for pharmaceutical organizations to align data usage with stringent regulatory compliance [14], as well as the industry's conservatism and historical reluctance toward digital solutions [220, 221]. Most critically, the success of AI systems is highly dependent on the quality and interoperability of input data [68, 204]. Many pharmaceutical firms operate with fragmented IT infrastructures and siloed data systems, which pose substantial challenges in generating clean and integrated datasets suitable for AI applications [150].

Although AI has garnered increasing attention in operations and SC management, empirical research that examines real-world implementation and associated challenges in the pharmaceutical sector remains relatively limited [3]. As a result, many companies continue to have an unclear understanding of AI's full potential [202], struggling with the trust and motivation required for a conscious transition toward AI integration [204] that moves beyond the technological hype [205]. Behavioral research is particularly relevant in this context. Human and behavioral components of SC management are at least as critical as the operational and technical ones. Recognizing that individuals do not always act rationally, but are shaped by cultural and social influences, is essential for understanding the role of people's behaviors in SCs [222]. This is especially valuable during the technology adoption process, which requires organizations to undergo both technical and cultural change.

The TOE framework provides an appropriate theoretical lens for understanding this socio-technical transformation, offering insights into how technological, organizational, and environmental factors interact with human behavior to shape AI integration in the pharmaceutical industry. As outlined in the Introduction chapter, the RQ guiding this study is:

RQ6) *How do pharmaceutical firms manage the socio-technical transformation toward AI-enabled SC demand planning?*

3.3 Theoretical background

Originally developed by [69], the TOE framework is a widely utilized theoretical model to analyze the factors influencing the adoption of technological innovations at the organizational level. Unlike individual-centric models such as the Technology Acceptance Model (TAM) [36] or the Innovation Diffusion Theory (IDT) [24], which focus on user perceptions or innovation spread, TOE offers a multidimensional perspective. It integrates internal and external determinants, positing that adoption behaviors are shaped by the interplay of three core contexts: technological, organizational, and environmental [223].

The *technological* dimension encompasses both the availability and characteristics of internal and external technologies relevant to the firm. This includes current practices, equipment, and infrastructures within the firm, as well as the set of technologies accessible externally. Within SC operations, assessing the readiness for AI implementation involves evaluating the availability of the necessary IT infrastructure [206] for data collection (e.g., sensors, IoT devices, RFID) and integration (e.g., business information technologies like Enterprise Resource Planning (ERP), Manufacturing Execution System (MES)), as well as decision-making practices—ranging from fully data-driven approaches to methods including human judgment, experience, and knowledge. For instance, drug demand forecasting typically relies on historical sales data but often incorporates human judgment to adjust for factors such as seasonal variations in disease prevalence, promotional activities, price changes, and competitor actions [215].

The *organizational* context includes internal factors such as firm size, structure, culture, resources, and management support. From an AI adoption standpoint, this involves assessing the overall organizational readiness, including leadership commitment, skill development, and cross-functional collaboration. For example, firms with strong management support are better positioned to allocate resources for AI deployment and influence employees' trust in AI, reducing their resistance to change [224]. Likewise, organizations that invest in developing advanced digital skills, nurturing a culture of continuous learning, and providing internal training opportunities, create a more favorable environment for AI adoption [204].

The *environmental* context refers to external pressures, including market competition, regulatory requirements, customer expectations, and supplier relationships. These forces can either drive or constrain the adoption of AI in SC demand planning. A supportive environment, such as favorable regulations, sufficient government funding, or competitive pressures, can encourage firms to implement AI [225]. Similarly, SC partnerships can facilitate adoption by enabling shared data resources, joint risk management, and coordinated innovation plans [68]. Conversely, stringent regulations or stagnant markets can act as barriers [226].

3.4 Methodology

3.4.1 Research design

The research employs an inductive qualitative approach through a single-case study design [227]. Prior research has similarly adopted inductive approaches to capture the dynamics related to the implementation of innovative projects and digital transformation in healthcare-related sectors (e.g., [228][229]). The adoption of a qualitative methodology is particularly appropriate given the exploratory nature of the research question and the need to investigate the complex socio-technical phenomena surrounding AI adoption in the pharmaceutical sector. In line with recent studies in SC digital transformation research [230, 231, 232], the inductive approach is complemented by the interpretative framework of grounded theory, which supports theory building through iterative data collection and analysis, and is well-suited to identifying emergent patterns in underexplored phenomena.

3.4.2 Case selection

The case selection followed theoretical sampling principles [233], focusing on a large Spanish pharmaceutical company (hereafter referred to as Company X), whose commercial activity is primarily concentrated in Spain and other European markets. Company X is a leader in the development, manufacturing, and marketing of generic medicinal products, biosimilar medicines, products for women's health, and sport nutritions. It also operates as a contract manufacturer for third parties.

Over the past three years, Company X has undertaken a broader digital transformation of its

SC, centered on the implementation of SAP S/4HANA and SAP Integrated Business Planning (IBP). In particular, IBP was introduced to support Sales and Operations Planning (S&OP) with the objective of improving demand forecasting accuracy, optimizing inventory levels, stabilizing manufacturing operations, and increasing responsiveness to demand variability. Before this transformation, demand planning activities relied heavily on Excel-based processes, which were increasingly inadequate given the scale and complexity of the company's product portfolio (approximately 1,800 SKUs).

Within this digital transformation trajectory, Company X is currently piloting an AI–based demand forecasting solution through a proof-of-concept (POC) project. The AI initiative is positioned as an incremental enhancement of the existing planning system rather than a disruptive replacement. At the time of the study, the project was at an early maturity stage, characterized by experimentation, limited scope, and strong reliance on external technological expertise. The scope of the AI POC is focused on demand planning and forecasting. In its first phase, the project aims to improve the quality of historical sales data by training machine learning algorithms to automatically detect and correct outliers—such as atypical sales spikes—currently adjusted manually by the demand planning team. This phase is designed to benchmark the performance of the AI model against the existing statistical forecasting algorithms embedded in SAP IBP, using the same internal sales data as input. In a second phase, the project plans to extend the model by incorporating external demand signals, including wholesalers' sell-out data, competitors' stock-out information, and other market-related variables. This extension reflects the structural characteristics of the pharmaceutical distribution channel in Spain, where demand observed at the manufacturer level is often decoupled from end-customer consumption due to inventory buffering and promotional practices by wholesalers. The integration of such external signals is expected to enhance forecast responsiveness to real market dynamics.

The organization represents what [227] defines as a revelatory case study, demonstrating an accelerated digital transformation trajectory that challenges traditional assumptions about technological adoption in the pharma industry. While pharmaceutical companies have historically lagged behind other sectors in digital transformation [220], Company X completed the transition from Excel-based planning to SAP IBP in 2023 and initiated an AI pilot for demand forecasting by 2025. This rapid evolution, particularly notable for a regionally focused generic pharmaceutical company, makes the case well-suited for examining the dynamics of AI adoption and digital transformation in a traditionally conservative sector.

3.4.3 Data collection

Following established qualitative research protocols [25], data collection employed multiple sources of evidence through a systematic process spanning six months (February-July 2025).

The primary data collection consisted of 10 in-depth interviews (40-60 minutes each) with key informants selected to represent different perspectives on the digital transformation and AI adoption processes in the company. Participants included internal stakeholders such as managers from SC, demand planning, operations, and digital transformation specialists, as well as technology providers and system integrators. Further details about the interviewees can be found in Table 3.1. This dual perspective approach provides a comprehensive understanding of the phenomenon [234], capturing both organizational dynamics and technical implementation challenges.

The semi-structured interviews followed a carefully designed protocol with open-ended questions focusing on both the digital transformation journey of the company and the AI adoption process. The interview guide was developed based on the TOE framework to ensure comprehensive coverage of technological, organizational, and environmental factors influencing AI implementation. All interviews were recorded with permission, transcribed verbatim, and validated by participants to ensure accuracy [235]. To complement and triangulate the interview data, secondary data, including internal documents (e.g., strategic plans, implementation reports, training materials), and archival data (e.g., websites, reports, and press releases), were also collected.

Interviewee number	**Role**	**Affiliation**
1	SC Director	Company X
2	Demand Planner	Company X
3	Lean Production Lead	Company X
4	Technology Manager	System Integrator A
5	Organizational Development Manager	Company X
6	Continuous Improvement Manager	Company X
7	Manufacturing Operations Manager	Company X
8	Managing Director	System Integrator B
9	Principal Presales Consultant	Tech company
10	MES &IIoT Manager	System Integrator C

Table 3.1: Characteristics of the interview sample

3.4.4 Data analysis

The analytical approach adopted in this study followed the systematic methodology proposed by [25], proceeding through multiple coding stages to ensure analytical rigor and theoretical development. Following the recommendations of [236], NVivo software was used to manage and organize the coding process. The inductive method was complemented with the interpretative approach provided by grounded theory [237], which allows researchers to move back and forth from observation to abstraction and to iteratively build and refine an emergent theory, with constant comparison between emerging themes and existing literature.

Firstly, informant-centric terms and concepts were identified, staying close to the participants' own language and expressions (*first-order concepts*). Related first-order concepts were then aggregated into theoretically distinct themes. This process involved multiple researchers independently coding the data and subsequently comparing interpretations to ensure analytical reliability [238]. A total of six *second-order themes* were identified and consolidated into three *aggregate dimensions*. The analysis was iterative, involving frequent returns to the data to ensure theoretical saturation [233].

The data structure, presented in Figure 3.1, visually represents the progression from raw data to theoretical concepts [25]. It provides a static depiction of the phenomenon and serves as the foundation for the grounded model in Figure 3.2, which explicates the underlying dynamics observed in the data.

To ensure methodological rigor and enhance the trustworthiness of the findings, several validation procedures were implemented in line with established guidelines for qualitative research [239].

Construct validity was strengthened through systematic triangulation of data sources and perspectives, with findings cross-validated using multiple data sources and incorporating insights from both internal and external stakeholders [240].

Internal validity was enhanced through pattern matching and explanation-building processes. Emerging patterns were iteratively compared with those predicted by existing theory while remaining open to novel insights, and actively seeking and addressing alternative explanations [227].

To establish *reliability*, a detailed case study protocol was developed, and a comprehensive database of all collected data was maintained, ensuring a clear chain of evidence linking the RQ, the collected data, and the resulting conclusions.

While acknowledging the inherent limitations of single-case research, *external validity* was enhanced through careful theoretical sampling and rich contextual description. The case selection deliberately focused on an organization offering unique insights into rapid demand planning digital transformation within a traditionally conservative industry, thereby enabling readers to assess the transferability of the findings to other contexts.

3.5 Findings

Overall, the findings indicate that the adoption of AI in the pharmaceutical industry is shaped by a complex interplay of technological, human, and institutional factors. The three aggregate dimensions identified are: *Integrated socio-technical resources*, *Institutional frictions*, and *AI value realization* (Figure 3.1). These dimensions illustrate how organizations build the necessary digital and human capabilities for AI, the institutional barriers that constrain its deployment, and the mechanisms through which AI begins to deliver tangible benefits.

3.5.1 Integrated socio-technical resources

The findings revealed *Integrated socio-technical resources* as a foundational dimension in AI adoption, combining digital integration capabilities with human and organizational elements.

A recurring theme across participants was the persistence of manual and paper-based processes, particularly in pharmaceutical production. This reliance on manual work was frequently viewed as a barrier to digital transformation and AI readiness. As one participant explained,

"*They are not so interested in having everything automated and all connected. For them, it's more important the quality and all the audits than the automation. For example, in the agri-food sector, the competence is really high. They have completely automatic plans, which means that from the guy in front of the ERP, they can trigger production, and the entire factory goes completely automatic. That's different from pharma. They don't care about being so efficient.*"

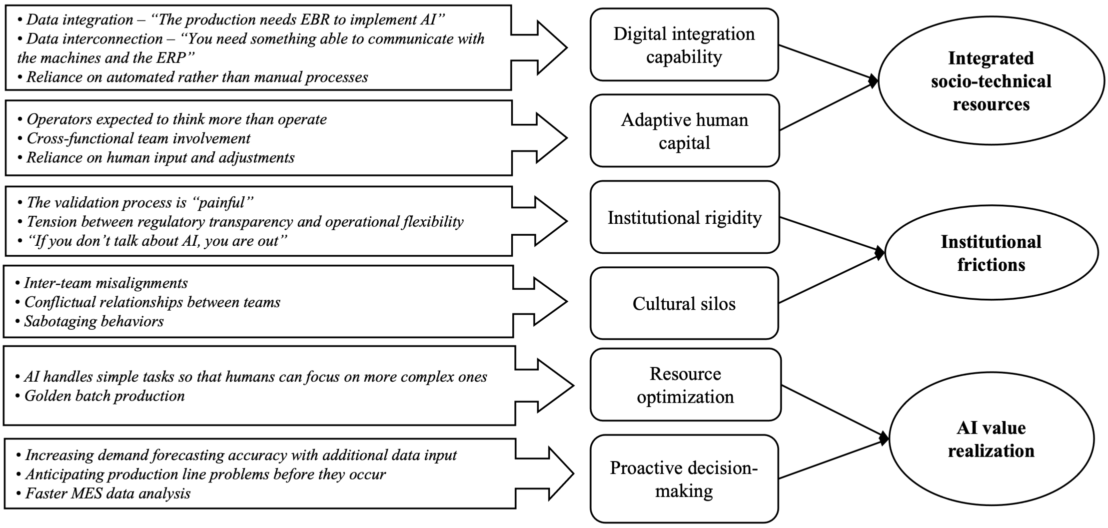


Figure 3.1: Data structure

Manual practices were described as deeply embedded in everyday operations, with even basic tasks still performed by hand and recorded using tools like Excel:

These people are used to working with papers. They have a lot of manual procedures... a lot of times that were recorded just using an Excel file", one informant remarked. Another recounted, "*When I joined the company three years ago, demand forecasting was done using an Excel file. No algorithm, nothing.*"

The same pattern was observed in manufacturing processes:

"*When you are producing something, it's like when you are in the kitchen, and you are cooking. You follow a recipe with paper instructions: add water, push the button for mixing, push the button for heating...*"

This operational reality underscores the need for greater automation to improve process control, data reliability, and overall efficiency. All participants emphasized that AI cannot function in isolation but requires large volumes of accurate, timely, and structured data, making digital integration systems such as ERP, MES, and EBR critical enablers. These systems generate the foundational data streams that allow AI to support tasks like demand forecasting, production optimization, and quality control.

The degree of AI readiness, however, varies across systems. ERP platforms (particularly SAP IBP) were often viewed as more AI-ready. One example involves the piloting of AI to enhance the accuracy of SAP IBP's demand forecast by integrating additional data inputs. MES platforms were also recognized as data-rich and promising for AI, but not prioritized for immediate application. As one participant noted,

"*We have such a huge collection of data in the MES that we are probably closest to applying AI models there, to predict how much our lines will increase efficiency if we are able to solve certain issues. Here, AI will give us speed. But, to be honest, our priority right now is not to apply AI models in the MES, because I will have the return anyway, with a good analysis performed by a good process engineer.*"

Instead, EBR is regarded as a critical precursor for AI deployment in production, despite being less mature at present. By capturing detailed and structured data for each manufacturing batch, EBR provides the necessary input for AI-driven quality control and process optimization. As one informant explained,

"*We want to apply AI models to the process control parameters. Because we have the money here, we can avoid the destruction of batches because of mistakes or parameters not controlled in the process. And avoiding quality controls performed in the lab. This will significantly reduce our lead time for the release of the batches. And the money, to be honest, is here.*"

Yet, technology alone was not sufficient. The second-order theme of "Adaptive human capital" highlights the evolving role of human operators, increasingly valued for cognitive, analytical, and collaborative skills rather than manual execution:

"*We want operators thinking more than operating. We have to develop new skills in these people—more analytical skills. It's someone now who has to interpret the results, the data, and make small decisions step by step.*"

This reflects a cultural shift toward empowering frontline workers to understand and act on digital information rather than simply following procedures. As one participant put it:

"*We are changing from a mindset that says, 'The important thing is to move the product. Everything is okay, go away.' Now the mindset is: we need to manufacture as much as possible, but we cannot permit one batch that's not okay. Quality is now one of the main goals of production.*"

Effective AI initiatives were found to depend on strong cross-functional collaboration, especially in demand planning, where the integration of insights from multiple departments was viewed as essential for accurate and context-sensitive outcomes. As one informant explained,

"*You have IT and you have demand planning, and no more people. The team should include sales or trade marketing, because these guys are the owners of the relationship with the wholesaler. They can explain better why we have this outlier or why we don't.*"

"*You need the collaboration of your sales colleagues to understand what is happening, why the forecast is increasing or decreasing, or the impact of an event.*"

In the context of EBR implementation, early and ongoing involvement of end users such as operators, maintenance technicians, and analysts was described as key for ensuring AI solutions fit operational realities, as they possess critical tacit knowledge:

"*We involve these people since the very beginning of the process to have expert users who understand the process, what we want to do, what the benefits are—to ensure that what we are doing digitally really fits the reality and meets their needs.*"

"*The knowledge is in the first line. If they have clear instructions, process knowledge, and real-time data, they should make the decision.*"

Training and communication also emerged as central to human adaptation. As one participant recalled,

"*Not only when we are implementing the project, but the team needs to communicate on the web page, or internally, on screens in the lunch area. It's very important to work in this line.*"

Another described a training initiative conducted in the company cafeteria:

"*We explained the goal of that project, how to use the application. We were not company people, but we were there as employees, so it was really easy to work with them.*"

3.5.2 Institutional frictions

Despite the advancement of socio-technical capabilities, the findings show that *Institutional frictions* often impede the full acceptance and deployment of AI systems.

The first source of friction is “Institutional rigidity”, referring to the structural constraints imposed by regulatory frameworks and validation processes in the pharmaceutical industry. Participants described these procedures as slow, inflexible, and resource-intensive:

"*One of the main issues for the pharma industry is that it’s a regulated environment. That means that everything should be approved. Even adding a new feature requires validation—lots of paperwork to prove the system will always work the same way.*"

Such exhaustive validation discourages continuous improvement and slows AI adoption, compared with more agile sectors:

"*All this validation process is for me the worst pain for the pharma industry. You will not find that in a food and beverage environment. For sure, there are regulations, but they don’t need to validate the environment.*"

A key tension arises around whether AI is used as a decision support tool or an automated decision-maker:

"*If the operator takes the decision based on AI suggestions, you don’t need to validate AI. But if AI is directly connected to the system and makes the decision, then you must validate everything—and that’s very complex.*"

This distinction influences both technical design and implementation strategy for AI systems. Participants also noted that regulatory expectations are often disproportionate to product risk. As one participant remarked,

"*In the pharmaceutical sector, we have a lot of exaggerated requirements, especially in solids manufacturing. For me, it’s normal to have higher standards for sterile or injectable products, but for solids—like paracetamol—, the standard should be the same as for manufacturing hot cookies.*"

To preserve flexibility, many firms maintain manual processes in areas where automation would increase compliance burdens: "*Some parts of the process are still manual because you need to add something manually.*"

"*Pharma companies might decide to digitalize only certain parts of a process. Others, which require more flexibility, remain manual.*"

The shift from manual to digital documentation also creates tension between data precision and operational flexibility. Several participants acknowledged that while manual systems allow for small adjustments—or even data manipulation—automated systems introduce rigidity by enforcing data precision and traceability. For example, one participant observed,

"*You have to weigh 12 kilograms. The tolerance range is from 11.99 to 12.01. If you put 12,05 kilograms manually, you could say, ‘Okay, this is 12.05, let’s go. ’ This is not a problem, because it’s just a small difference in the second digit. But with the system, you cannot say ‘let’s go’ because the label won’t be printed.*"

Another participant added, "*The problem is that if you are doing something manual in Excel, you can invent the numbers and tune a little bit. But when a machine collects data, it’s much harder to manipulate.*"

These examples illustrate how institutional rigidity constrains AI innovation. While such frictions serve essential quality and safety functions, they also shape how AI is introduced: cautiously, incrementally, and often in non-GMP-relevant areas where regulatory constraints are lower. This reflects a strategic effort to balance regulatory compliance with innovation by selecting AI applications that offer value without triggering additional institutional resistance.

Finally, the “hype” surrounding AI introduces additional friction:, "*The market is hot in terms of AI. Everybody speaks about AI, and everybody says, ‘Okay, I want AI.’ But customers don’t know where they want to apply AI, and some of them don’t have the maturity to implement AI.*"

Thus, enthusiasm and institutional immaturity coexist, revealing a paradox of AI aspiration without readiness: hype may accelerate adoption pressure but simultaneously reveal institutional and cognitive gaps that hinder meaningful implementation.

Equally constraining are the "Cultural silos", referring to persistent divisions and misalignments across organizational teams. Participants describe inter-team conflicts, weak communication, and even active resistance or “sabotage” of digital initiatives by those who feel threatened or excluded. These behaviors reflect deeper cultural resistance to change, where digital transformation efforts are viewed with suspicion rather than embraced as a collective endeavor. One participant illustrated this dynamic when describing the difficult relationship with the marketing team:

"*The relationship with the marketing team is more conflictual than smooth. It’s not a love story. Because, as we are challenging the forecasting results all the time, they don’t feel comfortable with the process.*"

Another participant emphasized the lack of shared ownership in AI-related projects,

"*They say, ‘Okay, this is your project. If you need something, you can ask me.’ But the mindset should be the opposite: this is a cross-functional project, so you have to be part of this.*"

Differences in trust and expectations toward AI further deepen misalignment:

"*For me, these guys expect that, if we are going to implement AI, they will never do a forecast because the forecast will be done by the system. And for me, this is a wrong expectation, because it’s true that the new system will provide us with a more accurate forecast, but you will always need the input of the sales guys, of the marketing guys, because there are a lot of things that happen in the market that it’s very difficult to predict in the system.*"

Cultural silos were also evident between business units and IT departments, or between system integrators and cybersecurity teams:

"*Sometimes the IT people don’t want to give you the rights you need. There are many battles just to install software as required.*"

"*The cybersecurity team is not well prepared; there is a lack of knowledge. Sometimes the client doesn’t fully understand the implications. Even when a complete architecture is defined and agreed upon with all the parts, cybersecurity can come in and just destroy everything.*"

Several participants contrasted operational and IT perspectives:

"*We apply AI to the production and quality on the shop floor. This is easy to understand for operations directors. But IT doesn’t understand what the factory needs, in terms of operations and process control. They think it’s simple, but they don’t know the factory context and often make decisions misaligned with business needs.*"

Resistance also emerged among frontline workers, who feared job security loss or increased oversight. As one participant remarked, "*You can find people doing everything possible to sabotage the project. They don't want it to succeed.*"

"*Workers initially think MES is meant to control them. And they react as, 'Now I will have the police here on the line 24/7'. Some still believe these systems are about control, and that perception won't change for some.*"

Participants also reported anxiety related to performance evaluation and personal incentives:

"*They saw the tool like a chip. They fear the company won't pay their bonus this year because the numbers may look very different from what they currently report in the Excel file.*"

3.5.3 AI value realization

The third aggregate dimension captures how organizations begin to convert digital and AI investments into tangible operational benefits. Under the second-order theme, "Resource optimization", participants described AI as enabling a more strategic allocation of resources. By offloading repetitive or low-complexity tasks to AI, human operators can shift their focus toward higher-value, analytical tasks. As one informant put it:

"*We have a large portfolio, around 1,800 SKUs, and our goal is to have at least 70 or 80% of the portfolio running automatically with AI. So, the marketing team can focus on the added value.*"

Another added:

"*The simple decisions will be made by AI. But nowadays, our technicians are making these simple decisions. In the future, if AI makes these simple decisions for me, I have to move on in my analysis to focus on the big ones, which nowadays, anybody is analyzing.*"

The pursuit of *golden batch* production—the ability to reproduce an optimal batch configuration consistently, without unnecessary manual checks or intervention—exemplified this logic:

"*Our vision is to be able to create a non-variable process that guarantees us the product will be within the quality control parameters without doing the control in the lab… Because I can detect if something is wrong or not early in the process.*"

AI thus supports not only quality assurance but also the reduction of waste, delays, and rework. As another interviewee noted:

"*AI helps me to avoid some situations, like 'no, it will be 50% okay', so you can say, 'okay, I take a look at how the product is being made, and maybe mix more, to be sure that the result will be okay'. You're avoiding waiting for the final quality control.*"

The second-order theme "Proactive decision-making" reflects a transition from reactive to anticipatory management, particularly in demand planning:

"*Our forecasting system only considers sales data as an input. The goal is to see if additional inputs, such as wholesale sell-out and stock-out, can help improve the forecast. Sometimes, in the pharmacy, you have a demand increase—for example, due to the flu—but you don't see this in our sales, because the wholesaler has a lot of stock.*"

This reflects a strategic intent to reduce demand-supply mismatches, improve service levels, and manage production capacity more efficiently.

Beyond demand forecasting, several interviewees emphasized AI's potential in predictive maintenance:

"*You can use it for predictive analytics—trying to know when a machine might break down in advance, so you can do a preventive action.*"

Together, these capabilities represent early but significant steps toward strategic, data-driven management, where AI becomes a driver of operational intelligence.

3.6 Discussion

The three aggregate dimensions identified in this study form a process-oriented understanding of how firms should evolve from the pre-adoption phase of AI to the realization of its operational benefits and value (Figure 3.2). The grounded theory suggests that AI adoption is a socio-technical transformation where digital integration and human adaptation must be coordinated within a supportive institutional environment.

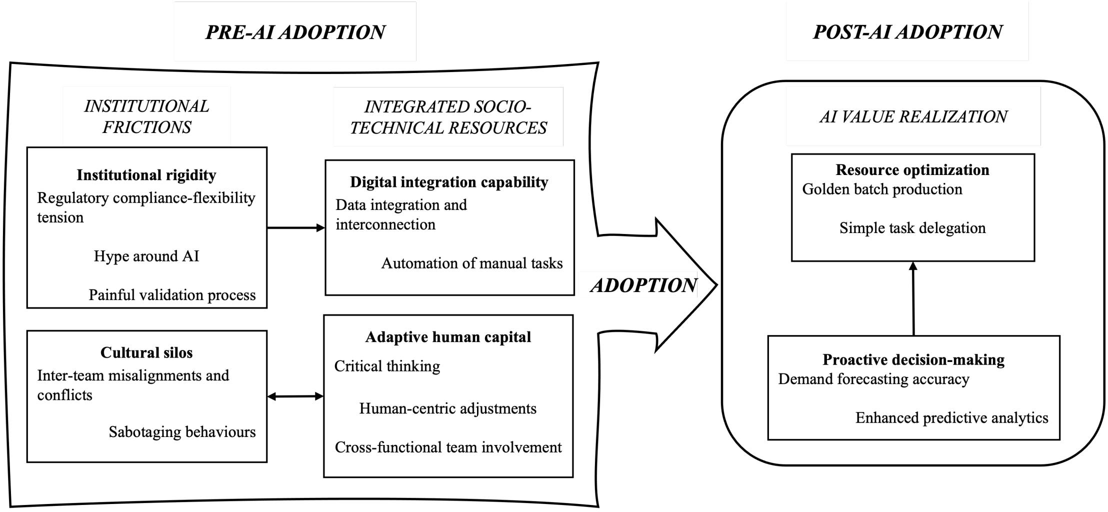


Figure 3.2: Grounded model

The following sections interpret these findings in light of existing theory, clarifying their contributions for both research and practice.

3.6.1 Digital integration and human capital as foundational capabilities

The first aggregate dimension aligns closely with Dynamic Capability Theory (DCT) [241], which posits that sustained competitiveness in dynamic environments depends on the ability to sense, seize, and reconfigure resources in response to technological change.

In the study's findings, dynamic capabilities manifest through the integration of digital systems over manual ones, and the adaptability of human capital. Digital integration capabilities constitute the technological backbone that enables automation, data integration, and interconnection. At the same time, human adaptability complements these technical foundations by allowing individuals to interpret data, make contextual judgments, collaborate across functions, and apply domain knowledge within evolving AI-supported environments. This shift demands not only technical upskilling but also cultural adaptation, and new forms of cross-functional engagement—reinforcing the notion that digital transformation is as much a social learning process as it is a technological one [242].

The ability to harmonize digital and human resources enables firms to reconfigure existing routines toward AI-driven operations. For instance, decision-making can be progressively “pushed to the line”, empowering frontline workers with analytical capabilities to act in real-time, rather than waiting for expert validation. This also aligns with literature positioning AI as a capability-enhancing technology [243], contingent upon firms’ ability to align human capital, workflows, and digital systems in mutually reinforcing ways. Importantly, digital maturity alone does not automatically translate into a need for AI adoption. In some cases, like MES data analysis, capable process engineers can achieve comparable performance without AI. Conversely, AI experimentation in demand planning was prioritized not only due to the structured nature of ERP data but also because of its strategic relevance to supply-demand alignment [216]. Similarly, the application of AI models to EBR data was viewed as strategically critical because it could drastically reduce batch release time and improve responsiveness.

3.6.2 Regulatory and cultural rigidity as frictions

The second aggregate dimension, *Institutional frictions*, can be interpreted through the lens of Institutional Theory (IT) [244], particularly in how organizations conform to regulatory, normative, and cultural pressures that shape—and often constrain—technological change.

The pharmaceutical industry’s formalized validation processes epitomize institutional rigidity. While they ensure compliance and safety, they also create inertia, slowing digital experimentation and AI integration. Findings illustrate how institutional logics of control and compliance interact with emerging digital logics of agility and data transparency, forcing organizations to negotiate a balance between regulatory legitimacy and operational flexibility. Consistent with the notion of "institutional isomorphism" [245], coercive and normative pressures in pharma lead to conservative and fragmented digital transformation. Manual procedures often persist not for their efficiency but to preserve flexibility. This dynamic reflects “decoupling” [244], where formal structures conform to external legitimacy demands while technical activities retain informal workarounds to maintain adaptability.

At the same time, mimetic pressures [245], fueled by the widespread “hype” surrounding AI, drive firms to pursue adoption often without a clear understanding of their digital maturity or the specific problems that AI is intended to solve. Such imitation-based behaviors result in fragmented initiatives that seldom progress beyond the pilot stage. This dynamic illustrates how institutional pressures can prompt premature adoption efforts, underscoring the need for a more capability-based approach to AI transformation.

Cultural silos emerged as another institutional friction, reinforcing structural rigidity. Misaligned incentives, lack of trust, and divergent expectations about AI autonomy foster resistance and even active sabotage, impeding the cross-functional integration required for AI systems to deliver value. These findings confirm prior research on organizational inertia and digital resistance [246], but this study extends it by revealing a mutual reinforcement loop: cultural silos hinder adaptive human capital, while a lack of empowered and informed employees perpetuates siloed behavior. One underlying cause lies in the divergent expectations about AI across teams, which aligns with prior research on trust dynamics between users and AI systems [247], with users anthropomorphizing AI and therefore developing different assumptions about its decision-making autonomy [248].

Overcoming this vicious cycle requires a cultural orchestration: leadership, training, and engagement strategies that reframe AI from a perceived threat to a collective tool for process excellence. Informal communication activities (e.g., lunchroom sessions) and the early involvement of shop-floor workers in system design emerged as effective micro-strategies for fostering engagement and ownership.

Findings also suggest the need to rethink the role of IT strategy, moving from a functional-level orientation to a fusion between IT and business strategy [249].

3.6.3 AI value realization as outcome

The third dimension, *AI value realization*, represents the tangible operational improvements that emerge when digital and human capabilities are successfully mobilized in an institutionally aligned context.

These findings align with the Socio-Technical Systems Theory (STS) [250, 251], which posits that organizational performance depends on the joint optimization of technical and social subsystems.

Data show that value is realized when only advanced DT is complemented by adaptive work practices [252]. AI acts as an enabler for offloading routine tasks—such as basic demand forecasting adjustments—and for reducing batch release delays by resolving quality-risk issues without waiting for final quality control, thereby preventing batch destruction. This allows humans to shift toward complex problem-solving, resulting in higher efficiency, reduced waste, and improved employee engagement—a virtuous cycle of augmentation rather than replacement, consistent with recent studies on human-machine complementarity [253, 254].

Similarly, the shift toward proactive decision making reflects an adaptive, open socio-technical AI configuration [255] where predictive analytics and human judgment continuously interact to anticipate issues in demand, supply, and production systems [204], but the study's findings extends this by showing the institutional and human groundwork required for such use cases to materialize. Importantly, this is not a static endpoint but may be part of a dynamic feedback loop: as AI systems generate value through resource optimization and proactive decision making, the resulting organizational learning reinforces digital integration and human adaptability and institutional alignment.

3.7 Conclusions

Drawing on rich qualitative evidence, this study provides insights into how organizations navigate the complex interplay of technological, human, and institutional factors in the adoption of AI within the pharmaceutical SC. The resulting grounded theory (Figure 3.2), derived from emerging concepts, themes, and dimensions—and their dynamic interrelationships—outlines a pathway of AI adoption from the development of technological and human capabilities, through organizational and institutional constraints, to tangible operational outcomes.

From a theoretical perspective, the study contributes to several ongoing research streams.

First, it advances the behavioral perspective of AI adoption, which remains underrepresented compared to the dominant technical focus on algorithmic development, predictive model design, and optimization performance [209]. This study extends the understanding of AI adoption beyond technical capability building to encompass analytical and collaborative capabilities, showing how AI value realization depends on the co-evolution of digital systems and human capital rather than on technological sophistication alone. In line with STS theory, AI value realization emerged as a feedback loop of augmentation, where AI offloads routine work to enable human problem-solving and organizational learning. DCT is further refined through evidence of how firms reconfigure digital and human resources in tandem, demonstrating that AI-driven transformation relies not only on sensing and seizing technological opportunities but also on cultivating adaptive social capital.

Second, the study responds to calls for empirical, process-oriented analyses of AI integration in SC management. Through an in-depth case study of an early adopter in the pharmaceutical industry, it provides contextualized, process-level evidence of how AI integration unfolds in practice—revealing the interplay between digital infrastructures, institutional constraints, and behavioral responses. This empirical grounding offers a more comprehensive understanding of the drivers, challenges, and enabling mechanisms that influence AI transformation trajectories, thereby bridging a methodological gap in the AI-driven SC demand planning research, which has been dominated by simulation-based or conceptual models [209].

Third, it expands research on AI in the pharmaceutical sector—an area identified as both critical and underexplored in the SC management literature [3, 213]. The findings demonstrate that pharmaceutical demand planning constitutes a particularly high-stakes context for AI adoption, where regulatory rigidity, data fragmentation, and risk sensitivity shape implementation strategies. By examining how pharmaceutical firms reconcile regulatory compliance with operational flexibility and tradition with innovation, the study enhances current understanding of AI adoption under institutional constraints. It contributes to IT by illustrating how regulatory and cultural rigidity shape firms' approaches to AI adoption, often leading to cautious and hybrid digital transformation strategies.

Finally, the study advances ongoing calls to deepen understanding of AI adoption in SC management [203, 205]. It proposes a process-oriented, grounded model that integrates the technological, organizational, and environmental dimensions of the TOE framework with behavioral factors. This model illustrates how firms move from capability development to value realization through iterative alignment between human, digital, and regulatory systems.

Beyond theory, the study also informs managerial practice by emphasizing the need for balanced strategies that combine digital investments with cultural change initiatives, institutional navigation, and human empowerment—key levers for transforming AI "hype" into sustainable organizational learning and performance. Managers are encouraged to engage cross-functional teams early, communicate transparently to reduce resistance, and involve system integrators as boundary spanners to align technical and organizational priorities. A phased AI implementation, starting with less critical or lower-risk processes, could allow organizations to build trust in the technology, identify challenges early, and progressively develop the necessary skills and capabilities. Moreover, hybrid approaches, which combine AI-generated insights with existing manual checks or human oversight, may ensure reliability while fostering confidence among employees. Finally, framing AI as an augmentation tool, rather than a replacement for human work, emphasizes how AI enhances employees' decision-making and problem-solving capabilities, fostering greater workforce acceptance. For pharmaceutical firms, this shift can unlock measurable outcomes such as improved forecast accuracy, reduced batch release time, and waste minimization.

Limitations of this study include its single-case focus, which, while offering revelatory depth and contextual richness [227], may constrain the generalizability of findings. Future research could employ multi-case or longitudinal methods to test the model across industries or track long-term cultural impacts. For instance, comparative studies between pharmaceuticals and less-regulated sectors could examine how institutional frictions vary and influence AI value realization. Quantitative validation of the process loop, for example, through surveys measuring socio-technical integration's impact on efficiency metrics, would complement this study's qualitative insights, providing empirical rigor to the interplay of TOE dimensions and the human factor. Explorations of ethical AI, such as bias in forecasting algorithms or data privacy in human-AI collaboration, would extend contributions, especially in pharma's high-stakes environment where trust gaps remain underexplored. Additionally, investigating micro-processes of human-machine interaction (e.g., via ethnographic methods) could deepen understanding of adaptive human capital, building on themes like cultural silos and motivation. Finally, examining how emerging trends like sustainability pressures moderate AI adoption, through mixed-methods designs, could test the model's applicability in global SC management.

Conclusions

As outlined in the Introduction chapter, this thesis was motivated by the growing importance of Digital Technologies (DT) and the corresponding lack of integrated management studies addressing their adoption within the Pharmaceutical Supply Chain (PSC). Building on this premise, the thesis adopted a multi-method approach by combining a *macro*-level systematic literature review, a *meso*-level study of inter-organizational dynamics, and a *micro*-level case study of a pharmaceutical manufacturing firm. The three studies address the RQs formulated at the outset of the thesis, providing complementary theoretical and empirical insights into the acceptance and adoption of DTs across multiple levels of the pharmaceutical ecosystem (Figure 4).

Across the three studies, a consistent pattern emerges, providing a clear response to RQ1: despite strong scholarly attention to disruptive DTs such as AI, blockchain, and drones, their actual implementation within the PSC remains at an early stage. This gap reflects a mismatch between the visibility of these DTs at the strategic and symbolic level and organizations' actual readiness to integrate them into everyday operations. As evidenced most clearly by the case study in Chapter 3, high market enthusiasm for AI may mask a lack of organizational maturity, resulting in fragmented pilot initiatives that struggle to scale and remain weakly integrated into core processes.

The analysis conducted through the UTAUT framework in Chapter 1 provide a direct answer to RQ2, showing that Performance Expectancy (PE) and Facilitating Conditions (FC) dimensions are the most frequently discussed determinants of DT adoption in the PSC, followed by Social Influence (SI) and Effort Expectancy (EE). However, their relevance and manifestation vary across technologies and organizational levels, highlighting technology-specific adoption factors and contextual contingencies.

PE is primarily associated with improvements in PSC security and the reliability of internal operations. Trust in the technology emerges as a critical underlying condition, as insufficient confidence in system performance and outputs can undermine perceived value and ultimately hinder adoption. With specific reference to AI, PE reflects expectations of proactive decision-making and resource optimization. As evidenced in Chapter 3, AI is expected to enable a shift from reactive management toward anticipatory demand planning, allowing human resources to transition from routine activities to higher-value strategic tasks. In addition, AI is expected to support “golden batch” production by enabling early detection of process variances, thereby reducing waste, delays, and the need for retrospective quality control. At the same time, the case study reveals that PE can also become a source of friction when expectations and trust in AI diverge across organizational units. Misaligned perceptions of AI’s value among functions such as operations, IT, quality, and planning give rise to cultural silos, conflicting priorities, and resistance to change. These dynamics undermine cross-functional collaboration and hinder the integration of AI into routine decision-making processes.

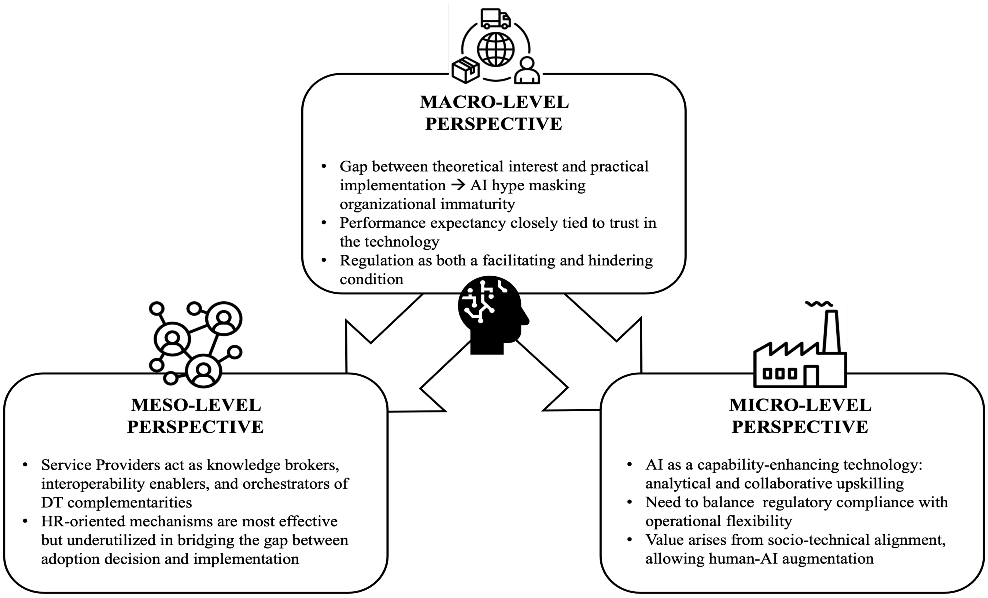
Internal FC-related factors mainly concern the lack of financial resources, as well as skills and competencies, both of which are perceived as significant obstacles to DT adoption. The case study findings particularly confirm the latter, demonstrating the need for an evolution of human resource capabilities beyond technical skills to include analytical competencies. Among external FC-related factors, a persistent tension emerges between regulatory enablement and regulatory constraint. On the one hand, regulations in the pharmaceutical sector are designed to promote quality, patient safety, and process reliability, thereby providing a structured framework that can support DT adoption. On the other hand, in the case of AI, these same regulatory requirements often clash with the “black-box” nature of certain AI algorithms, whose internal logic is difficult to interpret or justify ex post. As a result, as shown in Chapter 3, organizations face substantial challenges in validating AI-driven, autonomous decisions in line with regulatory expectations. To manage this uncertainty and reduce compliance risks, organizations frequently retain manual controls, positioning AI as a decision-support tool rather than as a fully autonomous system. Although this approach preserves operational flexibility, it simultaneously constrains the depth and scalability of AI integration within core SC processes.

The analysis of the SI dimension highlighted SC relationships as a key driver of DT adoption in the existing literature, without, however, explicitly examining the specific roles, behaviors, and support mechanisms of the different actors within the PSC - one of the gaps identified in Chapter 1 that motivated RQ4. Chapter 2 addresses this gap by revealing a differentiated pattern of inter-organizational influence: SPs emerge as facilitators and knowledge brokers of digital transformation, particularly through technological support actions such as enabling synergies with complementary technologies, identifying trusted partners, and ensuring interoperability with existing legacy systems. In contrast, GSs tend to play a more limited role in DT adoption, reflecting misaligned incentives and asymmetric exposure to digital transformation risks.

Finally, the analysis of EE emphasizes standardization and complexity of use as key determinants of organizations’ willingness to adopt DTs. For immature technologies such as AI, the lack of shared standards significantly constrains implementation capabilities. This finding is consistent with the results of Chapter 2, which identifies the definition of SC-level standards as one of the most widely adopted support mechanisms, in contrast to HR-oriented actions less frequently used.

Chapter 2 shows that some mechanisms (technological) are more widely adopted, while others (HR-oriented) prove more effective in bridging the gap between adoption decisions and implementation, providing a comprehensive answer to RQ5. Beyond formal training, HR-oriented support includes experiential and relational learning mechanisms, which help reduce the perceived complexity of DTs by transferring tacit knowledge and fostering collective learning across SC boundaries. This underscores the importance of a balanced socio-technical approach to digital transformation, consistent with the case study findings, which provide evidence relevant to

RQ6: realizing AI's value requires foundational capabilities in digital integration and adaptable human capital, which can be decisive in determining whether the technology becomes a fully operational asset or remains a symbolic, underutilized investment.



MACRO-LEVEL PERSPECTIVE

- Gap between theoretical interest and practical implementation → AI hype masking organizational immaturity
- Performance expectancy closely tied to trust in the technology
- Regulation as both a facilitating and hindering condition

MESO-LEVEL PERSPECTIVE

- Service Providers act as knowledge brokers, interoperability enablers, and orchestrators of DT complementarities
- HR-oriented mechanisms are most effective but underutilized in bridging the gap between adoption decision and implementation

MICRO-LEVEL PERSPECTIVE

- AI as a capability-enhancing technology: analytical and collaborative upskilling
- Need to balance regulatory compliance with operational flexibility
- Value arises from socio-technical alignment, allowing human-AI augmentation

Figure 4: Summary of the main research findings across the three analytical perspectives (*macro*, *meso*, and *micro*), with a focus on AI

Building on these insights, the following sections outline the main contributions of the thesis to both theory and managerial practice.

Theoretical contributions

First, this thesis contributes to the technology adoption literature by offering a holistic perspective on digital transformation in the PSC, examining multiple DTs and the factors shaping their adoption, in contrast to the predominantly single-technology focus of prior research in the broader healthcare context. The findings from the application of the UTAUT framework in Chapter 1 show that its four core dimensions - PE, EE, SI, and FC - apply across DTs but operate differently, deepening theoretical understanding of how adoption drivers and barriers are contingent upon technology-specific characteristics, particularly technological maturity. From the perspective of Innovation Diffusion Theory (IDT) [24], the thesis extends prior work that has predominantly focused on firm-level antecedents, such as top management support, highlighting the role of SC-level diffusion dynamics in enabling the transition from adoption decision to implementation of DTs.

Second, the research establishes that the adoption of DTs is a socio-technical process, requiring the co-evolution and joint optimization of human and technological systems, contributing to the Socio-Technical System (STS) theory [250]. The case study on AI adoption extends Dynamic Capabilities Theory (DCT) [241] by showing how organizations should reconfigure both digital and human resources simultaneously, developing analytical, collaborative, and adaptive capabilities in tandem with technological ones. Similarly, findings from Chapter 2 support the Organizational Learning Theory (OLT) [191] by highlighting that HR-oriented and learning-based mechanisms are among the most effective strategies for bridging the gap between adoption decisions and implementation of technologies such as AI, blockchain, and drones. This underscores the critical yet often underestimated role of organizational learning and internal capability-building in enabling successful digital transformation.

Third, the research contributes to the Institutional Theory (IT) [244] by demonstrating that digital transformation in the PSC is institutionally embedded, shaped by both regulatory and cultural forces. While previous literature has extensively examined regulation as an enabling or constraining factor (as discussed in Chapter 1), this thesis brings to light the equally critical influence of organizational culture, which is often overlooked within a traditionally conservative industry such as pharmaceuticals. The case study findings provide evidence that regulatory rigidity and cultural silos - stemming from divergent expectations, low trust in technology, and fragmented visions across departments - generate frictions that slow down digital transformation. By showing how firms try to reconcile regulatory compliance with operational flexibility, as well as tradition with innovation, this research extends IT in the context of DT adoption under institutional constraints.

Finally, by bridging individual and social levels of analysis, the thesis advances the understanding of digital transformation as a collective and collaborative phenomenon. Collaboration emerges as the cornerstone of DT, both within organizations and across the SC. At the organizational level, beyond leadership and top management support - recognized in Chapter 1 as key enablers - cross-functional collaboration and integration across teams emerge as a crucial but underexplored determinant of DT acceptance. At the inter-organizational level, beyond technology providers and system integrators, collaboration with service providers, such as logistics partners, is revealed as a pivotal strategy for accelerating digital adoption in the PSC.

Practical contributions

From a practical point of view, the thesis offers several insights for managers and policymakers to overcome adoption barriers and maximize value in the digital transformation of the PSC.

First, the research highlights the importance of technology-specific adoption management. Managers should recognize that each DT entails different drivers and obstacles along the UTAUT dimensions. By assessing the most relevant factors for each case, organizations can design tailored interventions to enhance adoption readiness and ensure technology-organization fit.

Second, the findings demonstrate that building human and organizational capabilities is essential to unlock the potential of DTs. Digital transformation cannot succeed through technology investment alone. Technological investments must be complemented by continuous skill development, experiential learning, and cultural adaptation. Firms should embed HR-oriented initiatives - such as training programs, cross-functional projects, and job sharing - into their DT strategies to foster digital fluency, trust, and collaboration. Informal communication and engagement strategies can further enhance employee involvement and reduce resistance to change.

Third, the research confirms that institutional and cultural alignment is as critical as technological readiness. Beyond ensuring regulatory compliance, managers must cultivate a culture that values innovative over traditional approaches. Overcoming cultural silos is fundamental to transforming fragmented digital initiatives into coherent, organization-wide strategies. Policymakers, in turn, can support this alignment by promoting regulatory clarity, interoperability standards, and shared digital infrastructures, fostering a more flexible yet compliant environment for innovation.

Finally, the thesis provides actionable insights on the ecosystem-level collaboration required to accelerate digital transformation. The results show that digital innovation in the PSC advances through interdependent networks of actors who co-create value through shared data and technological integration. In this context, service providers emerge as potential orchestrators, acting as technology brokers and knowledge intermediaries that connect innovation and operations across the SC. Managers should therefore prioritize strategic partnerships and data-sharing agreements, leveraging these relationships to scale innovation.

Overall, this thesis emphasizes the need for a systemic and integrated approach to digital transformation - one that synchronizes internal capabilities (human capital, learning, and culture) with external ecosystem dynamics (partnerships, regulation, and technological interoperability). By adopting this holistic perspective, pharmaceutical organizations can move from isolated digital experiments toward sustainable, value-driven transformation, achieving not only efficiency and compliance but also greater resilience, innovation, and responsiveness in healthcare delivery.

Appendix

Table A.1: Keywords used for the identification of UTAUT factors

UTAUT dimension	UTAUT factor	Keyword
PE	Data quality	Creation of valuable data
PE	Data quality	Data integrity
PE	Data quality	Data quality
PE	Data quality	Data sharing
PE	Data quality	Data size
PE	Data quality	No guarantee of information integrity
PE	Data quality	System quality
PE	Economic benefits	Utility of investment
PE	Economic benefits	Cost savings
PE	Economic benefits	Concern with the ROI
PE	Economic benefits	Cost-effectiveness
PE	Economic benefits	Cost-efficiency
PE	Economic benefits	Difficult cost-benefit analysis
PE	Economic benefits	Lack of information about benefits
PE	Economic benefits	Lack of incentives hindering greater investment
PE	Economic benefits	Operational efficiency
PE	Economic benefits	Ownership
PE	Economic benefits	Perceived advantages (ROI)
PE	Economic benefits	Price value
PE	Economic benefits	Reduced health care expenses
PE	Economic benefits	Uncertain ROI
PE	Employees’ job	Assurance of job security
PE	Employees’ job	Decreased human-human interaction
PE	Employees’ job	Employees’ fear of change

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UTAUT dimension	**UTAUT factor**	**Keyword**
PE	Employees' job	Ethical risk (job loss)
PE	Employees' job	Fear or replacing humans
PE	Employees' job	General satisfaction
PE	Employees' job	Increased job satisfaction
PE	Employees' job	Job loss
PE	Employees' job	Labor intensification
PE	Employees' job	Resistance to change
PE	Employees' job	Resistance to new technology
PE	Employees' job	Transition and integration of people
PE	General benefits	Consumer awareness
PE	General benefits	Awareness of potential benefits
PE	General benefits	Environmental friendliness
PE	General benefits	Environmental impact
PE	General benefits	False promises
PE	General benefits	Higher agility
PE	General benefits	Improved inventory management
PE	General benefits	Improved quality of care
PE	General benefits	Lack of awareness
PE	General benefits	Lack of awareness on use cases
PE	General benefits	Marketing problems
PE	General benefits	Necessity of the application
PE	General benefits	Operations automation
PE	General benefits	Organizational requirement
PE	General benefits	Perceived benefit
PE	General benefits	Perceived delivery risk
PE	General benefits	Perceived limitations
PE	General benefits	Performance expectancy
PE	General benefits	Performance gap
PE	General benefits	Perceived usefulness
PE	General benefits	Relative advantage
PE	General benefits	Scalability
PE	General benefits	Scarcity of data on performance
PE	General benefits	Skepticism
PE	General benefits	Technology perceived as weak and non-significant
PE	General benefits	Trouble building a valid business case
PE	General benefits	Unavailable pharmacist-patient consultation
PE	General benefits	Lack of awareness

Continued on the next page

UTAUT dimension	**UTAUT factor**	**Keyword**
PE	General benefits	Uncertainty of potential outcomes against the complexity involved
PE	Reliability	Reliability
PE	Reliability	Consistency
PE	Reliability	Data management
PE	Reliability	Lack of trust in technology capabilities
PE	Reliability	Lack of trust in the technology
PE	Reliability	Low confidence
PE	Reliability	Maintenance and system downtime
PE	Reliability	Motivation towards the technology
PE	Reliability	Over-reliance
PE	Reliability	Quality
PE	Reliability	Quality control and legislation process
PE	Reliability	Too high expectations
PE	Reliability	Trust among stakeholders
PE	Reliability	Uncertainty about effectiveness
PE	Reliability	Unreliability of available technology
PE	Safety	Safety associated with medicine delivery
PE	Safety	Too robotic appearence
PE	Safety	Safety concerns
PE	Safety	Interferences with medical equipment
PE	Safety	Medicine safety
PE	Safety	Patient safety
PE	Safety	Stakeholder safety
PE	Scalability	Autonomy
PE	Scalability	Scalability
PE	Scalability	Service life
PE	Scalability	Interoperability with existing systems
PE	Scalability	Difficulty in flying in adverse weather conditions
PE	Scalability	Assurance of sufficient battery life
PE	Scalability	Limited capability
PE	Scalability	Limited capacity
PE	Scalability	Limited load carrying capacity
PE	Scalability	Low autonomy and weight
PE	Scalability	Payload capacity
PE	Scalability	Latency
PE	Scalability	Ubiquity
PE	Security	Accessibility

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UTAUT dimension	**UTAUT factor**	**Keyword**
PE	Security	Confidentiality-transparency balance
PE	Security	Control
PE	Security	Cybersecurity policies
PE	Security	Data privacy and security
PE	Security	Data recording
PE	Security	Data security
PE	Security	Data sensitivity
PE	Security	High data ownership-related issues
PE	Security	Immutability
PE	Security	Immutability risk
PE	Security	Lack of data privacy and security
PE	Security	Ownership
PE	Security	Perceived level of information security
PE	Security	Piracy threat
PE	Security	Privacy and security concerns
PE	Security	Privacy of transactions
PE	Security	Robustness to security threats
PE	Security	Security
PE	Security	Security risk
PE	Speed	Accessibility
PE	Speed	Latency
PE	Speed	Processing power and time
PE	Speed	Slow processing speed
PE	Speed	Speed
PE	Speed	Accessibility
PE	Technological maturity	Afraid innovation will fail
PE	Technological maturity	Effectiveness
PE	Technological maturity	Immaturity
PE	Technological maturity	Immature regulations
PE	Technological maturity	Lack of maturity
PE	Technological maturity	Lack of specialized tools
PE	Technological maturity	Limited readiness of the technology
PE	Technological maturity	Maturity
PE	Technological maturity	Effectiveness
EE	Complexity	Complex architecture
EE	Complexity	Complex norms
EE	Complexity	Complexity and of the real world
EE	Complexity	Complexity of implementation
EE	Complexity	Complexity of technological environment

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UTAUT dimension	**UTAUT factor**	**Keyword**
EE	Complexity	Cost and time required for implementation
EE	Complexity	Effort expectancy
EE	Complexity	Familiarity
EE	Complexity	High complexity
EE	Complexity	Infrastructure usability and design
EE	Complexity	Lack of resources (time)
EE	Complexity	Lengthy and costly technology importation
EE	Complexity	Lower complexity
EE	Complexity	Staff and time
EE	Complexity	Uncertain development cost (time)
EE	Complexity	Unfamiliarity with the technology
EE	Ease of use	Difficult to use
EE	Ease of use	Ease of handling and maintenance
EE	Ease of use	Ease of implementation
EE	Ease of use	Ease of use
EE	Ease of use	Ease of logging
EE	Ease of use	Inability to understand technology technicalities
EE	Ease of use	Physical accessibility
EE	Ease of use	Technological feasibility
EE	Ease of use	User experience
EE	Ease of use	User-friendship
EE	Standardization	Clinical guidelines and practice standards
EE	Standardization	Difficult standardization
EE	Standardization	Identification of common standards
EE	Standardization	Industry standards and guidelines
EE	Standardization	Information stewardship
EE	Standardization	Interoperability
EE	Standardization	Lack of clear government standards
EE	Standardization	Lack of clear standards
EE	Standardization	Lack of data standardization
EE	Standardization	Lack of government standards
EE	Standardization	Lack of guidelines
EE	Standardization	Lack of industry standards
EE	Standardization	Lack of standard applications for specific user contexts
EE	Standardization	Lack of standards

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UTAUT dimension	**UTAUT factor**	**Keyword**
EE	Standardization	Lack of standardized regulations
EE	Standardization	Limited open standards
EE	Standardization	Standard regulations
EE	Standardization	Standardization
EE	Standardization	Technical standards
EE	Trialability	Effective testing
EE	Trialability	Habit
EE	Trialability	Lack of information
EE	Trialability	Project champions
EE	Trialability	Trialability
SI	Internal coordination	Alignment with strategic goals and needs
SI	Internal coordination	Change of responsibility
SI	Internal coordination	Clear responsibilities of healthcare professionals
SI	Internal coordination	Clear vision
SI	Internal coordination	Coordination among departments
SI	Internal coordination	Decentralization
SI	Internal coordination	Effective communication
SI	Internal coordination	Incentive alignment
SI	Internal coordination	Lack of health administration support
SI	Internal coordination	Lack of organization-wide coordination
SI	Internal coordination	Lack of strategic planning for sustainable operations
SI	Internal coordination	Physicians cooperation
SI	Internal coordination	Unclear mission and vision regarding waste management
SI	Organizational culture	Cooperation
SI	Organizational culture	Creativity
SI	Organizational culture	Culture
SI	Organizational culture	Integration with organizational culture
SI	Organizational culture	Introduction of organizational learning
SI	Organizational culture	Knowledge of the technology
SI	Organizational culture	Lack of research-oriented mindset and collaboration
SI	Organizational culture	Lack of understanding
SI	Organizational culture	Need for a mindset and cultural shift

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UTAUT dimension	**UTAUT factor**	**Keyword**
SI	Organizational culture	Resistance to change
SI	Organizational culture	Risk-taking culture
SI	Organizational culture	Working culture
SI	Organizational leadership	Innovative leadership influence
SI	Organizational leadership	Lack of leadership commitment
SI	Organizational leadership	Lack of top management support
SI	Organizational leadership	Leadership
SI	Organizational leadership	Top management support
SI	Competitor relationships	Competition
SI	Competitor relationships	Competitive and mimetic pressure
SI	Competitor relationships	Concerns of loss of competitive advantage
SI	Competitor relationships	Customer power
SI	Competitor relationships	Less number of software and system vendors
SI	Competitor relationships	Vendor pressure
SI	Stakeholder relationships	Acceptability
SI	Stakeholder relationships	Access appropriate stakeholders
SI	Stakeholder relationships	Awareness
SI	Stakeholder relationships	Change management
SI	Stakeholder relationships	Collective consent
SI	Stakeholder relationships	Competing interests between in-country health stakeholders
SI	Stakeholder relationships	Cultural resistance
SI	Stakeholder relationships	Customer acceptance and loyalty
SI	Stakeholder relationships	Ethical consideration (dignity)
SI	Stakeholder relationships	External leadership
SI	Stakeholder relationships	Fear of losing competitive advantage in joining the network
SI	Stakeholder relationships	Higher compatibility
SI	Stakeholder relationships	Information sharing
SI	Stakeholder relationships	Lack of public awareness
SI	Stakeholder relationships	Lack of trust among healthcare stakeholders
SI	Stakeholder relationships	Legal and ethical challenges
SI	Stakeholder relationships	Low risk aversion by consumers
SI	Stakeholder relationships	Public acceptance
SI	Stakeholder relationships	Public awareness
SI	Stakeholder relationships	Public engagement
SI	Stakeholder relationships	Public trust

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UTAUT dimension	**UTAUT factor**	**Keyword**
SI	Stakeholder relationships	Social acceptance
SI	Stakeholder relationships	Stakeholder agreement
SI	Stakeholder relationships	Stakeholder buy-in
SI	Stakeholder relationships	Stakeholder collaboration and communication
SI	Stakeholder relationships	Stakeholder engagement
SI	Stakeholder relationships	Stakeholder reluctance to share data
SI	Stakeholder relationships	Stakeholder safety
SI	Stakeholder relationships	Stakeholder support
SI	Stakeholder relationships	Stakeholder willingness to share data with third parties
SI	Stakeholder relationships	Transition and integration of people
SI	Stakeholder relationships	Trust
SI	Stakeholder relationships	User desirability
SI	SC relationships	Collaboration
SI	SC relationships	Collaboration with suppliers
SI	SC relationships	Communication between different SC stages
SI	SC relationships	Concerns about interoperability with existing SC systems
SI	SC relationships	Diverse interests
SI	SC relationships	External leadership with stakeholders
SI	SC relationships	Goal alignment
SI	SC relationships	Governance
SI	SC relationships	Increased traceability and transparency
SI	SC relationships	Indian health-care SC complexity
SI	SC relationships	Interoperability
SI	SC relationships	interoperability and integration across foreign firms
SI	SC relationships	Lack of agreement on DT architecture and governance
SI	SC relationships	Lack of buyer-supplier collaboration
SI	SC relationships	Lack of clear guidelines in manufacturing process
SI	SC relationships	Lack of collaboration and trust for freely data sharing)
SI	SC relationships	Lack of cooperation with suppliers
SI	SC relationships	Lack of experienced providers
SI	SC relationships	Lack of interoperability

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UTAUT dimension	**UTAUT factor**	**Keyword**
SI	SC relationships	Lack of IoT suppliers and service providers
SI	SC relationships	Lack of trust
SI	SC relationships	Lack of trust among SC partners
SI	SC relationships	Lack of urgency to innovate SC processes
SI	SC relationships	Limited open standard
SI	SC relationships	Negotiation with suppliers
SI	SC relationships	Network externalities
SI	SC relationships	Partnership with competent technology providers
SI	SC relationships	Peer pressure
SI	SC relationships	Regulation and governance
SI	SC relationships	Shift in focus
SI	SC relationships	Stakeholders' trust in technology
SI	SC relationships	Supply chain practices (information capture)
SI	SC relationships	Trust
SI	SC relationships	Trust among stakeholders
SI	SC relationships	Variety of interfaces within the PSC
FC	Economic constraints	Availability of financial resources
FC	Economic constraints	Cost
FC	Economic constraints	Cost of changing systems and business processes
FC	Economic constraints	Cost of equipment
FC	Economic constraints	Cost of implementation
FC	Economic constraints	Cost of installation
FC	Economic constraints	Cost of IT infrastructure
FC	Economic constraints	Cost of maintenance and support
FC	Economic constraints	Cost of RFID scanning
FC	Economic constraints	Cost of RFID tags
FC	Economic constraints	Cost of the technology
FC	Economic constraints	Cost of training
FC	Economic constraints	Cost of implementing the network
FC	Economic constraints	Cost of staff
FC	Economic constraints	Cost undisclosed
FC	Economic constraints	Cost-effectiveness
FC	Economic constraints	Difficulty sourcing funding
FC	Economic constraints	Economic aspects
FC	Economic constraints	Energy consumption

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UTAUT dimension	**UTAUT factor**	**Keyword**
FC	Economic constraints	Energy cost
FC	Economic constraints	Energy management
FC	Economic constraints	Financial barriers
FC	Economic constraints	Financial constraints
FC	Economic constraints	Financial cost
FC	Economic constraints	Financial issues
FC	Economic constraints	Financial readiness
FC	Economic constraints	High cost of machine and material
FC	Economic constraints	High cost of sensors
FC	Economic constraints	High cost of development and maintenance
FC	Economic constraints	High expenditure
FC	Economic constraints	High power consumption
FC	Economic constraints	Inadequate capital
FC	Economic constraints	Inadequate funds
FC	Economic constraints	Insufficient budget available
FC	Economic constraints	Insufficient R&D
FC	Economic constraints	Interoperability cost
FC	Economic constraints	Investment cost
FC	Economic constraints	IT budget
FC	Economic constraints	Lack of capital
FC	Economic constraints	Lack of financial support
FC	Economic constraints	Lack of funding for implementation
FC	Economic constraints	Lack of incentives
FC	Economic constraints	Lengthy and costly technology importation
FC	Economic constraints	Perceived financial cost
FC	Economic constraints	Setup cost
FC	Economic constraints	Uncertain development cost
FC	Economic constraints	Unknown cost
FC	Economic constraints	Up-front cost
FC	Environmental constraints	Demand volatility
FC	Environmental constraints	Market trend
FC	Environmental constraints	Market uncertainty
FC	Environmental constraints	Population
FC	HR competencies and skills	Adequate training
FC	HR competencies and skills	Adequate trained workforce
FC	HR competencies and skills	Awareness about technology
FC	HR competencies and skills	Awareness of users
FC	HR competencies and skills	Awareness program

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UTAUT dimension	UTAUT factor	Keyword
FC	HR competencies and skills	Culture of technology
FC	HR competencies and skills	Education
FC	HR competencies and skills	Experience
FC	HR competencies and skills	Expertise
FC	HR competencies and skills	HR team competencies
FC	HR competencies and skills	Human resources
FC	HR competencies and skills	Innovative environment
FC	HR competencies and skills	Knowledge gap
FC	HR competencies and skills	Lack of awareness
FC	HR competencies and skills	Lack of education and training
FC	HR competencies and skills	Lack of environmental awareness
FC	HR competencies and skills	Lack of green practices
FC	HR competencies and skills	Lack of expertise
FC	HR competencies and skills	Lack of qualified employees
FC	HR competencies and skills	Lack of skills
FC	HR competencies and skills	Lack of technology knowledge
FC	HR competencies and skills	Lack of technical expertise
FC	HR competencies and skills	Lack of training facilities
FC	HR competencies and skills	Lack of trust in technology capabilities
FC	HR competencies and skills	Lack of understanding of the technology
FC	HR competencies and skills	Leaders' knowledge of technica aspects
FC	HR competencies and skills	Limited in-country technical capacity
FC	HR competencies and skills	Limited technical expertise
FC	HR competencies and skills	Limited understanding
FC	HR competencies and skills	Need for mindset and cultural shift
FC	HR competencies and skills	Organizational readiness
FC	HR competencies and skills	Other capabilities for change
FC	HR competencies and skills	Practitioners education and marketing practice
FC	HR competencies and skills	Readiness
FC	HR competencies and skills	Reluctance to travel for training
FC	HR competencies and skills	Resistance to change
FC	HR competencies and skills	Skill development
FC	HR competencies and skills	Skill gap
FC	HR competencies and skills	Skilled manpower
FC	HR competencies and skills	Skilled professionals
FC	HR competencies and skills	Skills
FC	HR competencies and skills	Technical capabilities

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UTAUT dimension	**UTAUT factor**	**Keyword**
FC	HR competencies and skills	Technical expertise requirements
FC	HR competencies and skills	Technological knowledge
FC	HR competencies and skills	Trained professionals
FC	HR competencies and skills	Training
FC	HR competencies and skills	Training courses
FC	HR competencies and skills	Trained professionals
FC	HR competencies and skills	Unfamiliarity with the technology
FC	IT infrastructure	Algorithims limitations
FC	IT infrastructure	Appropriate infrastructure
FC	IT infrastructure	Availability of equipment
FC	IT infrastructure	Communication between system components
FC	IT infrastructure	Compatibility
FC	IT infrastructure	Compatibility issues
FC	IT infrastructure	Computational power
FC	IT infrastructure	Data heterogeneity
FC	IT infrastructure	Data integration
FC	IT infrastructure	Data quality issues
FC	IT infrastructure	Data management due to data inconsistency
FC	IT infrastructure	Data storage issue
FC	IT infrastructure	Difficulty in big data management
FC	IT infrastructure	Digital infrastructure
FC	IT infrastructure	EHR management
FC	IT infrastructure	Hardware
FC	IT infrastructure	High infrastructure requirement
FC	IT infrastructure	ICT infrastructure
FC	IT infrastructure	Implementation of two-dimensional barcode technology
FC	IT infrastructure	Integration with additional DTs
FC	IT infrastructure	Integration with existing warehouse infrastructure
FC	IT infrastructure	IoT infrastructure
FC	IT infrastructure	IT infrastructure
FC	IT infrastructure	Lack of compatibility with existing sistems
FC	IT infrastructure	Lack of data storage capability
FC	IT infrastructure	Lack of infrastructure
FC	IT infrastructure	Lack of interoperability with existing IT infrastructure

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UTAUT dimension	**UTAUT factor**	**Keyword**
FC	IT infrastructure	lack of knowledge management system
FC	IT infrastructure	Lack of proper infrastructure
FC	IT infrastructure	Lack of storage capacity
FC	IT infrastructure	Lack of wireless infrastructure
FC	IT infrastructure	Poor infrastructure
FC	IT infrastructure	Safe storage
FC	IT infrastructure	Software
FC	IT infrastructure	Storage capacity
FC	IT infrastructure	Storage issues
FC	IT infrastructure	Supportive infrastructure
FC	IT infrastructure	System interoperability
FC	IT infrastructure	System capacity issues
FC	IT infrastructure	Technical challenges (transaction throughput)
FC	IT infrastructure	Technical infrastructure
FC	Organizational constraints	Competition with other strategic imperatives
FC	Organizational constraints	Change management
FC	Organizational constraints	Compatibility
FC	Organizational constraints	Difficult to integrate into existing processes
FC	Organizational constraints	Difficult robust operational organization
FC	Organizational constraints	Healthcare infrastructure
FC	Organizational constraints	Integration
FC	Organizational constraints	Lack of health data sharing protocols
FC	Organizational constraints	Overburden of regular duties
FC	Organizational constraints	Resilience of legacy procurement modalities
FC	Organizational size	Adaptability
FC	Organizational size	adaptation to current systems
FC	Organizational size	Availability of material
FC	Organizational size	Company size
FC	Organizational size	Hospital scale
FC	Organizational size	Organizational size
FC	Organizational size	Staff
FC	Other regulations	Compliance with regulations
FC	Other regulations	Application restrictions
FC	Other regulations	Compliance with regulatory requirements

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UTAUT dimension	UTAUT factor	Keyword
FC	Other regulations	Coordination with local autorities
FC	Other regulations	Current regulations and policies governing
FC	Other regulations	Cybersecurity policies and regulations
FC	Other regulations	Difficulty in defining legal boundaries in technology components
FC	Other regulations	Government policy
FC	Other regulations	Government incentives for adoption
FC	Other regulations	Incompatibility with existing laws and regulations
FC	Other regulations	Innovation propensity
FC	Other regulations	Intellectual property
FC	Other regulations	Involving stakeholders in developing regulations
FC	Other regulations	Lack of clarity on regulatory issues
FC	Other regulations	Lack of clear regulations
FC	Other regulations	Lack of clear regulatory guidance
FC	Other regulations	Lack of clarity on regulatory issues
FC	Other regulations	Lack of governance regulations and guidelines
FC	Other regulations	Lack of government initiatives
FC	Other regulations	Lack of government policies
FC	Other regulations	Lack of government support
FC	Other regulations	Lack of guidelines
FC	Other regulations	Lack of health policy
FC	Other regulations	Lack of regulations
FC	Other regulations	Lack of standardization
FC	Other regulations	Lack of worldwide RFID technology regulations
FC	Other regulations	Legal and ethical challenges
FC	Other regulations	Legal and IP issues
FC	Other regulations	Legal and regulatory standards
FC	Other regulations	Legal compliance to rules and regulations
FC	Other regulations	Legal concerns
FC	Other regulations	Legal framework
FC	Other regulations	Legislation process
FC	Other regulations	Lengthy and delayed drones regulations
FC	Other regulations	National standards

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UTAUT dimension	**UTAUT factor**	**Keyword**
FC	Other regulations	Need for proper regulation and enforcement of laws
FC	Other regulations	Patient compliance
FC	Other regulations	Patient rights
FC	Other regulations	Policy framework
FC	Other regulations	Questions of liability
FC	Other regulations	Regulation challenges
FC	Other regulations	Regulations
FC	Other regulations	Regulations of printed drugs and printers
FC	Other regulations	Regulatory
FC	Other regulations	Regulatory and safety requirements
FC	Other regulations	Regulatory challenges
FC	Other regulations	Regulatory compliance
FC	Other regulations	Regulatory concerns
FC	Other regulations	Regulatory guidelines
FC	Other regulations	Regulatory issues
FC	Other regulations	Regulatory limitations
FC	Other regulations	Regulatory mandates for manufacturers to participate
FC	Other regulations	Regulatory requirements
FC	Other regulations	Regulatory restrictions
FC	Other regulations	Regulatory statute wording
FC	Other regulations	Reluctance to data sharing due to regulatory constraints
FC	Other regulations	Uncertain government policies
FC	Physical constraints	Available resources
FC	Physical constraints	Limited by speed and size
FC	Privacy regulation	Confidentiality
FC	Privacy regulation	Data privacy
FC	Privacy regulation	Disclosure of confidentiality
FC	Privacy regulation	Individuals' privacy
FC	Privacy regulation	Informed consent
FC	Privacy regulation	Lack of data privacy
FC	Privacy regulation	Lack of standards and regulatory frameworks to ensure privacy
FC	Privacy regulation	Limited privacy
FC	Privacy regulation	Medical data privacy
FC	Privacy regulation	Privacy
FC	Privacy regulation	Privacy concerns

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UTAUT dimension	**UTAUT factor**	**Keyword**
FC FC	Privacy regulation Privacy regulation	Privacy issues Privacy of sensitive personal and health data
FC	Privacy regulation	Privacy risk
FC	Privacy regulation	Privacy threats
FC	Privacy regulation	Use of healthcare data
FC	Privacy regulation	Use of personal data
FC	Privacy regulation	Users' privay

Table A.2: Literature coverage of the UTAUT dimensions

DT	**PE**	**EE**	**SI**	**FC**
RFID	[256, 257, 131, 258, 137, 259, 260, 261, 74, 66, 38, 262, 263, 56, 264, 61, 76, 265, 266, 57, 267, 6, 268, 83, 269, 1, 81, 84, 226, 124]	[256, 63, 131, 137, 259, 260, 261, 66, 38, 79, 262, 56, 61, 76, 6, 84, 270, 226, 72],	[256, 63, 55, 131, 259, 261, 66, 38, 73, 56, 264, 61, 76, 271, 57, 267, 6, 80, 270, 226, 72, 124],	[256, 63, 131, 259, 256, 257, 131, 258, 137, 259, 260, 261, 66, 38, 79, 262, 73, 263, 56, 76, 265, 82, 271, 75, 57, 267, 6, 268, 83, 80, 269, 77, 1, 272, 84, 270, 226, 273, 72, 78, 124]
Iot	[274, 50, 86, 76, 64, 88, 85, 275]	[86, 76, 89, 88, 275]	[86, 76, 64, 88, 275]	[274, 50, 261, 86, 76, 64, 89, 88, 85, 275]

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DT	**PE**	**EE**	**SI**	**FC**
Blockchain	[276, 277, 278, 91, 279, 280, 28, 281, 127, 147, 13, 282, 283, 134, 67, 284, 285, 27, 286, 287, 30, 90, 87, 88, 52, 288, 289, 290, 128, 60, 291, 292, 49, 6, 293, 294, 295, 1, 85, 275, 133, 296, 297, 62, 126, 298, 58, 299]	[123, 277, 91, 12, 280, 28, 13, 134, 67, 284, 285, 286, 287, 30, 90, 87, 88, 52, 288, 289, 128, 292, 300, 89, 293, 294, 295, 85, 275, 133, 126, 298, 58]	[277, 279, 12, 280, 28, 127, 147, 13, 282, 301, 67, 284, 285, 27, 287, 30, 90, 87, 88, 52, 290, 128, 60, 292, 49, 300, 29, 294, 295, 1, 85, 275, 129, 133, 297, 62, 126, 298, 58]	[276, 123, 277, 278, 91, 279, 12, 28, 127, 147, 13, 282, 283, 134, 67, 284, 285, 27, 286, 30, 90, 87, 88, 52, 288, 290, 128, 291, 292, 49, 300, 89, 293, 294, 295, 1, 85, 275, 133, 296, 297, 126, 298, 58, 299]
E-logistics	[53, 92, 65]	[53, 92]	[53, 92, 65]	[53, 92, 65]
AI	[99, 97, 302, 95, 96, 98, 68, 6, 303, 14, 293, 304, 140]	[99, 97, 302, 93, 293, 304]	[99, 305, 96, 98, 93, 68, 14, 293, 304, 140]	[99, 302, 95, 96, 306, 98, 93, 68, 303, 14, 293, 304, 140]
Robots	[50, 104, 100, 106, 307, 308, 309, 101, 103]	[50, 106, 307, 309]	[104, 101]	[50, 104, 100, 307, 309, 103]
Drones	[136, 50, 108, 310, 311, 312, 110, 125, 135, 139, 111, 313, 314, 107, 32, 315, 316, 317, 130, 103]	[136, 125, 135, 139, 32, 316, 130]	[136, 132, 312, 110, 125, 135, 139, 111, 314, 32, 316, 130]	[136, 50, 108, 310, 132, 312, 110, 151, 105, 125, 135, 139, 111, 313, 31, 314, 107, 109, 32, 315, 317, 103]
EHR	[318, 138, 112, 54]	[59, 54]	[115, 113, 318, 138, 112, 54]	[115, 114, 113, 318, 138, 112, 54]
AM	[50, 116, 121, 319, 120, 51, 118, 33, 320]	[50, 116, 51, 321, 322, 323]	[116, 120, 303, 51, 320]	[122, 116, 121, 319, 119, 120, 303, 51, 118, 321, 33, 322, 323, 320]

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