POLIMI GRADUATE SCHOOL OF MANAGEMENT

Internet of Things for the Extended Enterprise

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Agenda

- Foreword
- Technologies for the Extended Enterprise
- Data Architecture
- Benefits Evaluation
- Q&A - Addendum

Q&A Addendum

- Artifical Intelligence, strategia e utilizzi in Supply CM
  - 2020, Iansiti & Lakahani, Competing in the Age of AI (vedi anche libri)
  - Papers:
    - Gen AI e SC Managhement, 2 papers con review della letteratura e survey a Managers
    - Paper: misuso dell''AI e crisi di riproducibilità

- Forecasting:
  - Passi da descriptive a prehemptive analytics
  - Processo di forecasting (framework teorico)
  - Esempio di descriptive analytics su «human in the loop» in un processo di forecasting

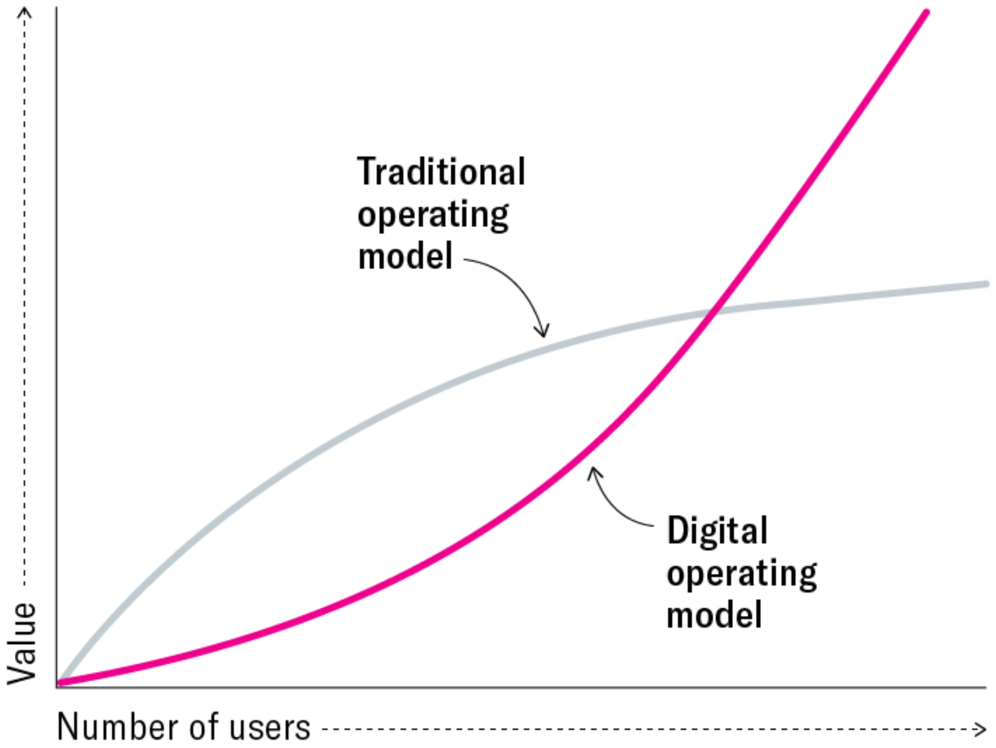
- Cloud Manufacturing / Manufacturing as a Service
  - Slide introduzione concettuale
  - Papers:
    - 2022 - Miragliotta and Tedaldi - MaaS state of the art

- Libri da leggere

AI Strategy

After hundreds of years of incremental improvements to the industrial model, the **digital firm is now radically changing** the scale, the scope and the learning paradigm.

AI-driven processes can be **scaled up** much more rapidly than traditional processes can, allow for **much greater scope** because they can easily be **connected with other digitized businesses**, and create incredibly powerful **opportunities for learning and improvement**—like the ability to produce ever more accurate and sophisticated customer-behavior models and then tailor services accordingly.



From: "Competing in the Age of AI," by Marco Iansiti and Karim R. Lakhani, January–February 2020

HBR

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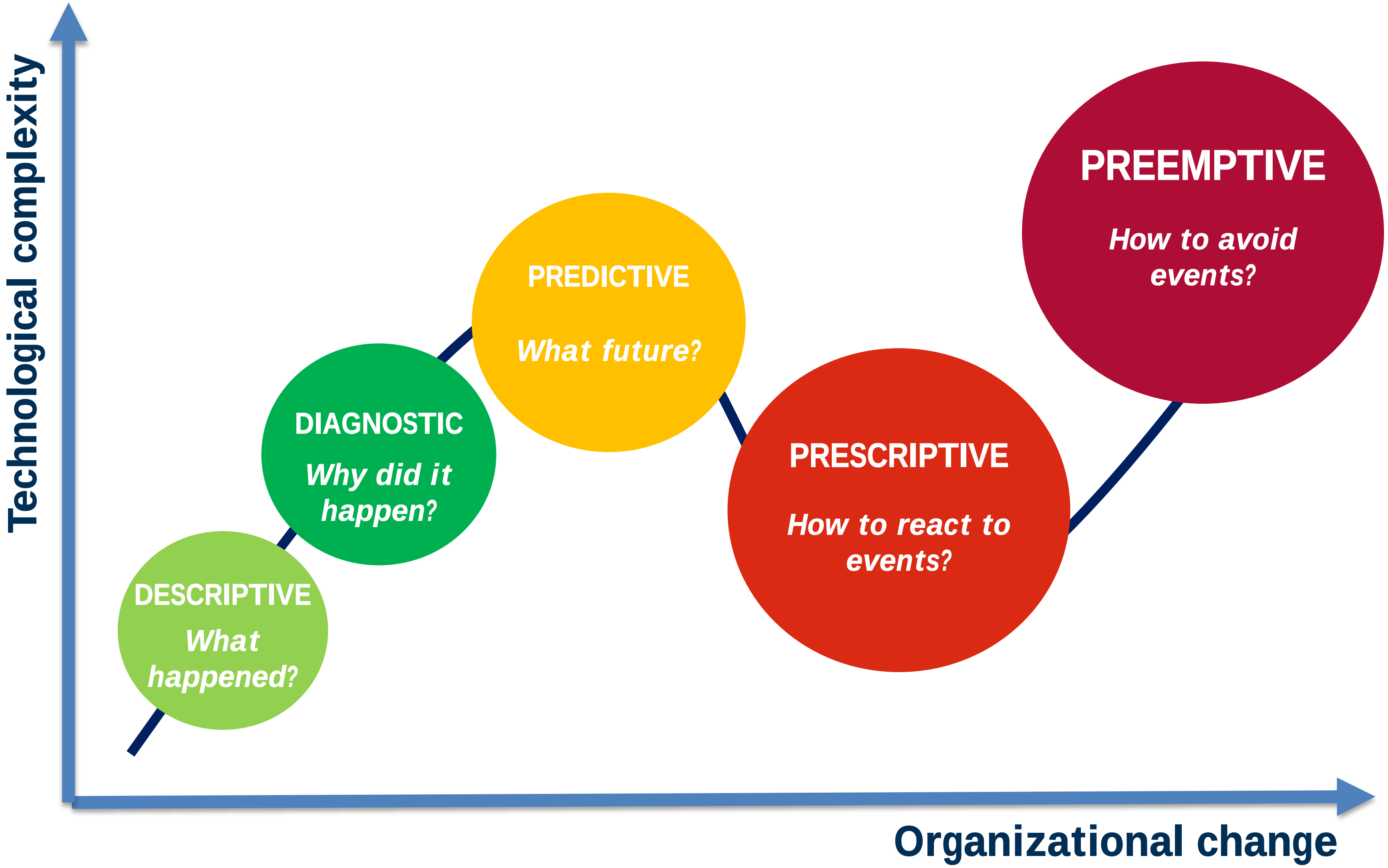
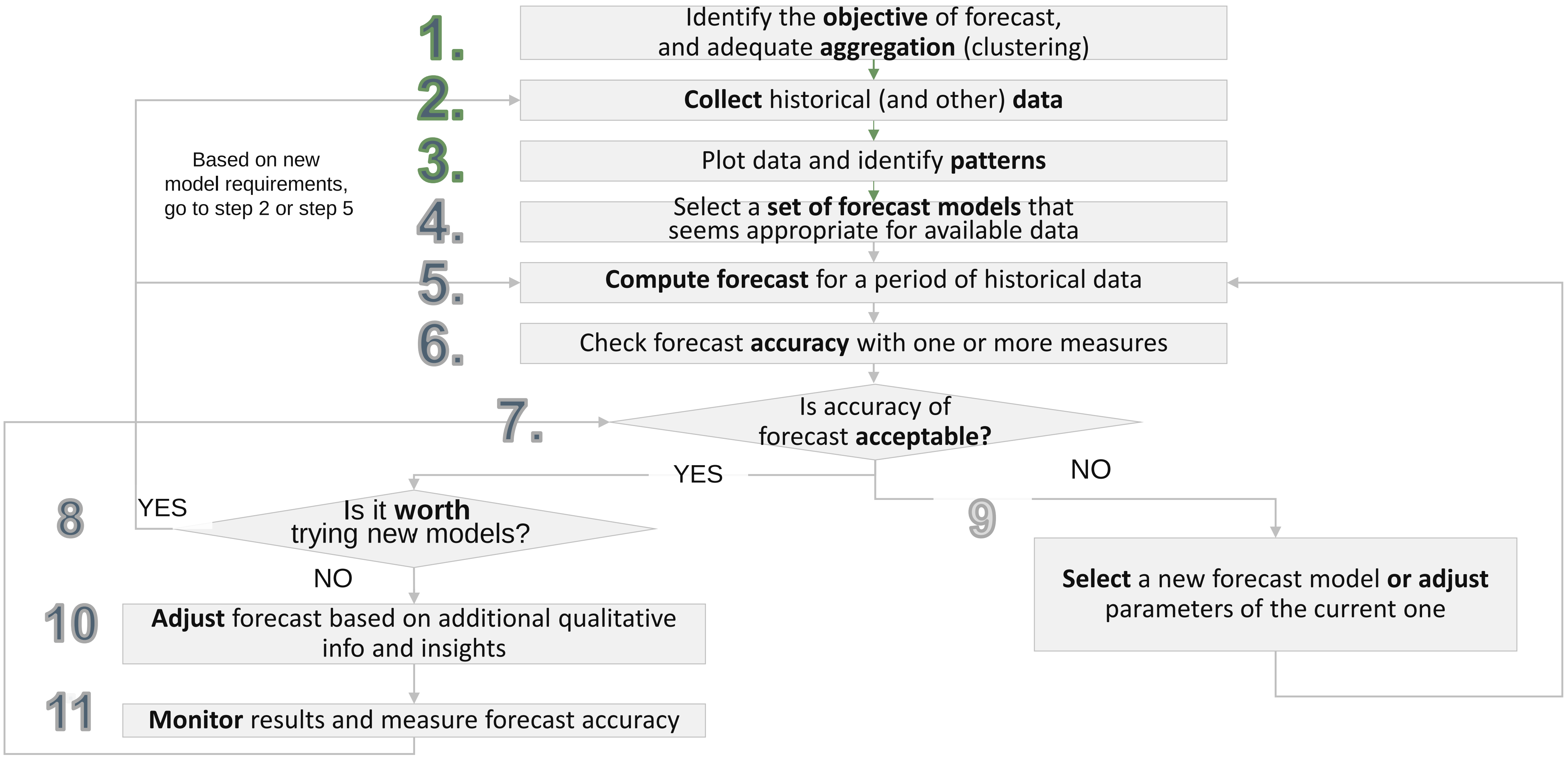
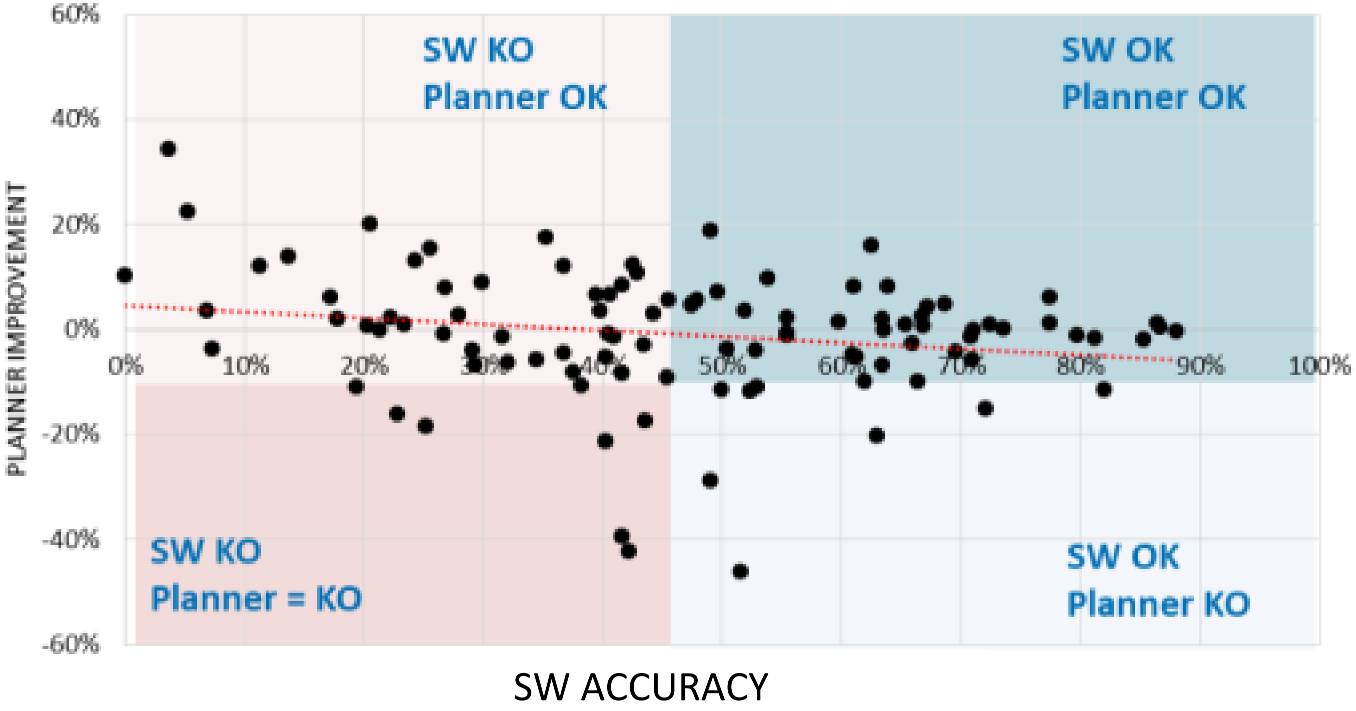
THE RISE OF BUSINESS APPS: DESCRIPTIVE ANALYTICS IS FINE!





1.
Identify the **objective** of forecast, and adequate **aggregation** (clustering)
2.
Collect historical (and other) **data**
3.
Plot data and identify **patterns**
4.
Select a **set of forecast models** that seems appropriate for available data
5.
Compute forecast for a period of historical data
6.
Check forecast **accuracy** with one or more measures
7.
Is accuracy of forecast **acceptable?**
YES
NO
8
Is it **worth** trying new models?
YES
Based on new model requirements, go to step 2 or step 5
NO
9
Select a new forecast model **or adjust** parameters of the current one
10
Adjust forecast based on additional qualitative info and insights
11
Monitor results and measure forecast accuracy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SW ACCURACY

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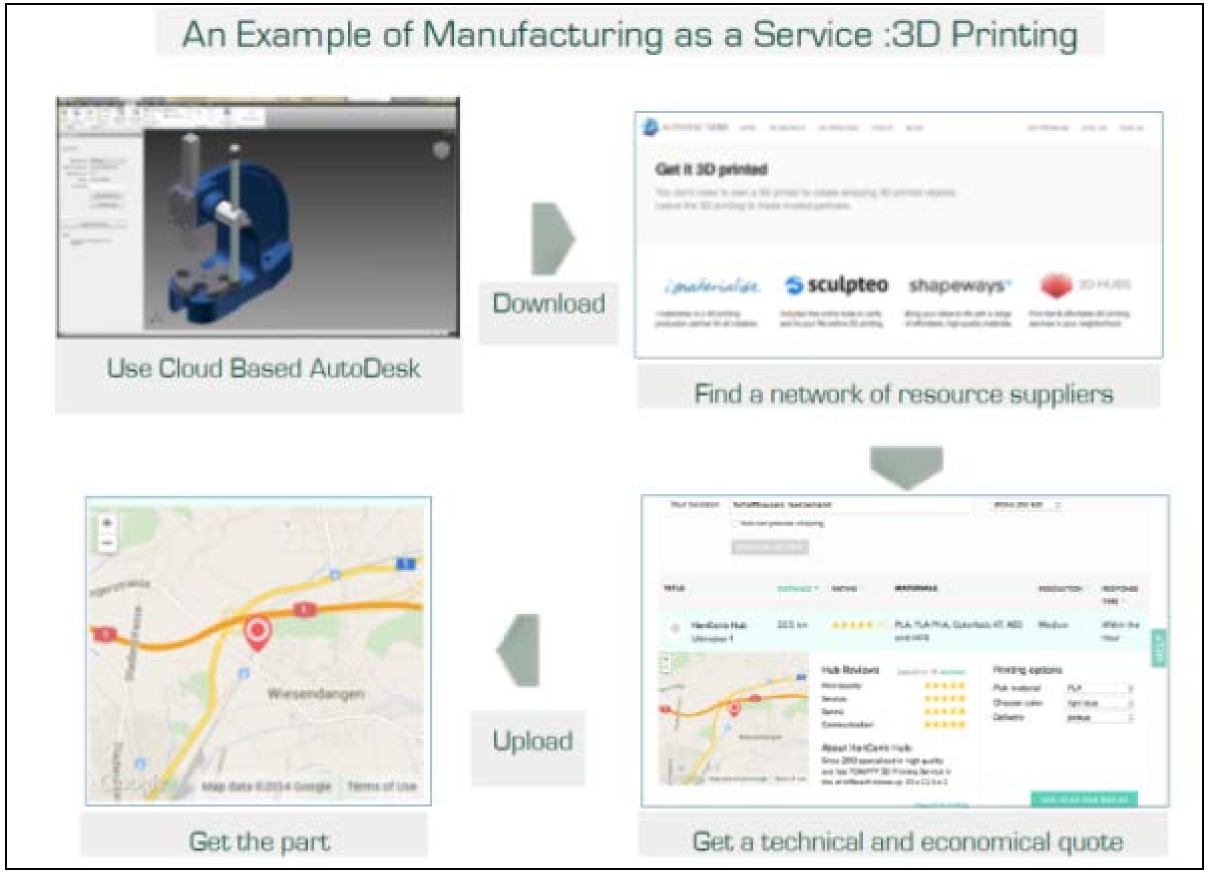
A few examples (in the world)

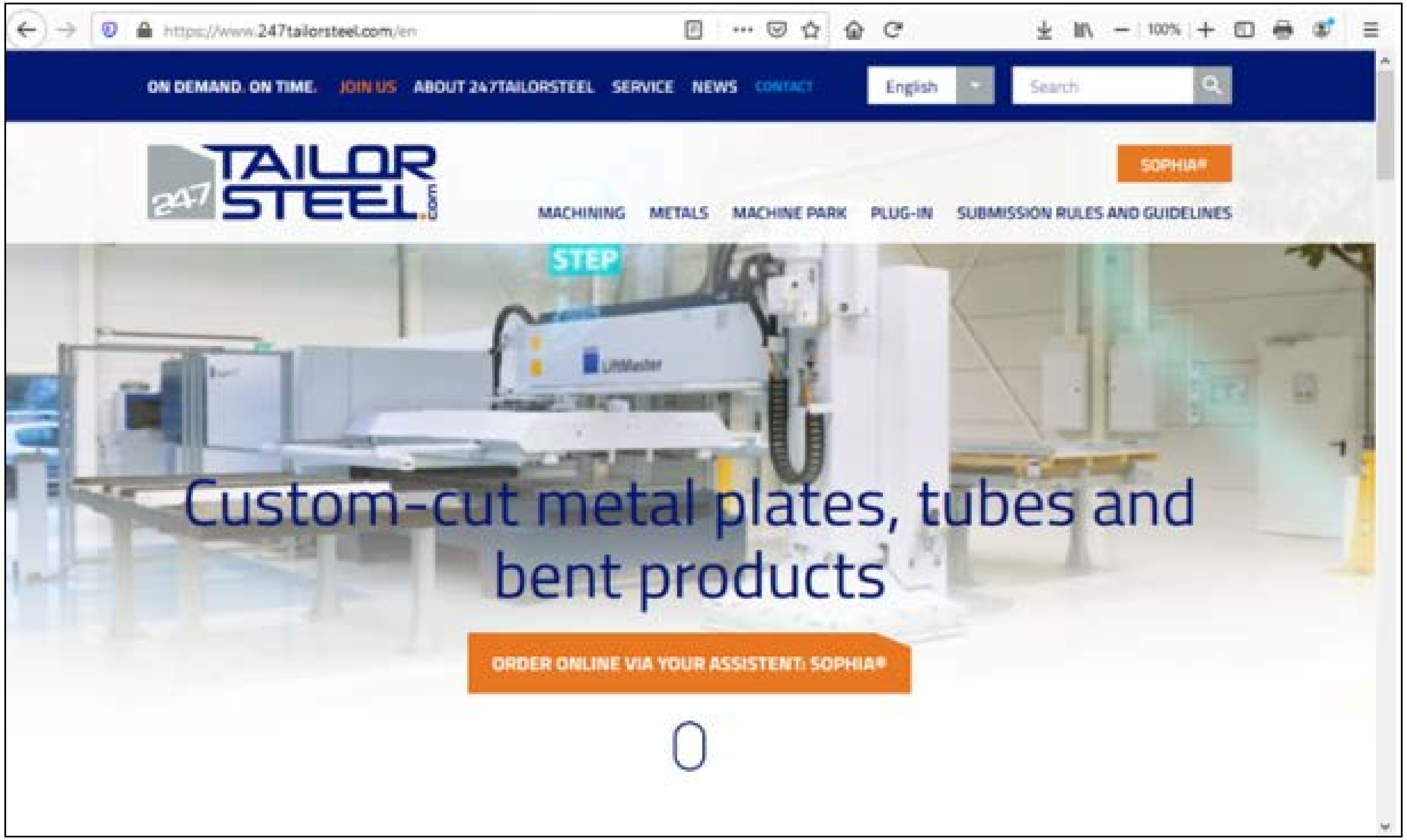
Additive Manufacturing

Company name	MakerCloud, Sculpteo, etc.
Company Size	(well funded) Startups



A few examples (in the world)

Metal Processing



MaaS – What's new?

- Is it just a marketplace concept evolution, or something different?

Cloud Manufacturing

ePurchasing vs. Cloud Manufacturing

	ePurchasing (marketplace)	Cloud Manufacturing
Variety vs. Volumes	Medium / Low to Medium	High / High
Human decision maker needed?	Sourcing = No, Procurement = Yes	No
Visibility on the business counterpart	High	Low
Liability	Part supplier	Service provider
Strategic Perspective	Virtual “arena” where supply meets demand	Becoming the only reference point for the final customer

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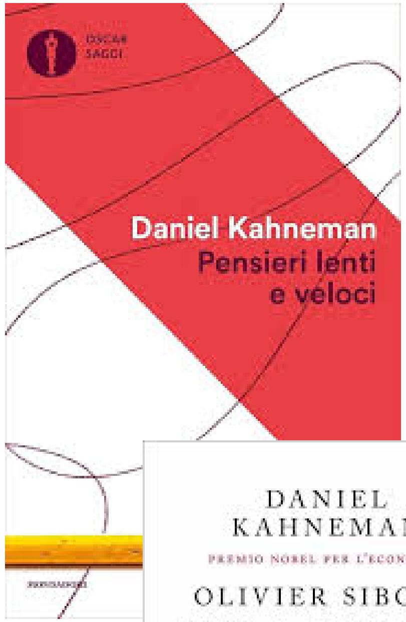
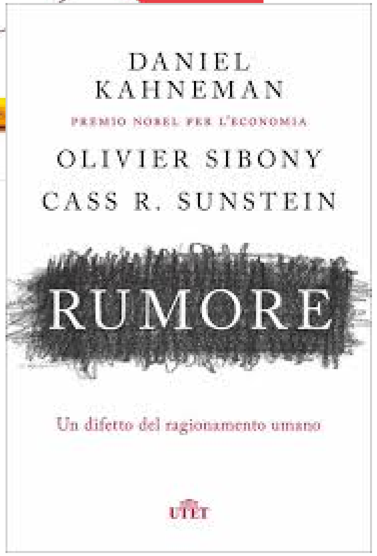


Prima questo



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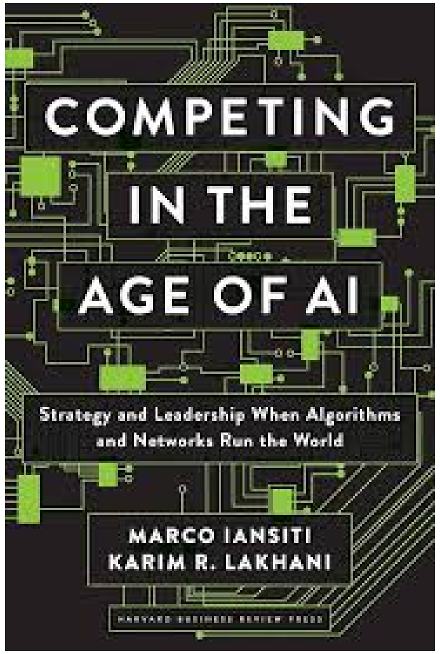
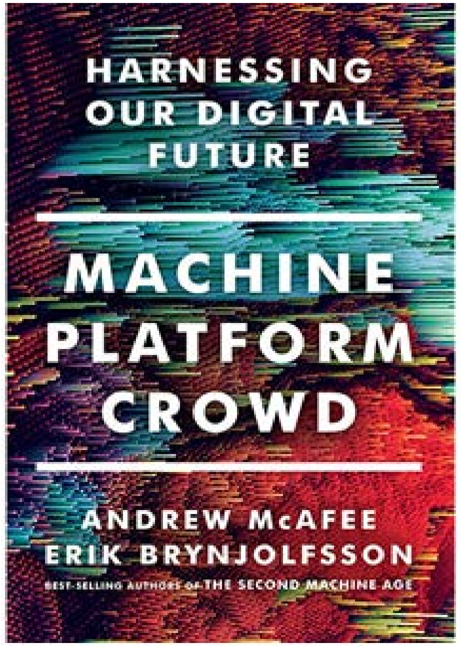


AI e Strategia



Varie, tra cui Platform thinking e Blockchain

Valutazione

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Early adopters of Manufacturing-as-a-Service (MaaS): state-of-the-art and deployment models

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Abstract

Purpose – Cloud Manufacturing (CM) is the manufacturing version of Cloud Computing and aims to increase flexibility in the provision of manufacturing services. On-demand manufacturing services can be requested by users to the cloud and this enables the concept of Manufacturing-as-a-Service (MaaS). Given the considerable number of prototypes and proofs of concept addressed in literature, this work seeks real CM platforms to study them from a business perspective, in order to discover what MaaS concretely means today and how these platforms are operating.

Design/methodology/approach – Since the number of real applications of this paradigm is very limited (if the authors exclude prototypes), the research approach is qualitative. The paper presents a multiple-case analysis of 6 different platforms operating in the manufacturing field today. It is based on empirical data and inductively researches differences among them (e.g. stakeholders, operational flows, capabilities offered and scalability level).

Findings – MaaS has come true in some contexts, and today it is following two different deployment models: open or closed to the provider side. The open architecture is inspired by a truly open platform which allows any company to be part of the pool of service providers, while the closed architecture is limited to a single service provider of the manufacturing services, as it happens in most cloud computing services.

Originality/value – The research shoots a picture of what MaaS offers today in term of capabilities, what are the deployment models and finally suggests a framework to assess different levels of development of MaaS platforms.

Keywords Manufacturing-as-a-Service (MaaS), Platform economy, Cloud manufacturing, Industry 4.0

Paper type Article

1. Introduction

Flexibility is a key word for competitiveness in nowadays dynamic and turbulent business environment (Vázquez-Bustelo *et al.*, 2007). Flexibility is widely accepted as one of the four operational capabilities of a manufacturing firm, among quality, dependability and costs (Ferdows and De Meyer, 1990; Brettel *et al.*, 2016) and becomes fundamental for business strategy (Gerwin, 1993). Naim *et al.* (2006) distinguish different types of "internal" flexibility of a company resulting into 4 different types of "external flexibility", i.e. product, volume, mix and delivery.

Thus, in order to boost flexibility, manufacturers and researchers have worked in two directions: within the company and along the value chain.

Within the company, the achievements of the flexible manufacturing systems FMSs (1980s) have led to reconfigurable manufacturing systems RMSs (Bortolini *et al.*, 2018). Along the value chain, new paradigms were sought to overcome the stiffness of traditional supply chains (e.g. Holonic and Grid manufacturing, the vision of Agile systems). These models were pointing in the right direction, as they were looking for a "radical" change to cope with the increased demand for flexibility. They were inspired by technological models dominant at the time and greatly influenced by the advent of the internet. Nevertheless, they pursued decentralized approaches, inspired by how the internet network is configured and controlled, that were partially in conflict with the traditional culture and structures of the manufacturing domain, which is usually characterized by hierarchical approaches (Yin *et al.*, 2018).

As a consequence, also due to other barriers such as lack of clear methodologies, lack of top management commitment, unavailability of appropriate technologies, high upfront investments required (Hasan *et al.*, 2007), the number of actual implementations of such manufacturing systems is very limited still today (Tao *et al.*, 2011a).

So, inspired by the evolution of dominant technological paradigms, a new paradigm was introduced in 2010 to the scientific community by (Li *et al.*, 2010): Cloud Manufacturing (CM). CM takes inspiration from the success of cloud computing (Xu, 2012), as it is can be defined as a model to enable convenient, on-demand network access to a shared pool of manufacturing services (Liu *et al.*, 2019). It mainly differs from previous paradigms because it goes back to a centralized management of resources/services through a platform managed by a "Cloud Operator" who sets the business rules; in this regard it is closer to traditional manufacturing management and control models.

A lively scientific debate opened on the concept of CM, trying to establish a clear connection with consolidated conceptual models, as those provided by NIST (National Institute for Standards and Technology) for cloud computing (i.e. "Public", "Private", "Community" and "Hybrid", cfr. Mell and Grance, 2011), to conceptualize deployment variants (Design-as-a-Service, Simulation-as-a-Service, Tao *et al.*, 2011b; Liu *et al.*, 2019), to clarify in which manufacturing context this paradigm could spread (Lu and Xu, 2019) or which business interactions may facilitate the creation of such a manufacturing environment (Tedaldi and Miragliotta, 2022).

After a ten-year debate, relevant knowledge gaps are still open, such as the inherent differences of MaaS deployment models, or metrics to assess the development of such a paradigm. This is mainly due to the scarcity of empirical examples. Eventually, in recent years, several platforms have emerged that resemble the characteristics of CM paradigm as envisioned by academics, and therefore they offer the first relevant opportunity to empirically address this situation. Relying on the new empirical background, this paper presents a multiple-case study research, addressing three research gaps:

RQ1. What is the state-of-the-art of MaaS platforms (prototypes excluded) that are currently in operations?

RQ2. What are the deployment models currently used by these platforms?

RQ3. How can we measure different levels of development of MaaS platforms?

These questions are relevant, especially in the light of Industry 4.0 paradigm, as the operations management community is looking for a clear picture about how far the current implementations are from the original concepts (RQ1), whether the different deployment models can generate different CM implementation paths (RQ2), and whether is possible today to build a framework to assess the maturity of a MaaS platform (RQ3).

The paper is therefore arranged as follows. In section 2, a literature review of Manufacturing as-a-Service (MaaS) and CM is performed, followed by a study on the platform economy. Section 3 presents the objective and the methodology used; whereas, section 4 deeply discusses the cases. The cross-case analysis is performed in section 5 were results are illustrated. Finally, section 6 discusses the results; while, section 7 concludes with suggestions for future research directions.

2. Theoretical background

2.1 CM as a heritage of previous manufacturing paradigms

From 1990 onwards, the research for new radical innovations was certainly justified to cope with the increasing uncertainty and turbulence of the context. Agile, Multi-agent based, Holonic and Grid manufacturing are paradigms arisen for this purpose.

On one hand, the Agile manufacturing *vision* gets to the bottom of the network configuration, where enterprises should be able to establish a network of shared resources that can be used by virtual enterprises which are born and die to respond quickly and effectively to market requests (Gunasekaran, 1998, Gunasekaran *et al.*, 2019).

On the other hand, Multi-agent based, Holonic and Grid manufacturing paradigms propose agile manufacturing *control systems*. Agents or holons (manufacturing systems that can be defined as "whole" or "part of a whole" manufacturing system) cooperate decentralize decisions (heterarchical structure) on distributed resources by providing autonomy and intelligence to the individual parties involved. They differ from traditional control approaches because they do not have a top-down approach characterized by centralization of planning, scheduling and control function decisions. Instead, they involve a "bottom up" approach because the control is devolved to intelligent, autonomous and integrated manufacturing components (Leita, 2009). In manufacturing grid, companies cooperate through the coordinated (but not centralized) sharing, integration and interoperability of a system of resources that are spatially distributed. This is possible through the interconnection of resources and the use of advanced IT and management techniques (Tao *et al.*, 2011a; Qiu, 2004).

All the paradigms previously described leverage on cooperation among enterprises where a network of resources is somehow shared. The main challenge for them is having a network of resources without centralized management. Although the Agile *vision* was clear when it was introduced, today further methodological support is still needed for agility implementation and improvement within companies (Medini, 2022). Today Multi-agent based and Holonic industrial implementations are limited to some specific contexts (Tao *et al.*, 2011a) because the investments required for them are high, they are complex *control system* to design, and manufacturers are skeptical about "local autonomous entities" (Leita, 2009).

Hence, these paradigms may not have been as successful as they aimed to, but they have certainly contributed positively to the research for new manufacturing models. Moreover, they have inspired decentralized control systems which are at the basis of the concept of cyber-physical systems (CPS) within the Industry 4.0 domain (Liu and Xu, 2016; Zheng *et al.*, 2021; Meindl *et al.*, 2021).

During the last ten years, the technological evolution in the field of computing (the success of cloud computing, in primis), and the advent of the fourth industrial revolution (Industry 4.0) have revitalized the need for a radical innovation (Zheng *et al.*, 2021) enabled by new digital technologies (Frank *et al.*, 2019). Therefore, in the context of the fourth industrial revolution, CM was born as a counterpart to cloud computing, from which it derives some peculiar characteristics. With regard to previous paradigms, CM control systems are quite different from those provided by Multi-agent, Holonic and Grid manufacturing. Nevertheless, CM could be another important model enabling the Agile manufacturing *vision*.

2.2 From cloud computing to CM

To better understand the CM paradigm this sub-chapter briefly runs through the history of cloud computing and its development trajectory.

During the last ten years cloud computing has deeply changed the way we make use of computing resources as they have been servitized: we can now get computing services on-demand, with pay-as-you-go/pay-per-performance models. This idea was not new: "creating a distributed computing infrastructure" and transforming computing as a "fifth utility" – after water, gas, electricity and telephony – was discussed already 30 years ago (Clark and McMillin, 1992; Foster *et al.*, 1997). Grid Computing is certainly the most known distributed computing paradigm pursuing the objective introduced above. It should enable a federation of shared computing resources resulting in a dynamic, distributed environment (Foster *et al.*, 2008). Foster explains that Grid computing should have these two characteristics (Foster, 2002):

(1) Coordinating resources that are not subject to centralized control;

(2) Using standard, open, general-purpose protocols and interfaces.

Nevertheless, Grid computing shows few implementations and only in specific contexts (e.g. university research) because of the never solved issues about coordinated resource sharing and problem solving in dynamic, multi-institutional organizations (Foster *et al.*, 2001).

The history shows that among distributed computing paradigms, only cloud computing (Mell and Grance, 2011) broadly succeeds in delivering computing services as they were an utility, and it has been unexpectedly characterized by opposite characteristics with respect to the grid paradigm (Mell and Grance, 2011):

(1) Involving computing resources which are pooled and centrally managed by the service provider;

(2) Using proprietary protocols and interface.

CM was naturally born from the concept of cloud computing and this is why the debate on this topic started around 2010 (Li *et al.*, 2010) and why the interest increased over the last years. Many authors have tried to give a comprehensive definition of the CM paradigm (Xu, 2012) and to describe the architecture of such a system (Huang *et al.*, 2013). Although academics have published several literature reviews (e.g. Adamson *et al.*, 2017; Henzel and Herzwurm, 2018), today there is not a conceptualization of this paradigm which is shared by the scientific community. Nevertheless, we decide to provide the reader with one of the most recent CM definitions given by Liu *et al.* (2019):

"A model for enabling aggregation of distributed manufacturing resources (e.g. manufacturing software tools, manufacturing equipment, and manufacturing capabilities) and ubiquitous, convenient, on-demand network access to a shared pool of configurable manufacturing services that can be rapidly provisioned and released with minimal management effort or service operator and provider interaction".

The system involves mainly three participants: the user, the cloud operator and the service provider. A CM system acts as a platform as it facilitates the relationship between two distinct groups of users (we'll see better in next Chapter 2.4).

Among the advantages for users we find MaaS guaranteed by the pool of available resources. In a CM environment, the supply chain is characterized by enhanced efficiency, increased flexibility (Wu *et al.*, 2013).

Service providers mainly benefit from CM systems as they increase efficiency of their production systems (e.g. reducing idle capacity, and getting in contact with a higher number of customers through the Internet network).

According to the literature of CM we are quite far from seeing a completed implemented CM platform because of many unsolved technical and business issues (Lu and Xu, 2019). Most prominent academic authors in this field recognize we are still in a liquid phase because we do not know how CM will be successfully implemented (Liu *et al.*, 2019).

The characteristics of CM (Liu *et al.*, 2019) aiming to realize MaaS can be resumed as follows (Tedaldi and Miragliotta, 2022):

(1) Centralized management: resources are centrally managed by the cloud operator (i.e. turning user requirements into tasks to be allocated and scheduled)

(2) High-information sharing: service providers and users communicate a great quantity of information with the cloud operator;

(3) On-demand: resources appear to be immediately available to provide the user with services;

(4) Service-oriented: great flexibility in sourcing (high customization level for users in product, delivery date, volumes and mix), fast response time, flexible contractual relationship;

(5) Resource pooling: resources are pooled and generally the user could have no control or knowledge over the exact location of the provided resources;

(6) Ubiquitous manufacturing and broad network access: services are anywhere available and accessible through standard devices (e.g. smartphone and laptop)

(7) Dynamism with uncertainty, rapid elasticity and scalability: resources can be elastically provisioned (and released) to scale rapidly outward (and inward) as it is requested.

2.3 Manufacturing-as-a-service (MaaS)

"Manufacturing as-a-service" (MaaS) is – of course – related to the concept of servitization within manufacturing sector. In general, servitization strategies refer to the business trend in which companies find a new source of competitiveness in adding services to their traditional offerings (Vandermerwe and Rada, 1988; Baines *et al.*, 2009; Bortoluzzi *et al.*, 2022). The servitization domain is characterized by so-called product-service systems (PSSs), "an integrated product and service offering that delivers value in use" (Baines *et al.*, 2007). With PSSs, it is more important the "sale of use" instead of selling the product. The very famous example is the following: Rolls Royce started selling working hours of their engines, instead of products. The PSS can be seen as the convergence of two trends: the "servitization of products" and the "productization of services".

The MaaS concept is related to servitization but it is focused on the relationship customer-supplier instead of the product-service.

In fact, the MaaS conceptualization first appears in literature when Goldhar and Jelinek (1990) describe the characteristics of a new flexible sourcing method characterized by peculiar features, e.g. high variety to the extent of customization of product design, customer participation in the design of the product, fast response time, flexible contractual relationship, high information content transactions where vendors and customers "learn", and transactions become more efficient over time.

During the last ten years, in the manufacturing sector, we have experienced quite a big change in the servitization trend, due to the advent of Industry 4.0 and its enabling digital technologies (Paschou *et al.*, 2020).

The maturity of technologies such as Internet of things (IoT), cloud computing and the achievements of the platform economy pushed academics and practitioners to experiment solutions to enable MaaS. In particular, the success of cloud computing originates CM which aims to realize MaaS (Wu *et al.*, 2013; Zhang *et al.*, 2014; Rahman *et al.*, 2018).

2.4 Platform economy

With the term "Platform Economy" or "Digital Platform Economy" we refer to the economy generated by platforms which are dramatically changing our lives, e.g. socializing with Facebook.com, finding jobs on Linkedin.com, shopping on Alibaba.com, finding accommodations with Airbnb.com, moving thanks to Uber.com drivers (Kenney and Zysman, 2016). There is no consensus on either the definition of this phenomenon, or its name. Many authors label this economy as "Sharing Economy", others as "Creative Economy", others distinguish "Gig Economy". Regardless of the terminology used, we should agree in recognizing that it is certainly one of the most impactful trends over the last twenty years.

The debate on CM and MaaS has grown in recent years of deep transformations, and maybe it has attracted the attention from academics right in light of this phenomenon.

Platforms are usually two-sided and aim at facilitating the interaction between two groups of users: demand-side users and supply-side providers (Ardolino *et al.*, 2016; Eisenmann *et al.*, 2009). One of the main problems of platforms is creating a business model to get both sides of the platform on-board (Eisenmann *et al.*, 2006) while taking into account network externalities which affect their success (Rochet and Tirole, 2003). In fact, we can recognize "same-side effects" when users on one side attract other users to the same side of the platform, while we have "cross-side effects" when users from one side attract user to the other side (Eisenmann *et al.*, 2006; Gawer and Cusumano, 2014).

In CM, the centralized management of the resources implies that, over and above users and providers, a third-party (i.e. the cloud operator) exists which coordinates tasks and services on a specific infrastructure; for all intents and purposes, it is a platform which connects two groups of users (Gawer and Cusumano, 2014; Eisenmann *et al.*, 2006; Rochet and Tirole, 2003).

Platform-mediated networks can be open or closed to each of the roles involved: to the provider- and to the user-side of the system (Eisenmann *et al.*, 2009), some examples are following. Uber.com provides mobility services for all the people interested in and it leverages on people who wants to share their spare time and cars, without many restrictions. A different case is represented by a car-sharing enterprise who offers its cars for mobility as a service: the platform is open to the user side but it is closed to the provider one. The booking platform of the university library enable students and professors to reserve books belonging to the university, it means that is closed on both sides of the platform (Table 1).

3. Methodology

Since the number of platforms implementing solutions closed to the MaaS concept is limited, we cannot perform any quantitative analysis. Qualitative research (Glaser and Strauss, 1967) is a suitable option, thus we decide to perform multiple case-studies (Yin, 2003) on enterprises which have developed platforms which increase sourcing flexibility and somehow resemble the MaaS characteristics.

In light of the emerging platform economy and theoretical developments on the CM topic introduced in Chapter 2, we use case studies to describe different maturity levels for each of the CM characteristics. In fact, Yin states (2003) that "existing theories are the starting point of case study research, [. . .] propositions provide direction, reflect theoretical perspective and guide the search for relevant evidence" (Yin, 2003; Ridder, 2017).

The selection of the cases starts with the identification of companies which are currently offering on-demand manufacturing services. We get 13 possible cases to analyze and we move forward to collect some data about their funding (if startup), main capabilities offered as a service, founding date, openness/closure to the provider side (Table 2). Among these companies

Table 1. Platforms: Openness and Closure at provider vs user side

Ex. Platform	Provider side	User side
Uber	Open	Open
Common *Car-sharing company*	Closed	Open
Common *University library*	Closed	Closed

Source(s): This table has been developed by the Corresponding Author, Tedaldi G

Company	Provider side	Main capabilities offered	Found. Year	Tot funding [$ mil.]
Techpilot	Open	Many	1999	n.a
QuickParts (3D Systems)	Closed	Additive manufacturing	1999	Undisclosed
Shapeways	Closed	Additive manufacturing	2007	107.5
Sculpteo (acq. By BASF)	**Closed**	**Additive manufacturing**	**2009**	**10.8**
Xometry	**Open**	**Many**	**2013**	**197**
Fictiv	Open	Many	2013	58
Hubs (acq. By Protolabs)	Open	Many	2013	32
Chizel (acq. By Truventor)	Open	Many	2014	Undisclosed
Fastradius	Open	Many	2014	67.8
Weerg	**Closed**	**CNC machining**	**2015**	**n.a**
247TailorSteel	**Closed**	**Tube processing**	**2015**	**n.a**
Orderfox	**Open**	**Many**	**2017**	**n.a**
Fractory	**Open**	**Sheet metal processing**	**2017**	**10.6**

Source(s): This table has been developed by the Corresponding Author, Tedaldi G

Table 2. Companies offering on-demand manufacturing services, preliminary analysis – **Companies selected for the study**

presented in Table 2, the first 3 have been rejected because they were founded more than 15 years ago and this is too far from the phenomena in scope which arose from about 2010 onwards. Excluding them, we choose to study all the companies which seem to be "Closed" to the provider side as they are just 3 and focused on different capabilities (i.e. Tube processing, Sheet metal processing and Additive Manufacturing). Among the "Open" configurations, we select the youngest of the sample (Orderfox e Fractory) and Xometry as it is the most funded of the sample. Fictiv, Hubs, Chizel and Fastradius have been neglected as they seem similar to Xometry but raised less in term of funding. At the end of the process 6 companies have been selected which can be regarded as representative of the heterogeneity of the platforms in this field, namely: Orderfox, Xometry, Fractory, 247TailorSteel, Sculpteo, Weerg.

The unit of analyses is represented by the web-based platform and its users, i.e. the CM system. To answer to the research questions, we collected additional information about capabilities offered, operational flow, funding, number of employees and number of manufacturing sites supporting the platform.

We analyzed the web-based platforms making simulations of requests for quotation (RFQ) to better qualify the platforms characteristics from a user perspective, as well as paying attention to what happens beyond the platform, i.e. on the provider-side, and detailed the operational flows from RFQ to product delivery.

Moreover, data collected include semi-structured interviews with employees from the companies (transcribed and available on request) carried out between 2020 and March 2022, information from official websites of the companies and from other secondary sources available online (e.g. white papers, online video interviews and demo video). Since some of them are funded startup we have also sourced data from crunchbase.com, which collects specific info about new ventures (e.g. founders, foundation year and funding). The triangulation method has been adopted to ensure validity of data gathered. Moreover, although the research is mainly exploratory in kind, we have adopted an interpretive approach using theory in the earlier stage of the study to create a starting research framework for the empirical investigation (Walsham, 1995).

Finally, we perform a cross-case analyses to investigate the capabilities offered today by MaaS platforms and their deployment models. Moreover, the emerging differences between the platforms studied are used to inductively build a framework to assess different levels of development for each CM characteristic.

4. Case description

In this chapter we introduce the companies analyzed, their capabilities and the main features of the platforms developed.

4.1 Orderfox

Orderfox (Orderfox.com) is a German company founded in 2017 and arisen to facilitate the relationship customer-supplier by creating a portal supporting the exchange of information. The platform basically offers two kinds of service: (I) suppliers search and (II) RFQs publication in a marketplace.

Users at the demand-side of the platform can register for free; it means Orderfox chooses the strategy to subsidize the demand-side of the platform also to attract user to the supplier-side. The “suppliers search” tool allows selecting attributes of the desired supplier (e.g. capabilities, nationality, dimension and certifications) and shows the results on a map. As a “buyer” of the platform the user creates an RFQ and details it (i.e. adding drawing, any kind of documents and notes). After having decided whether to select specific recipients or publish worldwide, the RFQ is shared with service providers selected. The option of selecting specific recipients can be interesting if we are going to submit sensitive data through the RFQ (e.g. drawings).

Service providers at the supplier-side can access the marketplace (a registration fee is required to have unlimited access) where all the RFQs are listed and detailed. In this case, we note the provider knows who submitted the RFQ and decides whether to apply or not for specific jobs; in case of acceptation, she/he answers to the RFQ.

4.2 Weerg

Weerg (Weerg.it) is an Italian company founded in 2015 and offers additive manufacturing (AM) and CNC machining services through a web-based platform which provides instant quoting to RFQs. The platform is open both to business customers and consumers.

To submit an RFQ the process is guided by the rules of the platform. The user uploads CAD drawings, selects the technology, the material, finishing services and instantly visualizes prices on the basis of the delivery date (the sooner it is, the higher is the cost). Eventually, the user places the order and the product is finally delivered to the customer.

Service providers are represented by the single facility owned by the cloud operator, i.e. Weerg. As the founder says, their strength reckons on “transparency of prices, speed of execution, certainty of deliveries”.

4.3 247TailorSteel

This company is one of the eldest analyzed (founded in 2007), but it has started an interesting project in 2015 resulting in a platform offering metal sheet and tube processing (e.g. laser cutting, bending services). As in the Weerg case, the cloud operator is the same entity owning the resources providing the manufacturing services. It differs from Weerg because the platform is not web-based but works on a Software program (namely, “Sophia”) to be installed on a laptop. As for Weerg, the user uploads the CAD drawing and after having selected the specs she/he receives the quote, almost instantly. Even in this case, the delivery options are fully customizable and the price takes into account of that.

One of the most interesting things of this case is that Sophia is totally integrated with the production site. Once the order is confirmed, the production plan is updated and the CAM instructions are directly delivered to the machine which will realize the parts ordered (Scholten, 2017). This is possible because they developed Sophia together with machinery manufacturers providing the resources owned by 247TailorSteel (Tedaldi and Miragliotta, 2022).

4.4 Sculpteo

The company was founded in 2009, and it has been acquired by Basf (www.basf.com) in 2019. Sculpteo is specialized in providing users with additive manufacturing services (i.e. design and production for several additive manufacturing technologies and materials available).

Sculpteo developed a web-based platform to provide users with instant price and fast delivery times of parts desired. The user simply drags and drops 3D files (.stl or.obj files are suggested but others are allowed) in the window and configures the material and finishing options. It is possible to choose among three delivery options (i.e. "standard", "economic", "express") with different lead times (1–3, 7, 14 days).

Manufacturing resources are mainly represented by 20 3D printers owned by the company and distributed in 2 factories settled in San Francisco (USA) and Paris (France).

4.5 Fractory

Fractory is a startup providing manufacturing services for sheet metal fabrication (e.g. plasma, laser cutting) and CNC machining. It has been founded in 2017 in Estonia, moved in UK in 2019 and raised about $ 11 million from investors.

As other companies, they have built a web-based platform equipped with an instant quoting engine providing quotes in real time to RFQs. From the user perspective, the operational flow is quite similar to the previous cases, as it requires CAD drawings, to specify the technology and the materials desired. Deliveries are not customizable but more than 100 different colors as coating options are available (e.g. matte or glossy).

Differently from the previous cases, Fractory does not own any manufacturing facility. It sells manufacturing services leveraging on a network of more than 50 manufacturers distributed mainly in UK. The company simplifies the sourcing process as it answers almost instantly to users RFQs, takes care about the production as well as the shipping/delivery.

Once the order is received, the algorithm finds the most suitable suppliers (among the registered Fractory providers) and the production is entrusted to the one which can respect the delivery date promised to the customer. On the one hand, the process is highly automated to the user side of the platform; on the other hand the relationships with service providers are managed almost manually.

4.6 Xometry

Xometry is an American company founded in 2013 and headquartered in Geithersburg, Maryland (USA). It has attracted great attention of investors and raised a total of $197m of funding received. Recently it has acquired Shift, (a German company which was working on the concept of "on-demand" manufacturing), and the European expansion has officially started. It offers CNC Machining, sheet metal processing (e.g. waterjet, laser and plasma cutting), injection molding, 3D printing services, as well as other ones like urethane casting and finishing services.

The business model and operational flow are quite similar to those ones of Fractory. The company does not own any manufacturing asset but it guarantees product quality of its suppliers through the use of employees which control parts before the final shipping to the customer (even if trusted suppliers sometimes are allowed to directly ship to users).

On one hand, Xometry can be compared to Fractory, on the other hand we observe Xometry capabilities, materials are more extended and the level of service customization is much higher (e.g. thread, part marking and inserts). Moreover, it allows to get different prices on the basis of the delivery options, which are three: "Expedite" (2 days), "Standard" (7 days) and "Economy" (12 days) but in some regions of US are available shipping in 1 day.

A network of more than 5.000 manufacturers guarantees to this platform a higher level of elasticity with respect to the other cases and, consequently, a higher flexibility to users.

5. Cross-case analysis

5.1 Platforms seeking MaaS benefits

First of all, we can note that the analyzed platforms can belong to the MaaS paradigm since they reflect most of the characteristics of MaaS as envisioned by academics about 30 years ago. Orderfox is the platform farest from the MaaS concept as the responsibility of the platform operator along the users procurement journey (Ren *et al.*, 2017) is quite limited (Table 3). Although this platform reduces transaction costs for users searching for manufacturing partners, the benefits in terms of responsiveness and flexibility are very limited. In all the other cases, platform operators can "read" the service requirements (published by users), and they can take care of tasks until the final delivery of the service while managing all the activities in between (Table 3).

The results of this research show that MaaS platforms offering on-demand manufacturing services are mainly focusing on the production of mechanical components via additive manufacturing or CNC machining, as well as sheet metal products (Table 4).

Although these early adopters seem quite similar to each other, they differ on the deployment models and their levels of development if we compare them to the CM characteristics described in Chapter 2 (Table 5).

5.2 Deployment models for CM

As from the theoretical background, platforms contemplate the "opening" or "closing" on each side of the platform (i.e. provider and user sides). However – today-it seems that this idea cannot apply to MaaS platforms, in practice. In fact, it seems to be valid only on the provider side, while the user side is just always open to the public. Platforms studied therefore seem to work according to just two deployment models: open (Weerg, Xometry, Fractory) and closed (Sculpteo, 247Tailorsteel, Weerg) on the Provider side, while on the user side they are all generally public, open to anyone (Figure 1).

On the user side, these platforms probably choose to be "Public" since the development costs of the platform architecture are not compatible with a "Private" or "Community" use (reserved for a company or a small number of partner companies, respectively).

On the one hand, the "Open" platforms clearly aim for higher scalability, in the face of higher operating management costs (e.g. Xometry usually inspect parts before shipping to users). On the other hand, the closed platforms aim at the IT integration of production and logistics assets, requiring that the assets are under the strict control of the cloud operator (due to standards and interoperability issues). Therefore, it is not a coincidence that the platform operator is the direct owner of the resources and service provider (Figure 1). Certainly, from a technical point of view this approach is much more challenging but it allows these platforms to maximize operational efficiency.

5.3 A framework to assess different levels of development for early adopters

In this chapter we refer to the characteristics of CM presented in Chapter 2 and – from a comparison of the finding of the cases we selected – we draw different levels of development for each one, considering max 4 levels (L1, L2, L3 and L4) as commonly adopted by most of the maturity models (Fraser *et al.*, 2002; Schumacher *et al.*, 2016).

5.3.1 Centralized management. We identified 4 levels of centralized management.

L1. Resources are not managed by the platform operator. The platform operator just describes the service providers in term of capabilities. The user finds the right Provider in less time, looking at the online "providers catalogue";

L2. The platform operator creates a marketplace where RFQs are published. Service providers can answer to them, connect to the users and start a relationship;

Table 3. Cross-case analysis – Platforms responsibility along the procurement journey

	Cloud manufacturing process (Ren *et al.*, 2017)											
	1. Service publishing Sub-process		*2. Intelligent matching and virtual system establishing*						*3. Service Execution*			*4. Service Rating*
Company	Identification service requirements	Service customization (e.g. Design support)	Service providers selection	RFQ submission	Quotations management	Assessment and provider selection	Negotiation	Transaction and order placement	Production and order mgmt	Pre-shipping quality inspection	Shipping and delivery	Rating and billing
Orderfox			P	P	"Manual"; compared in hours/days				SP	SP	SP	P
Xometry	P	P*	P	P	"Automatic"; instant quoting	P	P	P	P (SP)	P (SP)	P*	P
Fractory	P		P	P		P	P	P	P (SP)	P (SP)	P*	P
247TailorSteel	P		P	P		P	P	P	P	P	P	P
Sculpteo	P		P	P		P	P	P	P	P	P*	P
Weerg	P		P	P		P	P	P	P	P	P*	P

Note(s): Legend: "" = User; P = Platform Operator; SP = Service Providers
P (SP) = P centrally manages the SP; P* = Indirectly, leveraging third parties
Source(s): This table has been developed by the Corresponding Author, Tedaldi G

L3. The platform operator directly answers to the RFQs while the service provider loses the contact with the final user. When the order is confirmed, the platform operator selects the service providers who would fulfill the order. The service provider can accept/deny the allocation suggested by the platform operator, and it does not lose the control of its own resources;

Table 4.
Cross-case analysis – Capabilities offered through the platform

Company	Additive manufacturing	Injection molding	CNC machining (e.g. milling, turning)	Sheet metal processing	Pipe processing	Electronics	Other (e.g. Urethane casting)
Orderfox	x	x	x	x	x	x	x
Xometry	x	x	x	x			x
Fractory			x	x			
247TailorSteel				x	x		x
Sculpteo	x						
Weerg	x		x				

Source(s): This table has been developed by the Corresponding Author, Tedaldi G

Table 5.
Cross-case analysis – Platforms data and their approach to the provider side "open" vs "closed"

Company	Found. Year	Tot funding [$ mil.]	Number of employees	Provider side approach	Number of manufacturers
Orderfox	2017	n.a	20–50	OPEN	17,000
Xometry	2013	197	300	OPEN	5,000
Fractory	2017	11	50–100	OPEN	50
247TailorSteel	2015**	n.a	>500	CLOSED	6
Sculpteo	2009	11	20–50	CLOSED	2
Weerg	2015	n.a	20–50	CLOSED	1

Note(s): **Company founded previously, but MaaS initiative started in 2015
Source(s): This table has been developed by the Corresponding Author, Tedaldi G

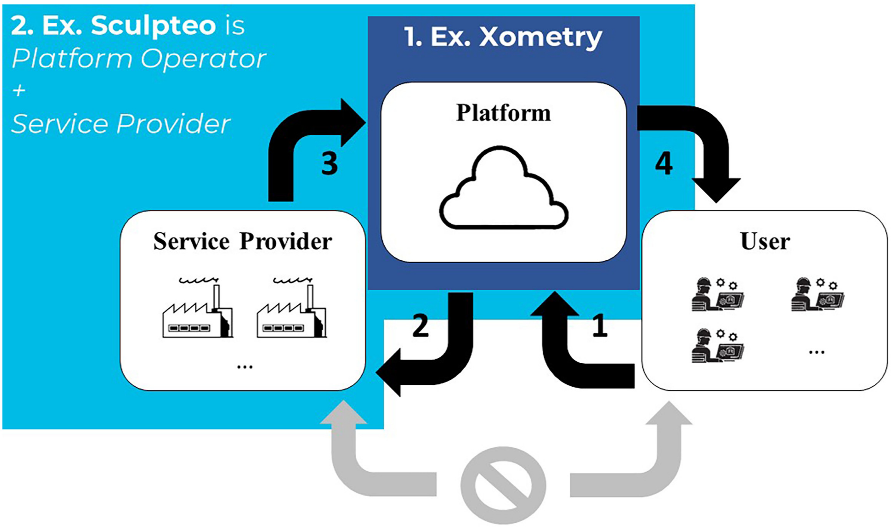

Figure 1.
MaaS deployment models

L4. The platform operator turns the order into tasks to be performed and unilaterally decides where to allocate them. Here, the service provider loses control of its own resources.

5.3.2 High information sharing. Information sharing between the platform and the other CM participants allow CM system to reach different level of automation of their processes:

L1. The platform operator is a traditional intermediary and just starts the relationship between customers and suppliers;

L2. The Platform is equipped with a repository of the RFQs. At this level, services are not requested by users through standardized mechanisms, thus the response to the RFQ cannot be automated. Nevertheless, the platform centralizes the communication, supports the negotiation with web-based tools (e.g. chat tools, repository of drawings and customers categories);

L3. The services are requested through standardized mechanisms and read by the platform operator (e.g. drawing with specific file formats). The response to the RFQs is automated. Nevertheless, once the order is confirmed, the allocation of the tasks to the resources is managed by human interactions between the platform operator and the service providers. This happens because the platform operator has no visibility on the availability of the resources (i.e. resources are not connected and virtualized);

L4. The information transactions are managed almost automatically. Resources are equipped with sensors which communicate data to the platform operator. The RFQs are requested through standardized mechanism and the response to the RFQs is automated by the Platform. Once the order is confirmed, the Platform automatically turns them into tasks to be performed by the resources and allocates them to the most suitable ones.

5.3.3 On-demand. For this feature we can simply specify whether a platform is immediately available to produce a service on request. Thus, we have only two levels:

L1. No: the platform just offers a marketplace where RFQ are published at any time but delivery of services is not guaranteed by the cloud operator;

L4. Yes: the Platform is available at any time and cloud operators guarantees the delivery of the manufacturing services whenever requested.

5.3.4 Service-oriented. This characteristic is focused on the relationship customer-supplier and 4 different levels of flexibility are found:

L1. The relationship with suppliers is traditional;

L2. Fast response time to RFQs, highly customized product. Users cannot change the delivery date suggested. A limited set of materials and finishing services (e.g. coating, colors) are available;

L3. Like “L2” but 3–5 delivery options are available with different pricing (e.g. “Economy”, “Express”);

L4. The relationship with suppliers is new (e.g. highly customized product and flexible relationship). It allows customizing materials, lead times, finishing and selecting other services.

5.3.5 Resource pooling. Here we specify whether the resources are pooled and we measure the level of distribution of the resources:

L1. Resources are not pooled and it is not present a network of physically distributed resources;

L2. Resources are pooled but owned by a single Provider which manage them;

L3. Resource are pooled and owned by a group of enterprises or a group of enterprises belonging to a parent company;

L4. Resources are pooled by a great number of enterprises and the platform is open to the service provider side.

5.3.6 Ubiquitous and broad network access. Manufacturing ubiquity means the user easily access the manufacturing network and can receive the service wherever she/he is (i.e. this is related to the worldwide presence of manufacturing resources) (Chen and Tsai, 2017):

L1. The platform runs on standard devices (e.g. web-based applications running on laptops, tablets, smartphones). Service providers are located in one country and users from other countries feel the distance from the manufacturer (e.g. longer lead time);

L2. Broad network access as for "L1" but here services come from an international network, even if still limited to 1 continent;

L3. As for L2 but services come from 2 continents; users from worldwide can still suffer the distance from manufacturers of the network;

L4. As for L3 but "Ubiquitous manufacturing" here is a customer experience, because resources are dispersed in 3 or more continents (e.g. North America, Europe and Asia).

5.3.7 Dynamism, rapid elasticity and scalability. These characteristics depend on the number of resources beyond the platform. From the cases analyzed, we can identify 4 different levels:

L1. The system is static and works with a very limited capacity. This level refers to platforms leveraging on just a couple of production facilities;

L2. The Platform responds to demand variations leveraging on a limited number of pooled resources, at the expense of the speed of response to the change. Here we find platforms leveraging on less than 10 production sites;

L3. At this level the system better responds to demand variations because a wide network of resources, but less than 50, is available;

L4. A great number of resources are available and resources appear to be unlimited to the user.

After having proposed a framework to measure different development levels of CM platforms, we can visualize on a spider chart the differences between the cases analyzed (Figure 2). As we have already noticed in chapter 5.2, companies like Orderfox are further away from the realization of a CM system, while the other ones seem to be closer but follow

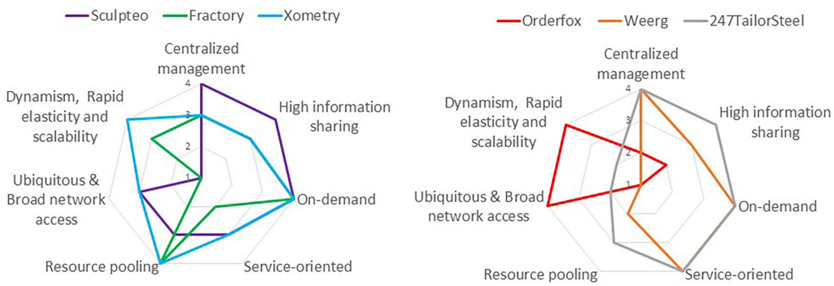

Figure 2.
Cross-case analyses – Different levels of development

different approaches. 247TailorSteel aims to achieve full integration of IT systems and equipment while Xometry clearly aims at increasing the number of manufacturing providers as much as possible to guarantee full scalability.

With respect to the diffusion of innovation theory Rogers (1962) and Valente (1996) explain that in a social context when an innovation occurs, adopters can be categorized on the basis of the time of adoption. Therefore, after several years of prototypes provided by "innovators" of the paradigm, the companies we have studied could be defined "Early adopters" as they represent first real and virtuous examples (in the history) of this innovative manufacturing model, in spite of their supposed incompleteness or missed MaaS goals.

6. Discussion

6.1 The rise of a MaaS platform economy

The first research question opening our study (RQ1) aims to show the state-of-the-art of MaaS platforms (prototypes excluded) which are currently operating. First of all, we observe from empirical evidence that initiatives of MaaS platforms are not very numerous, some of these ones are quite consolidated (hundreds of employees) and offer on-demand manufacturing services which were never seen before in supply chain management literature (e.g. instant quoting, deliveries in 1 day). Secondly, we observe that after a debate lasting more than 10 years, the first business goal of CM seems to be achieved, i.e. realizing "a controlled service environment that offers the rapid and flexible provisioning of manufacturing resources to meet manufacturing mission's demands" (Liu *et al.*, 2011).

In the literature Helo and Hao had already found empirical evidence of MaaS platforms in the context of sheet metal processing (Helo and Hao, 2017). This paper confirms that CM could spread through this capability, as well as through the additive manufacturing, but also CNC machining and other more exotic technologies, as we reported in the previous chapter.

The higher the number of capabilities offered, the higher is the complexity of the implementation of an integrated CM system. On one hand, Xometry realized effective platforms without full IT integration of resources, and they can offer a wide range of capabilities (Table 4). On the other hand, Weerg, Sculpteo and 247tailorsteel aim to realize a full IT integration and to maximize their efficiency. For this reason they are somehow forced to be closed on the provider side, with a very limited number of machineries/facilities. However, these three platforms are succeeding in their IT integration and processes automation. This finding seems to be partially in contrast with (Lu and Xu, 2019) as they wrote that "the diversity and complexity of manufacturing resources make CM impossible for the operator to purchase all manufacturing resources necessary for building a CM platform; [. . .] the main function of the operator is to manage and operate providers' manufacturing resources".

6.2 Deployment models

Once we have investigated the state-of-the-art (RQ1), we move on to RQ2 to discuss the different deployment models emerged from theoretical studies and compare them to what we find from the cases. In the literature of CM most of the authors define deployment models for CM as "Private", "Public", "Community" and "Hybrid" (Liu *et al.*, 2019), mirroring the definition given by NIST to cloud computing. In cloud computing environments there is the service provider which is just one and it does not collaborate or partner with anyone (e.g. Amazon EC2 owns its datacenter and develops its systems, by itself). Here in CM the context is more complex, and what does in mean being "private"? Liu *et al.* apply the concept of "private" on both sides of the platform as they were both closed: "in private cloud manufacturing systems [. . .] all entities are from the same organization, and only in-house manufacturing resources are aggregated in the cloud platform" (Liu *et al.*, 2019). In the same way, they say that the public deployment model should be opened on both sides of the platforms.

Deployment models found in the literature cannot explain why we find platform like Weerg or 247tailorsteel which are "closed" on the provider side, but "open" on the user side. For this reason, we suggest to take into consideration both sides of the platform when talking about CM deployment models. This achievement is in line with the work of Helo *et al.*, where they identify different CM "portals" in the field of sheet metal processing (Helo *et al.*, 2021). Their study shows that some CM portals (e.g. "manufacturer-customized portal") could be closed on the provider side while being open on the user side.

6.3 Measuring different levels of development

The third research question (RQ3) of our study aims to investigate whether it is possible to identify different levels of development for MaaS platforms. The framework introduced in chapter 5.3 is based on the characteristics of CM emerged in the theoretical background (Chapter 2) and 4 different levels of development have been identified inductively on each of them, from the analysis of the cases.

This framework cannot be considered a maturity model because the word maturity usually refers to an organization or a process regarding some specific target state (Schumacher *et al.*, 2016). In fact, within the MaaS domain we still do not know whether the two deployment models identified through this study will be sustainable in the long term.

Nevertheless, our work could be useful for researchers to build future models assessing the maturity of a MaaS platform because there are no papers in literature addressing this topic within the CM (or MaaS) domain. Jayasekara *et al.* (2019) introduced a model to assess the readiness of manufacturers (in place of platform operator) to adopt CM. They state that "Service Providers play the most important role in a CM environment, and the success of CM implementation depends on the readiness of manufacturers to transform their traditional business". After the present study, we may argue that manufacturers play the most important role just in the case of "Closed" environment, as in the "Open" configuration just minimal prerequisites are required to become service provider of the CM network.

7. Conclusions

The CM paradigm inherits challenges as well as drawbacks from the previous experiences of other manufacturing models which were born to increase flexibility in an increasingly uncertain and turbulent context. The Agile manufacturing vision seems to find in CM a new possible model enabling it.

This is possible thanks to the advent of digital technologies belonging to the fourth industrial revolution which reshape the servitization, the success of cloud computing and the achievement of the platform economy. Today we can observe several examples of platforms offering on-demand manufacturing services which we have never met in the history, and this is why we think that a MaaS platform economy is arising.

Results of the present study show that today MaaS platforms are mainly focusing on pretty simple mechanical parts through additive manufacturing, CNC machining and sheet metal processing. Performances in terms of flexibility offered, responsiveness, geographical coverage (and other dimensions) vary between the cases selected, nevertheless we define them MaaS Early Adopters as they share the same purpose.

With regard to the platform architecture we observe two different deployment models which both seem to work: "Open" and "Closed" to the provider side of the MaaS platform. In all cases encountered, MaaS platforms are "Public" and services are available to whomever. This is a major difference of CM with respect to the cloud computing paradigm where we have closed environment to the provider side while "Public" "Community", "Private" "Hybrid", to the user side.

Moreover, the cross-case analysis shows several differences between platforms studied on the basis of the characteristics of a CM platform. This point origins an inductive framework which has been proposed in this paper to assess the level of development of a MaaS platform.

The contribution from an academic perspective is threefold. First, this is one of the first papers showing real examples of companies delivering commercial MaaS solutions. This can support academics for future studies in this field. It is important as it seems that there is an increasing gap between research and what professionals are doing (i.e. following different development trajectories). In detail, academics in this field struggle to develop a “fully integrated” CM system, but it does not seem the only path possible to follow (cfr. Xometry, $193m funding, now listed). Secondly, this paper focuses on the deployment models adopted by MaaS platforms today which are different from those described in the literature (where it seems that CM can consider just “fully integrated” and “open to the provider side”). In general-on the basis of the deployment models-two development trajectories appear within the CM domain and the research should support both of them as long as they both seem to work. Thirdly, the framework proposed expands the theory as it has been inductively built from empirical cases and it could be use in the future to build models assessing the maturity of MaaS platforms.

From a managerial perspective, we show to manufacturers that MaaS platform economy is arising, and empirical evidence has been carried out in this paper. Secondly, cloud operators in this field could use this framework to evaluate themselves with reference to the players analyzed, or even others.

Future research directions pair with limitations of the study. First, it should be interesting to enlarge the empirical base of our results to evaluate the resilience of the framework proposed, and eventually expand it and validate it with experts in this field. Secondly, academics could monitor through longitudinal studies how these platforms evolve in order to discover whether – on the way to the CM maturity process – the deployment models identified in this study would change or which one will prevail over the other.

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Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence?

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ABSTRACT

The remarkable growth of ChatGPT, a Generative Artificial Intelligence (Gen-AI), has triggered a significant debate in society. It has the potential to radically transform the business landscape, with consequences for operations and supply chain management (O&SCM). However, empirical evidence on Gen-AI's effects in O&SCM remains limited. This study investigates the benefits, challenges, and trends associated with Gen-AI/ChatGPT in O&SCM. We collected data from O&SCM practitioners in the UK ($N = 154$) and the USA ($N = 161$). As we used the organizational learning theory for the research, our findings reveal increased efficiency as a significant benefit for both adopters and non-adopters in both countries, while indicating security, risks, and ethical as prominent concerns. In particular, it appeared that the integration of Gen-AI/ChatGPT leads to the enhancement of the overall supply chain performance. Moreover, organizational learning can speed up the results of Gen-AI/ChatGPT in O&SCM. No wonders that adopters express their satisfaction about the post-implementation benefits of the technology, which include reduced perceived challenges for pre-implementation, and greater optimism about future Gen-AI/ChatGPT utilization compared to non-adopters. Adopters also display diverse behavioral patterns toward efficiency, agility, responsiveness, etc. This study provides valuable insights for scholars, practitioners, and policymakers interested in comprehending Gen-AI/ChatGPT's implications in O&SCM for both adopters and non-adopters. Additionally, it underscores the importance of organizational learning processes in facilitating successful Gen-AI/ChatGPT adoption in O&SCM.

1. Introduction

The emergence of ChatGPT (Chat Generative Pre-trained Transformer) is transforming business processes and models in virtually all types of industries (Informs, 2023; Kumar et al., 2023; Kothari, 2023; Agrawal et al., 2022). ChatGPT is a cutting-edge artificial intelligence (AI), more specifically, a generative AI chatbot API based on large language models (LLMs) trained by the amount of data to generate new content (Budhwar et al., 2023). In a brief and straightforward manner, Generative AI (Gen-AI) is a powerful artificial intelligence that can generate different types of content, from music and texts to codes and mathematical equations, etc., according to the interactions of prompt queries. Thus, this is part of a new generation of AI with unprecedented interaction with humans (Budhwar et al., 2023).

The potential of Gen-AI/ChatGPT for all types of businesses and organizations is causing a bustle in society as a whole (Gordijn and Have, 2023; Larsen and Narayan, 2023). According to emerging literature on Gen-AI/ChatGPT, this technology is already bringing in its wake far-reaching changes in a number of industries, while also bringing about opportunities and challenges (Informs, 2023). However, the technology presents several drawbacks and limitations. From a financial perspective, despite its potential to support research in this domain, it still cannot deal efficiently with data synthesis and privacy issues (Dowling and Lucey, 2023).

In the fields of education and business, Gen-AI/ChatGPT is flagging profound positive changes in a considerably short time, but its use

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reaveals some threats (Agrawal et al., 2022; Heidt, 2023; Larsen and Narayan, 2023). All of this has led scholars to debate the actual role of Gen-AI/ChatGPT and the need to adopt rules for AI-related ethical practices in the education and research domains (Nature Editorial, 2023; Stokel-Walker, 2023). Besides, Gen-AI/ChatGPT is causing similar concerns in several businesses and industries, like healthcare (Vaishya et al., 2023). For example, although it can support the patient's journey and the hospital's efficiency in medicine and healthcare, there are several concerns about its ethical use (King, 2023): the quality of recommendations; limited capacity on specific topics; etc. As they feature among the most (positively/negatively) affected areas by Gen-AI/ChatGPT, education and healthcare are our main focus here. For example, while Gen-AI/ChatGPT can contribute to the support of students with disabilities (Lyerly, 2023), its ethical use remains problematic (Abdulai and Hung, 2023; Bouschery et al., 2023).

Overall, there are a lot of concerns about the ethical use of the technology, as there is also a need for urgent standardization, governance, and policies (Budhwar et al., 2023; Chen, 2023; Cotton et al., 2023). For instance, from the finance industry perspective, scholars have already reported the potential for data handling with this technology, but at the same time, it fails in data synthesis and amplifies the ethical concerns of organizations (Dowling and Lucey, 2023). In fact, there is no area that is not impacted both positively and negatively Gen-AI/ChatGPT. Even the academic community has expressed huge worries about the use of Gen-AI/ChatGPT in research and teaching (Susnjak, 2022; Bommarito II & Katz, 2022; Qadir, 2023). For example, Gen-AI/ChatGPT can help write convincing abstracts without plagiarism, but fortunately for academics, the writing style can be detected by other AI tools (Gao et al., 2022). Other benefitis of Gen-AI/ChatGPT in education include offering opportunities to learn in a personalized manner with robust feedback (Baidoo-Anu & Owusu Ansah, 2023).

In the field of journalism, there is a debate about how Gen-AI/ChatGPT will transform jobs, collaborations between AIs and humans, the risks, and ethical concerns (Pavlik, 2023). In the healthcare field, Gen-AI/ChatGPT promises to support the creation of unprecedented levels of operations efficiency. For example, Gen-AI/ChatGPT can improve the efficiency of the overall processes, including accuracy, in writing patients' clinic letters, thus bringing customer satisfaction (Ali et al., 2023). Concerning global warming and other climate problems, the same technology is well fitted to minimize their impacts. In particular, it can well improve accuracy in climate projections, model parametrization, interpretation, scenario modeling, and environmental assessments (Biswas, 2023). In the automotive industry, Gen-AI/ChatGPT is well taken advantage of by smart vehicles, as reported by Gao et al. (2023), notably in order to leverage critical features like safety and the user experience. While the potential and future of Gen-AI/ChatGPT (Paul et al., 2023; Ray, 2023) are being investigated by a number of studies, barriers to the technology are also at the centerstage of debates.

Regarding the potential of Gen-AI/ChatGPT in operations and supply chain management (O&SCM), studies achieved so far are virtually from grey literature [e.g., Gartner and Forbes (Pukkila, 2023; Raveendran, 2023)]. To date, a few studies have been published in academic outlets to approach the interplay between Gen-AI/ChatGPT and O&SCM (Hendriksen, 2023; Wang et al., 2023; Cribben & Zeinali, 2023). In spite of the potential of Gen-AI coupled with ChatGPT in the field of O&SCM to reshape the business models, the field seems not ready yet to explore the benefits of this union (Hendriksen, 2023). For instance, Gen-AI/ChatGPT can bring some benefits to the O&SCM, such as the improvement of the processes efficiency, forecast enhancement, order fulfillment, as well as quick analysis of a large amount of data to support quick and better decisions, and more strong support and training for their employees (Hendriksen, 2023). To date, there is no doubt that Gen-AI/ChatGPT can transform the way of collaboration and communication between members in the supply chain (Hendriksen, 2023; Siotia, 2023). In addition, Wang et al. (2023), in the context of manufacturing, proposed an industrial GPT in order to enhance efficiency and flexibility in services.

The existing literature about the Gen-AI/ChatGPT in O&SCM shows that it is still at the infancy stage, but the empirical evidence on how Gen-AI/ChatGPT may affect the O&SCM area is roughly absent, as well as the theorization of the technology's exploration in that domain (Hendriksen, 2023; Cribben & Zeinali, 2023). Thus, the literature about Gen-AI/ChatGPT is emerging and growing fast in traditional fields like information systems (Dwivedi et al., 2023a), healthcare (Vaishya et al., 2023), manufacturing (Badini et al., 2023), marketing (Peres et al., 2023), entrepreneurship (Short and Short, 2023), tourism (Nautiyal et al., 2023), government (Kreps and Jakesch, 2023), among others. However, in the O&SCM fields, there is a scarcity of papers published in reliable outlets (Hendriksen, 2023) exploring the dynamics of this relationship, the threats, and the learning process. Because of this, this study aims to provide an overall perspective of this new AI paradigm to O&SCM and the role of organizational learning to support its adoption. Accordingly, our study is guided by the following research questions (RQ):

RQ1. How can the O&SCM field benefit from the Gen-AI/ChatGPT integration?

RQ2. What kind of threat in this relationship could lure the attention of supply chain managers?

RQ3. What role do organizations and supply chains play in integrating Gen-AI/ChatGPT in their operations?

Our study is supported by the organizational learning theory background, which focuses not only on knowledge creation and sharing by people and organizations, but also on how to apply it to gain efficiency and add value (Qian et al., 2023; Cangelosi and Dill, 1965). By exploring Gen-AI/ChatGPT through the organizational learning theory, our study can contribute to advancing the traditional theory by revealing how organizations are dealing with this cutting-edge technology in their network to gain more knowledge. Additionally, the organizational learning theory enables this study to disclose the differences between adopters and non-adopters of Gen-AI/ChatGPT in O&SCM.

Due to the novelty of the topic, the aforementioned questions need to be answered by focusing on an empirical approach based on primary data about Gen-AI/ChatGPT on O&SCM. We collected data from two representative countries, the UK and the USA supply chains practitioners. In this regard, our paper could well help scholars, practitioners, and policymakers to better grasp the main benefits, challenges, and trends in the interplay between Gen-AI/ChatGPT and O&SCM.

The rest of this paper is structured as follows. Section 2 presents the latest advances in the literature about Gen-AI/ChatGPT. In sequence, in Section 3, we provide the details of the methodology design. Then, Section 4 presents the analysis of results, followed by the discussion and implications in Section 5. Finally, Section 6 points out the limitations and valuable insights for future research studies, and Section 7 draws the concluding remarks.

2. Theoretical background and literature review

2.1. Organizational learning theory

The organization learning theory is a well known and traditional theory on management and organizational fields (Qian et al., 2023; Cohen and Levinthal, 1990; Cangelosi and Dill, 1965). It concentrates on the knowledge creation as well on its use by the people from the organization. In this regard, organization learning theory approaches show how organizations build a learning culture, which in turn can support knowledge sharing, thus affecting processes and efficiency in production/processes. Therefore, all hierarchical levels of organizations should be engaged in a lifelong learning culture.

The extant literature applying organizational learning theory perspectives made substantial advances in many fields over the last years. For instance, Argote and Miron-Spektor (2011) successfully proposed a framework that supports a better understanding of the interaction between organizational experience and knowledge creation, in which the context plays an important role.

Recently, Tortorella et al. (2020) found that organizational learning theory at the organizational level mediates the adoption of new digital technologies, which in turn supports higher levels of operational performance. Thus, the authors reported that organizations that promote learning and knowledge sharing are more likely to capture higher benefits due technology adoption. In addition, it seems that organizational learning can indeed facilitate the adoption and benefits of AI. In this sense, organizational learning appears to reduce potential barriers to AI (Ransbotham et al., 2020).

2.2. Gen-AI/ChatGPT literature

The recent emerging literature on Gen-AI/ChatGPT has made significant progress in a short period of time (Brynjolfsson et al., 2023; Dwivedi et al., 2023a; Korzynski et al., 2023; Haque et al., 2022; Budhwar et al., 2023). For instance, Dwivedi et al. (2023a) provided a well-articulated presentation about the ChatGPT and its disruptive potential to individuals, organizations, and society. The authors identified three emerging categories: knowledge, transparency, and ethics; digital transformation: organizations and society; teaching, learning, and scholarly research.

On the one hand, part of the extant literature has suggested unprecedented benefits that Gen-AI/ChatGPT can bring to individuals, firms, organizations, and supply chains; these are mainly related to productivity and efficiency improvement. For instance, Brynjolfsson et al. (2023) found that low-skilled workers using Gen-AI in their activities can improve their productivity better than skilled workers. In parallel, there are a lot of criticisms and concerns about the ethical use of Gen-AI/ChatGPT (Liebrenz et al., 2023, Mhlanga, 2023). On this point, Susnjak (2022) found that ChatGPT can be a real threat to the integrity of online exams. Besides, other studies also reported some related concerns. This is the case of Gao et al. (2022), who investigated the ChatGPT capacity to write abstracts in the medical field. They concluded that the tool presents a robust capacity to write original abstracts, consequently making it difficult for reviewers to distinguish between human and machine writings. In addition, Bouschery et al. (2023) suggest that the interaction between Gen-AI and humans can contribute to “augmenting human innovation”. The same authors experimented with GPT-3 to write the abstract of the paper. Despite the ability of the technology to support this type of activity, there remains some limitations, which has been nurturing a debate among scholars about the role of humans in this relationship (Bouschery et al., 2023; Budhwar et al., 2023; Gao et al., 2022).

The interaction with Gen-AI and the specific role of humans was a subject of a paper by a leading human resource journal. Budhwar et al. (2023) agree on the potential of Gen-AI to support problem-solving activities, but at the same time, they warn against the unknown risks. In addition, Vaishya et al. (2023) reports that ChatGPT can support medical personnel in the health sector, mainly in patients’ data report summarization and clinical trials, but that the technology harbors several limitations: biased orientations; low level of medical knowledge and interpretation; etc.

2.3. Gen-AI/ChatGPT in operations and supply chain

It is true that the literature on Gen-AI/ChatGPT is rapidly growing in fields like healthcare (Kothari, 2023; Dhudasia et al., 2023; Li et al., 2023), education (Nikolic et al., 2023; Baidoo-Anu & Owusu Ansah, 2023), information systems (Bahrini et al., 2023), hospitality and tourism (Dogru et al., 2023; Dwivedi et al., 2023b). However, in O&SCM-related fields, it is still at the nascent stage of its development (Hendriksen, 2023; Kumar et al., 2023).

In this regard, Kumar et al. (2023) investigated real cases in the retail context, and reported a trade-off concerning the potential of ChatGPT to support customers 24 h a day. Still, regarding customized recommendations, the tool can cause customer dissatisfaction due to its inability to recognize unusual languages.

In a general perspective of AI for O&SCM, Hendriksen (2023) highlights that Gen-AI/ChatGPT integration depends on human understanding and interpretation. Another issue raised is the lack of O&SCM-related theoretical perspectives to better understand technology-human relationship and how to potentialize the results and minimize the risks. Since the majority of publications approaching Gen-AI/ChatGPT in O&SCM comes from grey literature, the above statement can be evidenced.

Gen-AI/ChatGPT as they appear in O&SCM reports have major benefits from the operational perspective, which can help organizations improve their decision-making processes by automating repetitive tasks based on Gen-AI/ChatGPT (inventory management, purchase orders, invoice, and delivery (Ashcroft, 2023; Gravier, 2023)).

Like the nascent academic literature on Gen-AI/ChatGPT, the grey literature also presents some concerns about Gen-AI/ChatGPT integration. For instance, the quality of responses from Gen-AI/ChatGPT is dependent on how the user enters the questions, the manner and reliability in which the system is fed, and the manner of handling confidential information (Pukkila, 2023), among others. Finding accurate and relevant information from Gen-AI/ChatGPT seems to be a considerable issue in the logistics and supply chain fields.

Considering the human-machine integration, or more specifically, the human relationship with Gen-AI/ChatGPT, Ritala et al. (2023) argue that the knowledge of workers and the organizations can coexist harmoniously by a well-delimited boundary about repetitive tasks, which is currently the focus of Gen-AI/ChatGPT, while creative activities should be performed by humans (potentially with the support of Gen-AI/ChatGPT). However, the authors are concerned about the increased use of Gen-AI/ChatGPT for creativity tasks, which results in a big impact on the traditional functions of workers.

3. Methodology approach

We used primary data due to the novelty of the topic, which requires an exploratory approach. In addition, “Primary data collection has the advantage of being specific to the study question, minimizing missingness in key information, and providing an opportunity for data correction in real time” (Dhudasia et al., 2023, p. 2).

We developed a questionnaire adapted from Queiroz et al. (2023), which investigated the metaverse benefits, challenges, and trends (see Appendix A). To assess the benefits, challenges, and trends of Gen-AI/ChatGPT in O&SCM, we employed a seven-point Likert scale, ranging from (1) “Strongly disagree” to (7) "Strongly agree". Thus, we recruited practitioners from the operations and supply chain fields from several sectors, like logistics/transportation, retail/wholesale, automotive, food, consumer goods, healthcare, agriculture, etc. We used an online survey panel approach (Holtom et al., 2022; Queiroz et al., 2022) by the well-known platform Profilic (Golgeci et al., 2022; Queiroz et al., 2023). Before the data collection, we tested the questionnaire with experienced academics and practitioners. The respondents were grouped into Gen-AI/ChatGPT adopters and non-adopters. We conducted a panel in the USA and the UK, in which the average reward per hour was £10.27 and £11.54, respectively, to the USA and the UK.

Since the topic under study here is under-explored by the literature, we opted for follow previous studies that have successfully used descriptive statistics approaches (Galbreath, 2009; Queiroz et al., 2023). In this regard, no construct or conceptual model was developed. Our study’s main target was to help understand the behavior of each item related to the benefits, challenges, and trends of Gen-AI/ChatGPT in the area of O&SCM.

Table 1 presents the main information from the participants. The pool had 315 respondents, with 161 from the USA, while 154 were from the UK. Regarding the adoption of Gen-AI/ChatGPT, we had expressive participation from adopters, accounting for 41.6%. Regarding the age distribution, we had similar participation from four respondent groups. Accordingly, the bracket's age interval [34–41], [26–33], [50+], and [42–49] accounted for 27.6%, 24.8%, 21.6%, and 19.4%, respectively. In relation to gender, male participants were responsible for 70.8%, females 28.6%, and others 0.6% of the responses. Concerning the highest level of education, undergraduate degree with 39.4%, College qualification (diploma/certificate) with 24.1%, and postgraduate degree (Master/Ph.D.) with 21.9% were the most frequent responses. Considering the company size, the majority of the respondents fall in the range [100–499] employees, accounting for 30.5%, followed by companies with more than 1000 employees (23.8%) and 1–49 employees (22.9%). With respect to occupation, the greater part was managers, accounting for 54.0%, and supervisors, with 20.0% of the participants. Finally, the majority of the respondents have a maximum of 2–5 years of experience in the position (41.6%) and 6–10 years (27.9%).

Table 1
Demographic profile of the participants.

Variable	*N=315*	*Percentage*
Country		
UK	154	48.9
USA	161	51.1
Gen-AI/ChatGPT Adoption		
Adopted	131	41.6
Non-adopted	184	58.4
Age		
18–25	21	6.7
26–33	78	24.8
34–41	87	27.6
42–49	61	19.4
50+	68	21.6
Gender		
Male	223	70.8
Female	90	28.6
Others	2	0.6
Education		
Primary qualification	2	0.6
Secondary qualification	44	14.0
College qualification (diploma/certificate)	76	24.1
Undergraduate degree	124	39.4
Postgraduate degree (Master/Ph.D.)	69	21.9
Company size		
1–49	72	22.9
50–99	45	14.3
100–499	96	30.5
500–999	27	8.6
≥ 1000	75	23.8
Occupation		
Supervisor	63	20.0
Coordinator	29	9.2
Manager	170	54.0
Director	24	7.6
C-Level	18	5.7
President/VP	11	3.5
Experience		
Less than one year	19	6.0
2–5years	131	41.6
6–10years	88	27.9
11–15years	37	11.7
16–20years	23	7.3
Over 20 years	17	5.4

4. Analysis of the results

We analyzed the results by three approaches. The first one is a pooled analysis, that is, a full sample ($N = 315$). In the second approach, we compared the UK and the USA. Finally, in the third, we compared the groups in the country. Thus, in all approaches, we established a comparison between Gen-AI/ChatGPT adopters and non-adopters.

4.1. Non-response bias

During data collection through surveys, some of the participants generally shun or discard some questions or even the full questionnaire. It can create a non-response bias. To assess if our study suffers from this phenomenon, we used the traditional early and late responses (Gupta et al., 2023; Armstrong and Overton, 1977). Thus, we performed a *t*-test in both samples (the UK and the USA) by comparing the first 60 early respondents with the 60 late respondents (Gupta et al., 2023). At a 5% level of significance, we found no differences between the respondents.

4.2. Reliability test

We performed Cronbach's alpha test to measure the reliability. We used the pooled sample in both countries. According to Table 2, all values outperform the recommended 0.7 threshold values (Gupta et al., 2023; Wamba et al., 2020).

4.3. Pooled analysis of Gen-AI/ChatGPT adopters and non-adopters

Table 3 presents the Top 5 benefits, challenges, and trends between adopters and non-adopters from the pooled sample. In terms of benefits between adopters and non-adopters, the two most ranked variables were "Efficiency" ($M_{ADOP} = 5.72$; $M_{NADO} = 5.19$) and "Responsiveness" ($M_{ADOP} = 5.40$; $M_{NADO} = 4.86$). In addition, "Service level" ($M_{ADOP} = 5.38$), "Revenue/profit" ($M_{ADOP} = 5.37$), and "Agility" ($M_{ADOP} = 5.34$) were also the most ranked benefits reported by adopters. Notably, of the Top 5 benefits reported by the two groups, four were the same (Efficiency, Responsiveness, Revenue/profit, and Agility). In addition, the Top 5 benefits from the adopters ranged from 5.72 to 5.34, while between non-adopters, the range was from 5.19 to 4.71.

Regarding the Top 5 challenges, "Security" was the major concern reported by adopters and non-adopters, respectively ($M_{ADOP} = 4.86$; $M_{NADO} = 5.32$). Seeing the convergence between the two groups about the challenges is very interesting. Accordingly, the Top 5 challenges were the same between adopters and non-adopters, only with a small consideration of the order in some variables. Thus, we had between adopters and non-adopters, "Privacy" ($M_{ADOP} = 4.64$; $M_{NADO} = 5.05$), "Trust in data sources" ($M_{ADOP} = 4.63$; $M_{NADO} = 5.17$), "Technology adoption and implementation" ($M_{ADOP} = 4.62$; $M_{NADO} = 5.22$), and "Risks" ($M_{ADOP} = 4.44$; $M_{NADO} = 5.07$).

Considering the trends, we had four equals for adopters and non-

Table 2
Cronbach's alpha test.

Category	Cronbach's alpha	
	USA	UK
Benefits	0.95	0.95
Challenges	0.94	0.92
Trends	0.86	0.82

Table 3
Top 5 benefits, challenges, and trends of the Gen-AI/ChatGPT in O&SCM (pooled sample).

Rank	Top 5 Benefits				Top 5 Challenges				Top 5 Trends			
	ADOP		NADO		ADOP		NADO		ADOP		NADO	
	Variable	Mean	Variable	Mean	Variable	Mean	Variable	Mean	Variable	Mean	Variable	Mean
1	**EFFI**	**5.72**	**EFFI**	**5.19**	**SECU**	**4.86**	**SECU**	**5.32**	**IOSC**	**5.18**	**IOSC**	**4.80**
2	RESP	5.40	RESP	4.86	PRIV	4.64	TECA	5.22	IBVO	4.99	CIRE	4.55
3	SERL	5.38	AGIL	4.82	TRDA	4.63	TRDA	5.17	FULL	4.94	IBVO	4.44
4	REPF	5.37	REPF	4.79	TECA	4.62	RISK	5.07	CIRE	4.89	FULL	4.34
5	AGIL	5.34	COTM	4.71	RISK	4.44	PRIV	5.05	ALAC	4.87	UHRS	4.21

Note1: ADOP = Adopters; NADO = Non-adopters; M_{ADOP}= Mean adopters; M_{NADO}= Mean non-adopters; EFFI = Efficiency; RESP = Responsiveness; SERL = Service level; REPF = Revenue/Profit; AGIL = Agility; COTM = Costs transactions minimization; SECU = Security; PRIV = Privacy; TRDA = Trust in data sources; TECA = Technology adoption and implementation; RISK = Risks; IOSC = Increased overall supply chain performance; IBVO = Increase the business value offered by the companies and supply chains; FULL = Fully adopted by companies and supply chain; CIRE = Costs of implementation reduction; ALAC = Adopted for all types of activities in the supply chain; UHRS = Unavailable human resources with ChatGPT skills. Note 2: Bold values refer to the first position in the list. Note 3: The intergroup variable's colors are to highlight that a variable was found in adopters and non-adopters groups in the category.

adopters, with the exception of the order. Thus, the following trends were identified as the most ranked between the adopters and non-adopters, “Increased overall supply chain performance” (M_{ADOP} = 5.18; M_{NADO} = 4.80), “Increase the business value offered by the companies and supply chains” (M_{ADOP} = 4.99; M_{NADO} = 4.44), “Fully adopted by companies and supply chain” (M_{ADOP} = 4.94; M_{NADO} = 4.34), and “Costs of implementation reduction” (M_{ADOP} = 4.89; M_{NADO} = 4.55). Also, the fifth-ranked trend among adopters was “Adopted for all types of activities in the supply chain” (M_{ADOP} = 4.87), and in the non-adopters, “Unavailable human resources with ChatGPT skills” (M_{NADO} = 4.21).

4.4. Top-5 benefits of Gen-AI/ChatGPT – USA and the UK (adopters x non-adopters)

Table 4 compares the Top 5 benefits reported in the UK and the USA by adopters and non-adopters. With reference to the adopters, we had “Efficiency” leading both countries (M_{UKadop} = 5.52; $M_{USAadop}$ = 5.82). From the UK, the rest of the list is composed of “Revenue/Profit” (M_{UKadop} = 5.43), “Service level” (M_{UKadop} = 5.37), “Costs transactions minimization” (M_{UKadop} = 5.33), and “Responsiveness” (M_{UKadop} = 5.24). In the USA, we had “Responsiveness” ($M_{USAadop}$ = 5.48), “Agility” ($M_{USAadop}$ = 5.46), “Service level” ($M_{USAadop}$ = 5.39), and “Innovation” ($M_{USAadop}$ = 5.38).

In relation to the non-adopters, the first four benefits were the same in both countries, including the order. Thus, we had “Efficiency” ($M_{UKnadop}$ = 5.08; $M_{USAnadop}$ = 5.34), “Responsiveness” ($M_{UKnadop}$ = 4.82; $M_{USAnadop}$ = 4.92), “Agility” ($M_{UKnadop}$ = 4.77; $M_{USAnadop}$ = 4.89), and “Revenue/Profit” ($M_{UKnadop}$ = 4.75; $M_{USAnadop}$ = 4.84). In addition, from the UK non-adopters, the fifth benefit reported was “Costs transactions minimization” ($M_{UKnadop}$ = 4.70), and in the USA, “Process remodeling” ($M_{USAnadop}$ = 4.83).

4.5. Top-5 challenges relating to Gen-AI/ChatGPT – the USA and the UK

In the matter of challenges, Table 5 highlights the Top 5 from adopters and non-adopters in the UK and the USA. In this vein, considering the adopters, four challenges were the same in both countries, without considering their order with “Security” (M_{UKadop} = 5.09; $M_{USAadop}$ = 4.74) appearing at the top of the list. The other challenges reported were “Trust in data sources” (M_{UKadop} = 4.93; $M_{USAadop}$ = 4.47), “Technology adoption and implementation” (M_{UKadop} = 4.87; $M_{USAadop}$ = 4.48), and “Privacy” (M_{UKadop} = 4.80; $M_{USAadop}$ = 4.55). Besides, “Ethical issues” was reported in the UK (M_{UKadop} = 4.85) and “Risks” in the USA ($M_{USAadop}$ = 4.34).

Concerning the non-adopters, four challenges reported were the same from the adopter's group in both countries, with the exception of the order in which they appear. Hence, “Security” ($M_{UKnadop}$ = 5.36; $M_{USAnadop}$ = 5.25), “Technology adoption and implementation” ($M_{UKnadop}$ = 5.14; $M_{USAnadop}$ = 5.33), “Trust in data sources” ($M_{UKnadop}$ = 5.13; $M_{USAnadop}$ = 5.22), “Privacy” ($M_{UKnadop}$ = 5.09; $M_{USAnadop}$ = 5.00). In addition, “Governance” also is on the list in the UK ($M_{UKnadop}$ = 5.09) and “Risks” ($M_{USAnadop}$ = 5.04) in the USA.

4.6. Top-5 trends of Gen-AI/ChatGPT – USA and the UK

Table 6 presents the Top 5 trends in the UK and the USA adopters and non-adopters. Regarding the adopter's group, we had four variables that were found in both countries. Accordingly, we had “Increased overall supply chain performance” (M_{UKadop} = 4.98; $M_{USAadop}$ = 5.28), “Increased the business value offered by the companies and supply chains” (M_{UKadop} = 4.76; $M_{USAadop}$ = 5.12), “Fully adopted by companies and supply chain” (M_{UKadop} = 4.65; $M_{USAadop}$ = 5.09), and “Adopted for all types of activities in the supply chain” (M_{UKadop} = 4.65; $M_{USAadop}$ = 4.99). Also, we had “Costs of implementation reduction” in

Table 4
Top 5 benefits (UK and USA, adopters and non-adopters).

Rank	Top 5 Benefits UK x USA (Adopters)				Top 5 Benefits UK x USA (Non-Adopters)			
	Variable	UK (Mean)	Variable	USA (Mean)	Variable	UK (Mean)	Variable	USA (Mean)
1	**EFFI**	**5.52**	**EFFI**	**5.82**	**EFFI**	**5.08**	**EFFI**	**5.34**
2	REPF	5.43	RESP	5.48	RESP	4.82	RESP	4.92
3	SERL	5.37	AGIL	5.46	AGIL	4.77	AGIL	4.89
4	COTM	5.33	SERL	5.39	REPF	4.75	REPF	4.84
5	RESP	5.24	INNO	5.38	COTM	4.70	PROR	4.83

Note1: M_{UKadop}=Mean UK adopters; $M_{UKnadop}$=Mean UK non-adopters; $M_{USAadop}$=Mean USA adopters; $M_{USAnadop}$= Mean USA non-adopters; EFFI = Efficiency; REPF = Revenue/Profit; SERL = Service level; COTM = Costs transactions minimization; RESP = Responsiveness; AGIL = Agility; INNO = Innovation; PROR = Process remodeling. Note 2: Bold values refer to the first position in the list. Note 3: The intergroup variable's colors are to highlight that a variable was found in adopters and non-adopters groups in the category.

Table 5
Top 5 challenges (UK and USA, adopters and non-adopters).

Rank	Top 5 Challenges UK x USA (Adopters)				Top 5 Challenges UK x USA (Non-Adopters)			
	Variable	UK (Mean)	Variable	USA (Mean)	Variable	UK (Mean)	Variable	USA (Mean)
1	**SECU**	**5.09**	**SECU**	**4.74**	**SECU**	**5.36**	**TECA**	**5.33**
2	TRDA	4.93	PRIV	4.55	TECA	5.14	SECU	5.25
3	TECA	4.87	TECA	4.48	TRDA	5.13	TRDA	5.22
4	ETHI	4.85	TRDA	4.47	PRIV	5.09	RISK	5.04
5	PRIV	4.80	RISK	4.34	GOVE	5.09	PRIV	5.00

Note1: M_{UKadop}=Mean UK adopters; $M_{UKnadop}$=Mean UK non-adopters; $M_{USAadop}$=Mean USA adopters; $M_{USAnadop}$= Mean USA non-adopters; SECU = Security; TRDA = Trust in data sources; TECA = Technology adoption and implementation; ETHI; Ethical issues; PRIV = Privacy; RISK; Risks; GOVE = Governance. Note 2: Bold values refer to the first position in the list. Note 3: The intergroup variable's colors are to highlight that a variable was found in adopters and non-adopters groups in the category.

Table 6
Top 5 trends (UK and USA, adopters and non-adopters).

Rank	Top 5 Trends UK x USA (Adopters)				Top 5 Trends UK x USA (Non-Adopters)			
	Variable	UK (Mean)	Variable	USA (Mean)	Variable	UK (Mean)	Variable	USA (Mean)
1	**IOSC**	**4.98**	**IOSC**	**5.28**	**IOSC**	**4.79**	**IOSC**	**4.83**
2	CIRE	4.76	IBVO	5.12	CIRE	4.69	IBVO	4.43
3	IBVO	4.76	FULL	5.09	IBVO	4.44	CIRE	4.34
4	FULL	4.65	ALAC	4.99	UHRS	4.39	FULL	4.32
5	ALAC	4.65	SFDC	4.99	FULL	4.35	ALAC	4.24

Note1: M_{UKadop}=Mean UK adopters; $M_{UKnadop}$=Mean UK non-adopters; $M_{USAadop}$=Mean USA adopters; $M_{USAnadop}$= Mean USA non-adopters; IOSC = Increased overall supply chain performance; CIRE = Costs of implementation reduction; IBVO = Increase the business value offered by the companies and supply chains; FULL = Fully adopted by companies and supply chain; ALAC = Adopted for all types of activities in the supply chain; SFDC = Supply chains fully digitalized with ChatGPT; UHRS = Unavailable human resources with ChatGPT skills. Note 2: Bold values refer to the first position in the list. Note 3: The intergroup variable's colors are to highlight that a variable was found in adopters and non-adopters groups in the category.

the UK ($M_{UKadop} = 4.76$) and "Supply chains fully digitalized with ChatGPT in the USA" ($M_{USAadop} = 4.99$).

Finally, considering the Top 5 trends between the UK and the USA non-adopters, we had four being the same between the UK and the USA. Of these four, three were the same reported by the adopters, "Increased overall supply chain performance" ($M_{UKnadop} = 4.79$; $M_{USAnadop} = 4.83$), "Increase the business value offered by the companies and supply chains" ($M_{UKnadop} = 4.44$; $M_{USAnadop} = 4.43$), "Fully adopted by companies and supply chain" ($M_{UKnadop} = 4.35$; $M_{USAnadop} = 4.32$), and one reported between non-adopters in both countries "Costs of implementation reduction" ($M_{UKnadop} = 4.69$; $M_{USAnadop} = 4.34$). From the UK non-adopters, we also found "Unavailable human resources with ChatGPT skills" ($M_{UKnadop} = 4.39$) and in the USA, "Adopted for all types of activities in the supply chain" ($M_{USAnadop} = 4.24$).

4.7. A comparison of the Top-5 benefits, challenges, and trends of Gen-AI/ChatGPT between adopters and non-adopters (UK x UK) and the (USA x USA)

Table 7 points out a comparison of the adopters and non-adopters in the same country. Thus, the UK adopters and non-adopters share similar behavior, in which four variables were the same EFFI ($M_{UKadop} = 5.52$; $M_{UKnadop} = 5.08$), REPF ($M_{UKadop} = 5.43$; $M_{UKnadop} = 4.75$), COTM ($M_{UKadop} = 5.33$; $M_{UKnadop} = 4.70$), and RESP ($M_{UKadop} = 5.24$; $M_{UKnadop} = 4.82$). Regarding the USA adopters and non-adopters, they agreed on three benefits, including the order, EFFI ($M_{USAadop} = 5.82$; $M_{USAnadop} = 5.34$), RESP ($M_{USAadop} = 5.48$; $M_{USAnadop} = 4.92$), and AGIL ($M_{USAadop} = 5.46$; $M_{USAnadop} = 4.89$).

Four of the Top 5 challenges reported by the UK adopters and non-adopters were the same. That is, SECU ($M_{UKadop} = 5.09$; $M_{UKnadop} = 5.36$), TRDA ($M_{UKadop} = 4.93$; $M_{UKnadop} = 5.13$), TECA ($M_{UKadop} = 4.87$; $M_{UKnadop} = 5.14$), and PRIV ($M_{UKadop} = 4.80$; $M_{UKnadop} = 5.09$). In view of the USA adopters and non-adopters, the Top 5 challenges were the same between the group of respondents, with the exception of the order. Hence, we found SECU ($M_{USAadop} = 4.74$; $M_{USAnadop} = 5.25$), PRIV ($M_{USAadop} = 4.55$; $M_{USAnadop} = 5.00$), TECA ($M_{USAadop} = 4.48$; $M_{USAnadop} = 5.33$), TRDA ($M_{USAadop} = 4.47$; $M_{USAnadop} = 5.22$), and RISK ($M_{USAadop} = 4.34$; $M_{USAnadop} = 5.04$).

Finally, considering the findings from the Top 5 trends between the UK adopters and non-adopters, four were similar between the groups, in which the first three were in the same order. Therefore, IOSC ($M_{UKadop} = 4.98$; $M_{UKnadop} = 4.79$), CIRE ($M_{UKadop} = 4.76$; $M_{UKnadop} = 4.69$), IBVO ($M_{UKadop} = 4.76$; $M_{UKnadop} = 4.44$), and FULL ($M_{UKadop} = 4.65$; $M_{UKnadop} = 4.35$). From the USA adopters and non-adopters, we also found four trends reported by both groups. In this respect, we found IOSC ($M_{USAadop} = 5.28$; $M_{USAnadop} = 4.83$), IBVO ($M_{USAadop} = 5.12$; $M_{USAnadop} = 4.43$), FULL ($M_{USAadop} = 5.09$; $M_{USAnadop} = 4.32$), and ALAC ($M_{USAadop} = 4.99$; $M_{USAnadop} = 4.24$).

4.8. Some use cases of Gen-AI/ChatGPT

Due to the nascent stage of the Gen-AI/ChatGPT field, especially in the O&SCM, there is a scarcity of use cases. In this vein, Table 8 points out four use cases from representative fields. The first one is about DHL, one of the giant logistics companies which are in the intention adoption stage of Gen-AI/ChatGPT; that is, the company is in the process of identifying the potential and the challenges, especially in warehouse operations. The second use case is about Instacart, a leading grocery delivery and pick-up service. The company is transforming the processes and the way that people shop for food and its delivery. The third use case is from Salesforce, a big tech company focused on sales and customer relationship management. The company integrated the ChatGPT into their app "Slack". Now, the customers (B2B) are able to improve several processes related to the sales journey. Finally, in the fourth use case, we

Table 7
Top 5 benefits, challenges, and trends in the UK (Adopters and non-adopters) and the USA (Adopters and non-adopters).

Top 5 benefits in the UK (Adopters and non-adopters) and the USA (Adopters and non-adopters)							
UK Adopters (Mean)		UK Non-adopters (Mean)		USA Adopters (Mean)		USA Non-adopters (Mean)	
EFFI	**5.52**	**EFFI**	**5.08**	**EFFI**	**5.82**	**EFFI**	**5.34**
REPF	5.43	RESP	4.82	RESP	5.48	RESP	4.92
SERL	5.37	AGIL	4.77	AGIL	5.46	AGIL	4.89
COTM	5.33	REPF	4.75	SERL	5.39	REPF	4.84
RESP	5.24	COTM	4.70	INNO	5.38	PROR	4.83

Top 5 challenges in the UK (Adopters and non-adopters) and the USA (Adopters and non-adopters)							
UK Adopters (Mean)		UK Non-adopters (Mean)		USA Adopters (Mean)		USA Non-adopters (Mean)	
SECU	**5.09**	**SECU**	**5.36**	**SECU**	**4.74**	**TECA**	**5.33**
TRDA	4.93	TECA	5.14	PRIV	4.55	SECU	5.25
TECA	4.87	TRDA	5.13	TECA	4.48	TRDA	5.22
ETHI	4.85	PRIV	5.09	TRDA	4.47	RISK	5.04
PRIV	4.80	GOVE	5.09	RISK	4.34	PRIV	5.00

Top 5 trends in the UK (Adopters and non-adopters) and the USA (Adopters and non-adopters)							
UK Adopters (Mean)		UK Non-adopters (Mean)		USA Adopters (Mean)		USA Non-adopters (Mean)	
IOSC	**4.98**	**IOSC**	**4.79**	**IOSC**	**5.28**	**IOSC**	**4.83**
CIRE	4.76	CIRE	4.69	IBVO	5.12	IBVO	4.43
IBVO	4.76	IBVO	4.44	FULL	5.09	CIRE	4.34
FULL	4.65	UHRS	4.39	ALAC	4.99	FULL	4.32
ALAC	4.65	FULL	4.35	SFDC	4.99	ALAC	4.24

Note1: M_{UKadop}=Mean UK adopters; $M_{UKnadop}$=Mean UK non-adopters; $M_{USAadop}$=Mean USA adopters; $M_{USAnadop}$=Mean USA non-adopters; EFFI = Efficiency; RESP = Responsiveness; SERL = Service level; REPF = Revenue/Profit; AGIL = Agility; COTM = Costs transactions minimization; INNO = Innovation; PROR = Process remodeling; SECU = Security; PRIV = Privacy; TRDA = Trust in data sources; TECA = Technology adoption and implementation; RISK = Risks; ETHI; Ethical issues; GOVE = Governance; IOSC = Increased overall supply chain performance; IBVO = Increase the business value offered by the companies and supply chains; FULL = Fully adopted by companies and supply chain; CIRE = Costs of implementation reduction; ALAC = Adopted for all types of activities in the supply chain; UHRS = Unavailable human resources with ChatGPT skills; SFDC = Supply chains fully digitalized with ChatGPT; Note 2: Bold values refers to the first position in the list. Note 3: The intergroup variable's colors are to highlight that a variable was found in adopters and non-adopters groups in the category.

Table 8
Examples of use cases in related O&SCM fields.

Use case	Context	What is it doing?	Achievements	
DHL (Leading logistics company)	Intention to adopt ChatGPT	The company is in the process of identifying and understanding this technology's potential in logistics and supply chains. The company is convinced about ChatGPT's potential to automate processes to support efficiency improvement. Also, DHL believes that Gen-AI/ChatGPT can be widely used in warehouse operations and in the driver's cabin.	The company is mapping the potential and the challenges of integrating and working with Gen-AI/ChatGPT	https://dhl-freight-connections.com/en/trends/chatgpt-and-the-like-artificial-intelligence-in-logistics/
Instacart (Leading grocery delivery and pick-up service)	The company created a plugin in collaboration with OpenAI to integrate ChatGPT	Instacart is an innovative grocery and delivery pick-up company that operates in the USA and Canada. With the support of the ChatGPT plugin, customers are able to shop for food more efficiently and ask for recipes from ChatGPT. In addition, derived from the conversation, ChatGPT can create the orders to be delivered to the customer in an easy way	The collaboration between customers and the Instacart ChatGPT plugin creates customized experiences for the customers regarding the shopping processes, recipes, orders, and delivery.	https://www.instacart.com/company/updates/instacart-chatgpt/
Salesforce ("Leading cloud-based software company for sales and customer relationship")	The company, in collaboration with OpenAI, developed a conversational interface	The conversational interface named "ChatGPT app for Slack" can instantly summarize large amounts of information and find answers instantly about any topic. Also, it can be used to identify the best practices of a topic or draft messages in a few seconds.	The ChatGPT app for Slack is being released, but its efficiency and high-level interaction capacity can elevate the productivity of any firm related to sales processes and other processes derived.	https://www.salesforce.com/news/stories/chatgpt-app-for-slack/
Zalando ("Leading European online platform for fashion")	The company is launching an assistant to support the customer's experience on the platform	The company expects that the assistant can improve the customer's interaction and navigation through the assortment and support discovery and shopping in a better way.	The company intends to launch the assistant for web and app versions. The company expects to improve the processes related to customer product identification, products available for delivery, etc.	https://corporate.zalando.com/en/technology/zalando-launch-fashion-assistant-powered-chatgpt

highlight the Zalando company, a fashion-leading European platform. With ChatGPT, the company expects a substantial improvement in the customer's product identification, as well as in the management of products available for delivery, etc. These use cases reinforce our results from the survey about the potentials of ChatGPT, mainly related to efficiency, responsiveness, service level, agility, etc.

5. Discussion

Regarding our first question ("*How can the O&SCM field benefit from the Gen-AI/ChatGPT integration?*"), in the pooled analysis ($N = 315$), our findings suggest important convergence between adopters and non-adopters). These findings are in line with the scarce literature on Gen-AI in O&SCM and related fields (Hendriksen, 2023). And with the real use cases found, this thought is reinforced. For instance, four of the Top-5 benefits were the same between the adopters and non-adopters (EFFI, RESP, REPF, and AGIL). In addition, we analyzed the benefits of comparing the countries. Accordingly, in the Top 5 benefits reported by the adopters in the UK and the USA supply chain practitioners, three were the same (EFFI, SERL, and RESP). Between the non-adopters, four were the same (EFFI, RESP, AGIL, and REPF). In this sense, these results are aligned with a recent conceptual paper about AI/Gen-AI in O&SCM, which discusses related efficiency benefits (Hendriksen, 2023).

Furthermore, "Efficiency" ranked in the first position between adopters and non-adopters in both countries. In this regard, the result of the efficiency at the top is in harmony with the emerging literature on Gen-AI/ChatGPT (Brynjolfsson et al., 2023; Carvalho & Ivanov, 2023; Paul et al., 2023). It is important to point out that our results are similar to a recent study from Queiroz et al. (2023), which investigated the benefits, challenges, and trends of the metaverse in O&SCM. For example, while we found that "Efficiency" was ranked top in the Gen-AI/ChatGPT context, in the metaverse, it ranked second.

Besides, it is interesting to note the differences between the groups. For example, results show that firms already using Gen-AI/ChatGPT tend to better valorize their benefits. When comparing adopters with non-adopters in the same country, It appears that those of the UK shared the same four benefits (EFFI, REPF, COTM, and RESP). Meanwhile, adopters and non-adopters in the USA shared three benefits (EFFI, RESP, and AGIL).

In relation to the second question ("*What kind of threat in this relationship could lure the attention of supply chain managers?*"), we identified the main challenges. The Top-5 benefits were the same between the adopters and non-adopters (SECU, PRIV, TRDA, TECA, and RISK). When analyzing each country, the most representative challenges were related to the four of the Top-5 benefits (SECU, TRDA, TECA, and PRIV) being shared by adopters and non-adopters. Thus, "Security" was the major concern between the UK adopters and non-adopters and with the USA adopters. Again, the result about "Security" as one of the major concerns is in accordance with the extant literature (Carvalho & Ivanov, 2023; Paul et al., 2023).

In addition, in the USA non-adopters, the major concern was about the "Technology adoption and implementation". In relation to the trends, comparing the UK with the USA adopters, four were the same (IOSC, IBVO, FULL, and ALAC). From the non-adopters, also four were the same in both countries (IOSC, CIRE, IBVO, and FULL). Our results suggest an inverse behavior between adopters and non-adopters. Hence, the perception of the challenges is higher among the non-adopters when compared with the adopters. In other words, after the adoption, the perception of the challenges tends to be reduced due to the learning curve.

With regard to the challenges, four of the Top 5 (SECU, TRDA, TECA, and PRIV) were shared by adopters and non-adopters in the UK, while in the USA, the Top 5 were the same for the two groups (SECU, PRIV, TECA, TRDA, and RISK). Considering the challenges of the "Technology adoption and implementation" between the adopters and non-adopters is an important challenge to consider (Queiroz et al., 2023). In addition, while "Security" was the most representative challenge reported by the Gen-AI/ChatGPT adopters, in the metaverse study from Queiroz et al. (2023), it featured in the Top 3 only by non-adopters.

To answer our third question ("*What role do organizations and supply chains play in integrating Gen-AI/ChatGPT in their operations?*"), we identified the main trends related to Gen-AI/ChatGPT in O&SCM. The pooled analysis indicated that adopters and non-adopters shared the altogether four of the top-5 trends (IOSC, IBVO, FULL, and CIRE). Our findings suggest that the adopters, more than non-adopters, tend to perceive more potential in the future of *Gen-AI/ChatGPT* in O&SCM. In addition, three trends were the same between the adopters and non-adopters in both countries (IOSC, IBVO, and FULL). In this regard, it can be seen that the "Increased overall supply chain performance" is one of the most expected by the O&SCM field in the UK and the USA. Finally, in the UK, adopters and non-adopters shared four trends (IOSC, CIRE, IBVO, and FULL), against four trends of the Top 5 (IOSC, IBVO, FULL, and ALAC) in the USA.

5.1. Contributions to theory

The literature on Gen-AI/ChatGPT in O&SCM is scarce (Hendriksen, 2023). Considering empirical approaches, to date, there is no relevant literature published in top-tier journals. Our findings therefore represent important contributions to the emerging literature on Gen-AI/ChatGPT in O&SCM-related fields and to the organizational learning theory. Also, our study fills the gap due to the lack of analyses concerning Gen-AI with management theories (Korzynski et al., 2023). For example, we demonstrate that Gen-AI/ChatGPT in O&SCM can be a strategic ally to support the organization's lifelong learning and knowledge share culture (Budhwar et al., 2023; Mhlanga, 2023). Gen-AI/ChatGPT can create a learning culture focused on efficiency (Budhwar et al., 2023).

Besides, the Gen-AI/ChatGPT general literature is aware of and apprehensive about the risks and ethical aspects of the use of this technology; our findings provide a new perspective based on the organizational learning theory approach, which advocates risks minimization following Gen-AI/ChatGPT adoption. For instance, Vidal-Salazar et al. (2012) found that organizational learning can contribute to developing companies' capacities, thus ushering in more proactiveness in their operations. As for the findings of our study, they suggest that organizational learning and knowledge sharing play a decisive role in minimizing the risks and preventing undesirable behavior of using technology.

In addition, our findings suggest that adoption/implementation of Gen-AI/ChatGPT leads to a quicker integration and use of the tool for a set of key activities, but also helps organizations expecting gains in efficiency (Brynjolfsson et al., 2023). These findings are, of course, supported by the organization learning theory. While the specialized literature demonstrates that companies will harness Gen-AI/ChatGPT benefits only if they integrate the technology into their operations, learning how to deal with the same is also key (Ransbotham et al., 2020).

The literature actually acknowledges the potential of digital technologies to improve the performance of organizations, which is enabled by organizational learning (Tortorella et al., 2020). Thus, Gen-AI/ChatGPT, as a disruptive learning tool, can play a decisive role in creating and sharing knowledge between different hierarchical levels. Moreover, the findings of our study advance the discussion about the learning culture's impact on both the best practices and knowledge creation and sharing through the adoption and implementation of cutting-edge technologies like Gen-AI/ChatGPT in O&SCM.

In comparison to some challenges/threats of Gen-AI/ChatGPT in O&SCM, such as security and privacy, which were reported as severe challenges in the tourism field (Carvalho & Ivanov, 2023), we found similar behavior in the O&SCM field. This means that our study contributes not only to expanding the body of knowledge regarding Gen-AI/ChatGPT threats, risks, and challenges (Carvalho & Ivanov, 2023; Paul et al., 2023) in the area of O&SCM, but also to showing that this technology could give rise to the same impacts and challenges across a vast array of technical fields. Of course, our study points to the role of organizational learning to face and/or minimize these adversities. For example, through a learning culture and knowledge sharing, some of the potential challenges can be addressed (Ransbotham et al., 2020). On the one hand, as much as Gen-AI/ChatGPT is integrated into the organization's learning culture, they will be less affected by the perception of the challenges. On the other hand, companies operating in a context where organizational learning is lacking may witness an amplification of the challenges related to Gen-AI/ChatGPT among non-adopters.

Finally, there is a huge scarcity of empirical studies of Gen-AI/ChatGPT in O&SCM. Because of this, our study provides substantial directions to the literature on Gen-AI/ChatGPT in O&SCM. We identified an inverse behavior of the adopters and non-adopters about the benefits, challenges, and trends, which is reported in Fig. 1. As a reminder, the literature reporting the dynamics of the adopters and non-adopters of Gen-AI/ChatGPT, the benefits, challenges, and trends of the technology is still scarce. Cognizant of this, our study tries to bridge the existing gap while reinforcing the potential key role of organizational learning in supporting organizations and supply chains so that capabilities (Ojha et al., 2018; Tortorella et al., 2020) can be created and leveraged by skilled people (Budhwar et al., 2023).

From all said above, three insightful propositions may be formulated:

Proposition 1. *The benefits of Gen-AI/ChatGPT in O&SCM tend to be perceived as stronger after implementation of the technology*.

Proposition 2. *The challenges of Gen-AI/ChatGPT in O&SCM tend to be reduced after adoption of the technology*.

Proposition 3. *The early adopters of Gen-AI/ChatGPT in O&SCM are more likely to perceive its positive trends and potential than the non-adopters*

5.2. Contributions to practice and policy

The findings of our study have notable implications for practitioners and policymakers. Firstly, practitioners should consider carefully the potential benefits and the challenges that Gen-AI/ChatGPT can bring to their O&SCM. That is, not all benefits or challenges will have the same impact on a particular supply chain. The maturity level of an organization's learning process can facilitate the Gen-AI/ChatGPT adoption/implementation and the attainment of their benefits. In addition, non-adopters tend to face amplified challenges about the negative effects, while the perception of the effects tends to reduce after the implementation. Because of this, our study reinforces the need for a lifelong learning culture supported by top managers and strong collaboration among the firm departments and with the supply chain members.

In this context, our study reinforces the importance of organizational learning processes – for senior managers, employees in general, and at the organizational level – that supports the early adoption of technologies such as Gen-AI/ChatGPT. It is essential to the diffusion of the benefits of knowledge sharing and the reduction of the challenges like security and privacy by a learning culture. Considering the policymaker's perspective, our results reinforce the need for an urgent advance in the security, privacy, standardization, ethical concerns, and governance of Gen-AI/ChatGPT. In this vein, companies could propagate the use of Gen-AI/ChatGPT through their network to identify the best practices, reduce inherent risks, and develop relevant policies.

6. Limitations of this study, and future research directions

In relation to the limitations, the major is related to the lack of empirical studies about Gen-AI/ChatGPT, mainly in the O&SCM field, to compare our results. Another limitation is that our study used two mature and leading G-7 economies (the UK and the USA). Future studies could test the same research framework considering other countries from other geographic regions, like emerging and low- and middle-income markets. Besides, the three interesting propositions of our study can be empirically investigated in these contexts.

7. Conclusion

Our study empirically investigated the role of Gen-AI/ChatGPT in O&SCM, focusing on adopters and non-adopters from the UK and the USA. We based our argumentation on the organizational learning theory. The findings suggest that efficiency is a major benefit for the companies that have adopted it and that they have not adopted it yet. Similarly, security was a major concern and the expectation (trends) about the future increased supply chain performance. We found interesting convergences and differences between the adopters and non-adopters of Gen-AI/ChatGPT in O&SCM, which can be explored and explained by the organizational learning theory. For instance, on the one hand, the organizational learning capacity shows that the benefits of the Gen-AI/ChatGPT in O&SCM are more perceived between adopters than non-adopters. On the other hand, the challenges, barriers, and threats tend to be amplified between non-adopters. Similarly, these adversities turn out to be minimized after the implementation of the technology. That is, organizational learning definitively can contribute to speeding up the diffusion of Gen-AI/ChatGPT in O&SCM and, at the same time, reduce the risks. In addition, our findings suggest that adopters are more positive than non-adopters when it comes to the technology trends. In conclusion, Gen-AI/ChatGPT in O&SCM offers a good number of benefits (i.e., efficiency improvement, productivity, etc.), but also various challenges and threats (i.e., ethical use, privacy, integration with humans, etc). The organizational learning theory has proven to feature among the most adherent theories enabling a better understanding of the evolution of Gen-AI/ChatGPT in O&SCM. Finally, our study opens up insightful avenues for new studies and provides directions and support to practitioners and policymakers about the dynamics of Gen-AI/ChatGPT in O&SCM.

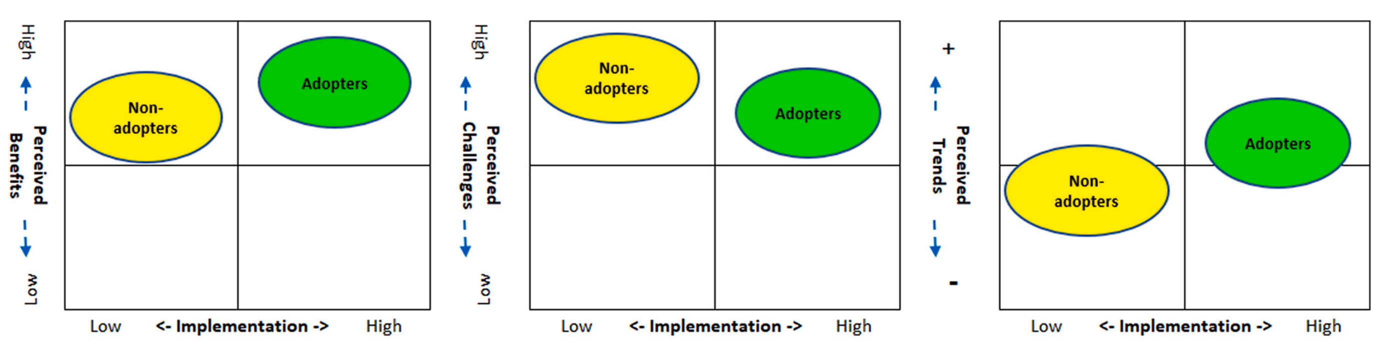

Fig. 1. Matrix of the ChatGPT adopters x non-adopters benefits, challenges, and trends perceptions.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpe.2023.109015.

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Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation

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ABSTRACT

This research examines the transformative potential of artificial intelligence (AI) in general and Generative AI (GAI) in particular in supply chain and operations management (SCOM). Through the lens of the resource-based view and based on key AI capabilities such as learning, perception, prediction, interaction, adaptation, and reasoning, we explore how AI and GAI can impact 13 distinct SCOM decision-making areas. These areas include but are not limited to demand forecasting, inventory management, supply chain design, and risk management. With its outcomes, this study provides a comprehensive understanding of AI and GAI's functionality and applications in the SCOM context, offering a practical framework for both practitioners and researchers. The proposed framework systematically identifies where and how AI and GAI can be applied in SCOM, focussing on decision-making enhancement, process optimisation, investment prioritisation, and skills development. Managers can use it as a guidance to evaluate their operational processes and identify areas where AI and GAI can deliver improved efficiency, accuracy, resilience, and overall effectiveness. The research underscores that AI and GAI, with their multifaceted capabilities and applications, open a revolutionary potential and substantial implications for future SCOM practices, innovations, and research.

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Generative artificial intelligence; GAI; artificial intelligence; supply chain; operations management

1. Introduction

The accelerated advancement of Artificial Intelligence (AI), illustrated by the introduction of tools such as ChatGPT (OpenAI 2023a), GitHub Copilot (Github 2023), and DALL-E (OpenAI 2023b), has garnered a mix of excitement, intrigue, and apprehension (The White House 2022). These technologies belong to the realm of Generative AI (GAI), a branch of Machine Learning (ML) that can create new content, including text, images, music, or video, by learning patterns from existing data (Brynjolfsson, Li, and Raymond 2023). The remarkable strides in GAI can be attributed to four elements: increased computing power, pioneering model architecture, the potential for 'pre-training' using vast quantities of unlabelled data, and advancements in training techniques (Brynjolfsson, Li, and Raymond 2023). A model's performance heavily hinges on its scale, which is influenced by the amount of computing power utilised for training, the number of model parameters, and dataset size (Kaplan et al. 2020). Pre-training large language models (LLMs) involves significant resources, with thousands of GPUs working for weeks to months. For instance, a single training run for a GPT-3 model, with its 175 billion parameters trained on 300 billion tokens, is estimated to cost $5 million in computing alone (Brown et al. 2020). It's worth mentioning that the GPT-3 model, although substantial, is eclipsed by the undisclosed size and cost of GPT-4, which powers ChatGPT (OpenAI 2023c).

This progression of size and computational capacity has catalysed a significant increase in productivity. A study conducted by Harvard Business School (HBS) and the consulting firm Boston Consulting Group (BCG) revealed that individuals utilising ChatGPT-4 at BCG demonstrated superior performance across all measured dimensions compared to their peers (Dell'Acqua et al. 2023). The benefits of AI augmentation were evident across the skills spectrum, with consultants below the average threshold experiencing a remarkable 43% increase, and those above witnessing a 17% improvement in their scores, regardless of the performance metrics used. Likewise, Goldman Sachs' recent report suggests GAI could potentially uplift global GDP by 7%, an immense impact for a single technology (Financial

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Times 2023). The analysis of various use cases and the share of the workforce engaging in primarily cognitive tasks deems this projection plausible, though the ultimate productivity and growth effects of AI remain uncertain. For instance, a study by Noy and Zhang (2023) illustrated that ChatGPT notably boosts worker productivity for midlevel professional writing tasks. Another study by Brynjolfsson, Li, and Raymond (2023) demonstrated a 14% productivity rise for call centre operators using GAI, with the least experienced workers seeing gains over 30%. Interestingly, customer sentiment improved when interacting with operators aided by GAI, possibly contributing to reduced employee attrition.

According to Hulten's theorem, in competitive markets, the impact of a productivity increase in a specific sector on overall productivity and output equals the magnitude of the productivity surge multiplied by the size of the sector (Hulten 1978). Hence, as concluded by Baily, Brynjolfsson, and Korinek (2023), if GAI enhances the productivity of cognitive workers by an average of 30% over a couple of decades and cognitive work contributes to about 60% of the economy's total value (as indicated by the wage bill for cognitive tasks), this translates into an 18% augmentation in aggregate productivity and output over the same period.

As disruptive technologies, AI and GAI will lead to a surge in productivity and revolutionise Supply Chain and Operations Management (SCOM) (Ivanov et al. 2021; Richey Jr et al. 2023; Sheffi 2023), extending its limits and irreversibly altering the job landscape. We are already witnessing these transformations. At the time of writing this paper, Walmart is harnessing GAI to automatically negotiate optimal prices with some vendors (Bloomberg 2023). Simultaneously, Maersk's Chief Technology and Information Officer has indicated the shipping giant's plan to integrate GAI substantially into its business operations (CNBC 2023). The adoption of GAI is not limited to retail and shipping industries. For instance, DHL is keen on harnessing ChatGPT, with a vision to automate processes and enhance efficiency in logistics, from warehouse operations to driver's cabins (DHL 2023). Meanwhile, Instacart, a leading grocery delivery service in the USA has collaborated with OpenAI to integrate ChatGPT to allow customers to efficiently shop, request recipes, and process orders for delivery (Instacart 2023). Additionally, the potential for GAI's application in supply chain communication and decision-making is further highlighted by recent insights from the Wall Street Journal (Young 2023), indicating a growing interest and experimentation in the field.

However, despite the enthusiasm of the early adopters, there is an observable gap in the theoretical preparedness of the SCOM discipline to accommodate this impending revolution (Hendriksen 2023). Some researchers have begun to explore the potential that digitalisation and AI offer in enhancing supply chain efficiency (Perano et al. 2023; Richey Jr et al. 2023). Other studies have shed light on the capabilities of AI systems in mitigating disruptions in the wake of the COVID-19 pandemic (Nayal et al. 2022). There are also promising attempts to analyse AI's potential in manufacturing and Industry 4.0 applications (Rai et al. 2021), and to understand its potential synergies with other disruptive technologies (Ivanov et al. 2021).

These perspectives provide valuable insight, but they tend to focus on AI's application without necessarily viewing the technology through the lens of its functional capabilities. As such, they may not fully capture the breadth and depth of disruption that AI tools can bring to SCOM. Therefore, in the face of such technological disruption, it becomes essential to reflect on the fundamental questions:

- RQ1: How does GAI enhance the capabilities of traditional AI in the context of SCOM?
- RQ2: What are the practical implications of AI and GAI capabilities for the future of Supply Chain and Operations Management?

By answering the stated research questions, our intention is to illuminate the multifaceted nature of AI, discern the unique contributions of GAI, and understand their practical implications within the diverse domains of Supply Chain Operations Management (SCOM). By systematically addressing these inquiries, we strive to establish the Capability-based Framework for analysing and implementing AI and GAI in SCOM. This framework is intended to serve as a crucial tool for both researchers and practitioners, enabling them to identify existing research gaps and devise appropriate methodologies. Our ultimate goal is to facilitate an effective dialogue between AI capabilities and SCOM areas, thereby fostering robust research trajectories and impactful applications within the field.

The remainder of this paper is organised as follows: We first introduce state-of-the-art AI and its capabilities, followed by an in-depth exploration of GAI. Subsequently, we present a framework centred on AI and GAI capabilities within the SCOM context. After that, a comprehensive discussion follows, encompassing managerial implications and avenues for future research. We conclude the paper by summarising our key findings and insights.

2. Background

As the dawn of AI transforms from potential into reality, it is crucial to understand and acknowledge the broad spectrum of capabilities this technology holds. In the quest to define AI's capabilities, it is indispensable to encompass the insights from the originators, visionaries, and practitioners who have been steering the evolution of this field. The AI pioneers, prominent scientists, philosophers of AI, leading tech companies, and consulting firms each carry a unique perspective shaped by their experiences and areas of expertise (see Appendix 1 for exact definitions). Alongside these perspectives, integrating the Resource-Based View (RBV) is crucial. RBV, a strategic framework focussing on internal resources for competitive advantage, highlights how AI's capabilities can be leveraged as unique, valuable, and inimitable resources within organisations, particularly in SCOM (Fan et al. 2022). Weaving together these multifaceted insights, this section aims to unravel and discuss not only the definitions and interpretations of AI's capabilities but also their strategic implications within the RBV framework. This approach seeks to establish a comprehensive and nuanced understanding of state-of-the-art AI, positioning it as a pivotal resource in the ever-evolving landscape of SCOM and setting the stage for future advancements in this dynamic field.

2.1. *AI capabilities through the lens of the resource-Based view*

The Resource-Based View (RBV) is a strategic framework that focuses on the internal resources of a firm to achieve a sustainable competitive advantage. Originating from Barney (1991), the RBV posits that firms with valuable, rare, inimitable, and non-substitutable resources are more likely to maintain competitive superiority (Barney 1991). This perspective has been widely acknowledged and applied in various fields, including SCOM (Fan et al. 2022; Hitt, Xu, and Matz Carnes 2016; Ketchen Jr, Wowak, and Craighead 2014; Schroeder, Bates, and Junttila 2002).

Within the RBV framework, capabilities are considered a special type of resource. They are organisationally embedded, non-transferable, firm-specific resources that enhance the productivity of other resources within the firm (Makadok 2001). This perspective aligns well with the rapidly evolving field of AI, where capabilities developed through technological advancement become pivotal in achieving strategic goals. In the RBV context, the advent of AI as a pivotal digital technology fundamentally alters the landscape of strategic managerial resources. RBV underscores the importance of valuable, rare, inimitable, and non-substitutable resources in achieving competitive superiority. In this light, AI and GAI, in particular, challenge traditional notions within RBV, particularly concerning human cognitive capabilities, which have long been seen as a source of competitive advantage due to their unique and scarce nature (Helfat and Peteraf 2003; Kraaijenbrink, Spender, and Groen 2010; Kunc and Morecroft 2010). It is highlighted that the integration of AI in decision-making processes signifies a shift, suggesting that firms may need to diversify their managerial skills to harness AI's potential effectively (Krakowski, Luger, and Raisch 2023). The role of AI in RBV is twofold: it can either substitute or complement human cognitive capabilities. While its substitution may erode the traditional advantages attributed to human skills due to AI's low marginal reproduction costs and minimal imitation barriers (Brynjolfsson and McAfee 2014), its complementary role can create new strategic advantages by combining human expertise with AI's capabilities (Agrawal, Gans, and Goldfarb 2018). This duality underscores the need for a nuanced understanding of AI in organisational strategy and resource management (Krakowski, Luger, and Raisch 2023). As such, AI in general and GAI in particular serve not only as a technological tool but also as a driver for redefining and reconfiguring strategic resources within the RBV framework, especially in dynamic environments like SCOM.

Incorporating dynamic capabilities (Teece, Pisano, and Shuen 1997) into the RBV enhances our understanding of how organisations can leverage AI for strategic advantage. Dynamic capabilities, defined as the firm's ability to adapt, integrate, and reconfigure internal and external skills and resources, are crucial in environments marked by rapid technological change (Helfat and Peteraf 2003; Teece, Pisano, and Shuen 1997). In the context of RBV, these capabilities enable organisations to possess valuable resources like AI and effectively utilise them in alignment with evolving market conditions and operational challenges.

2.2. *Defining the core AI capabilities*

By analysing the definitions of AI, we could identify such core capabilities as *Learning*, *Perception*, *Prediction*, *Interaction*, *Adaptation*, and *Reasoning* (see Appendix 1). The capabilities are defined and further theoretically justified as follows:

Table 1. Core AI Capabilities gleaned from the various definitions of AI.

	Core AI Capabilities					
Definition of AI	Learning	Perception	Prediction	Interaction	Adaptation	Reasoning
McCarthy (1959)						✓
Samuel (1959)	✓					
Holland (1975) and Fogel (1995)					✓	
LeCun, Bengio, and Hinton (2015)	✓					
Andrej Karpathy (Lex Fridman Podcast 2022)				✓		
Goertzel (2016)	✓					
Agrawal, Gans, and Goldfarb (2019)			✓			
Ruslan Salakhutdinov (Xu et al. 2015)		✓				
European Commission (2018b)	✓	✓		✓		
U.S. Department of Defense (2018)	✓	✓	✓			
Chinese AI National Strategy (Webster et al. 2017)				✓	✓	✓
High-Level Expert Group on AI (Samoili et al. 2020)	✓	✓		✓	✓	✓
OECD (2019)			✓			✓
McKinsey (2023)	✓	✓	✓		✓	
Accenture (2019)	✓	✓		✓		
Amazon (2023)	✓					
Tesla (2023)		✓				✓
Google (2023)	✓	✓				✓

- *Learning*. The AI system learns from data to predict, analyse, and make decisions. The capability includes Supervised Learning (Hastie et al. 2009), Unsupervised Learning (Hastie et al. 2009), Semi-Supervised Learning (Berthelot et al. 2019), and Transfer Learning (Torrey and Shavlik 2010).
- *Perception*. AI's capability to understand and interpret the world by mimicking human senses. The capability includes Computer Vision (Chai et al. 2021), Audio Processing (Purwins et al. 2019), and Natural Language Processing (Otter, Medina, and Kalita 2020).
- *Prediction*. AI's ability to forecast future outcomes based on historical data and patterns (Wu, Zhang, and Zhou 2022). This capability extends beyond just numerical or categorical data, spanning text, images, audio, and more, and includes regression (Mitra, Saha, and Kumar Tiwari 2023), classification (Shahin et al. 2023), time series forecasting (Doganis, Aggelogiannaki, and Sarimveis 2008), and anomaly detection (Kim and Kim 2023).
- *Interaction*. AI interacts and makes decisions in an environment, including interactions with humans. The capability includes Reinforcement Learning (Rolf et al. 2023) and Human-AI Interaction (Panagou, Neumann, and Fruggiero 2023).
- *Adaptation*. AI's ability to adapt and improve over time based on new data and changing environments. The capability includes Continuous Learning (Li et al. 2023) and Evolutionary Algorithms (Xiao et al. 2014).
- *Reasoning*. AI's ability to reason, plan and make decisions, which is crucial for complex tasks. The capability includes Symbolic Reasoning (Brooks 1991), Planning (Leo Kumar 2019), and Decision Making (McDonnell, Joshi, and Qiu 2005).

Table 1 differentiates definitions of AI based on the capabilities. It is important to highlight that the overall taxonomy of AI capabilities has some overlaps with Samoili et al. (2020). The definitions are aligned with Choi et al. (2022) and Ivanov et al. (2021) in order to fit better in SCOM context. It is essential to emphasise that these capabilities hardly exist in isolation; they often need to work together in an integrated manner to realise the full potential of AI in SCOM.

2.3. GAI leads to new capabilities

Viewing through the lens of RBV, competitive advantage is traditionally linked to the possession of valuable, rare, inimitable, and non-substitutable resources such as GAI technologies (Krakowski, Luger, and Raisch 2023). However, the true competitive edge extends beyond merely owning these strategic resources to dynamically leveraging them (Helfat et al. 2023; Helfat and Peteraf 2003). This perspective necessitates continuously adapting AI and GAI capabilities to align with new market trends, seamlessly integrating them into organisational processes, and reconfiguring them to address emerging challenges in SCOM.

At its core, GAI models aim to understand and mimic the underlying distribution of a given dataset, enabling the generation of novel content that closely resembles the original data. These models, including Generative Adversarial Networks (GANs) (Goodfellow et al. 2014), Variational Autoencoders (VAEs) (Kingma and Welling 2019), and Transformer-based architectures (Vaswani et al. 2017) like GPT (OpenAI 2023a) and DALL-E (OpenAI 2023b), are revolutionising diverse aspects of AI, from *Learning* and *Perception* to *Prediction*, *Interaction*, *Adaptation*, and *Reasoning*. Understanding the algorithms and models that form the backbone of GAI offers a window into the future, providing us with the tools to envision how GAI can enhance existing AI capabilities. The models' ability to generate diverse and complex outputs has far-reaching implications, particularly when these capabilities are applied to various elements of supply chain and operations management. As we delve into the specific capabilities of AI and how GAI can augment them, we begin to see a future where AI's ability to learn, perceive, predict, interact, adapt, and reason is exponentially expanded, opening new possibilities for innovation, efficiency, and resilience in supply chain and operations management. Please refer to Appendix 2 for rigorous description and technical details.

2.3.1. Learning enhanced by GAI

GAI models, notably those developed from advanced machine learning frameworks such as GANs and VAEs, hinge on learning as a fundamental mechanism (OpenAI 2017). Their operating principle is to capture the essence of the training data and model its distribution to generate new, original content. This unique capability gives rise to exciting opportunities such as the creation of synthetic datasets, an invaluable asset when real data is limited, non-existent, or subject to privacy concerns.

The capacity to create synthetic data not only extends the breadth of information accessible for AI models to learn from but also potentially enhances the diversity of data. This, in turn, can reduce bias and improve the generalizability of AI systems. These generated datasets can reflect real-world complexities while preserving the privacy and anonymity necessary in many use cases (Hacker, Engel, and Mauer 2023).

Learning in GAI is further empowered by the application of Transformer models (Yu et al. 2022). These models are renowned for their attention mechanism, which allows them to assign varying weights of importance to different parts of the input. This means that the model can recognise and understand long-range dependencies in the data, significantly augmenting its learning ability. Transformers, for example, underpin the sophisticated language model GPT, enabling it to generate coherent, contextually relevant text or computer code (Jackson and Rolf 2023; Jackson, Saenz, and Ivanov 2023) over extended passages.

2.3.2. Perception enhanced by GAI

GAI contributes significantly to enhancing AI's *Perception* capability, as evident in various applications across diverse fields. In the realm of computer vision, generative models demonstrate a profound capability to fabricate entirely new images or manipulate existing ones (Han et al. 2022). These models can, for instance, increase resolution, remove noise, fill in missing parts, or even alter the style of images, creating an indispensable tool in many digital imaging and medical imaging tasks (Bi, Zhu, and Meng 2021).

In the sphere of natural language processing (NLP), Transformer models such as GPT have set a new benchmark in text generation. These models generate text so realistic that it is often indistinguishable from human-written text, spanning from simple sentences to full-length articles. Their ability to capture the complexity of language semantics and syntax showcases an exceptional capacity to perceive and comprehend complex patterns, akin to human language understanding (Floridi and Chiriatti 2020).

Extending this capability, generative models have shown remarkable success in code generation (Jackson, Saenz, and Ivanov 2023), a task that similarly involves perceiving and understanding complex patterns. Models like Codex (Xu et al. 2022) and Copilot (Github 2023), using the Transformer architecture, can produce functional code based on specific instructions or requirements. This advancement could revolutionise software development, making it more efficient and accessible.

2.3.3. Prediction enhanced by GAI

GAI holds significant potential to enhance AI's predictive abilities by creating realistic future scenarios based on historical data patterns. For instance, Lee, Cheon, and Hwang (2021) illustrates the application of GAN architectures to generate time-series data. In the context of supply chain and operations management, these models can generate plausible projections of future data points, such as demand forecasts, inventory requirements, available capacity, or supplier performance assessments.

The generated scenarios could offer nuanced insights, facilitating comprehensive contingency planning. This fact can support strategic decision-making by modelling a range of possible outcomes, thereby illuminating potential opportunities and risks (Jo 2023). Consequently, it aids in building more robust and resilient supply chain systems and operational management structures that can withstand unexpected disruptions.

2.3.4. Interaction enhanced by GAI

GAI models, especially those that leverage the Transformer architecture like the GPT series, are revolutionising the interaction between humans and AI. These models generate contextually appropriate and human-like responses, making AI more conversational and, thus, more user-friendly (Jo 2023).

This capability finds a myriad of applications (Dwivedi et al. 2023). In customer service, for instance, AI can generate human-like responses to handle queries, significantly enhancing customer experience. Similarly, in the realm of virtual assistants, these models can produce more natural and contextually relevant responses, increasing user engagement and satisfaction. The human-AI interaction facilitated by GAI could profoundly impact various industries, creating new avenues for businesses to interact with customers and gather valuable insights.

2.3.5. Adaptation enhanced by GAI

Adaptation forms an integral part of GAI, especially in GANs. In these models, two networks – a generator and a discriminator – are involved in a continuous learning process from each other (Goodfellow et al. 2014). This learning dynamic creates an evolving learning environment within the model, enabling it to refine and improve its generation capability over time.

While this aspect mainly pertains to the model's internal learning dynamics, it emphasises the inherent adaptability of GAI models. This adaptability signifies their potential to respond to new data or changing environments over time, a critical requirement for many real-world applications.

2.3.6. Reasoning enhanced by GAI

GAI models, although primarily known for their content generation abilities, have shown potential to indirectly support tasks that require *Reasoning* (Epstein et al. 2023). For instance, they can generate simulations or scenarios that assist in the planning and decision-making processes (Vanhaelen, Lin, and Zhavoronkov 2020).

These models' ability to create a variety of complex scenarios infuses an additional layer of depth and realism into the reasoning process. For example, in supply chain and operations management, they can simulate various operational conditions or market dynamics, providing a more comprehensive basis for strategic decisions. As such, GAI can significantly contribute to enabling more robust and effective decision-making outcomes.

2.3.7. Unleashing artificial 'Creativity' with GAI

One of the most transformative new capabilities endowed by GAI is the ability to generate creative content, a faculty often reserved for the human intellect. Be it penning an engaging article, designing an image from a text description, or even composing harmonious melodies, these models have displayed a level of creativity previously unimagined in the realm of AI (Brynjolfsson, Li, and Raymond 2023). This development indicates a paradigm shift in the capabilities of AI models, blurring the lines between human creativity and machine learning (Jo 2023). We assign the name Artificial '*Creativity*' to this newfound capability. It signifies the potential of AI systems to concoct original, useful, and often unexpected ideas or outputs that closely mirror the manifestations of human creativity (Brynjolfsson, Li, and Raymond 2023). These outputs could range from the creation of unique designs and solutions to the generation of innovative strategies in complex fields such as Supply Chain and Operations Management (SCOM). In the context of SCOM, this artificial creativity can be harnessed to simulate new market scenarios, develop alternative operational strategies, or predict unexpected demand trends. By using GAI to imagine diverse situations or solutions, businesses can use a creative toolbox for tackling strategic problems or operational bottlenecks. However, it's vital to note that this AI-enabled '*Creativity*' is an extension of the model's training on vast datasets and its capacity to recombine learned elements in innovative ways (Dwivedi et al. 2023). It is essentially a data-driven process where the AI model leverages patterns and structures from the data it was trained on to generate unique and creative solutions. It doesn't involve personal experiences or subjective interpretations as human creativity often does. In this context, it's essential to remember that, despite its remarkable capabilities, GAI does not possess cognition in the way humans do. The concept of creativity when applied to AI, therefore, remains a functional term referring to the capacity of these models to generate novel and potentially useful outputs. We consciously abstain from delving into philosophical discussions regarding AI cognition and the essence of true creativity. In this paper, our focus lies in a practical orientation toward AI, emphasising its capabilities and the corresponding real-world applications. We aim to explore how GAI, with its unprecedented creative abilities, can be applied to transform various aspects of SCOM, paving the way for more robust, innovative, and efficient solutions in this domain.

3. Framework based on AI and GAI capabilities in SCOM

Supply chain engineering and management are burning topics in the industry (Dolgui and Proth 2010; Ivanov and Sokolov 2009). The rapid development and integration of AI and GAI into these industries necessitate a shift in the manner we comprehend and analyse these technological advancements (Brynjolfsson, Li, and Raymond 2023; Jo 2023). A new perspective, which emphasises the capabilities of these technologies rather than simply the underlying algorithms or paradigms, offers a more practical and instrumental viewpoint, especially for the field of SCOM (Choi, Wallace, and Wang 2018; Mithas et al. 2022).

AI and GAI, characterised by their capabilities, can be viewed as functional tools designed to fulfill certain

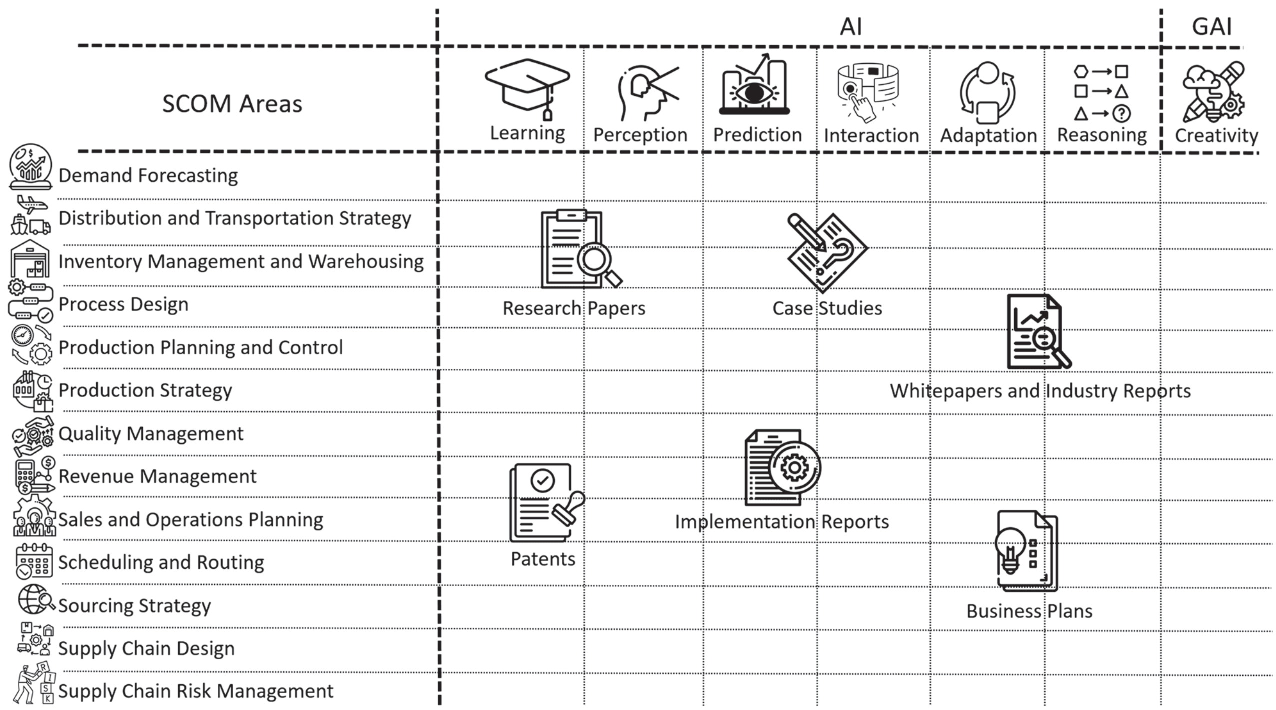

Figure 1. High-level view of the proposed framework and its critical elements.

roles or perform specific tasks. This perspective is especially suited to SCOM, where the emphasis lies on the functional aspects and the effects of technology on the operations and management of the supply chain (Kumar, Mookerjee, and Shubham 2018). Through the lens of capabilities, AI and GAI can be studied in terms of their functionality: *Learning*, *Perception*, *Prediction*, *Interaction*, *Adaptation*, *Reasoning*, and *Creativity*.

To build a framework that allows for the systematic analysis of AI and GAI applications in SCOM, we draw upon the seminal work of Ivanov et al. (2021). This work outlines critical areas within SCOM in the context of Industry 4.0, including but not limited to Demand Forecasting, Distribution and Transportation Strategy, Inventory Management and Warehousing, Process Design, Production Planning and Control, Production Strategy, Quality Management, Revenue Management, Sales and Operations Planning, Scheduling and Routing, Sourcing Strategy, Supply Chain Design, and Supply Chain Risk Management. Since AI and GAI in particular form integral parts of the Industry 4.0 concept (Olsen and Tomlin 2020), we maintain that the areas identified by Ivanov et al. (2021) retain their validity and applicability within the AI and GAI context. Figure 1 provides a high-level view of the proposed framework and illustrates the core areas of SCOM as well as identified AI and GAI Capabilities.

In this section, we illustrate how our proposed framework can be applied to dissect existing applications of AI and GAI in SCOM. Table 2 provides a matrix that maps these applications against the capabilities and SCOM areas, presenting a snapshot of the current landscape of AI and GAI applications in SCOM. Nevertheless, we assert that our study does not aim for exhaustive coverage of the AI and GAI applications in SCOM. Instead, the matrix should serve as a guiding example, elucidating how the proposed framework can be utilised to systematically study and explore AI and GAI in SCOM.

3.1. Forecasting

3.1.1. Demand forecasting

Demand Forecasting is one of the pivotal activities in supply chain and operations management, serving as the compass that guides inventory, production, and distribution decisions (Li and Li 2022). In recent years, the role of AI in refining this key process has become increasingly significant. AI algorithms are now widely used for demand forecasting, leveraging vast datasets to unravel intricate patterns and make predictions. With their ability to learn and adapt over time, these AI models increase forecasting accuracy and contribute to efficient and agile operations management, optimising the overall supply chain process (Jackson and Ivanov 2023; Mithas et al. 2022).

For example, Chien, Lin, and Lin (2020) addresses demand uncertainty in semiconductor distribution. The *Learning* capability is embodied by the use of deep

Table 2. Analyzing AI and GAI Capabilities in SCOM areas using the proposed framework.

Area and Reference	Learning	Perception	Prediction	Interaction	Adaptation	Reasoning	Creativity
Forecasting							
Chien, Lin, and Lin (2020)	✓		✓	✓	✓	✓	
Kantasa-Ard et al. (2021)	✓		✓	✓	✓		
Tremblet, Thevenin, and Dolgui (2023)	✓		✓		✓	✓	
Distribution and Transportation							
Huang et al. (2023)	✓		✓	✓	✓		
Inventory Mgmt. and Warehousing							
Kumar, Mookerjee, and Shubham (2018)	✓	✓					
Jackson, Saenz, and Ivanov (2023)				✓			✓
Process Design							
Kusiak (2020)	✓	✓	✓		✓		
Production Planning and Control							
Liu et al. (2022)	✓	✓	✓		✓		
Production Strategy							
Chen et al. (2021)	✓		✓	✓			
Quality Mgmt.							
Shahin et al. (2023)		✓	✓				
Revenue Mgmt.							
Ferreira, Simchi-Levi, and Wang (2018)	✓		✓				
Sales and Operations Planning							
Oroojlooyjadid et al. (2022)	✓		✓	✓	✓		
Scheduling and Routing							
Tyasnurita, Özcan, and John (2017)	✓		✓		✓		
Sourcing Strategy							
Van Hoek et al. (2022)	✓			✓			✓
Amazon Business (2021)	✓	✓		✓			✓
Supply Chain Design							
Priore et al. (2019)	✓				✓		
Supply Chain Risk Mgmt.							
Wong et al. (2022)	✓		✓				

reinforcement learning. The model learns from data patterns to determine the best forecasting model for each product, echoing aspects of supervised learning as a reward feedback mechanism drives it. The *Prediction* capability is central to the system's function, as it forecasts future demand patterns based on historical data, possibly employing time series forecasting methods. The *Interaction* capability is evident in the system's use of reinforcement learning, enabling it to make decisions in its operational environment, which includes diverse supply chain entities. The system's ability to dynamically select forecasting models points to its *Adaptation* capability, as it can adjust its strategies based on evolving demand patterns, indicative of continuous learning. Lastly, the *Reasoning* capability underpins the system's capacity to choose the optimal demand forecast model for each product, which involves decision-making processes. The AI system reasons, plans, and makes strategic decisions to mitigate the adverse effects of demand uncertainty.

Kantasa-Ard et al. (2021) presents a demand forecasting approach for complex supply chains using a Long Short-Term Memory (LSTM) model, with its hyperparameters tuned by a hybrid of genetic algorithms and scatter search. The study demonstrates the superior performance of the LSTM model in forecasting fluctuating demand, especially when compared to other supervised learning methods, thereby aiding in reducing distribution costs in a physical internet supply chain network. AI's capabilities are manifested in several ways. The *Learning* capability is demonstrated through the use of LSTM, a Supervised Learning method, which learns from historical demand data to make future predictions. The *Prediction* capability is central to the paper's theme as the LSTM model is utilised for demand forecasting, a form of time series forecasting. The *Interaction* capability could be inferred through the AI's engagement with the supply chain environment, making decisions that affect the system's operational efficiency, although this isn't directly addressed. *Adaptation* is evident in using a hybrid genetic algorithm and scatter search to optimise LSTM's hyperparameters, enabling the model to adjust and improve over time based on new data and different demand scenarios.

Bouquet et al. (2023) explores AI-based predictive frameworks for solar energy management. The proposed solution implementats LSTM model epitomises AI's *Learning* capability, particularly in Supervised Learning. This capability is harnessed to analyse historical solar electricity generation data, enabling the model to accurately forecast future patterns. The study's focus on refining accuracy in solar electricity generation forecasts further underscores AI's *Prediction* capability, which is pivotal for enhancing grid reliability and efficiency in the context of Smart Grids. Additionally, the application of the LSTM model in a dynamic energy management environment suggests an implicit use of the Interaction capability, where AI's decisions directly influence operational efficiency. While not explicitly stated, elements of *Adaptation* and *Reasoning*are likely at play as the model adjusts to varying data inputs and complex grid scenarios, optimising solar energy management through strategic decision-making and continuous learning.

3.1.2. Production capacity forecasting

Indeed, AI-based forecasting is not limited to demand. Demand is only a part of the flows circulating within the supply chain. That is why forecasting data patterns from the supply side is pivotal. Forecasting production capacity planning is instrumental for end-to-end supply chain planning.

For example, Tremblet, Thevenin, and Dolgui (2023) presents a comprehensive exploration of AI capabilities, particularly emphasising *Learning*, as it delves into machine learning models like decision trees and artificial neural networks to understand production dynamics. It underscores the *Prediction* capability by forecasting production capacity utilisation, ensuring that production plans align with real-world constraints. The paper illustrates a tool that aids production planners in estimating capacity consumption and highlights *Reasoning* capability, ensuring that decisions are made with regard to available resources. Furthermore, the paper's emphasis on models that swiftly adapt to the intricacies of a manufacturing environment, especially when computational time is limited, which highlights the *Adaptation* capability.

Another prominent research by Tremblet, Thevenin, and Dolgui (2023) dives into the challenges manufacturers face when using lot-sizing models within advanced planning systems. The paper emphasises the *Learning* capability by investigating the integration of machine learning to refine capacity consumption approximations. This focus on machine learning showcases the paper's commitment to *Prediction*, aiming to produce more accurate and implementable production plans. The paper's focus on producing guaranteed feasible plans and its scalability underscores its *Adaptation*.

3.2. Distribution and transportation strategy

Huang et al. (2023) deals with the optimisation of the shortest path interdiction problem, a significant challenge within the scope of Distribution and Transportation Strategy in SCOM. The core objective is to maximise the length of the shortest pathway a follower can traverse, considering a limited interdiction budget. In this context, strategic decisions influence the follower's choice of the shortest path. The research proposes an innovative solution utilising AI capabilities, specifically *Learning*, *Prediction*, *Interaction*, and *Adaptation*. The central strategy involves the deployment of a Reinforcement Learning (RL) framework, an AI technique under the *Interaction* capability. The RL model allows the system to interact with a dynamic environment, where the state and action spaces may be large or continuous. The use of RL underscores the value of AI's *Learning* and *Interaction* capabilities in the solution. It also touches on AI's *Prediction* capability as the model anticipates the follower's choice based on the leader's actions. Alongside the RL framework, a Pointer Network is used to manage variable output sizes, a component linked to the *Learning* capability of AI, particularly supervised learning. This innovative approach allows the model to learn sequences of varying lengths, helping it adapt to different problem sizes, and demonstrating AI's *Adaptation* capability. The study extensively tested the performance of the proposed RL model through computational experiments. The tests used instances generated from two distinct network topologies, grid networks and random graphs, representing different practical scenarios in physical distribution and transportation. This rigorous testing exemplifies the *Reasoning* capability of AI in action, with strategic planning, decision-making, and adaptation to varying scenarios.

3.3. Inventory management and warehousing

Kumar, Mookerjee, and Shubham (2018) presents an innovative approach to addressing pervasive issues in supply chain management, focussing on inventory distortion. It proposes the application of No Code AI in the retail industry as a time and cost-efficient solution. AI capabilities are demonstrated in the following ways. At the heart of this study lies the *Learning* capability of the AI system. The proposed enables non-technical companies to construct machine learning models based on production quantity and inventory replenishment. This capability to learn from data and predict future patterns is essential in mitigating the prevalent problem of inventory distortion, consequently reducing substantial revenue losses. *Prediction* is another AI capability highlighted in this study. By building machine learning models using No Code AI, the AI system can forecast future inventory needs based on production quantity. This predictive power is central to tackling inventory distortion, offering valuable foresight to prevent stock-level issues and thereby increase sales.

Jackson, Saenz, and Ivanov (2023) exemplifies an intriguing intersection of AI capabilities, namely

Creativity and *Interaction*, within the realm of logistics simulation model development. Primarily, the novel application of Natural Language Processing (NLP) via the GPT-3 Codex model demonstrates the creative aspect of AI. This AI model, fine-tuned and integrated into a user-friendly interface, uses its creative prowess to generate Python code for simulating queuing and inventory control systems. By taking verbal descriptions as input, the system not only constructs functionally valid simulations but also exhibits an understanding of domain-specific vocabulary, illustrating a form of innovative problem-solving. Moreover, the *Interaction* capability becomes apparent as the GPT-3 Codex serves as an intelligent intermediary between human inputs and the resultant simulations. Its ability to interpret, translate, and execute domain-specific instructions from a human operator encapsulates the essence of effective Human-AI interaction. This leads to an optimised workflow, allowing experts to focus on high-level strategic aspects, thus integrating AI as a creative and interactive facilitator in simulation model development within logistics.

3.4. Process design

Kusiak (2020) investigates the transformation of manufacturing processes, underscored by advancements in process technology, information technology, and data science. It highlights the role of Convolutional Neural Networks (CNNs) and GANs in developing predictive models for the manufacturing enterprise, following the digital twin concept. The *Learning* capability of AI is highlighted through the use of CNNs and GANs. These machine learning algorithms learn from the patterns inherent in manufacturing data to generate predictive models. In terms of *Perception*, the study indirectly hints at the use of CNNs, commonly employed in tasks related to Computer Vision. In a manufacturing context, this could involve tasks like anomaly detection or pattern recognition, which contribute to process efficiency and quality control. The *Prediction* capability is central to the paper's focus. Through machine learning algorithms, the AI system can forecast future scenarios based on past patterns and trends, thus aiding in strategic decision-making and risk mitigation. The *Adaptation* capability is indicated by the use of GANs, which inherently involve adaptation as part of their learning process. GANs consist of a generator and a discriminator network, which learn from each other continuously. This points to an inherent adaptive behaviour, allowing the models to refine and optimise their predictions over time based on new data and changing scenarios.

3.5. Production planning and control

Liu et al. (2022) proposes a predictive approach for production progress (PP) in make-to-order manufacturing workshops is proposed, leveraging big data and the Industrial Internet of Things (IIoT) for production data acquisition. This approach demonstrates multiple AI capabilities. The *Learning* capability is at the heart of the paper's approach, with the use of CNN and LSTM, both of which learn from the massive historical and current order data to make accurate PP predictions. Moreover, the use of transfer learning, a form of supervised learning, is emphasised, allowing the CNN and LSTM models to utilise knowledge learned from previous tasks, thus improving computational efficiency. This method embodies the *Adaptation* capability, as the models are not trained from scratch each time but adapt based on past learning. The *Perception* capability is manifested in the CNN's extraction of features from the order data, effectively making sense of the various inputs. Finally, the *Prediction* capability is central, with the paper addressing the importance of accurate PP forecasting in the context of dynamic optimisation of the production process and ensuring on-time delivery of orders.

3.6. Production strategy

AI has also significantly impacted the production and manufacturing industries within the context of the Industry 4.0 paradigm, which promotes the use of smart devices and data-driven factories (Rai et al. 2021).

For example, Chen et al. (2021) proposes a new perspective and harnesses the potential of AI in characterising and modelling strip breakage predictively. It leverages the capabilities of AI, specifically *Learning* and *Prediction*, to create an innovative model. In the learning phase, the system uses historical multivariate time-series data from the cold rolling process, extracted in a run-to-failure manner. It incorporates a sliding window strategy for data annotation. This process reflects supervised learning and semi-supervised learning, which is included in the *Learning* capability of AI. For the prediction phase, breakage-centric features are identified from physics-based approaches, empirical knowledge, and data-driven features. These features embody AI's *Perception* capability, which includes computer vision, audio processing, and natural language processing. The system applies these features to strip breakage modelling using Recurrent Neural Networks (RNNs). RNNs fall under AI's prediction capability, specialising in recognising underlying patterns in time-series data. It uses regression and time series forecasting, elements of the prediction capability, to model possible strip breakage. The interaction between the AI system and the data and the dynamic environment of manufacturing illustrates AI's *Interaction* and *Adaptation* capabilities. The paper discusses an experimental study using real-world data from a cold-rolled electrical steel strip manufacturer, showcasing the effectiveness of the proposed approach, thus highlighting the AI's *Reasoning* capability in understanding the problem, planning a solution, and making decisions.

3.7. Quality management

Shahin et al. (2023) demonstrates the applications of AI capabilities, particularly *Perception* and *Prediction*, in the context of modern manufacturing settings underpinned by Industry 4.0 technologies. The *Perception* capability of AI is highlighted by the development and deployment of computer vision models designed to autonomously detect and classify damaged packages from their intact counterparts. This capability effectively emulates human visual inspection but performs the task with higher accuracy and speed, which is especially crucial in high-volume production environments. The *Prediction* capability is embodied in the AI model's ability to forecast potential waste in terms of resources and time and deteriorations in customer satisfaction by preventing damaged packages from proceeding to shipping operations. The YOLO v7 model is utilised here, having demonstrated high precision, accuracy, and recall values in the training and validation stages, thereby supporting the effectiveness of these AI capabilities.

3.8. Revenue management

Ferreira, Simchi-Levi, and Wang (2018) presents a price-based network revenue management problem. The issue revolves around a retailer's objective to maximise revenue from multiple products with limited inventory over a finite selling season. The research addresses the common practice where the demand function contains unknown parameters, which must be learned from sales data. This circumstance employs the *Learning* and *Prediction* capabilities of AI.

3.9. Sales and operations planning

AI holds significant potential in optimising and revolutionising the sales and operations process Schlegel, Birkel, and Hartmann (2021).

In the domain of sales and operations planning within SCOM, the 'beer game' exemplifies the need for effective supply chain coordination (Kimbrough, Wu, and Zhong 2002). The game emulates a decentralised multiagent network, where agents aim to minimise overall costs while working with limited information. Oroojlooyjadid et al. (2022) introduces a novel approach utilising deep reinforcement learning (RL), an instance of AI's *Interaction* capability, to optimise decision-making in the game. The RL algorithm, once trained, performs in real-time and outperforms traditional strategies, particularly when other agents exhibit human-like, unpredictable behaviour, showcasing AI's *Prediction* capability. The results of applying this methodology are promising. When interacting with teammates who adhere to a base-stock policy, the deep RL algorithm generates near-optimal order quantities. Intriguingly, the algorithm outperforms the base-stock policy when other agents display more human-like, unpredictable ordering behaviour. These results stand consistent when tested with real-world datasets, emphasising the algorithm's *Prediction* capability in forecasting and adjusting to human behaviour. The research also demonstrates the AI's *Adaptation* ability, as it shows that the trained model can robustly accommodate changes in cost coefficients.

3.10. Scheduling and routing

The applications of machine learning are becoming increasingly common and diverse. Bai et al. (2023) provides a comprehensive review of hybrid methods that use machine learning in conjunction with analytical strategies to address the Vehicle Routing Problem (VRP), an intensely studied combinatorial optimisation problem. Despite the disparate fields of relevant research and confusing terminologies, the paper underscores the significant potential of machine learning in enhancing VRP modelling and improving the performance of both online and offline VRP algorithms. The discussion concludes by highlighting the challenges and prospects in VRP research, suggesting a promising role for machine learning in the evolution of VRP solutions.

For example, Tyasnurita, Özcan, and John (2017) explores the application of AI, specifically the capabilities of *Learning*, *Prediction*, and *Adaptation*, in solving the Open Vehicle Routing Problem (OVRP), a task notorious for its computational complexity. The task is achieved through a selection hyper-heuristic, a search method controlling a predetermined set of low-level heuristics. The aim of the study is to create an 'apprentice' hyper-heuristic that learns from an 'expert' hyper-heuristic responses to a training set of problem instances and then applies this learned knowledge to unseen problem instances. *Learning* capability is demonstrated through the use of a Time Delay Neural Network (TDNN). The TDNN learns from the data generated by the expert hyper-heuristic's decisions on which low-level heuristic to apply during the search process. The AI's *Prediction* ability is utilised when the TDNN, now trained, predicts which low-level heuristic to apply when confronted with unseen problem instances. This represents a typical application of classification tasks, where the AI predicts a certain class or category (in this case, the suitable low-level heuristic) based on past learning. *Adaptation* as an AI capability is also present in the study. The TDNN might adapt its selection of low-level heuristics based on the performance of previous decisions, incorporating continuous learning to optimise the solution.

3.11. Sourcing strategy

Van Hoek et al. (2022) describes how Walmart used AI to improve negotiations with its suppliers, a previously inefficient task due to the sheer number of suppliers and the lack of personalisation in the agreements. The AI-powered software, Pactum AI, used a text-based chatbot to interact with suppliers, negotiate terms, and make decisions that benefitted both parties involved. Here, I will provide a breakdown of the AI capabilities displayed in the case as per the framework provided.

The *Learning* capability is evident in how Walmart employed an ML algorithm through a software product known as Pactum AI to automate negotiations with a multitude of tail-end suppliers. The AI system was trained using predefined scripts in a supervised learning environment, where internal buyers created scenarios for the algorithm to learn from. These scenarios later produced structured scripts that guided suppliers throughout the negotiation process. *Interaction* comes to the forefront when we consider the negotiation process itself. It's essentially a complex form of interaction where the AI-powered chatbot is engaging with human suppliers on behalf of Walmart. This AI-facilitated negotiation process proved to be not just efficient but also flexible and scalable, going beyond the capabilities of human agents. In this context, the AI system is displaying an advanced form of Human-AI Interaction, learning from each interaction and adjusting its responses according to the feedback received from the supplier. A degree of *Creativity*, inherent in GAI, is also instrumental in this application. The use of a chatbot in negotiations points to an ability to generate new, contextually appropriate content that mimics human interaction. This creative element can be observed in how the chatbot uses its training to create unique negotiation dialogues with each supplier. The chatbot's ability to adapt its language and negotiation strategies based on the supplier's responses is indicative of the creative potential of GAI.

Amazon Business (2021) recently presented how AI is revolutionising procurement processes in businesses. The *Learning* and *Prediction* capabilities of AI are utilised to process large amounts of procurement data and deliver strategic insights. The Amazon Business Spend Visibility tool employs machine learning to analyse and learn from the organisation's buying patterns, which significantly reduces the need for human labour and provides accurate and useful insights for strategic planning. This application of AI supports quicker decision-making and allows professionals to redirect their time to other tasks. AI's *Interaction* capability is illustrated in how Amazon Business automates the competitive bidding for strategically sourced items and identifies cost-effective alternatives for routine supplies. This not only increases sourcing speed but also enables better pricing and procurement efficiencies. Furthermore, the concept of GAI and its Creative capabilities can be perceived in the context of Amazon Business's personalised buying experience. ML collects data from an individual's on-site behaviour and order history and generates curated search results and relevant recommendations.

3.12. Supply chain design

In the ever-evolving landscape of contemporary business, firms grapple with high competition and dynamic environmental conditions (Puche et al. 2016). This flux notably impacts Supply Chain Design, a complex critical area due to multiple intervening factors and their intricate interactions across the supply chain. Navigating such complexity to arrive at optimal configuration often becomes insurmountable (Inman and Blumenfeld 2014).

Priore et al. (2019) brings to light the application of AI to simplify these complex scenarios and enable superior management of inventory flow. The study leverages an inductive learning algorithm, an illustration of Supervised Learning, to create a dynamic framework. This framework facilitates the establishment of the most suitable replenishment policies by adeptly adapting to environmental changes – a clear demonstration of AI's *Learning* and *Adaptation* capabilities. The utilisation of AI in *Learning* and *Adaptation* lends itself remarkably well to the three-echelon supply chain model presented in this paper, which is governed by seven variables – cost structure, demand variability, three lead times, and two partners' inventory policy.

3.13. Supply chain risk management

Supply chain risk management involves strategies aimed at identifying, assessing, mitigating, and monitoring unexpected events that could negatively impact any part of a supply chain. Due to the need for rapid and adaptive decision-making based on vast and complex data sources, supply chain risk management is a promising application area for AI (Baryannis et al. 2019).

For example, Wong et al. (2022) emphasises the role of AI, particularly its *Learning*, *Prediction*, and *Reasoning* capabilities, in enhancing the efficiency and agility of supply chain risk management, especially for small to medium-sized enterprises. These enterprises face an ever-changing and volatile business environment, and traditional models struggle to react dynamically to these challenges. AI offers a unique solution, enabling supply chains to not only adapt to these fluctuations but also make informed decisions that could significantly reduce potential costs and resource expenditures. The researchers used AI to examine its impact on supply chain risk management, providing a unique perspective rooted in the resource-based view. They employed a multi-faceted approach that included partial least squares-based structural equation modelling and artificial neural network, showcasing AI's *Learning* capability in deriving insights from complex datasets. The AI's *Predictive* capability was exhibited in modelling various potential scenarios that would otherwise remain unanswered by traditional infrastructures. By forecasting different outcomes based on historical patterns and data, AI proved invaluable in guiding decision-making processes under high levels of demand uncertainties, thus helping to mitigate supply chain risks.

4. Discussion

This section provides a discussion regarding the future role and potential of AI and GAI in SCOM and attempts to find the potential interactions with other cutting-edge technologies. Besides, this section sheds light on the managerial implications and outlines promising directions for future research.

4.1. Summary of our findings

Our exploration surfaced AI as a multifaceted technology equipped with capabilities spanning *Learning*, *Perception*, *Prediction*, *Interaction*, *Adaptation*, and *Reasoning*. Moreover, we found GAI to possess the transformative potential to enhance these existing AI capabilities and introduce a new one, namely *Creativity*. This fact essentially reconfigures the boundaries of AI applications within SCOM.

Our findings resonate with the propositions presented in a recent study by Wamba et al. (2023). Their research states that the perceived benefits of GAI in SCOM intensify after implementation. Besides, the authors suggest that the challenges associated with GAI diminish following its adoption. These findings align with our observation of GAI's transformative potential in enhancing AI capabilities. Additionally, Wamba et al. (2023) highlight that early adopters of GAI in SCO are more inclined to recognise its positive trajectories and potential compared to non-adopters. This fact underscores the importance of early engagement with emerging technologies to fully grasp and harness their transformative capabilities in the SCOM domain. Similarly, one of the remarkable aspects of our findings is the synergistic relationship between AI and the core elements of Industry 4.0 (Dolgui et al. 2019). The fourth industrial revolution, characterised by the fusion of digital, biological, and physical worlds, hinges heavily on AI capabilities (Schwab 2017). As a result, AI is playing an instrumental role in driving this transformation, creating interconnected, efficient, and intelligent systems (Ivanov and Dolgui 2020). Coupled with other cutting-edge technologies such as *IoT* (Luo, Thevenin, and Dolgui 2022), *5G* (Dolgui and Ivanov 2022), Metaverse (Dolgui and Ivanov 2023), *Blockchain* (Dolgui et al. 2020), *Big Data* (Jahani, Jain, and Ivanov 2023) and *Cloud* technologies, AI is pivotal in powering the digital transformation encapsulated by Industry 4.0 (Ivanov, Dolgui, and Sokolov 2022).

For instance, the IoT, with its network of interconnected devices, leverages AI to glean insights from vast amounts of data, thus enhancing decision-making and operational efficiency (Luo, Thevenin, and Dolgui 2022). Similarly, the advent of *5G* technology significantly boosts AI's ability to interact with and control remote systems, enhancing its capabilities in *Interaction* and *Adaptation* (Dolgui and Ivanov 2022). Additionally, *Metaverse* and AI collectively hold the promise of creating entirely new, immersive, and interactive digital experiences (Dolgui and Ivanov 2023). *Blockchain* (Dolgui et al. 2020), with its emphasis on transparency and security, complements AI in areas such as supply chain risk management and quality control. Lastly, *Cloud* and especially *Edge* technologies serve as a platform to amplify AI's potential, providing the computational power necessary to handle the intensive tasks that AI undertakes (Ivanov, Dolgui, and Sokolov 2022).

It is also essential to recognise the transformative power of Intelligent Digital Twins (*iDTs*) in the context of supply chain resilience (Ivanov 2023). *iDT* is a promising concept of a human-AI system that digitally replicates physical supply chains. Integrating *iDTs* in SCOM offers a more holistic, adaptive, and proactive approach to managing supply chain disruptions and uncertainties as we transition into an era where digital transformation is paramount. As Industry 5.0 (Ivanov 2023) is approaching, the role of AI and specifically GAI, will undoubtedly become even more profound. Industry 5.0 is expected to further enhance the human-machine collaboration that AI and GAI enable, creating even more personalised, efficient, and adaptive systems. Therefore, in our study, we are not merely considering AI and GAI in isolation but as part of a broader technological ecosystem that is fundamentally altering how industries operate. This perspective paints a more holistic picture of the transformative potential of AI and GAI in SCOM.

4.2. Theoretical implications

In the theoretical implications of our study, the RBV provides a strategic lens through which to understand the burgeoning role of AI and GAI in SCOM. RBV posits that the possession of valuable, rare, inimitable, and non-substitutable resources is pivotal for achieving competitive superiority (Helfat and Peteraf 2003). In this context, AI, and more specifically GAI, emerge as critical resources, redefining traditional concepts of competitive advantage within the RBV framework.

Such AI capabilities as Learning, Perception, Prediction, Interaction, Adaptation, Reasoning, and Creativity, when viewed through the RBV lens, are not merely technological assets but strategic resources that enhance organisational productivity and innovation. The advent of GAI technologies, such as GANs, VAEs, and Transformer-based architectures, further extends these capabilities, introducing elements like Creativity into the AI repertoire. This evolution suggests a necessary shift in organisational strategies, where firms must dynamically leverage these AI and GAI capabilities to stay competitive. The integration of these advanced technologies necessitates a continuous adaptation to market trends, effective incorporation into existing processes, and a readiness to reconfigure them to meet new challenges in SCOM (Krakowski, Luger, and Raisch 2023).

Furthermore, our analysis aligns with the argument presented by Helfat et al. (2023) and Krakowski, Luger, and Raisch (2023), highlighting the need for a nuanced understanding of AI in organisational strategy and resource management. As AI technologies evolve, they not only serve as a technological tool but also as a catalyst for redefining and reconfiguring strategic resources within organisations. This theoretical implication points towards an emerging paradigm in which AI and GAI are not just components of technological infrastructure but are central to the strategic resource base of firms, significantly impacting their capacity for innovation, efficiency, and resilience in SCOM.

4.3. Managerial implications

Our study, especially the development and application of the framework linking AI and GAI capabilities to SCOM areas, holds several implications for supply chain and operations management practitioners. Here are some of the key takeaways:

- Identifying Potential Applications: The proposed framework systematically identifies where and how AI and GAI can be applied in SCOM. Managers can use it as a guide to evaluate their operational processes and identify areas where AI and GAI can deliver improved efficiency, accuracy, and overall effectiveness.
- Decision-Making Enhancement: The AI and GAI capabilities, particularly *Prediction* and *Reasoning*, can greatly augment decision-making processes (Choi, Wallace, and Wang 2018). AI's ability to analyse large volumes of data can facilitate more informed, data-driven decisions (Rai et al. 2021), while GAI's creative capability can introduce novel solutions and strategies that were not previously considered.
- Process Optimization: AI and GAI can be instrumental in refining SCOM processes. For instance, demand forecasting can be significantly enhanced using machine learning, while production planning can be optimised using AI-driven prediction models. Additionally, GAI can generate innovative approaches for inventory management (Jackson, Saenz, and Ivanov 2023), sourcing strategies (Bloomberg 2023), and other critical SCOM areas (CNBC 2023).
- Investment Prioritization: Understanding the functional capabilities of AI and GAI can help managers make more informed decisions about where to invest resources. By identifying which capabilities align most closely with their operational needs, managers can prioritise investments in AI technology that offer the greatest potential benefits (Brynjolfsson, Li, and Raymond 2023).
- Skill Development: As AI and GAI become more embedded in SCOM, there will be a growing need for skills in managing and working with these technologies (Sheffi 2023). Organizations will need to invest in training and development to equip their workforce with the necessary skills to effectively utilise AI and GAI tools.

Our study underscores the transformative potential of AI and GAI in SCOM. The proposed framework serves as a critical tool for managers, helping them navigate the complex landscape of AI, identify promising applications, make informed decisions, optimise processes, manage risks, prioritise investments, and build necessary skills within their teams. The integration of AI and GAI in SCOM promises to usher in a new era of innovation, efficiency, and resilience in the field.

4.4. Limitations and future research

Although our study provides valuable insights and a useful tool for SCOM practitioners, it bears several limitations that warrant discussion and serve as a launchpad for future research directions. First, the current study is not an exhaustive literature review but a demonstration of how our proposed framework can be applied to analyse existing AI and GAI applications in SCOM. We focussed on illuminating the functional capabilities of AI and GAI and aligning them within the SCOM realm through a few pertinent examples. While this approach enables us to highlight the transformative potential of AI and GAI in SCOM, it does not encapsulate the full breadth of their applications as depicted in the broader literature. Future research would benefit significantly from employing our proposed framework as a lens for a more comprehensive literature review. Such an endeavour would not only provide a more detailed snapshot of the current landscape of AI and GAI applications in SCOM but also serve to validate and refine the framework.

Second, our framework, while robust and informed by the pioneering work of Ivanov et al. (2021), may benefit from expansion and refinement. The SCOM domain is complex and multifaceted, and while the framework captures a broad range of areas within SCOM, a more granular categorisation could provide deeper insights into specific operational and managerial challenges (Choi, Wallace, and Wang 2018). Future research could explore expanding the framework to incorporate more nuanced SCOM categories, thus providing a more detailed mapping of AI and GAI capabilities and their applications.

Finally, our study has primarily considered AI and GAI within the context of SCOM. However, as core components of the broader Industry 4.0 landscape, the roles and impacts of AI and GAI are significantly broader (Dolgui et al. 2019). Future research should explore the implications of AI and GAI in driving the transition from Industry 4.0 to Industry 5.0, where human-machine collaboration and the convergence of physical, digital, and biological systems are anticipated to be even more pronounced (Ivanov 2023). Such research would deepen our understanding of the role of AI and GAI in this transformative period and the ways in which they can shape the future of industries beyond SCOM.

5. Conclusion

In conclusion, our investigation into the nature of AI, as seen through the lens of RBV, reveals that defining AI transcends a singular dimension. This complexity arises from diverse perspectives encompassing its multifaceted applications and capabilities (Barney 1991; Helfat et al. 2023). Adopting an instrumental view (Bostrom 2016), we focus on AI's functional capabilities – *Learning*, *Perception*, *Prediction*, *Interaction*, *Adaptation*, and *Reasoning* – as crucial elements that drive its application in SCOM.

Further, our analysis of GAI underscores its transformative enhancement of AI's capabilities, particularly through the introduction of *Creativity*. Pioneering technologies like GANs, VAEs, and transformer-based models expand the boundaries of what AI can achieve, demonstrating GAI's unique ability to generate novel, data-mimicking content.

Finally, applying our framework to integrating AI and GAI within SCOM, we leverage these technologies as functional tools, aligning their diverse capabilities with key SCOM processes. This approach, informed by Ivanov et al. (2021), bridges AI and GAI capabilities with critical SCOM areas, illustrating the significant role AI and GAI play in the context of Industry 4.0. In essence, our exploration, grounded in RBV, showcases how AI's capabilities, enhanced by GAI, become strategic resources that redefine and enrich SCOM practices.

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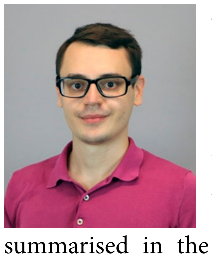

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Data availability statement

The authors confirm that the data supporting the findings of this study are available.

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Appendices

Appendix 1. Extracting AI Capabilities from its Definition

A.1 Perspective of AI researchers

McCarthy (1959), one of the founding fathers of the field of AI, emphasised that *Reasoning* capabilities are key to AI. Namely, ‘*A programme has common sense if it automatically deduces for itself a sufficiently wide class of immediate consequences of anything it is told and what it already knows.*’. Another pioneer of AI, Minsky, 1969 supposed that AI should possess all the cognitive capabilities attributed to humans. Namely, ‘*AI is the science of making machines do things that would require intelligence if done by men.*’ (Minsky 1968). On the other hand, Samuel (1959) provide a more instrumentalist definition of AI that highlights *Learning* as a key capability. Namely, ‘*AI is the field of study that gives computers the ability to learn by using sampled data without being explicitly programmed.*’. Other prominent researchers highlight adaptability as the most critical capability of AI systems. For example, Holland (1975), a pioneer in evolutionary computations, proposed an idea of a pattern recognition device based on the artificial adaptive system. Another pioneer in evolutionary computations, Fogel (1995) defined AI as ‘*Any system that generates adaptive behaviour to meet goals in a range of environments can be said to be intelligent.*’

Among modern AI researchers, the definition of AI also ranges from more specific and instrumental to more philosophical and abstract. For example, Yann LeCun, Yoshua Bengio, and Geoffrey Hinton highlight *Learning* as a key capability and define it as ‘*a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification*’ (LeCun, Bengio, and Hinton 2015). However, they also emphasise that in the future, ‘*a major progress in AI will come about through systems that combine representation learning with complex reasoning*’ (LeCun, Bengio, and Hinton 2015). Ng (2023) understands AI as ‘*a huge set of tools for making computers behave intelligently and in an automated fashion.*’ Demis Hassabis views AI as ‘*a process that converts unstructured information into useful and actionable knowledge.*’ (Financial Times 2017). Andrej Karpathy, in his recent interview, highlighted *Interaction* as a critical capability by defining AI as ‘*an automated human-like system that we can interact with in a digital or physical realm.*’ (Lex Fridman Podcast 2022). Goertzel (2016) defines intelligence as ‘*the ability to detect patterns in the world and in the agent itself.*’, which primarily focuses on the *Learning* capability since pattern recognition is a subset of machine learning (Bishop and Nasrabadi 2006). Shedding light on the economics of AI, Agrawal, Gans, and Goldfarb (2019) highlight predictive capabilities as the core in the business and economics context. For example, one of the provided definitions states that ‘*AI is a prediction technology, predictions are inputs to decision making, and economics provides a perfect framework for understanding the trade-offs underlying any decision.*’ (Agrawal, Gans, and Goldfarb 2018). The team of AI researchers, including Ruslan Salakhutdinov and Yoshua Bengio pointed out that one of the most important challenges in AI is ‘*to mimic the remarkable human ability to compress huge amounts of salient visual information into descriptive language.*’. Besides, the authors highlight that the AI systems ‘*must be powerful enough to solve the computer vision challenges of determining which objects are in an image, but they must also be capable of capturing and expressing their relationships in a natural language.*’ (Xu et al. 2015), which emphasises *Perception* capability, especially visual and natural language processing.

A.2 Perspective of international organisations and national agencies

As the field of AI advances, different national agencies have formulated their own unique perspectives and interpretations of what constitutes AI. These various visions underscore the broad nature of AI and its distinct applications and capabilities. For example, the U.S. Department of Defense provides a multi-faceted definition of AI by defining it as ‘*the ability of machines to perform tasks that normally require human intelligence – for example, recognising patterns, learning from experience, drawing conclusions, making predictions, or taking action – whether digitally or as the smart software behind autonomous physical systems.*’, which highlights such capabilities as *Learning*, *Perception* and *Prediction* (U.S. Department of Defense 2018). The European Commission understands AI as ‘*systems that display intelligent behaviour by analysing their environment and taking action to achieve specific goals*’ (European Commission 2018a). The definition is further detailed in European AI Strategy and the Flagship report on AI. The letter postulates that AI is ‘*a generic term that refers to any machine or algorithm that is capable of observing its environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions.*’, which puts forward such capabilities as *Learning*, *Perception*, and *Interaction* (European Commission 2018b). Even though the Chinese AI National Strategy doesn’t provide any definition but instead focuses on the technological, economic, and geopolitical implications, the documents mainly focus on such capabilities as *Reasoning*, *Learning*, *Interaction*, and *Adaptability* (Webster et al. 2017). The High-Level Expert Group (HLEG) on AI came up with the most detailed, verbose, and nuanced definition that encompasses such AI capabilities as *Reasoning*, *Learning*, *Perception*, *Interaction*, and *Adaptation*. According to HLEG, AI is ‘*a software or hardware system that, given a complex goal, acts in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best actions to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.*’ (Samoili et al. 2020).

International Organisations also have quite different viewpoints. For example, the Organisation for Economic Co-operation and Development (OECD) defines AI as ‘*a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions* *influencing real or virtual environments.*', which highlights predictive capabilities along with the *Reasoning* that is essential for decisions and recommendations (OECD 2019). World Economic Forum, on the other hand, defines AI very broadly and vaguely as '*a collective term for machines that replicate the cognitive abilities of human beings.*' (World Economic Forum 2017).

A.3 Perspective of Industry

Industry and business definitions of AI can often be best understood by referencing leading technology companies and consulting firms. Given this paper's primary focus on Supply Chain and Operations Management (SCOM), the perspectives and visions of these industry leaders are particularly significant.

According to McKinsey (2023), AI can be defined as '*algorithms that are trained on data and can detect patterns and learn how to make predictions and recommendations by processing data and experiences, rather than by receiving explicit programming instruction. The algorithms also adapt in response to new data and experiences to improve their efficacy over time.*'. This definition is very multifaced and points out such capabilities as *Learning*, *Prediction*, *Reasoning* (necessary for recommendations), *Perception*, and *Adaptation*. According to Accenture (2019), AI is '*a constellation of many different technologies working together to enable machines to sense, comprehend, act, and learn with human-like levels of intelligence.*', which emphasises such capabilities as *Perception*, *Learning*, and *Interaction*.

Amazon (2023), in their definition of AI, especially highlights the *Learning* capability by defining AI as '*the field of computer science dedicated to solving cognitive problems commonly associated with human intelligence, such as learning, problem-solving, and pattern recognition.*'. Tesla (2023), on the other hand, aims to achieve a general solution for fully self-driving vehicles and bi-pedal robotics and focuses on such technological advancements as 'vision and planning, supported by efficient use of inference hardware.', which pays special attention to *Perception* and *Reasoning*. Google (2023), in its definition, also emphasises *Perception* and *Reasoning* as well as *Learning* by defining AI as 'a set of technologies that enable computers to perform a variety of advanced functions, including the ability to see, understand and translate spoken and written language, analyse data, and make recommendations.

Appendix 2. Algorithms behind GAI

GAI is a class of AI models that are capable of generating new content that resembles the data they were trained on. In essence, GAI models, including GANs, VAEs (OpenAI 2017), and Transformers (Vaswani et al. 2017), explained in the subsequent subsections, have made significant contributions to various areas of AI, enhancing existing capabilities and paving the way for new applications. The attention mechanism in Transformers, in particular, has led to breakthroughs in handling long-range dependencies in data, leading to more sophisticated generative capabilities.

A.4 Generative adversarial networks

The idea behind GANs is that there are two neural networks, a generator G, and a discriminator D, that are set up in a sort of competition. G takes random noise as input and generates a sample data output. Initially, this generated data won't resemble the desired output at all, but over time the generator learns to produce more accurate results. At the same time, D takes as input a data sample and outputs the probability of that sample coming from the real dataset (as opposed to the generator). The discriminator is also trained over time, improving its ability to tell the difference between real and fake data. The training process involves both networks trying to outsmart each other, hence the term 'adversarial'. The generator tries to produce data that the discriminator can't distinguish from real data, and the discriminator tries to get better at telling the difference. Through this process, the generator learns to produce very realistic data (Goodfellow et al. 2014).

According to its inventors, Goodfellow et al. (2014), the adversarial modelling framework can be explained more formally by considering both G and D as fully connected artificial neural networks (Petersen and Voigtlaender 2020). To learn the generator's distribution p_g over data x, we define a prior on input noise variables $p_z(x)$, then represent a mapping to data space as $G(z;\theta_g)$, where G has parameters θ_g and can be considered a differentiable function. Discriminator $D(x;\theta_g)$ outputs a single scalar. $D(x)$ represents the probability that x came from the data rather than p_g. D is trained to maximise the probability of assigning the correct label to both training examples and samples from G. G is simultaneously trained to minimise $\log(1 - D(G(z)))$ (See Figure A1). In other words, D and G play the following two-player minimax game with value function $V(G, D)$:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x\sim p(x)}[\log(D(x))] + \mathbb{E}_{z\sim p(z)}[\log(1 - D(G(x)))] \quad \text{(A1)}$$

GANs offer a transformative approach to the core capabilities of AI in the context of SCOM. Firstly, GANs inherently demonstrate the *Learning* capability, as the generator refines its outputs based on feedback from the discriminator. This iterative feedback loop also showcases the *Adaptation* capability, as the generator continually adjusts to produce more realistic data. The *Prediction* capability is evident as GANs can generate new, synthetic data instances that can be used to predict or simulate various scenarios in SCOM. In turn, the adversarial nature of GANs is an instance of the *Interaction* capability.

A.5 Variational autoencoders

VAEs are an alternative approach to generative modelling based on the concept of a latent variable (Doersch 2016). VAEs have rapidly become one of the favoured methodologies for unsupervised learning involving complex distributions. The allure of VAEs is derived from their foundation on common function approximators, such as neural networks, and their compatibility with training through stochastic gradient descent (Doersch 2016).

The model assumes that there exists some hidden variable (z), which generates an observation (x). It is only possible to observe (x), but we would like to infer the characteristics of (z) by computing $p(z \mid x)$ as:

$$p(z \mid x) = \frac{p(x \mid z)p(z)}{p(x)} \quad \text{(A2)}$$

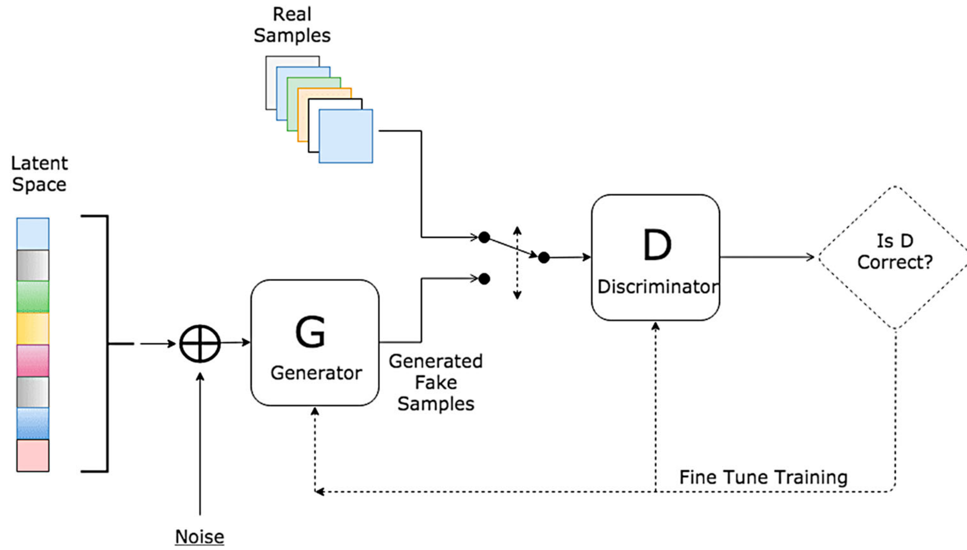


Figure A1. Generative Adversarial Framework. Adapted from Gharakhanian (2023).

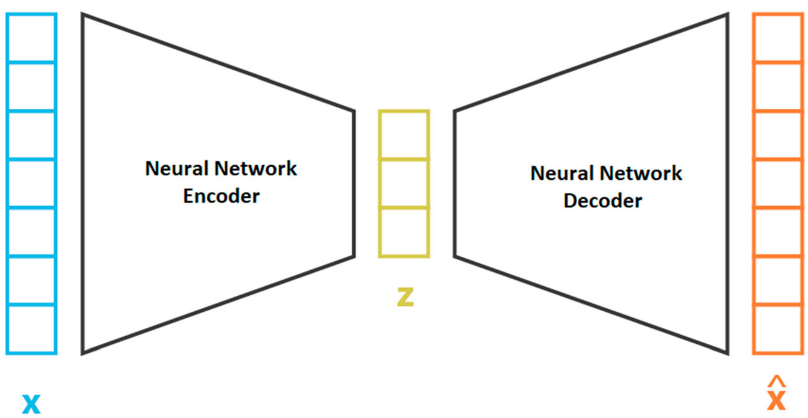


Figure A2. Variational Autoencoder visualised. Adapted from Rocca (2023).

However, computing $p(x)$ is practically challenging and involves dealing with an intractable distribution:

$$p(x) = \int p(x \mid z)p(z)\,\mathrm{d}z \tag{A3}$$

Therefore, the strategy behind VAEs is to approximate $p(z \mid x)$ by a tracktable distribution $q(z \mid x)$. The distribution $q(z \mid x)$ is selected and parametrised such that it is similar to $p(z \mid x)$, which is achieved by minimising Kullback–Leibler (KL) divergence (Kullback and Leibler 1951) as $\min KL(q(z \mid x) \| p(z \mid x))$, which is equivalent to maximising $\mathbb{E}_{q(z \mid x)}[\log p(x \mid z) - KL(q(z \mid x) \| p(z))]$ (Kingma and Welling 2019). Please, refer to Doersch (2016) and Kingma and Welling (2019) for complete derivation and more detailed explanations. In this setting, $q(z|x)$ can be used to infer the latent variables used to generate an observation. The idea could be implemented in a neural network architecture where the encoder model learns a mapping from x to z and the decoder learns the opposite mapping from z to x (See Figure A2). The learning is performed through the minimisation of the following loss function:

$$L(x, \hat{x}) + \sum_j KL(q_j(z \mid x) \| p(z)) \tag{A4}$$

VAEs bring forth an approach that can significantly enhance the core capabilities of AI in the context of SCOM. The *Learning* capability is at the heart of VAEs, as they employ neural networks to learn complex distributions in an unsupervised fashion. This learning is not simply about reproducing data but also involves understanding the underlying latent variables, which is crucial to the *Perception* capability. The latent space representation in VAEs showcases the *Adaptation* capability, as it captures the essence of data and can be adjusted to generate variations of the original data.

A.6 Large language models and transformers

From a formal standpoint, the learning objective is simplified to estimating the distribution from corpora, given a set of training examples $(x_1, x_2, \ldots, x_n)$, where each example represents a sequence of symbols with variable length $(s_1, s_2, \ldots, s_n)$. Since both natural and programming languages are ordered sequentially, the joint probabilities over symbols (or tokens) can be factorised as the product of conditional probabilities:

$$p(x) = \prod_{i=1}^{n} p(s_n \mid s_1, s_2, \ldots, s_{n-1}) \tag{A5}$$

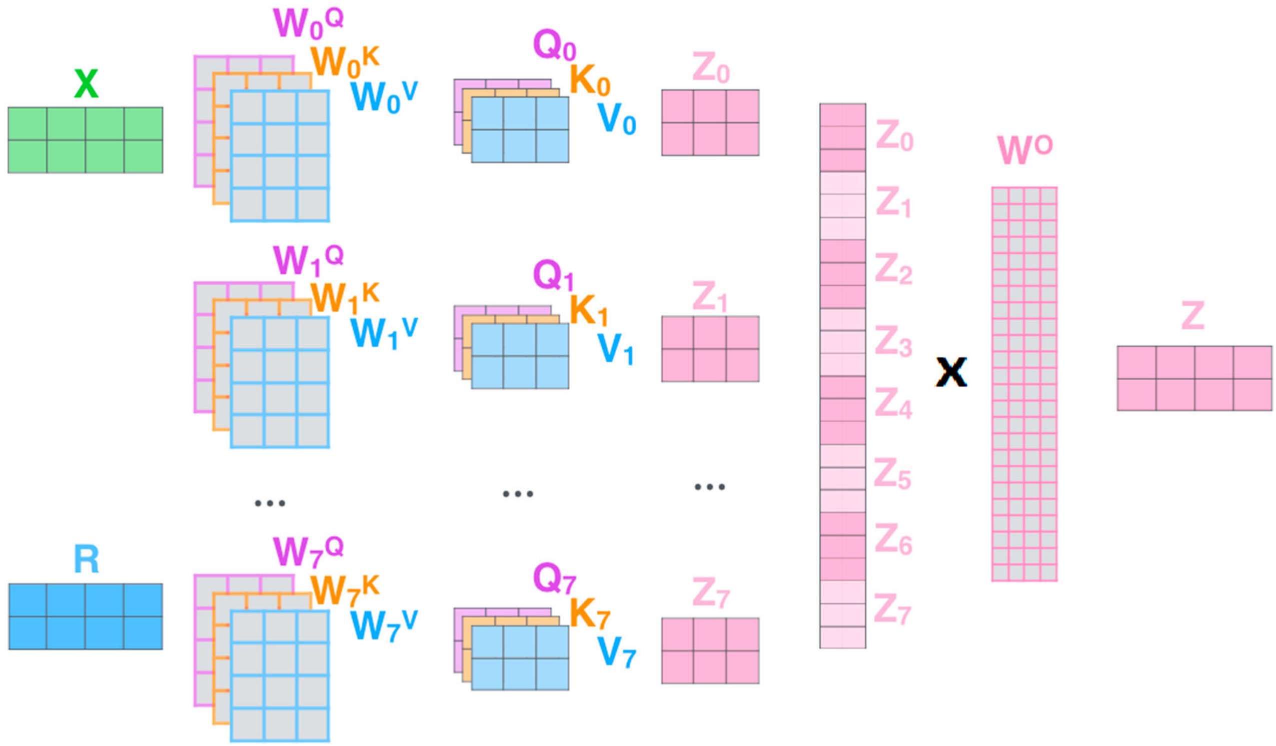


Figure A3. The matrix operations behind the Transformer. The illustration is adapted from Alammar (2018) and Rush (2018).

This assumption allows one to perform tractable sampling and estimation of $p(x)$ and other conditional probabilities of the form $p(s_{n-k}, \ldots, s_n \mid s_1, \ldots, s_{n-k-1})$ (Bengio et al. 2003).

In the recent five years, there have been significant improvements in the performance of language models based on conditional probabilities of the form (Equation (A5)). The most notable advances can be attributed to self-attention architectures like the Transformer (Vaswani et al. 2017). Encoder-decoder structure constitutes a core behind the Transformer's architecture. The role of the encoder is to map an input sequence of symbol representations $(x_1, x_2, \ldots, x_n)$ to a sequence of representations $(z_1, z_2, \ldots, z_n)$. The decoder produces an output $(y_1, y_2, \ldots, y_n)$ given $(z_1, z_2, \ldots, z_n)$ as an input. This process is autoregressive in the sense that the previously generated symbols are used as additional input (Graves 2013). Both encoder and decoder use stacked self-attention mechanisms as well as fully connected layers.

The encoder is composed of a series of N identical layers, each containing two sublayers. The first sublayer incorporates a multi-head self-attention mechanism, while the second sublayer features a position-wise, fully connected feed-forward network, reminiscent of multilayer perceptron architectures. To enable residual connections, all sub-layers and embedding layers produce outputs of the same dimension, d_{model}. Similarly, the decoder is structured with a stack of N identical layers. A self-attention function is designed to map a query and its associated key-value pairs to an output, with the query, keys, values, and output all represented as vectors. The output is calculated as a weighted sum, where the weights corresponding to the respective values are determined using a feed-forward artificial neural network. The scaled dot-product attention serves as a crucial element within the self-attention mechanism. To enhance computational efficiency, the attention function is executed on a collection of queries simultaneously. Inputs consisting of queries and keys with dimension d_k, as well as values with dimension d_v, are consolidated into matrices Q, K, and V. This approach not only streamlines the process but also allows for more effective handling of complex language modelling tasks within the Transformer architecture.

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (A6)$$

The Q, K, and V matrices are linearly projected h times to d_k, and d_v dimensions, respectively. After that, the self-attention function is performed on each of these projections, resulting in d_v-dimensional output vector. As a result, multi-head attention allows the model to access information from different representation subspaces at different positions.

$$MultiHead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O \quad (A7)$$

where $head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$ with parameter matrices $W_i^Q \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{model}}$. Besides the sub-layers, each of the layers in both encoder and decoder contains a fully connected feed-forward network that can be represented as a composite function $FFN(.)$. $FFN(.)$ is equipped with Rectified Linear Unit (ReLU) activation function and includes two linear transformations.

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \quad (A8)$$

The Transformer takes advantage of the learned embeddings to convert the input and output tokens to vectors of the dimension d_{model}, which is basically the embedding size. Besides, the regular learned linear transformation and *softmax*(.) activation function convert the decoder output to estimated probabilities of the next token to appear in the sequence. Figure A3 illustrates the matrix operations behind the Transformer architecture.

The self-attention mechanism, central for Large language models, emphasises the *Perception* capability, comprehending context and relationships within sequences. This mechanism, combined with the autoregressive nature of Transformers, amplifies the *Prediction* capability, as models predict subsequent tokens given prior context. The Transformer's multi-head attention, which processes different parts of an input concurrently, demonstrates *Adaptation*, allowing the model to adjust its focus dynamically. Lastly, Transformers have the potential to enhance the *Reasoning* capability when integrated with decision-making tools, enabling context-rich decisions in SCOM scenarios based on textual insights.

ILLUSTRATION BY ADRIÀ VOLTÀ

IS AI LEADING TO A REPRODUCIBILITY CRISIS IN SCIENCE?

Scientists worry that ill-informed use of artificial intelligence is driving a deluge of unreliable or useless research. **By Philip Ball**

During the COVID-19 pandemic in late 2020, testing kits for the viral infection were scant in some countries. So the idea of diagnosing infection with a medical technique that was already widespread – chest X-rays – sounded appealing. Although the human eye can't reliably discern differences between infected and non-infected individuals, a team in India reported that artificial intelligence (AI) could do it, using machine learning to analyse a set of X-ray images[1].

The paper – one of dozens of studies on the idea – has been cited more than 900 times. But the following September, computer scientists Sanchari Dhar and Lior Shamir at Kansas State University in Manhattan took a closer look[2]. They trained a machine-learning algorithm on the same images, but used only blank background sections that showed no body parts at all. Yet their AI could still pick out COVID-19 cases at well above chance level.

The problem seemed to be that there were consistent differences in the backgrounds of the medical images in the data set. An AI system could pick up on those artefacts to succeed in the diagnostic task, without learning any clinically relevant features – making it medically useless.

Shamir and Dhar found several other cases in which a reportedly successful image classification by AI – from cell types to face recognition – returned similar results from blank or meaningless parts of the images. The algorithms performed better than chance at recognizing faces without faces, and cells without cells. Some of these papers have been cited hundreds of times.

"These examples might be amusing", Shamir says – but in biomedicine, misclassification could be a matter of life and death. "The problem is extremely common – a lot more common than most of my colleagues would want to believe." A separate review in 2021 examined 62 studies using machine learning to diagnose COVID-19 from chest X-rays or computed tomography scans; it concluded that none of the AI models was clinically useful, because of methodological flaws or biases in image data sets[3].

The errors that Shamir and Dhar found are just some of the ways in which machine learning can give rise to misleading claims in research. Computer scientists Sayash Kapoor and Arvind Narayanan at Princeton University in New Jersey reported earlier this year that the problem of data leakage (when there is insufficient separation between the data used to train an AI system and those used to test it) has caused reproducibility issues in 17 fields that they examined, affecting hundreds of papers[4]. They argue that naive use of AI is leading to a reproducibility crisis.

Machine learning (ML) and other types of AI are powerful statistical tools that have advanced almost every area of science by picking out patterns in data that are often invisible to human researchers. At the same time, some researchers worry that ill-informed use of AI software is driving a deluge of papers with claims that cannot be replicated, or that are wrong or useless in practical terms.

There has been no systematic estimate of the extent of the problem, but researchers say that, anecdotally, error-strewn AI papers are everywhere. "This is a widespread issue impacting many communities beginning to adopt machine-learning methods," Kapoor says.

> **"I SEE A LOT OF COMMON MISTAKES REPEATED OVER AND OVER."**

Aeronautical engineer Lorena Barba at George Washington University in Washington DC agrees that few, if any, fields are exempt from the issue. "I'm confident stating that scientific machine learning in the physical sciences is presenting widespread problems," she says. "And this is not about lots of poor-quality or low-impact papers," she adds. "I have read many articles in prestigious journals and conferences that compare with weak baselines, exaggerate claims, fail to report full computational costs, completely ignore limitations of the work, or otherwise fail to provide sufficient information, data or code to reproduce the results."

"There is a proper way to apply ML to test a scientific hypothesis, and many scientists were never really trained properly to do that because the field is still relatively new," says Casey Bennett at DePaul University in Chicago, Illinois, a specialist in the use of computer methods in health. "I see a lot of common mistakes repeated over and over," he says. For ML tools used in health research, he adds, "it's like the Wild West right now."

How AI goes astray

As with any powerful new statistical technique, AI systems can make it easy for researchers looking for a particular result to fool themselves. "AI provides a tool that allows researchers to 'play' with the data and parameters until the results are aligned with the expectations," says Shamir.

"The incredible flexibility and tunability of AI, and the lack of rigour in developing these models, provide way too much latitude," says computer scientist Benjamin Haibe-Kains at the University of Toronto, Canada, whose lab applies computational methods to cancer research.

Data leakage seems to be particularly common, according to Kapoor and Narayanan, who have laid out a taxonomy of such problems[4]. ML algorithms are trained on data until they can reliably produce the right outputs for each input – to correctly classify an image, say. Their performance is then evaluated on an unseen (test) data set. As ML experts know, it is essential to keep the training set separate from the test set. But some researchers apparently don't know how to ensure this.

The issue can be subtle: if a random subset of test data is taken from the same pool as the training data, that could lead to leakage. And if medical data from the same individual (or same scientific instrument) are split between training and test sets, the AI might learn to identify features associated with that individual or that instrument, rather than a specific medical ailment – a problem identified, for example, in one use of AI to analyse histopathology images[5]. That's why it is essential to run 'control' trials on blank backgrounds of images, Shamir says, to see if what the algorithm is generating makes logical sense.

Kapoor and Narayanan also raise the problem of when the test set doesn't reflect real-world data. In this case, a method might give reliable and valid results on its test data, but that can't be reproduced in the real world.

"There is way more variation in the real world than in the lab, and the AI models are often not tested for it until we deploy them," Haibe-Kains says.

In one example, an AI developed by researchers at Google Health in Palo Alto, California, was used to analyse retinal images for signs of diabetic retinopathy, which can cause blindness. When others in the Google Health team trialled it in clinics in Thailand, it rejected many images taken under suboptimal conditions, because the system had been trained on high-quality scans. The high rejection rate created a need for more follow-up appointments with patients – an unnecessary workload[6].

Efforts to correct training or test data sets can lead to their own problems. If the data are imbalanced – that is, they don't sample the real-world distribution evenly – researchers might apply rebalancing algorithms, such as the Synthetic Minority Oversampling Technique (SMOTE)[7], which generates synthetic data for under-sampled regions.

However, Bennett says, "in situations when the data is heavily imbalanced, SMOTE will lead to overly optimistic estimates of performance, because you are essentially creating lots of 'fake data' based on an untestable assumption about the underlying data distribution". In other words, SMOTE ends up not so much balancing as manufacturing the data set, which is then pervaded with the same biases that are inherent in the original data.

Even experts can find it hard to escape these problems. In 2022, for instance, data scientist Gaël Varoquaux at the French National Institute for Research in Digital Science and Technology (INRIA) in Paris and his colleagues ran an international challenge for teams to develop algorithms that could make accurate diagnoses of autism spectrum disorder from brain-structure data obtained by magnetic resonance imaging (MRI)[8].

The challenge garnered 589 submissions from 61 teams, and the 10 best algorithms (mostly using ML) seemed to perform better using MRI data compared with the existing method of diagnosis, which uses genotypes. But those algorithms did not generalize well to another data set that had been kept private from the public data given to teams to train and test their models. "The best predictions on the public dataset were too good to be true, and did not carry over to the unseen, private dataset," the researchers wrote[8]. In essence, this is because developing and testing a method on a small data set, even when trying to avoid data leakage, will always end up overfitting to those data, Varoquaux says – that is, being too closely focused on aligning to the particular patterns in the data so that the method loses generality.

Overcoming the problem

This August, Kapoor, Narayanan and their co-workers proposed a way to tackle the issue with a checklist of standards for reporting AI-based science[9], which runs to 32 questions on factors such as data quality, details of modelling and risks of data leakage. They say their list "provides a cross-disciplinary bar for reporting standards in ML-based science". Other checklists have been created for specific fields, such as for the life sciences[10] and chemistry[11].

Many argue that research papers using AI should make their methods and data fully open. A 2019 study by data scientist Edward Raff at the Virginia-based analytics firm Booz Allen Hamilton found that only 63.5% of 255 papers using AI methods could be reproduced as reported[12], but computer scientist Joelle Pineau at McGill University in Montreal, Canada (who is also vice-president of AI research at Meta) and others later stated that reproducibility rises to 85% if the original authors help with those efforts by actively supplying data and code[13]. With that in mind, Pineau and her colleagues proposed a protocol for papers that use AI methods, which specifies that the source code be included with the submission and that – as with Kapoor and Narayan's recommendations – it be assessed against a standardized ML reproducibility checklist[13].

But researchers note that providing enough details for full reproducibility is hard in any computational science, let alone in AI.

And checklists can only achieve so much. Reproducibility doesn't guarantee that the model is giving correct results, but only self-consistent ones, warns computer scientist Joaquin Vanschoren at the Eindhoven University of Technology in the Netherlands. He also points out that "a lot of the really high-impact AI models are created by big companies, who seldom make their codes available, at least immediately." And, he says, sometimes people are reluctant to release their own code because they don't think it is ready for public scrutiny.

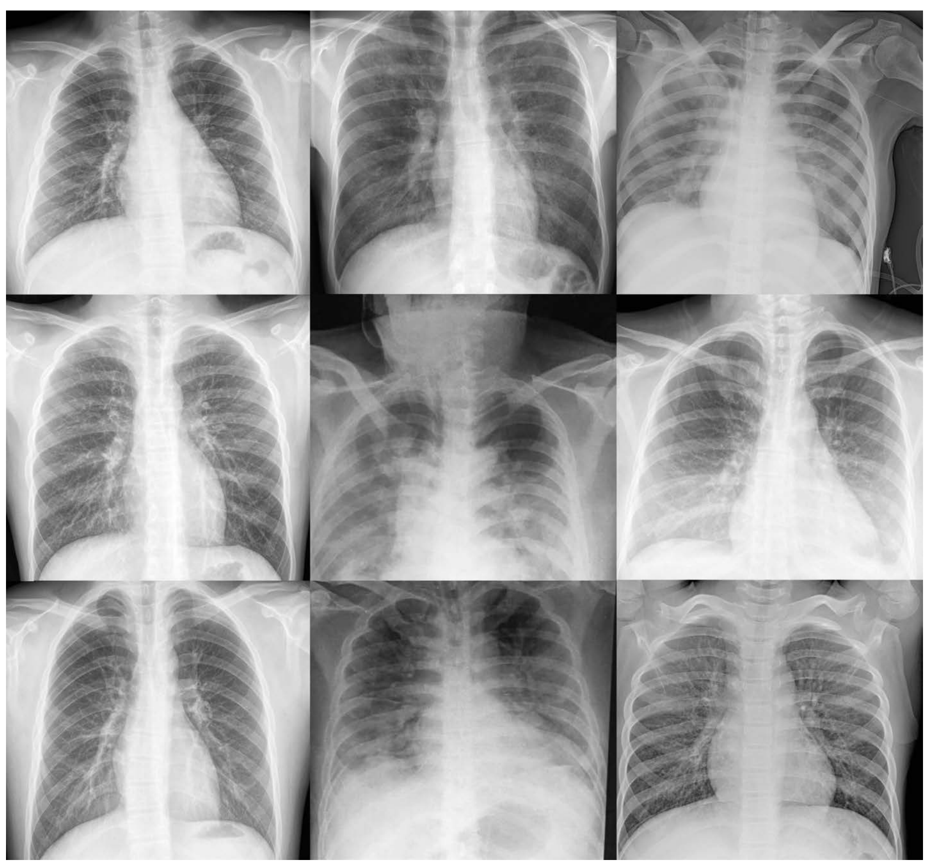
"WE COULD SEE A GREATER AMOUNT OF INTEGRITY ISSUES IN SCIENCE."

Although some computer-science conferences require that code be made available to have a peer-reviewed proceedings paper published, this is not yet universal. "The most important conferences are more serious about it, but it's a mixed bag," says Vanschoren.

Part of the problem could be that there simply are not enough data available to properly test the models. "If there aren't enough public data sets, then researchers can't evaluate their models correctly and end up publishing low-quality results that show great performance," says Joseph Cohen, a scientist at Amazon AWS Health AI, who also directs the US-based non-profit Institute for Reproducible Research. "This issue is very bad in medical research."

The pitfalls might be all the more hazardous for generative AI systems such as large language models (LLMs), which can create new data, including text and images, using models derived from their training data. Researchers can use such algorithms to enhance the resolution of images, for instance. But unless they take great care, they could end up introducing artefacts, says Viren Jain, a research scientist at Google in Mountain View, California, who works on developing AI for visualizing and manipulating large data sets.

"There has been a lot of interest in the microscopy world to improve the quality of images, like removing noise," he says. "But I wouldn't say these things are foolproof, and they could be introducing artefacts." He has seen such dangers in his own work on images of brain tissue. "If we weren't careful to take the proper steps to validate things, we could have easily



Chest X-ray images of healthy people (left); those with COVID-19 (centre); and those with pneumonia (right).

done something that ended up inadvertently prompting an incorrect scientific conclusion."

Jain is also concerned about the possibility of deliberate misuse of generative AI as an easy way to create genuine-seeming scientific images. "It's hard to avoid the concern that we could see a greater amount of integrity issues in science," he says.

Culture shift

Some researchers think that the problems will only be truly addressed by changing cultural norms about how data are presented and reported. Haibe-Kains is not very optimistic that such a change will be easy to engineer. In 2020, he and his colleagues criticized a prominent study on the potential of ML for detecting breast cancer in mammograms, authored by a team that included researchers at Google Health[14]. Haibe-Kains and his co-authors wrote that "the absence of sufficiently documented methods and computer code underlying the study effectively undermines its scientific value"[15] — in other words, the work could not be examined because there wasn't enough information to reproduce it.

The authors of that study said in a published response, however, that they were not at liberty to share all the information, because some of it came from a US hospital that had privacy concerns with making it available. They added that they "strove to document all relevant machine learning methods while keeping the paper accessible to a clinical and general scientific audience"[16].

More widely, Varoquaux and computer scientist Veronika Cheplygina at the IT University of Copenhagen have argued that current publishing incentives, especially the pressure to generate attention-grabbing headlines, act against the reliability of AI-based findings[17]. Haibe-Kains adds that authors do not always "play the game in good faith" by complying with data-transparency guidelines, and that journal editors often don't push back enough against this.

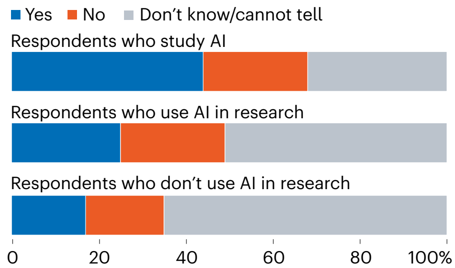
The problem is not so much that editors waive rules about transparency, Haibe-Kains argues, but that editors and reviewers might be "poorly educated on the real versus fictitious obstacles for sharing data, code and so on, so they tend to be content with very shallow, unreasonable justifications [for not sharing such information]". Indeed, authors might simply not understand what is required of them to ensure the reliability and reproducibility of their work. "It's hard to be completely transparent if you don't fully understand what you are doing," says Bennett.

In a *Nature* survey this year that asked more than 1,600 researchers about AI, views on the adequacy of peer review for AI-related journal articles were split. Among the scientists who used AI for their work, one-quarter thought reviews were adequate, one-quarter felt they

QUALITY OF AI REVIEW IN RESEARCH PAPERS

A *Nature* survey of more than 1,600 scientists found split opinions on the quality of peer-review of research papers that use AI.

Q: Do you think that journal editors and peer-reviewers, in general, can adequately review papers in your field that use AI?



SOURCE: *NATURE* **621**, 672–675 (2023).

were not and around half said they didn't know (see 'Quality of AI review in research papers' and *Nature* **621**, 672–675; 2023).

Although plenty of potential problems have been raised about individual papers, they rarely seem to get resolved. Individual cases tend to get bogged down in counterclaims and disputes about fine details. For example, in some of the case studies investigated by Kapoor and Narayanan, involving uses of ML to predict outbreaks of civil war, some of their claims that the results were distorted by data leakage were met with public rebuttals by the authors (see *Nature* **608**, 250–251; 2022). And the authors of the study on COVID-19 identification from chest X-rays[1] critiqued by Dhar and Shamir told *Nature* that they do not accept the criticisms.

Learning to fly

Not everyone thinks there is an AI crisis looming. "In my experience, I have not seen the application of AI resulting in an increase in irreproducible results," says neuroscientist Lucas Stetzik at Aiforia Technologies, a Helsinki-based consultancy for AI-based medical imaging. Indeed, he thinks that, carefully applied, AI techniques can help to eliminate the cognitive biases that often leak into researchers' work. "I was drawn to AI specifically because I was frustrated by the irreproducibility of many methods and the ease with which some irresponsible researchers can bias or cherry-pick results."

Although concerns about the validity or reliability of many published findings on the uses of AI are widespread, it is not clear that faulty or unreliable findings based on AI in the scientific literature are yet creating real dangers of, say, misdiagnosis in clinical practice. "I think that has the potential to happen, and I would not be shocked to find out it is already happening, but I haven't seen any such reports yet," says Bennett.

Cohen also feels that the issues might resolve themselves, just as teething problems with other new scientific methods have. "I think that things will just naturally work out in the end," he says. "Authors who publish poor-quality papers will be regarded poorly by the research community and not get future jobs. Journals that publish these papers will be regarded as untrustworthy and good authors won't want to publish in them."

Bioengineer Alex Trevino at the bioinformatics company Enable Medicine in Menlo Park, California, says that one key aspect of making AI-based research more reliable is to ensure that it is done in interdisciplinary teams. For example, computer scientists who understand how to curate and handle data sets should work with biologists who understand the experimental complexities of how the data were obtained.

Bennett thinks that, in a decade or two, researchers will have a more sophisticated understanding of what AI can offer and how to use it, much as it took biologists that long to better understand how to relate genetic analyses to complex diseases. And Jain says that, at least for generative AI, reproducibility might improve when there is greater consistency in the models being used. "People are increasingly converging around foundation models: very general models that do lots of things, like OpenAI's GPT-3 and GPT-4," he says. That is much more likely to give rise to reproducible results than some bespoke model trained in-house. "So you could imagine reproducibility getting a bit better if everyone is using the same systems."

Vanschoren draws a hopeful analogy with the aerospace industry. "In the early days it was very dangerous, and it took decades of engineering to make airplanes trustworthy." He thinks that AI will develop in a similar way: "The field will become more mature and, over time, we will learn which systems we can trust." The question is whether the research community can contain the problems in the meantime.

Philip Ball is a science writer in London.

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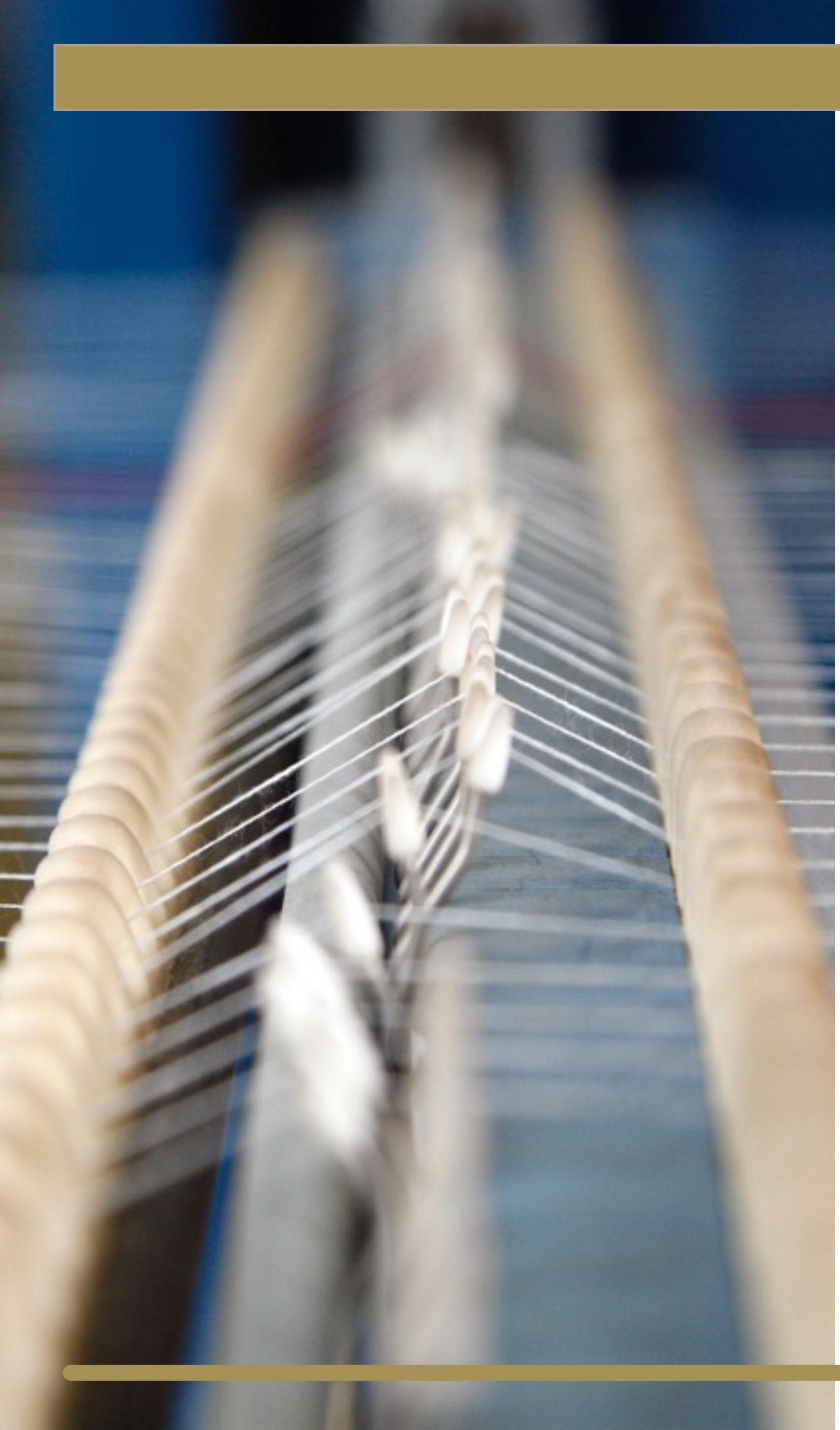

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Obiettivi del nuovo Digital Customer Hub:

Il touchpoint web come punto di contatto preferenziale nella relazione con il cliente

- Creare un touch point ”digitale” come canale preferenziale nella relazione con il cliente
- Sviluppare una soluzione di e-commerce evoluta con servizi a valore aggiunto per il cliente nelle diverse fasi della journey lavorativa
- Connesso con l’ecosistema digitale aziendale e «guidato» dal crm
- Raccogliere dati nelle diverse fasi della customer-journey per poter migliorare experience e performance, basandosi su un approccio data-driven

MARTINELLI GINETTO

GROUP

Fabio Orlando
Digital Marketing Manager
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www.martinelliginettogroup.it

Testimonianza Würth Italia
eSupply Chain Management

WÜRTH

DAVIDE FERRANTE

Head of eProcurement
(Digital Transformation & System Integration Dept.)
presso Würth Italia

Leader mondiale

Il Gruppo Würth è Leader mondiale nella distribuzione di sistemi per il fissaggio e il montaggio.

La storia del Gruppo Würth coincide con la vita del Prof. Dr. h. mult. Reinhold Würth, che trasformò la ferramenta fondata nel 1945 da suo padre a Künzelsau – nella Germania occidentale – in quello che è oggi un Gruppo internazionale, leader mondiale nella distribuzione di prodotti e sistemi professionali per il fissaggio ed il montaggio.

80 PAESI
OLTRE 400 AZIENDE

	DE	Int.	Total
Würth Line	3	123	**126**
AC's	74	217	**291**
Total	77	340	**417**

WÜRTH

Il Gruppo Würth

Un Mondo in continua evoluzione

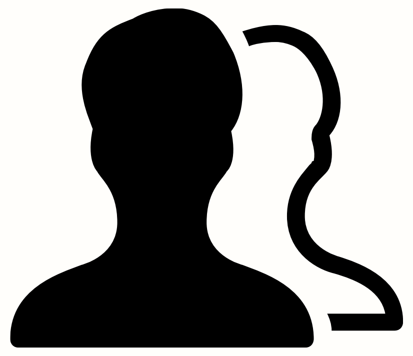
Würth: il nome significa prodotti di alta qualità e servizi eccellenti.
Il Gruppo Würth è, tuttavia, molto di più della sola distribuzione di materiali per il fissaggio ed il montaggio. Una speciale filosofia aziendale e valori condivisi sostengono il successo che da tempo sostiene la crescita tanto della sede tedesca quanto delle oltre 400 aziende presenti in tutto il mondo.

Fatturato 2023

20,38 Mrd EUR

Clienti

oltre **4.000.000**



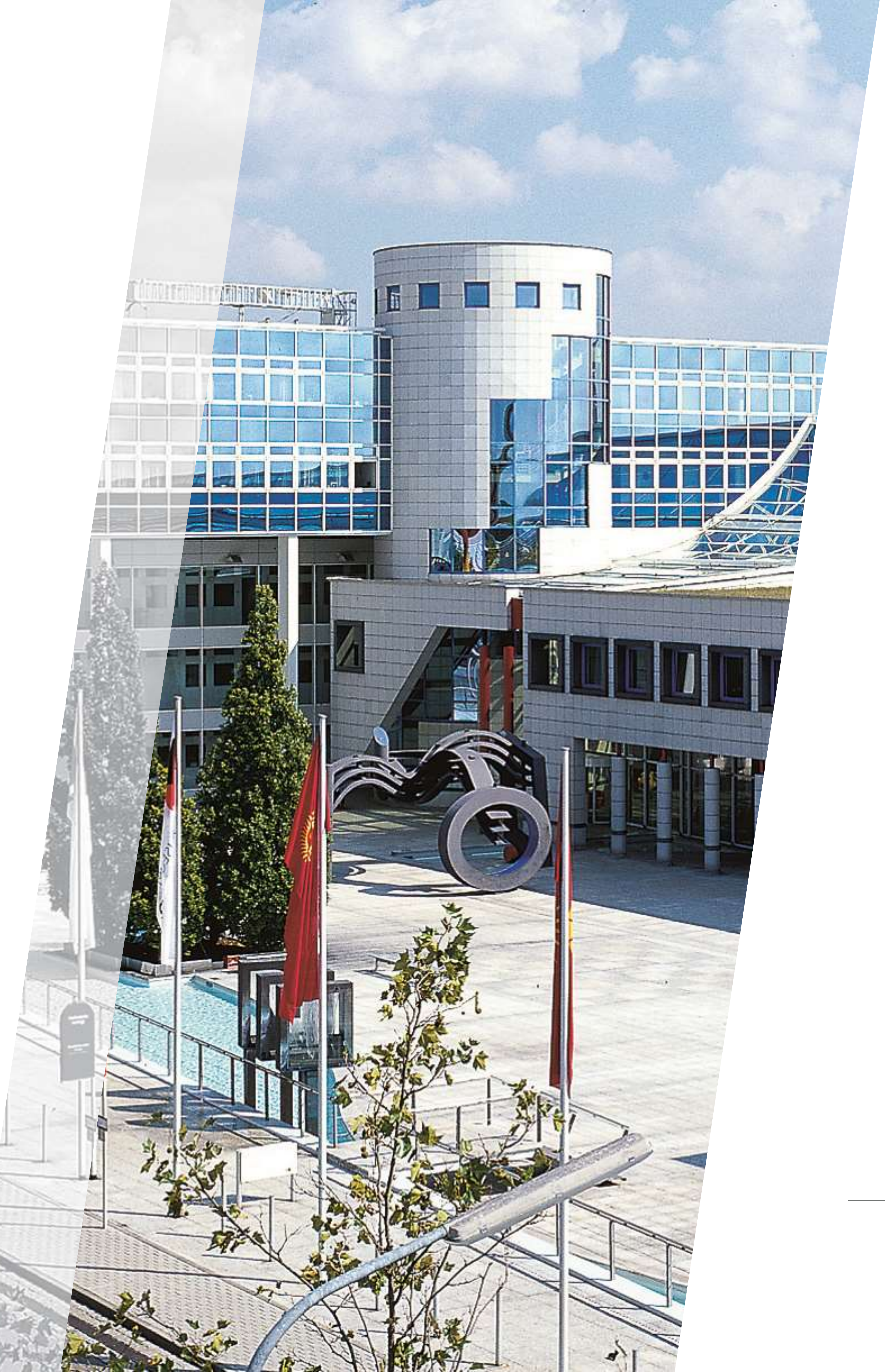
Collaboratori

oltre **87.000**

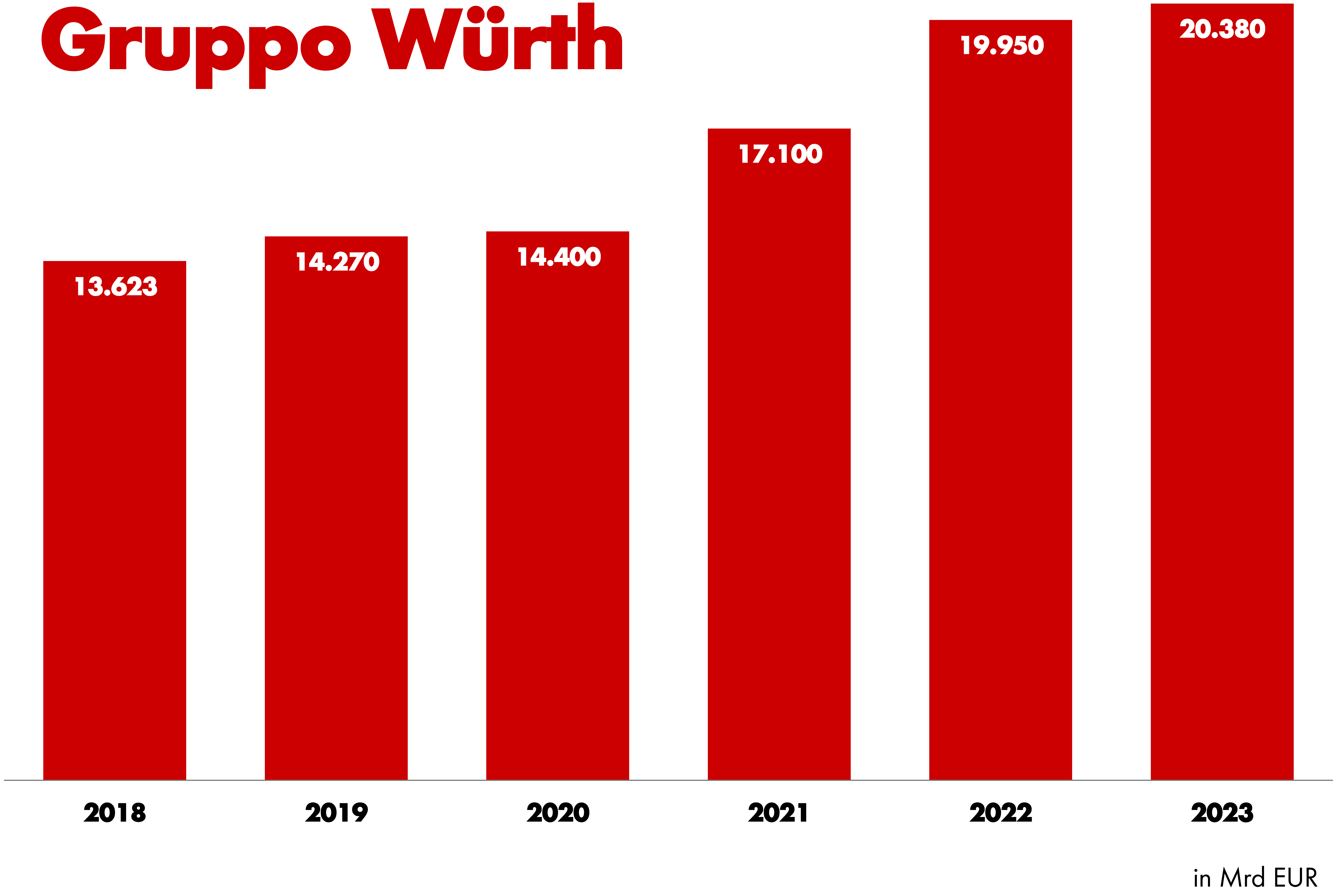
di cui **45.000 Tecnici Venditori**

Prodotti in gamma

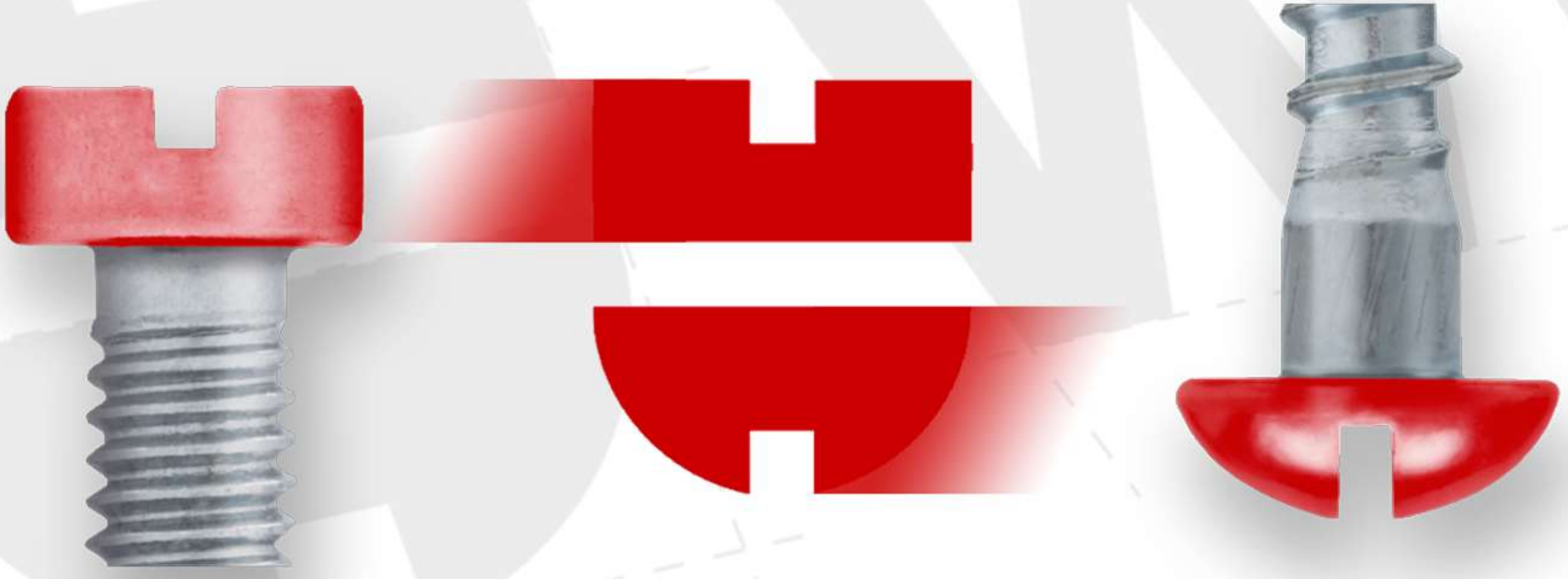
oltre **130.000**



Fatturato del
Gruppo Würth



Un Marchio in continua **evoluzione**



1945 1973 1983 2010

Una **vite a testa cilindrica e una a testa rotonda** affiancate l'una all'altra, insieme al nome Würth: questo è il cuore del nostro marchio.
Un prodotto simbolo del core business dell'azienda, della sua concretezza e precisione.

WÜRTH

Würth Italia

«Ad ogni Cliente la sua Würth»

È questo il grande impegno assunto dall'azienda, per soddisfare le richieste di ciascun Cliente con qualità e specializzazione. Attiva in Italia dal 1963, è cresciuta esponenzialmente divenendo oggi il partner di riferimento per oltre 280.000 professionisti.

Fatturato 2023
847 Mio EUR

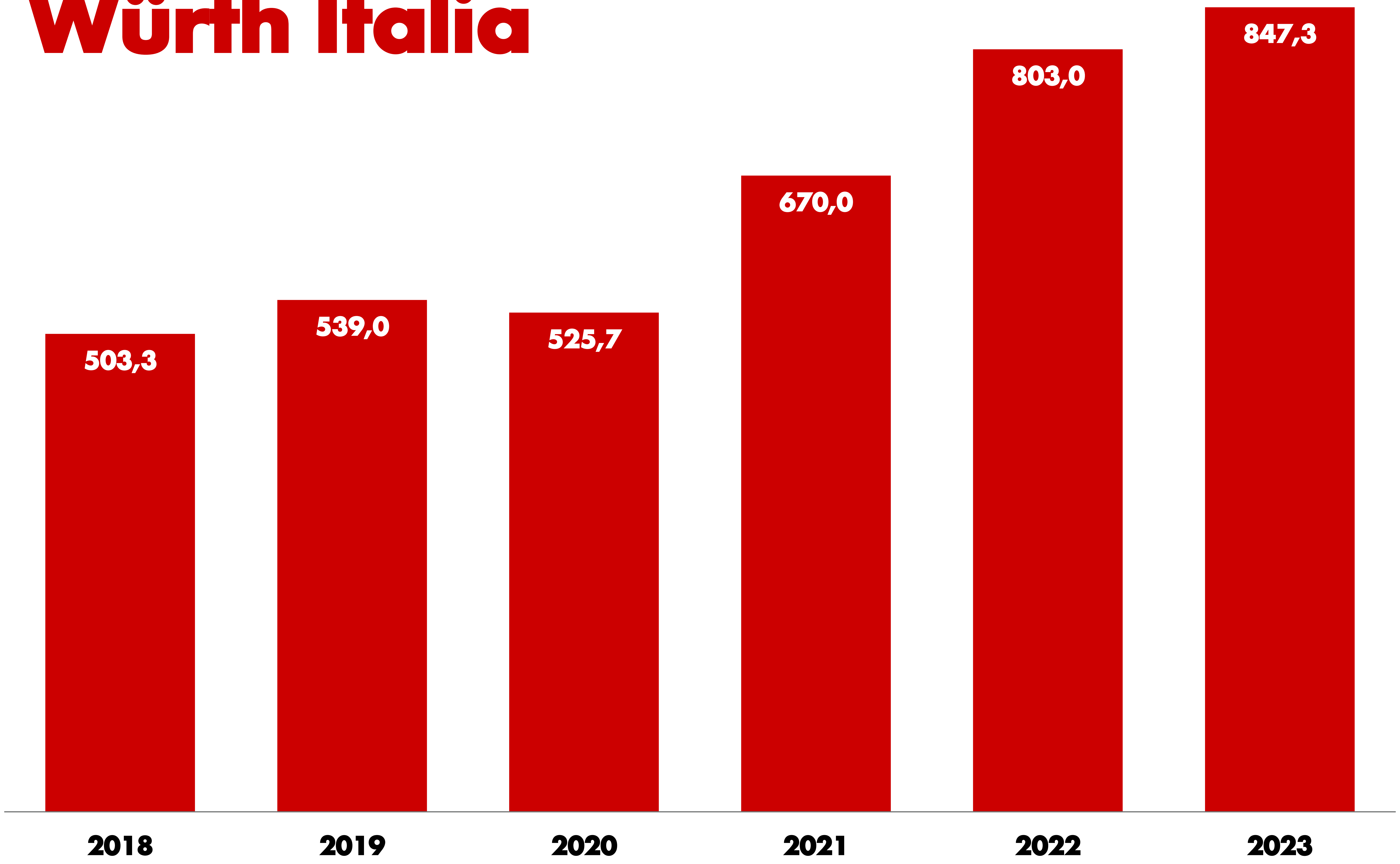
Clienti
oltre **300.000**

Collaboratori
4.000
di cui 2.500 Tecnici Venditori

Prodotti in gamma
oltre 130.000

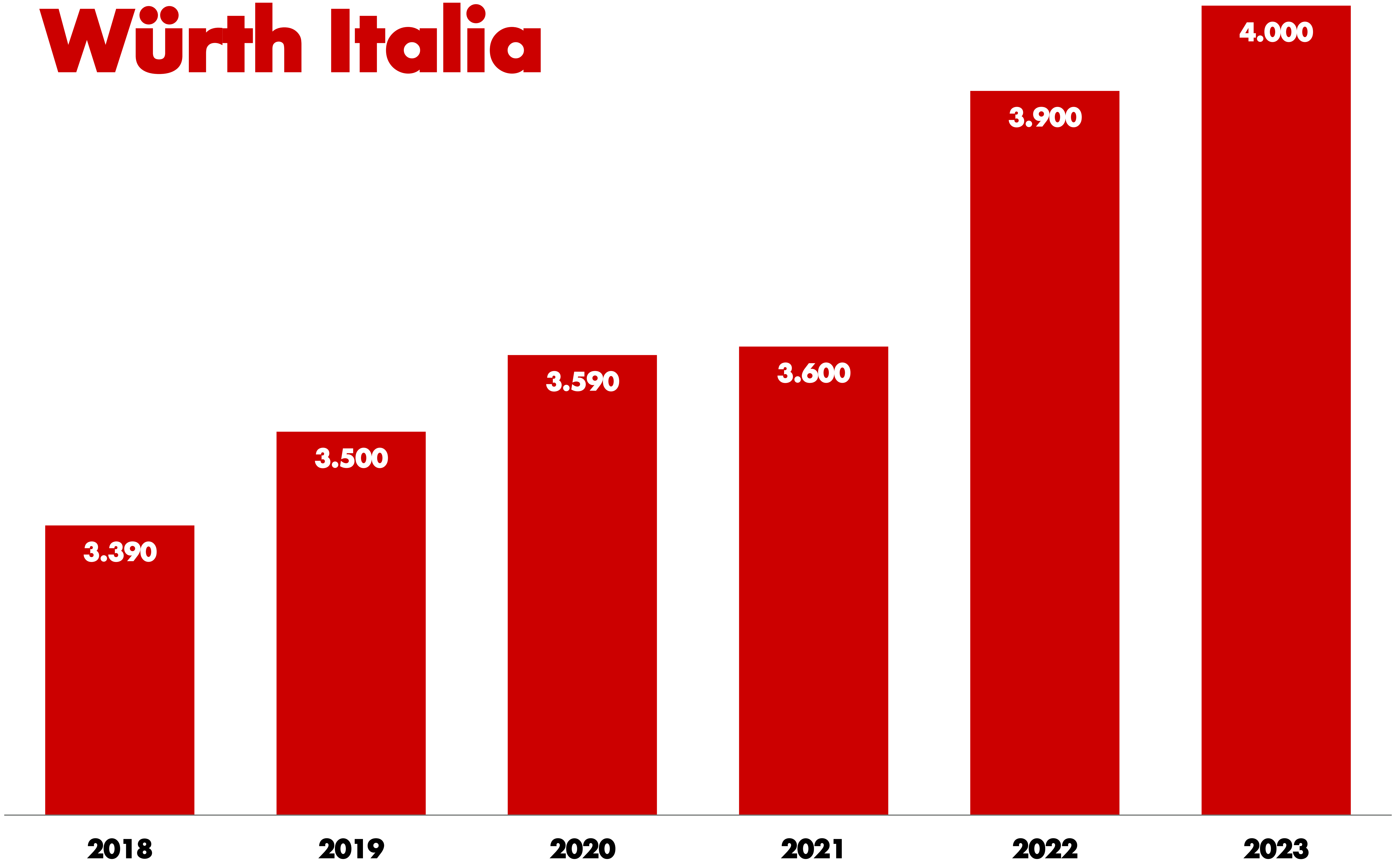
Negozi
oltre **300**

Fatturato
Würth Italia

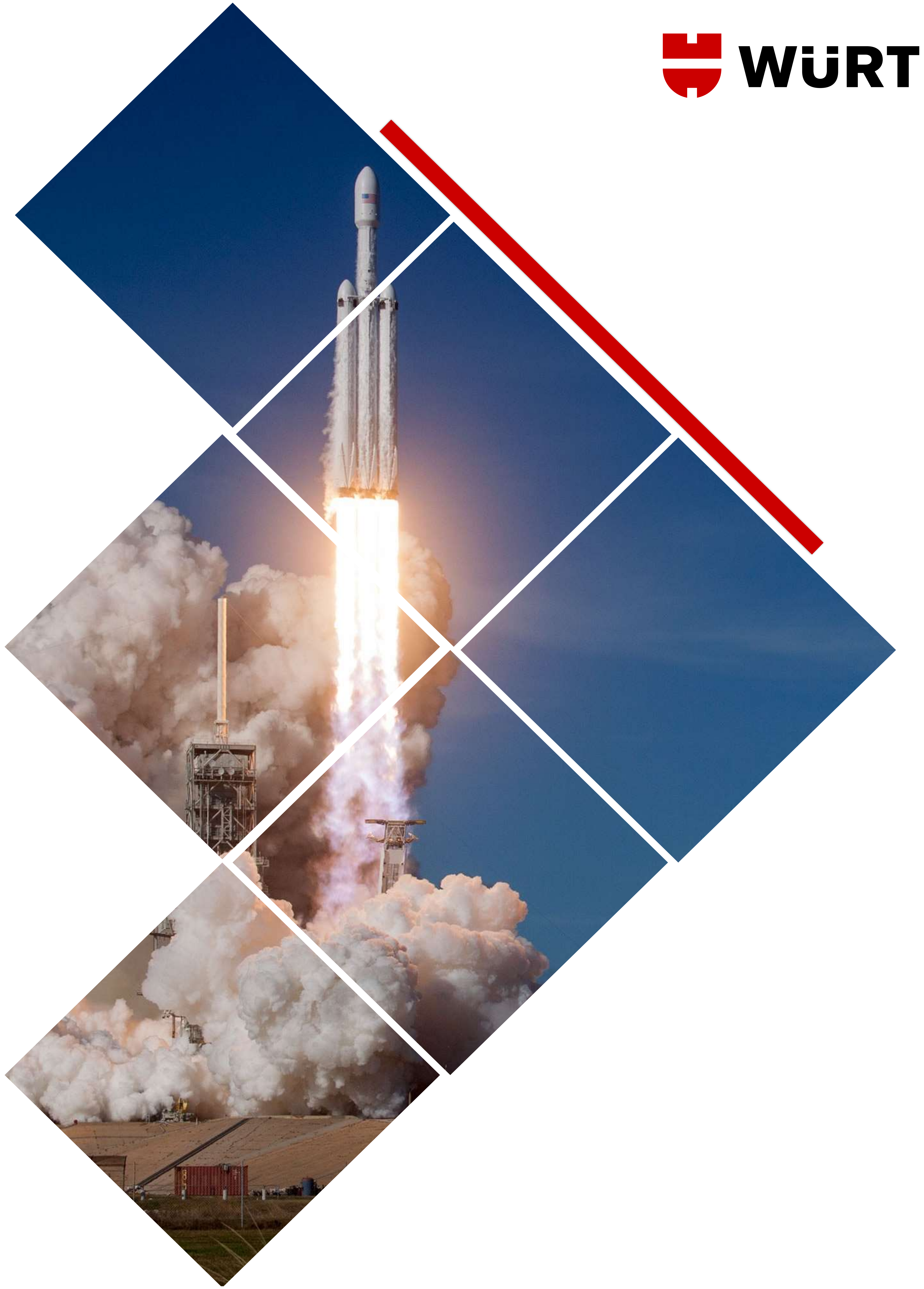


*in Mio EUR

Collaboratori di Würth Italia



La nostra Mission
Numeri 1 nella vendita



Vogliamo entusiasmare i nostri Clienti!

Amiamo la vendita. Ma non vogliamo semplicemente vendere. Vogliamo entusiasmare i nostri Clienti! Suggerire loro soluzioni inaspettate, creative e adatte alle loro esigenze. Per aiutarli a far crescere il loro business.

La nostra Vision
100%Qualità.
100% Servizio.

Il nostro nome contiene una promessa

Il marchio Würth è sinonimo di qualità superiore,
servizio eccellente e affidabilità assoluta.
Una solidità dimostrata. Sigillata e impressa.

La nostra Strategy
Ad ogni Cliente la sua Würth!

Ogni Cliente è un mondo a sé.

Piccole o grandi imprese, operanti a livello nazionale o internazionali, hanno tutte differenti necessità. Perché ogni Cliente è un mondo a sé, e noi le seguiamo con servizi personalizzati e tagliati su misura in base alle sue richieste.

A un passo da te

Grazie ad una forte presenza logistica, agli oltre 2.500 Tecnici Venditori qualificati e agli oltre 200 Punti Vendita sparsi su tutto il territorio nazionale, siamo in grado di seguire da vicino ogni Cliente.

Consulenza a 360°

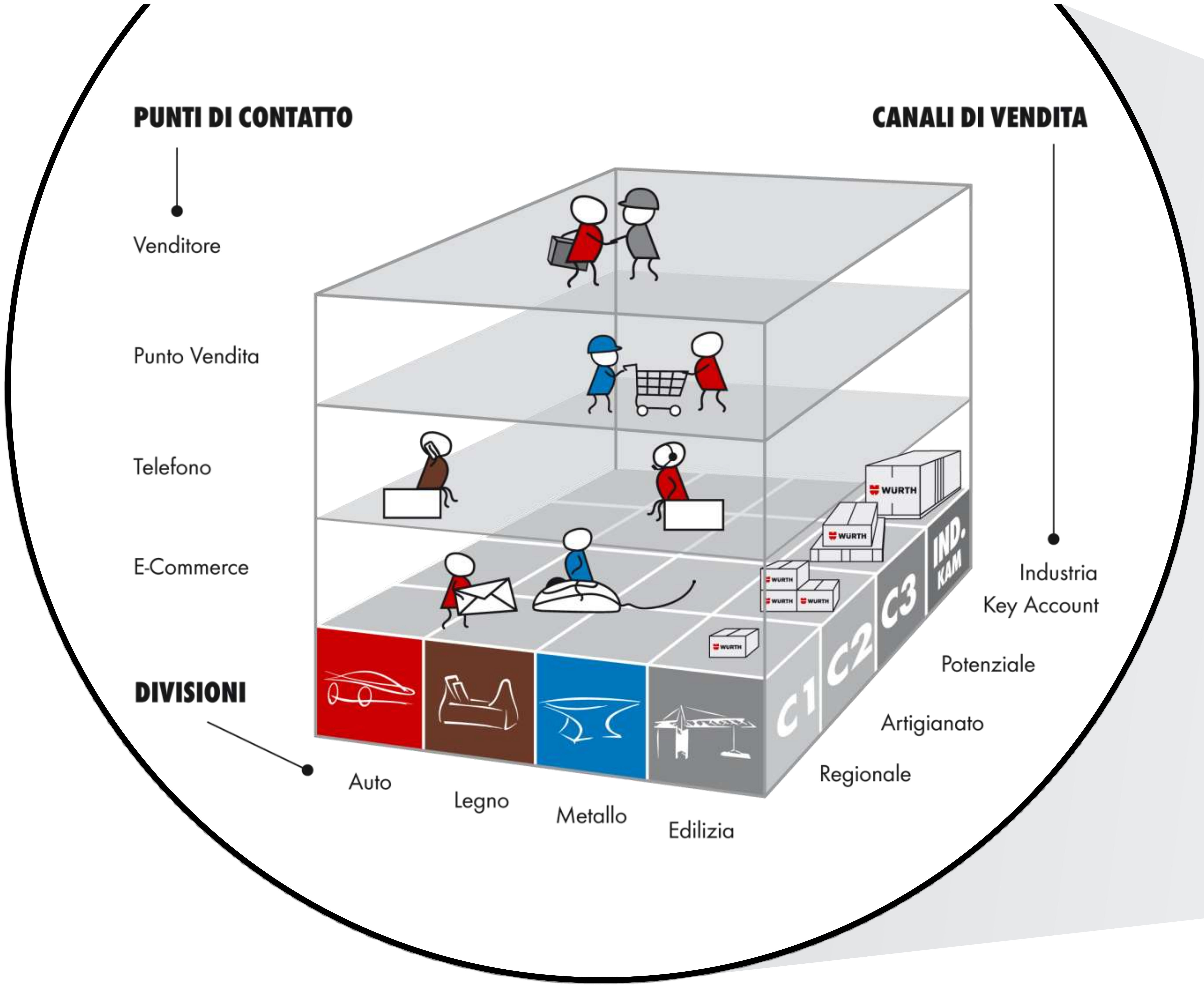
Consulenza su prodotti, assistenza in fase di progettazione, dimensionamento dei sistemi completi, studio di nuovi componenti, predisposizione di materiali tecnici e sopralluoghi. Per affiancare la nostra clientela a 360°.

WÜRTH

Ufficio Tecnico e Assistenza diretta sul campo

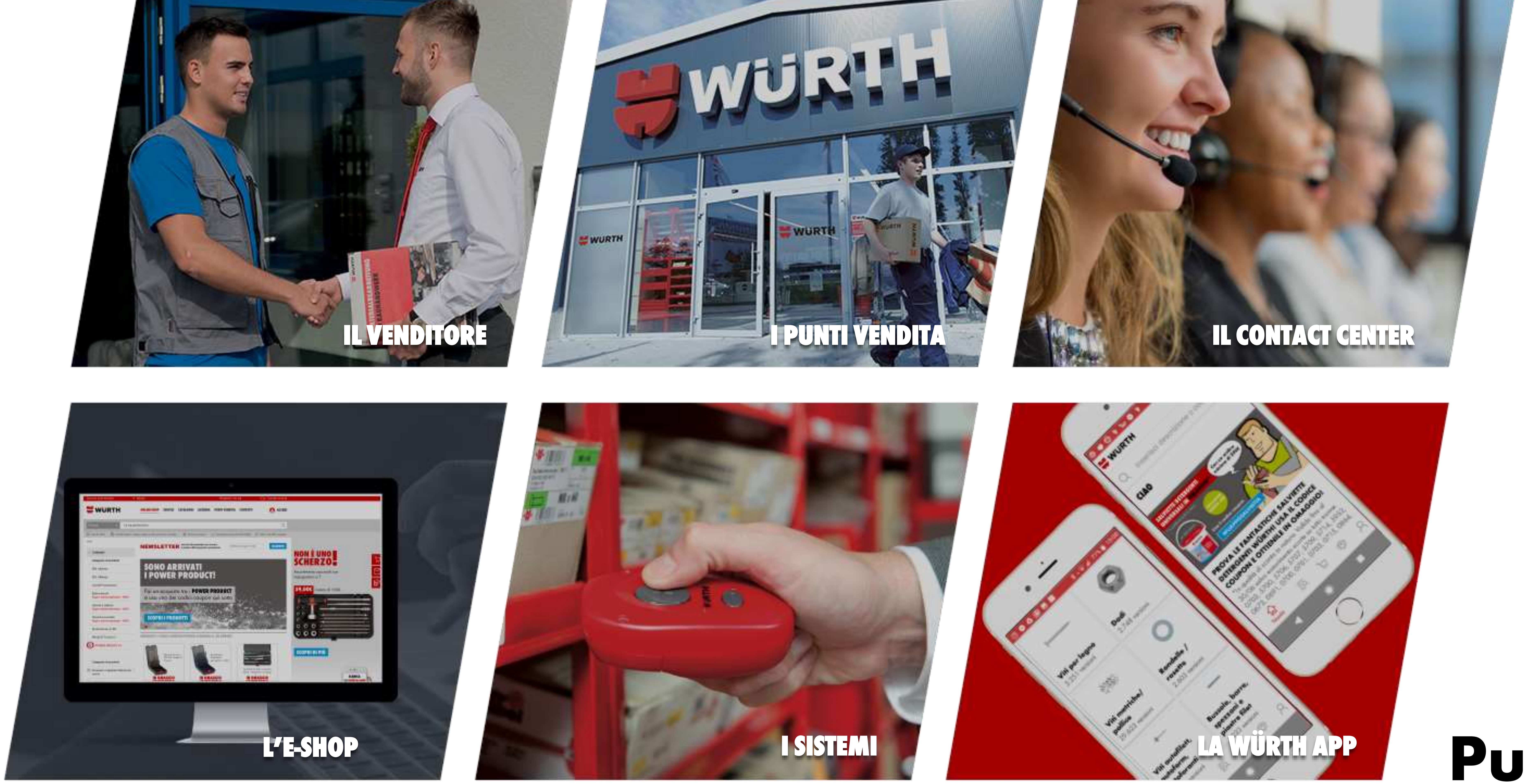
Un team qualificato di ingegneri e tecnici specializzati al servizio del Cliente, in grado di offrire supporto in fase di progettazione e installazione e garantire l'utilizzo migliore delle gamme tecniche proposte tramite servizi di consulenza e lo sviluppo di documentazione tecnica.

Il nostro modello di Business



Divisioni di Vendita

Nel tempo la gamma dei prodotti Würth si è **sempre più specializzata**, con il vantaggio di avere un partner unico ma di poter disporre di molte soluzioni specialistiche. Questo è il valore di un grande Gruppo come Würth Italia, con **8 Divisioni di Vendita** per soddisfare le esigenze di ogni singolo Cliente nei diversi ambiti merceologici.



Punti di Contatto

Comunicazione e servizi si moltiplicano

Il nostro compito è quello di soddisfare le esigenze di qualsiasi tipologia di cliente. Perché ogni richiesta ha bisogno di risposte precise, ogni problematica di soluzioni puntuali, ogni Cliente di servizi personalizzati in base alle sue necessità.

LOGISTICA W-IT

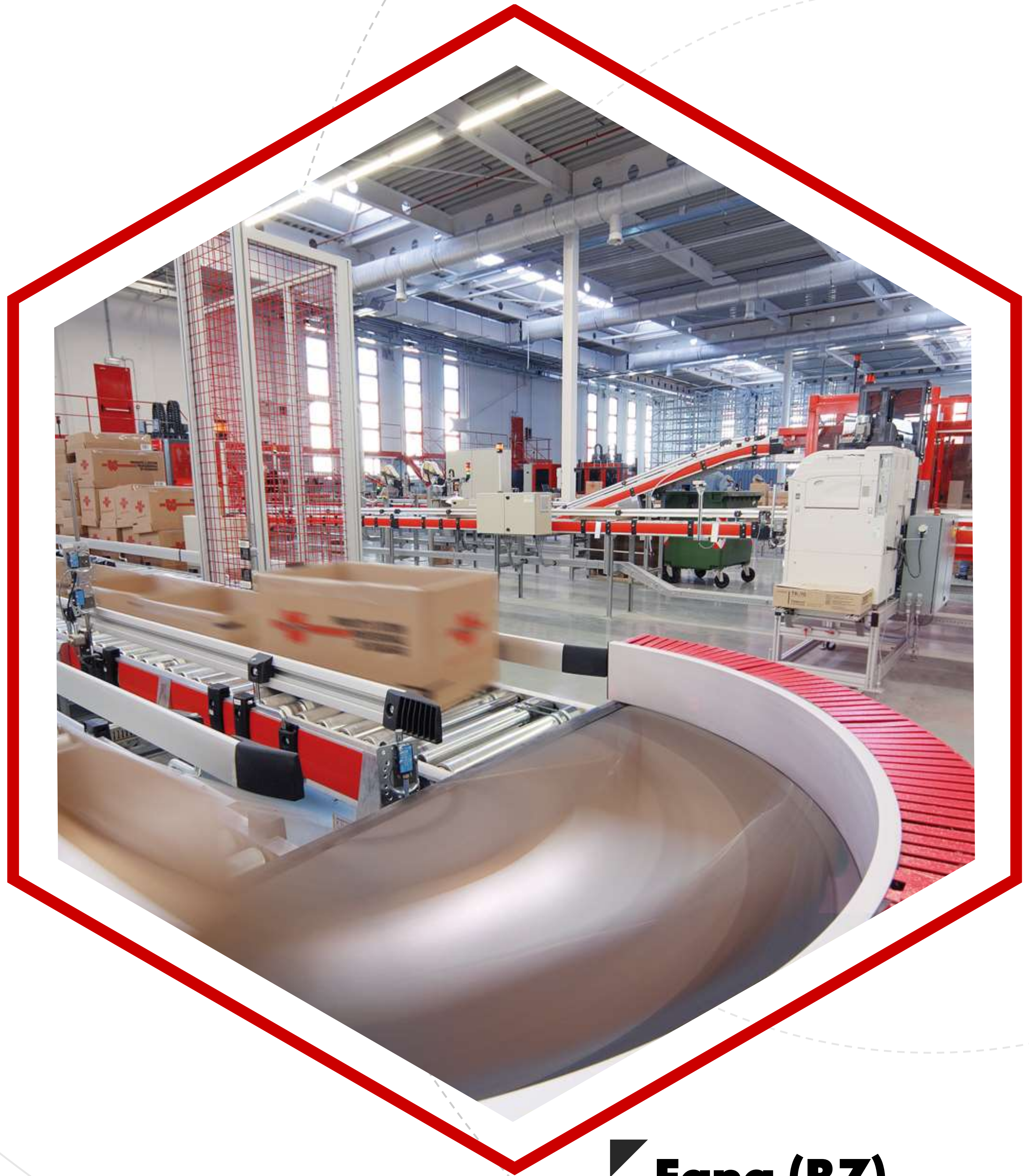
Le sedi
e i centri logistici

Würth Srl ha fissato a **Egna** (Bolzano) la propria Sede legale e amministrativa, dove si trova anche il deposito centrale. È inoltre presente sul territorio nazionale con un Centro Logistico a **Crespellano** (Bologna) e uno a **Capena** (Roma), che dal 2006 ospita anche uffici e servizi.

Media grado di servizio: 99%

La percentuale delle posizioni disponibili a magazzino e quindi evase, rispetto al totale delle posizioni entrate

Dati Logistici



Egna (BZ)
ca. 34.000 m²

Capena (RM)
ca. 30.000 m²

60%
Percentuale ordini evasi in giornata

17.000/gg
Colli/gg

33.000/gg
righe d'ordini

190 t/gg
Volumi evasi

10.000/gg
Ordini /gg

LOGISTICA EGNA RINNOVAMENTO ED ESPANSIONE

WÜRTH
WÜRTH
MENDEL SPECK
WÜRTH
WÜRTH


WÜRTH

Logistica Impatto ZERO

L'edificio è realizzato con le più moderne tecniche di isolamento e con l'energia prodotta da un impianto fotovoltaico di 200 KWp, installato sulla copertura dell'edificio, ed un impianto geotermico da 180 kWp, con le sonde geotermiche installate all'interno dei pali di fondazione.

Highlights nuova Logistica Egna

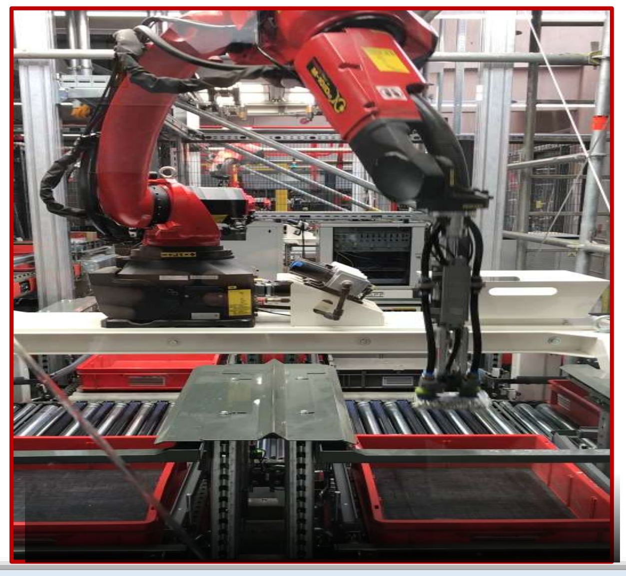
Magazzino automatico (Shuttle)


AGV - AMR


Commissionamento GtP:
Postazioni ad alta prestazione
e POSTAZIONI MULTIFUNZIONALI / VAS


Robot
- Pallettizatori
- Depallettizzatori
- Picking

Automazione e Digitalizzazione dei Processi Logistici



AUTOMAZIONE

DIGITALIZZAZIONE

GOODS RECEIVING

- Robot per deconsolidamento automatico
- Controllo peso automatico in entrata merci
- Notifica della spedizione dal fornitore

TRANSFERS

- Aree di magazzino connesse da nastro trasportatore
- Spostamento merci fatto da AGV / AIV
- Trasferimenti guidati da RF e percorsi ottimizzati

PICKING

- Strategie di picking GtP:
  - robot per picking automatico
  - picking GtP ad alte prestazioni
- Sistemi pick by e pick to light systems / sequenziamento dei pick

PACKAGING

- Creazione e chiusura automatica dei cartoni
- Riduzione volume, applicazione etichette e inserimento documento automatici
- Case calculation ottimizzata e rilevamento volume

SHIPPING

- Pallettizzazione automatica
- Buffering delle spedizioni nello shuttle
- Consolidamento delle spedizioni


WÜRTH
SOSTENIBILITÀ
Sostenibilità

OBIETTIVO:

RIDUZIONE DELLE EMISSIONI INQUINANTI ENTRO 2030

RIDUZIONE DEI CONSUMI

PRODUZIONE ENERGIA RINNOVABILE

COMPENSAZIONE DELLE EMISSIONI NON EVITABILI


GREEN CAR POLICY
WÜRTH
Nel 2026 passeremo da 512 auto
a basse emissioni
A oltre 1.600 auto
a basse emissioni


WÜRTH
Abbiamo una produzione di
2MW di energia solare
tra EGNA e CAPENA

WÜRTH

Le nostre forniture di energia elettrica

sono **100% green**

in **sedi** e **negozi**

WÜRTH

Produciamo **ENERGIA GEOTERMICA** nel Zero Impact Logistic Hub

WÜRTH

1 ALBERO PER OGNI COLLABORATORE
= 4.000 ALBERI

10.000 NUOVI ALBERI PIANTATI DAL 2023 IN 12 AREE ITALIANE

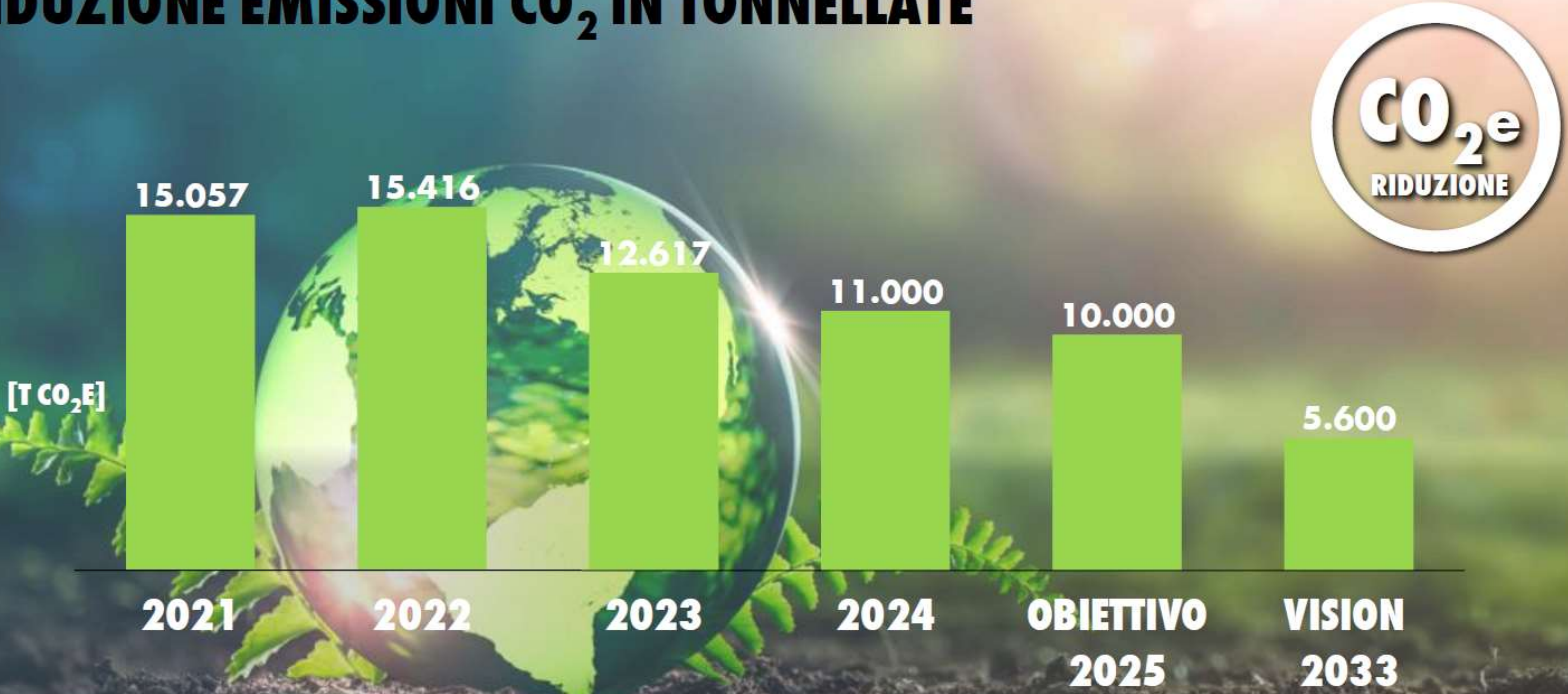
1 ALBERO PER OGNI CLIENTE ENTRO IL 2026
=350.000 ALBERI

OBIETTIVO 2030
1.000.000 ALBERI

IL NOSTRO PERCORSO VERSO UN'ECONOMIA CIRCOLARE

WÜRTH

RIDUZIONE EMISSIONI CO_2 IN TONNELLATE

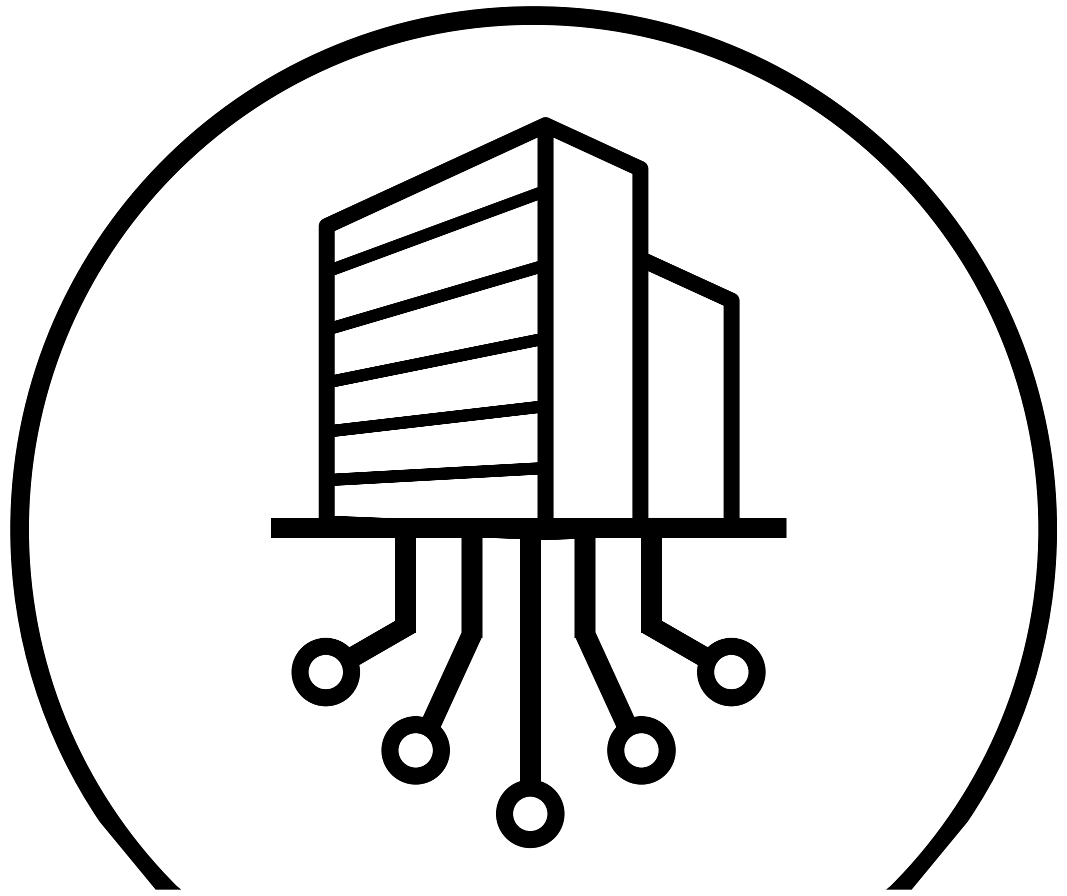



Azienda Digitale Würth
www.wuerth.it/aziendadigitale

WÜRTH

Azienda Digitale

Fai risparmiare tempo e denaro alla tua azienda.
Digitalizza e automatizza i processi di acquisto per prodotti
Würth nella tua azienda.



UFFICIO ACQUISTI 4.0 + SUPPLY CHAIN MANAGEMENT

wuerth.it/aziendadigitale

Accordi commerciali nel mondo dell'auto e moto

FCA FIAT CHRYSLER AUTOMOBILES
ALFA ROMEO
LANCIA
FIAT
FIAT PROFESSIONAL
ABARTH
Jeep
MASERATI
Ferrari

Audi
SEAT
ŠKODA
PORSCHE
LAMBORGHINI
PEUGEOT
KIA

Mercedes-Benz
MINI
smart
BMW
VOLVO
CITROËN
DS AUTOMOBILES
DUCATI

OPEL
Ford
TOYOTA
GM
LEXUS
NISSAN
HYUNDAI
SSANGYONG
INFINITI

WÜRTH | 60

Accordi commerciali nel mondo dell’auto e moto

MICHELIN
BRIDGESTONE
Continental
ACI GLOBAL

PIRELLI
EUROMASTER
Pneumatici e Manutenzione Veicoli
GOMME & service
NOI professionisti del pneumatico
MIDAS

Driver
PNEUMATICI E ASSISTENZA
AsConAuto
Associazione Nazionale Consorzi Concessionari Auto
UniAuto
Unione Consorzi Concessionari
BestDrive
You drive, we care.

IFSIC
Franchising • Service • Company S.p.A.
Società del Gruppo Continental AG

WÜRTH | 60

Accordi commerciali nel mondo dell'artigianato

enel · RIELLO · Siram by VEOLIA · EDISON EDF GROUP · SIAD · Veneta Cucine Progetti di Vita

Electrolux · LEONARDO · MANUTENCOOP FACILITY MANAGEMENT SPA · Terna Rete Italia TERNA GROUP · 2i Rete Gas · GRANA PADANO

LIDL · IKEA · MSC CROCIERE · Dussmann · SAIPEM · eni · DS Smith · Henkel · Smurfit Kappa

mondi · Virgin ACTIVE · FRI-EL GREEN POWER THE CLEAN ENERGY COMPANY · FERRETTI GROUP PASSION. INNOVATION. EXCELLENCE. · AZIMUT YACHTS · iren

amazon · OMYA · Air Liquide creative oxygen · FERSERVIZI GRUPPO FERROVIE DELLO STATO ITALIANE · ivsitalia.com LEADER NELLA RISTORAZIONE AUTOMATICA · NORDEX · PETRONAS

THE LINDE GROUP Linde · Ali GROUP · Tetra Pak PROTECTS WHAT'S GOOD · Schindler · Sirti · IMA SPA Sustain Ability · Culligan · ceam · ILCAM FURNITURE FRONTALS

Accordi commerciali nel mondo del cargo

IVECO · VOLVO · MAN · SCANIA · MASSEY FERGUSON

AGCO · FENDT · LAVERDA · TOYOTA INDUSTRIAL EQUIPMENT · LIEBHERR

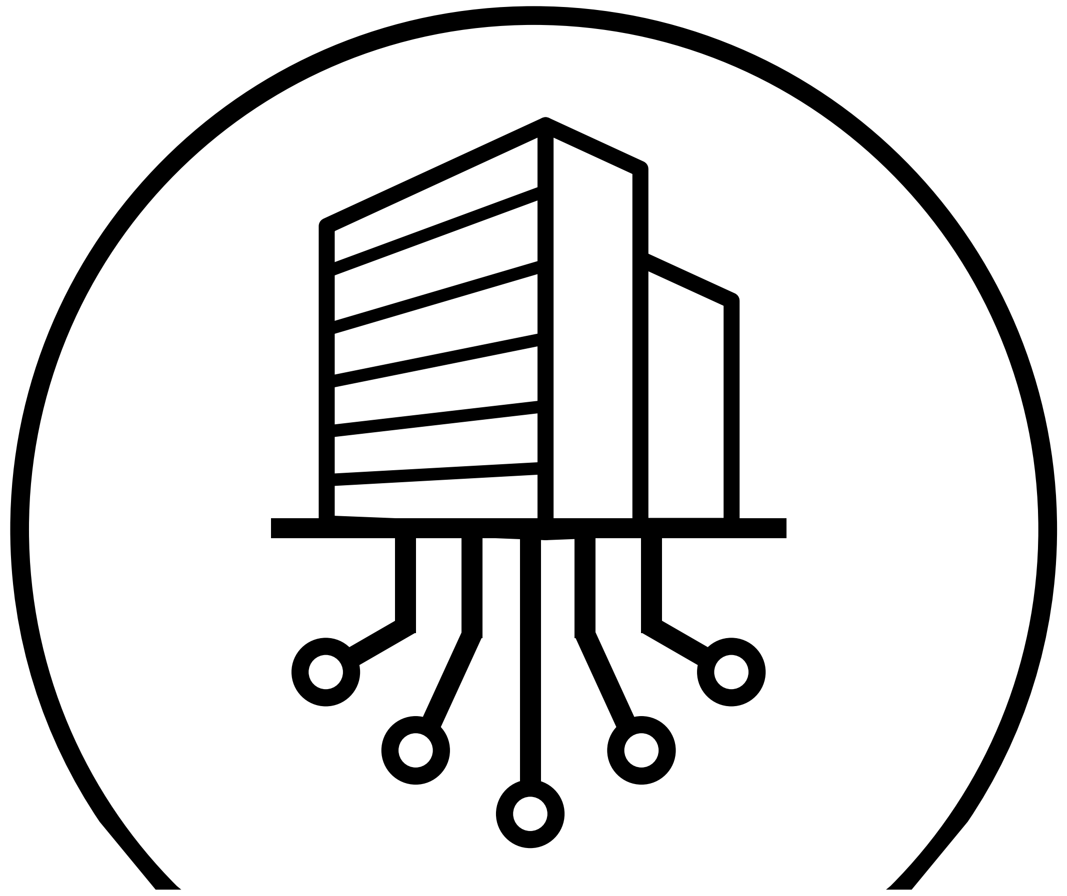
JCB · Linde Material Handling Linde · SAME DEUTZ-FAHR · CLAAS

BRT CORRIERE ESPRESSO · CNH INDUSTRIAL · GLS · FERCAM · NEW HOLLAND CONSTRUCTION · NEW HOLLAND AGRICULTURE

WÜRTH | 60

Azienda Digitale

Fai risparmiare tempo e denaro alla tua azienda.
Digitalizza e automatizza i processi di acquisto per prodotti Würth nella tua azienda.



UFFICIO ACQUISTI 4.0 + SUPPLY CHAIN MANAGEMENT

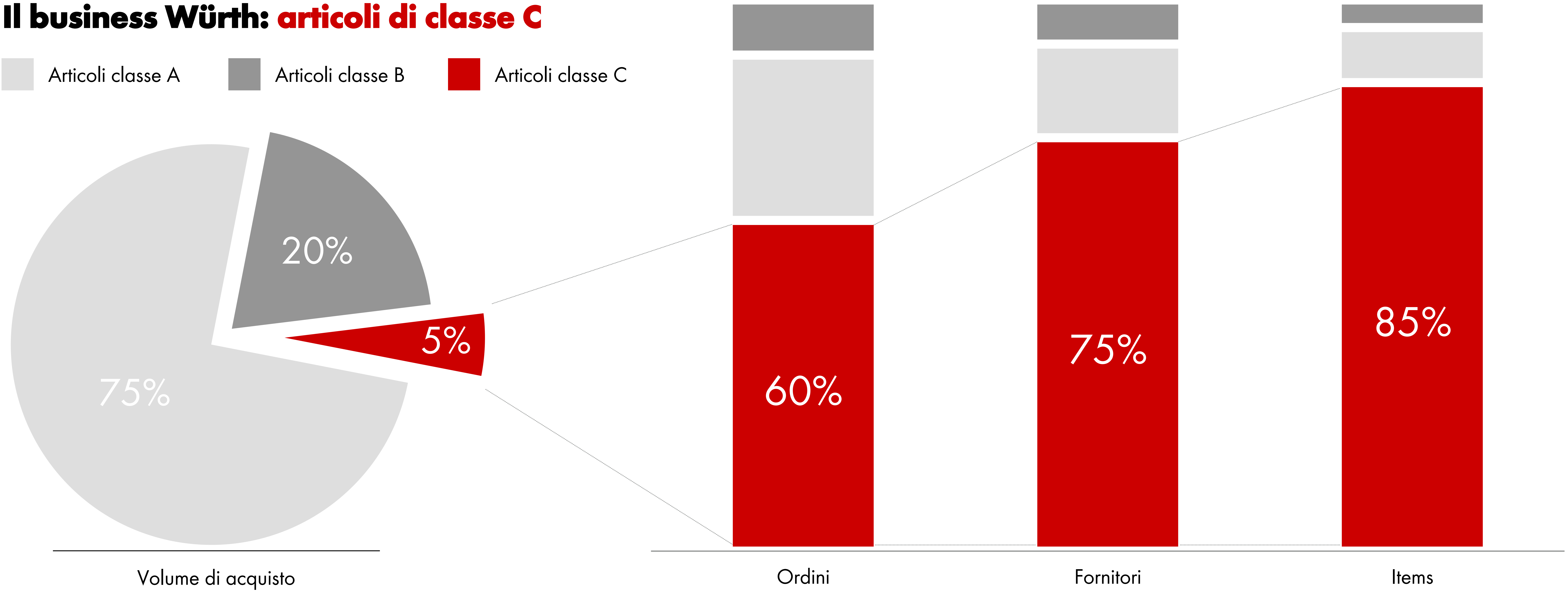
wuerth.it/aziendadigitale

Servizi/Soluzioni

La gestione degli articoli di **classe C** attraverso servizi e soluzioni dedicati.

Il 5% impiega tutte queste risorse

Il business Würth: articoli di classe C



Costo totale per il Cliente

dei componenti di **classe C**

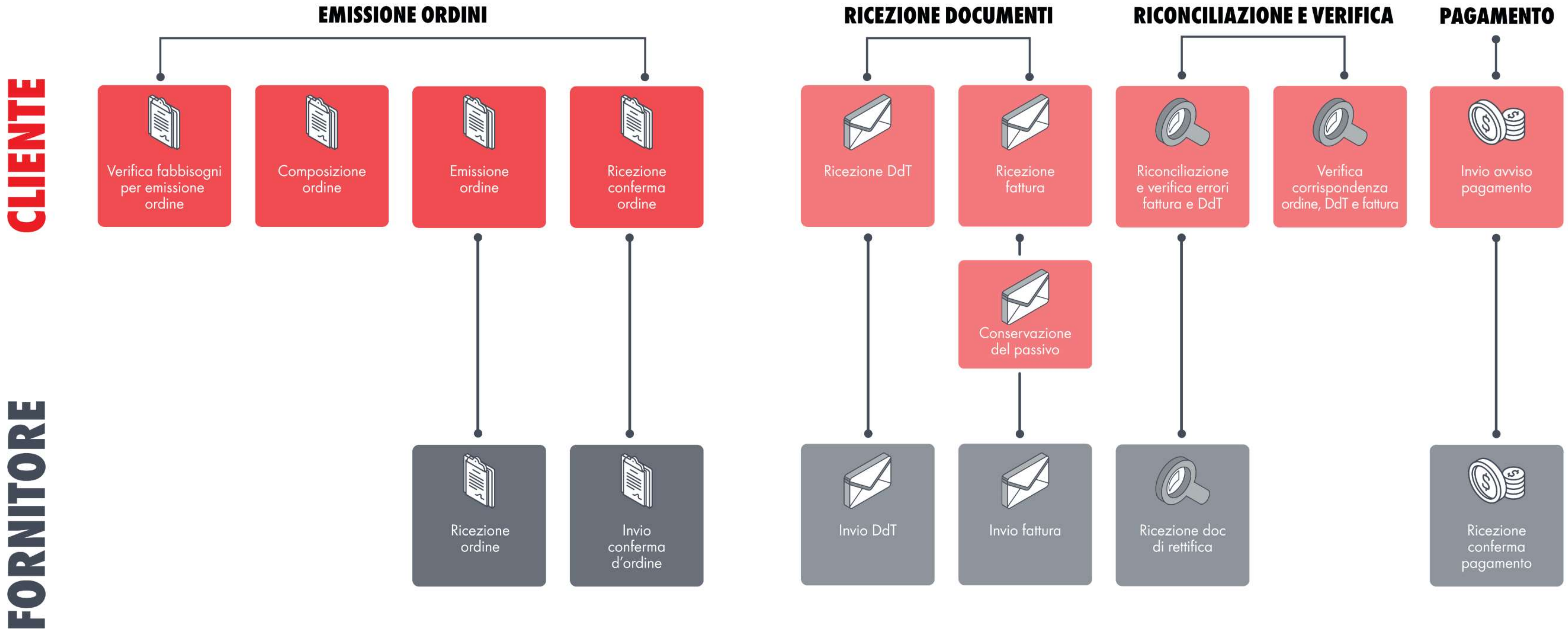
Costo totale degli articoli di **classe C**

Costo del materiale ~15%

Costo dei processi
per acquisto, gestione e previsione della domanda ~65%

Costo dei processi
mancato utilizzo delle macchine, risorse per rotture di stick, ecc... ~20%

COSA COMPORTA GESTIRE UN ORDINE IN UN AZIENDA?
QUANTE SONO LE ATTIVITÀ CHE COSTANTEMENTE BISOGNA SVOLGERE?

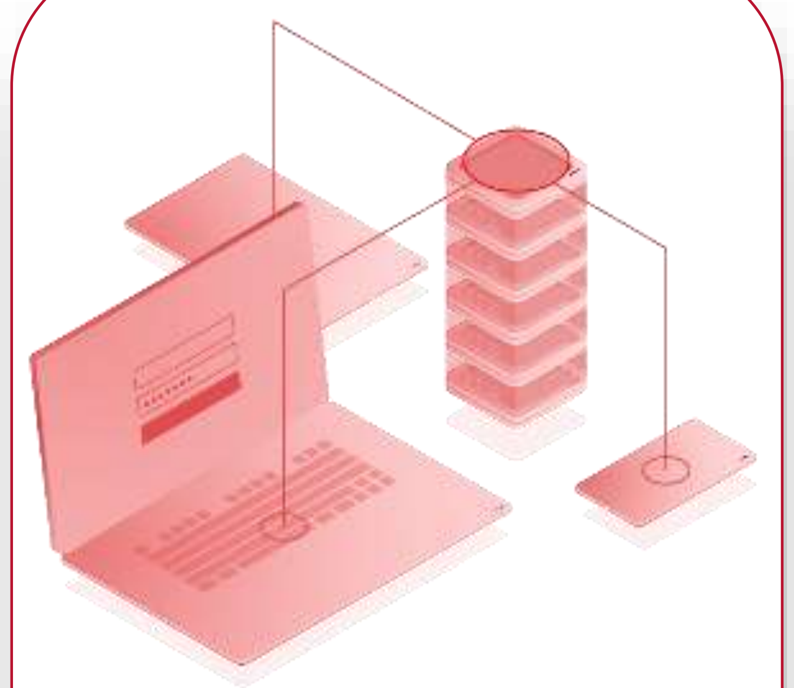


CHE SOLUZIONI PROPONE WÜRTH?

WÜRTH

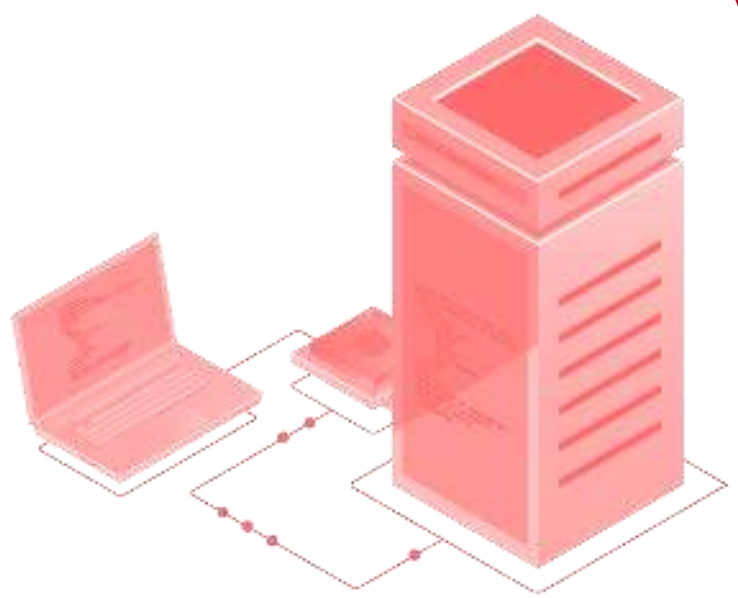
- **Sistemi logistici**
  - Vending machines
  - Kanban
  - Scaffali Orsy
- **Soluzioni eProcurement**
  - eShop
    - Würth APP
  - EDI
    - Ordini
    - Conferme Ordine
    - DDT
    - Fatture
    - Varie
  - B2B
    - Punch-Out
    - Cataloghi
  - OCI
  - API
  - SSO

SOLUZIONI E-PROCUREMENT



Eshop
Ecommerce website

Piattaforma digitale che consente ai clienti di acquistare prodotti tramite Internet.

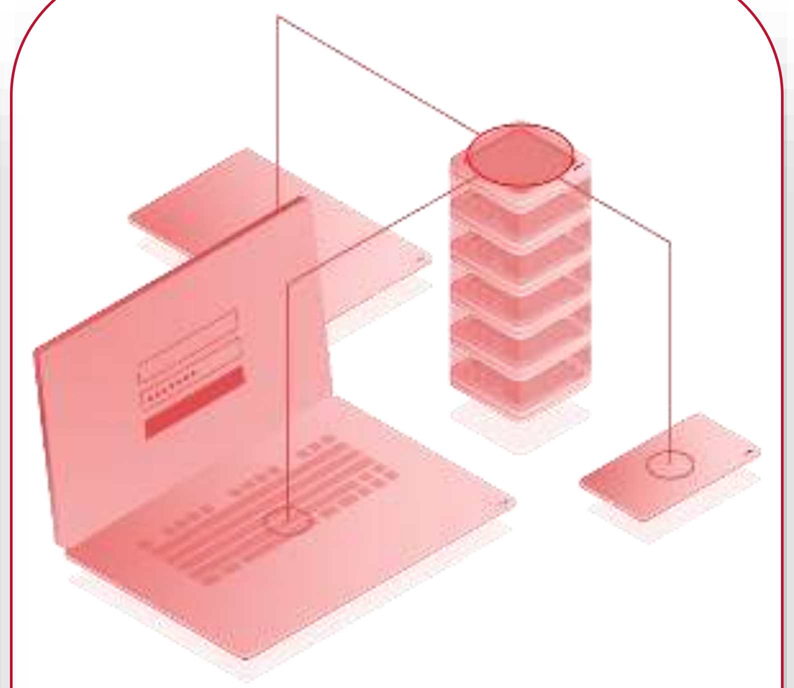


EDI
Electronic data Interchange

Flusso di informazioni e documenti automatic e digitalizzato (csv, xml...)

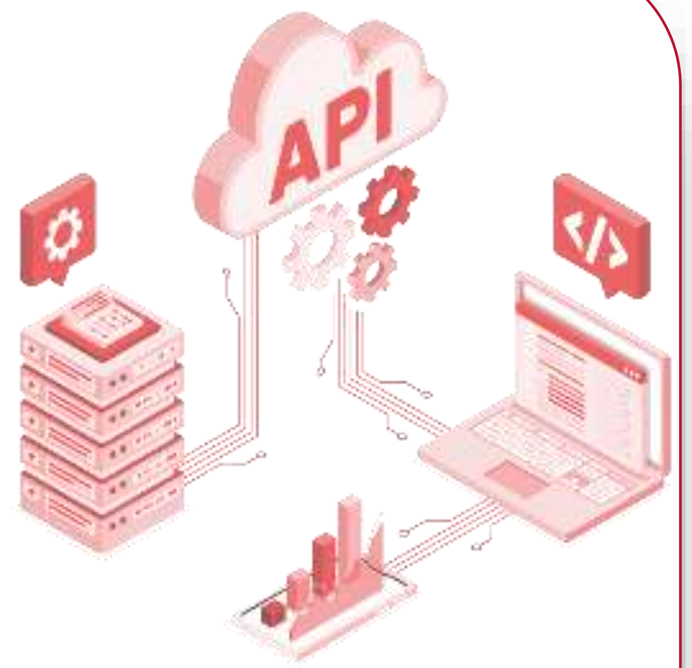
B2B
Business to Business Marketplace

Integrazione con i principali Marketplace (SAP Ariba, Jaggaer, Coupa, SupplyOn...)



OCI
Open Catalog Interface - Punchout

Integrazione e interfaccia con Würth Online Shop all'interno del ERP SAP



API
Application Programming Interface

Accesso su richiestaad informazioni presenti nel database Würth.

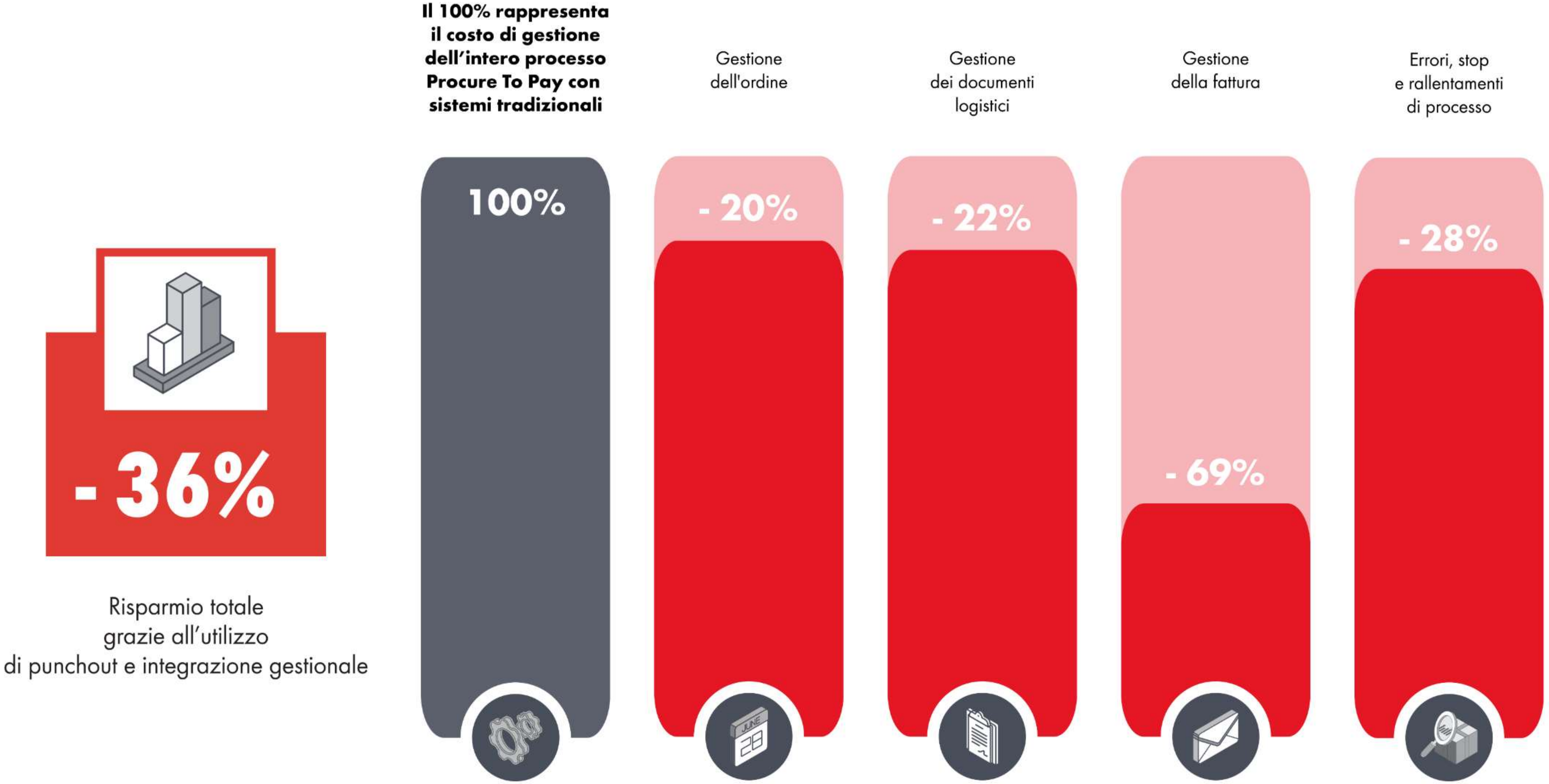
SSO
Single Sign On

Accesso diretto al Würth Online Shop con un solo set di credenziali

COME MIGLIORA LA PRODUTTIVITÀ IN UN'AZIENDA GRAZIE A PUNCHOUT E INTEGRAZIONE GESTIONALE IN TERMINI DI COSTI?

Processo digitalizzato

Processo tradizionale



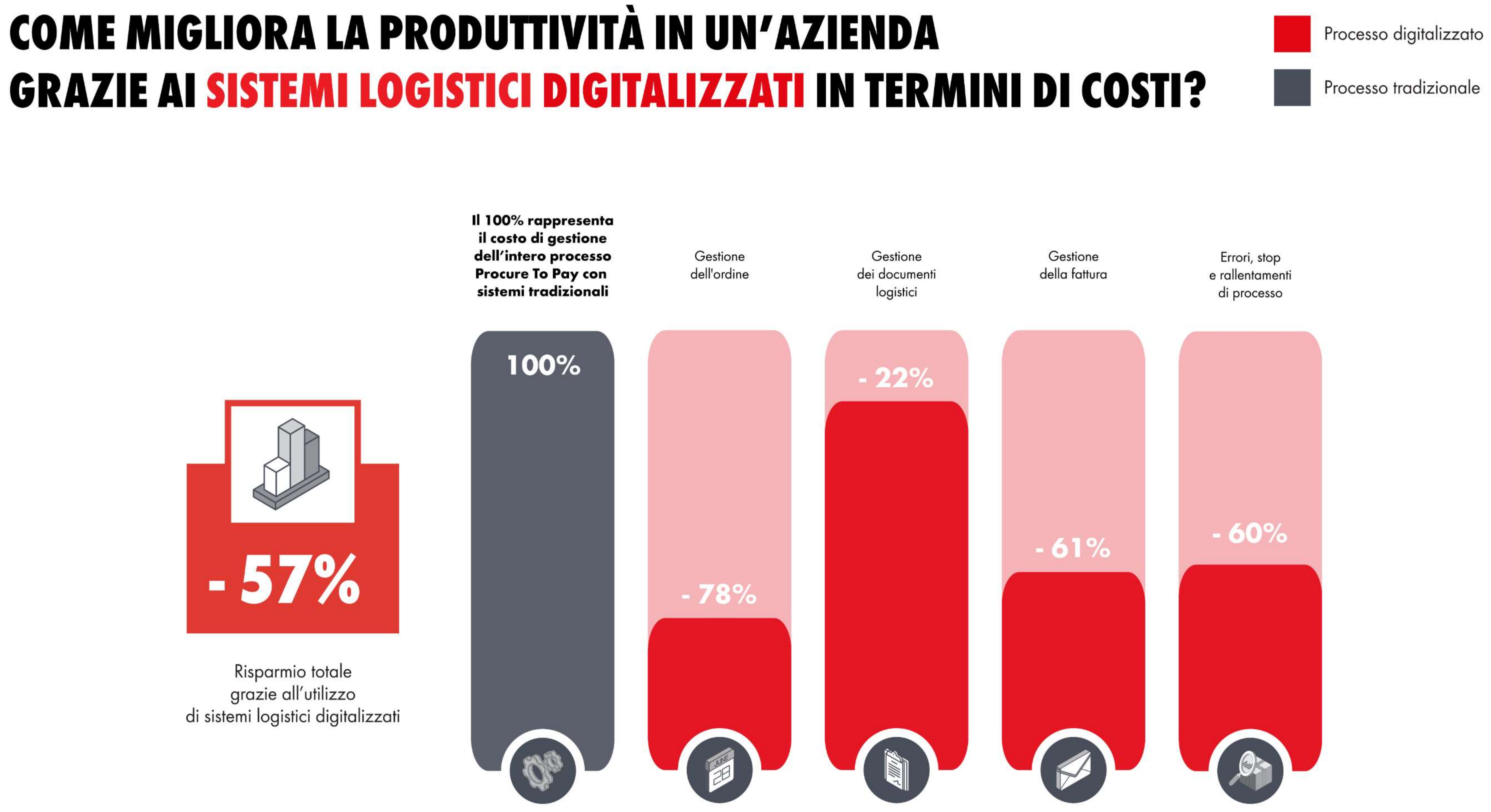
SISTEMI LOGISTICI

ORSY® = ORder SYstem
Il sistema modulare componibile e personalizzabile per creare e mantenere in ordine il magazzino

Servizi Kanban
Soluzioni per migliorare i processi di approvvigionamento e gestione degli articoli di classe C, sfruttando la tecnologia RFID per automatizzare le attività di riordino

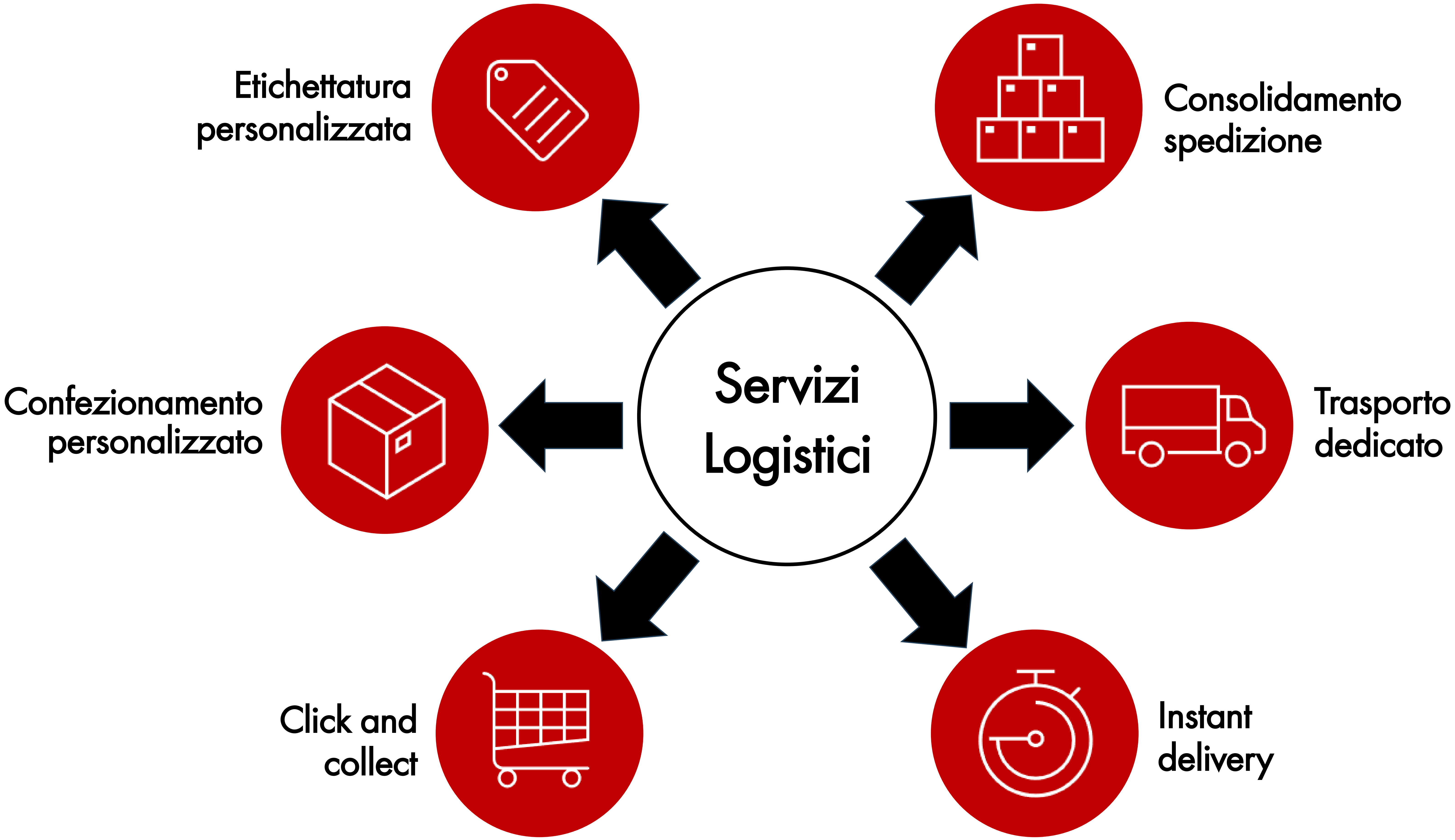
Distributori Orsymat®
Distribuzione automatica dei prodotti tramite sistemi a piatti, cassetti o bilance, con tracciamento e identificazione dei prelievi

Piattaforme tracciamento dati
Per l'analisi dei consumi e monitoraggio dei KPI di produzione



COME MIGLIORA LA PRODUTTIVITÀ IN UN'AZIENDA
GRAZIE AI SISTEMI LOGISTICI DIGITALIZZATI IN TERMINI DI COSTI?
Processo digitalizzato
Processo tradizionale
Il 100% rappresenta il costo di gestione dell'intero processo Procure To Pay con sistemi tradizionali
Gestione dell'ordine
Gestione dei documenti logistici
Gestione della fattura
Errori, stop e rallentamenti di processo
100%
- 78%
- 22%
- 61%
- 60%
- 57%
Risparmio totale grazie all'utilizzo di sistemi logistici digitalizzati

Come la logistica di Würth
semplifica il processo?



E molto altro...
Scoprilo con noi!

CASE HISTORY

Case History 1

Processo logistico e integrazione di sistema

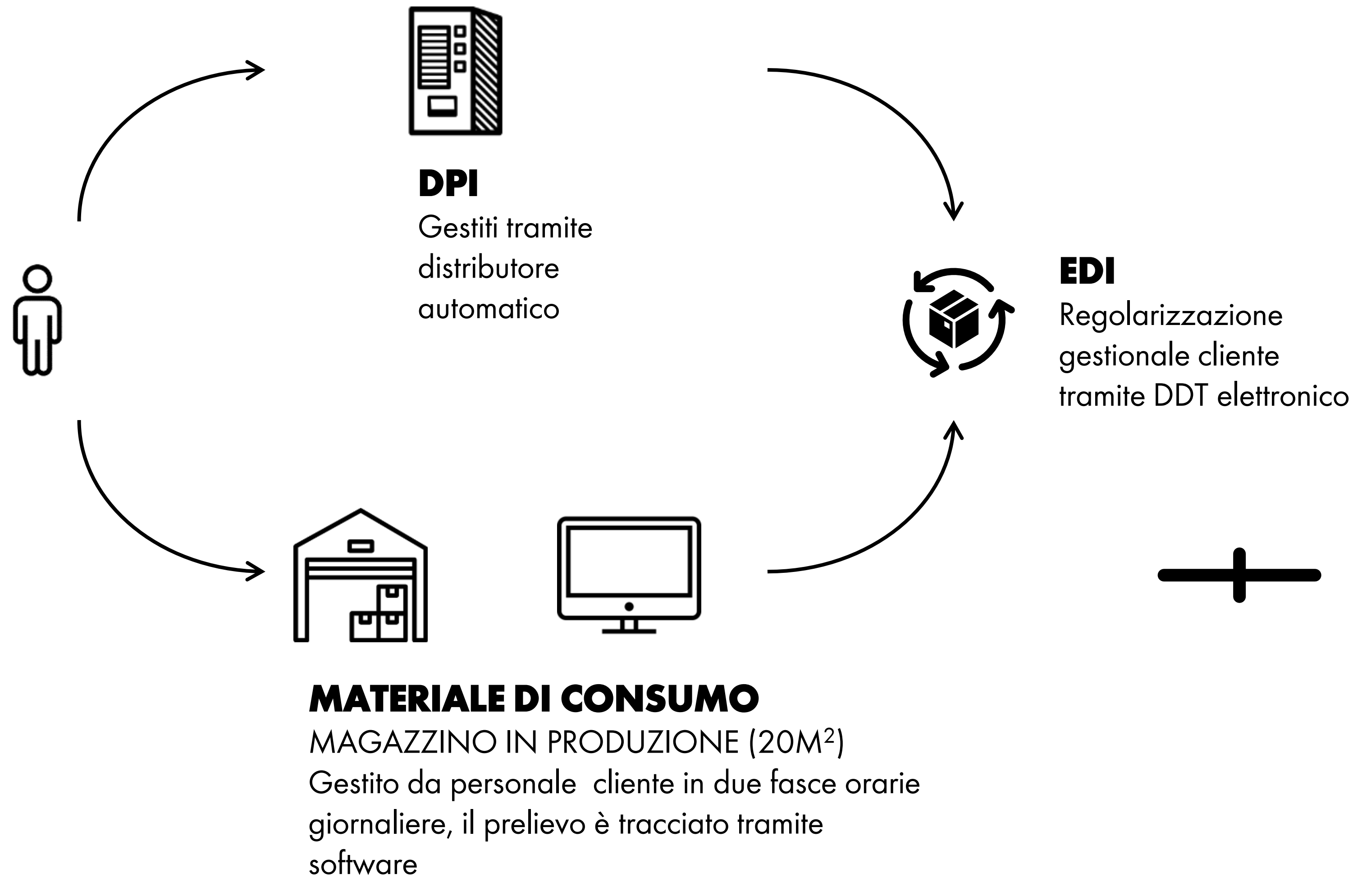
LOGISTICA CLIENTE AS-IS

Gestione del materiale di Consumo e DPI:

- Tutti i responsabili di linea avevano accesso al magazzino
- Nessun controllo sui prelievi
- 94% delle lavorazioni affidato a terzisti
- Spesa fuori controllo

Soluzione implementata

Soluzione implementata



93%

Articoli tracciati

30%

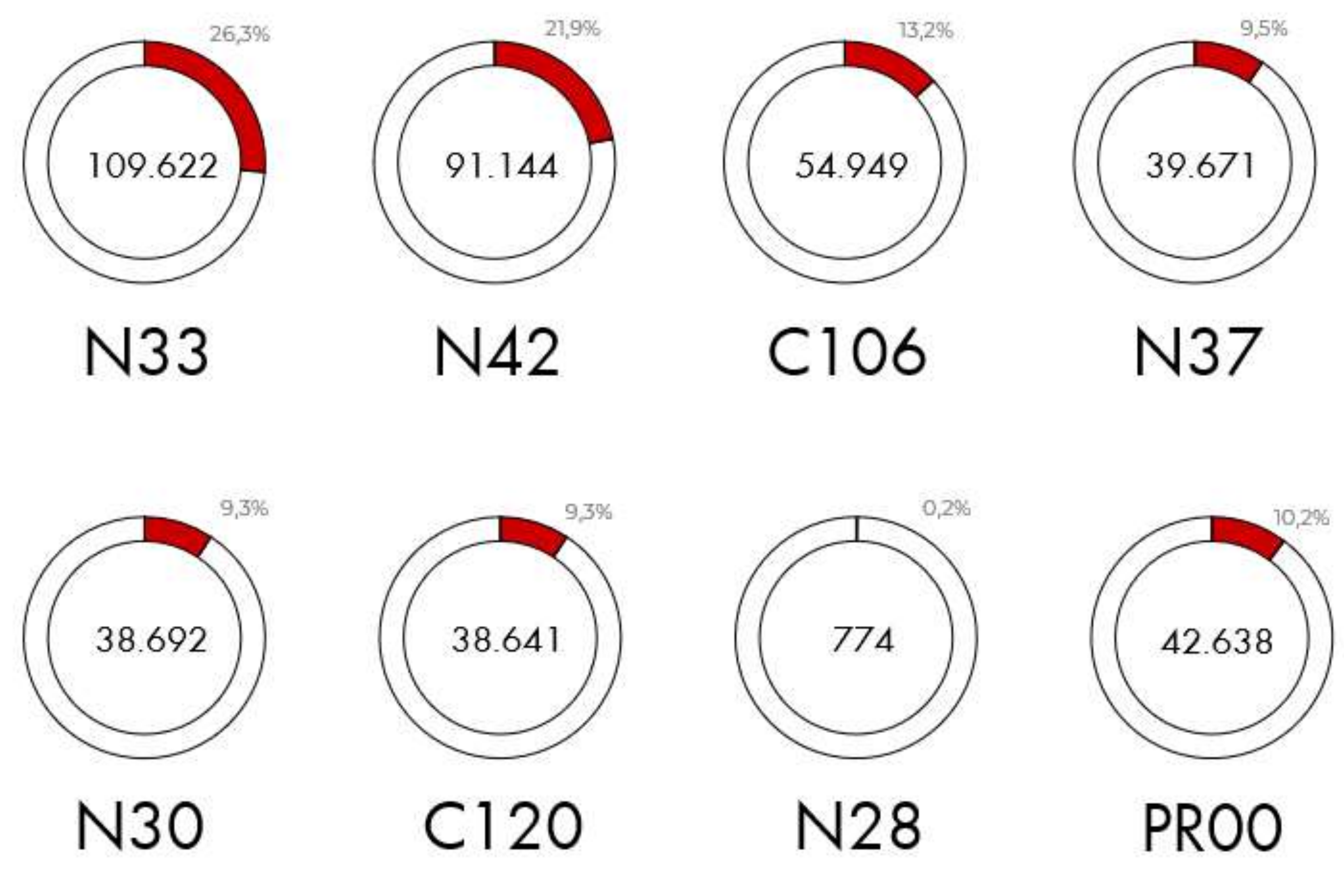
Riduzione sprechi

Creazione database statistico

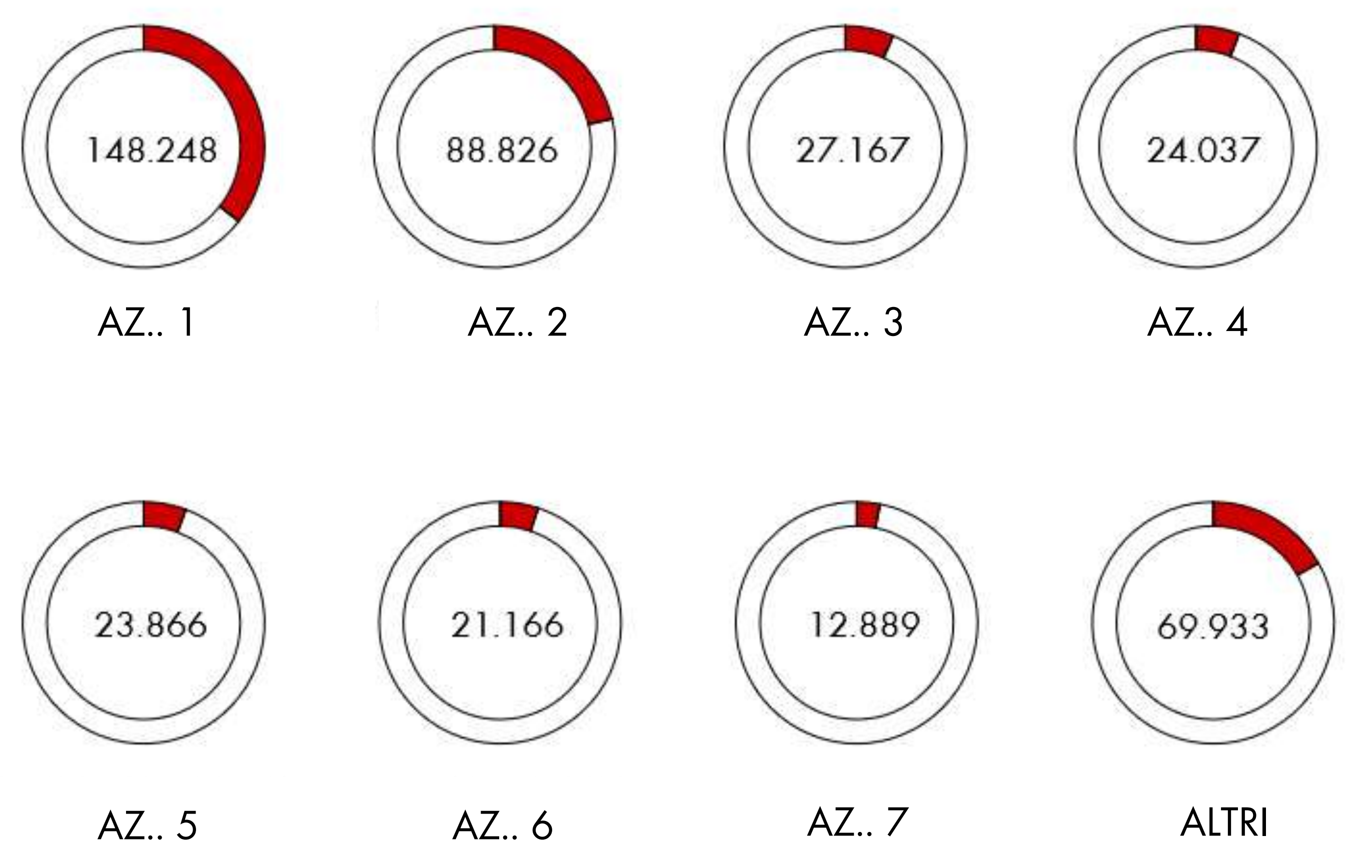
Database centralizzato per il cliente

WÜRTH

Prelevato per Linea



Prelevato per Azienda



ANALISI PRELIEVI – OP. C211

[SC]MTG VETRI A SCAFO CABINE LD

- Linea N42
- Azienda: AZ.1

ARTICOLO	#05	#06
DETERGENTE SIKA CLEANER 205 1LT	1	1
PRIMER SIKA AKTIVATOR P/VETRI 1LT	1	1
SILICONE SIKAFLEX 296 NERO 600ML	40	40
NASTRO CARTA 50X50 3M2328	2	2
NASTRO P/MASC. BLU 50MMX50M	2	2
PELL. TRASP. ROSSA 500MMX100M		1

ANALISI PRELIEVI – OP. C318

[1SV]MTG CUBIE+TUBO CATENE+SCAR POZZO

- Linea N33
- Azienda: AZ.3

ARTICOLO	#14	#15
SILICONE 3M 5200FC	24	24
ADESIVO 3M 3200 MARINE		10
SILICONE WUERTH BIANCO	10	
NASTRO G77A BLUE 50X25MT		1
ADESIVO IN STICK	10	

possiamo ipotizzare che servano:
24 cartucce di 3M 5200 e 10 di silicone (3M o Wuerth?)

Case History 2

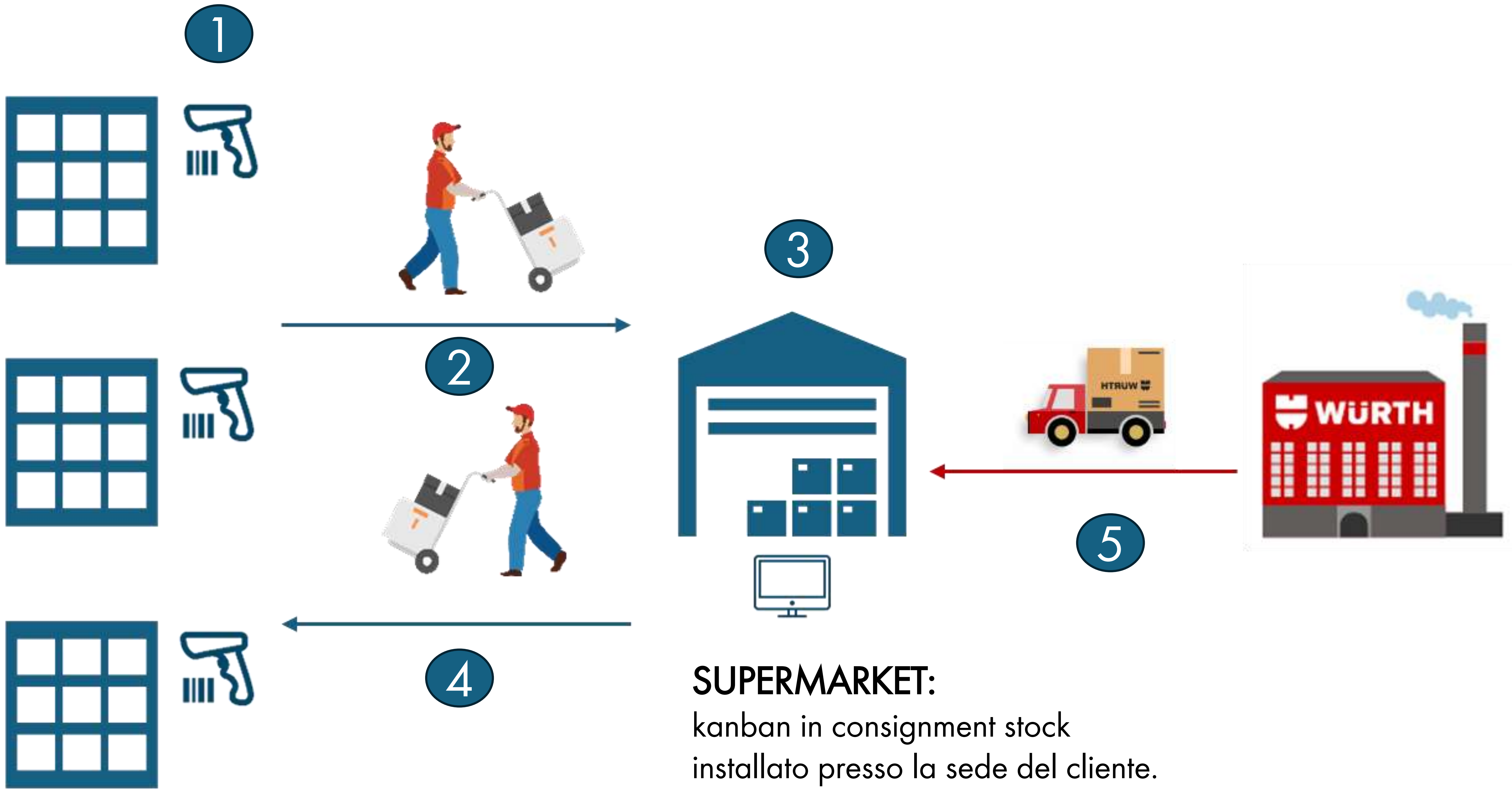
Ottimizzazione del processo logistico di approvvigionamento e distribuzione viteria

LOGISTICA CLIENTE AS-IS

Gestione della viteria:

- Numerosi fornitori coinvolti
- Fornitori non sempre affidabili
- Lead time di fornitura diversi
- Processo non standardizzato e time consuming per le figure aziendali

Soluzione implementata



SUPERMARKET:
kanban in consignment stock installato presso la sede del cliente.

BUFFER DI LINEA:
gestiti in logica kanban e dimensionati per assicurare il tempo di copertura richiesto ed evitare rotture di stock in linea.

1. Il refiller Würth gestisce il rifornimento delle **linee di produzione** del cliente. L'acquisizione delle etichette delle vaschette esaurite genera un ordine di ripristino.
2. Il refiller Würth trasferisce le vaschette vuote dalle linee al **supermarket in consignment stock** ubicato presso il cliente.
3. Appena ricevuto l'ordine di ripristino sul **portale dedicato** il refiller Würth riempie le vaschette vuote.
4. Le vaschette piene vengono riportate in linea.
5. Il replenishment del supermarket viene chiamato dal refiller Würth e alimentato direttamente dai magazzini Würth

Soluzione implementata

PUNTI DI FORZA:

- Ottimizzazione della gestione delle scorte:
    - Basso stock in linea (5 giorni alto-rotanti e 10 giorni basso-rotanti)
    - Gestione delle scorte sulle linee tirata dalla produzione del cliente
- Riduzione dei costi e dei tempi:
    - Abbattimento dei costi di gestione del magazzino per il cliente
    - Ottimizzazione dell'allocazione del tempo delle risorse del cliente che si possono dedicare ad attività a valore aggiunto
- Standardizzazione:
    - Standardizzazione del processo sia operativo sia informatico
    - Integrazione dei flussi con l'ERP cliente
- Partnership cliente – fornitore: costante presenza del personale Würth sul plant

Visita la nostra **Azienda Digitale**

WÜRTH

Azienda Digitale

Fai risparmiare tempo e denaro alla tua azienda.
Digitalizza e automatizza i processi di acquisto per prodotti Würth nella tua azienda.

https://www.wuerth.it/aziendadigitale/


Thank You!