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AI effect on Innovation Capacity in the context of Industry 5.0

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D

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FACULDADE DE **ECONOMIA**

BIOGRAPHICAL NOTES

Adrien Bécue (M) is AI & Cybersecurity Expert at Thales. He graduated from Toulouse Business School in 2003 with a Master's in Aerospace Management. In 2004, he joined the French Defence Procurement Agency (DGA) as a program purchaser for land weapon systems. In this position, he managed a portfolio of industrial and research projects driven by Network-Centric Warfare and Digital Battlefield transformations. He joined the EADS group 2008 to manage acquisition programs in Tactical Communication systems for the French Navy and the International Security Assistance Force (ISAF) deployed in Afghanistan. 2010, he became a Research & Technology Project Manager for border security and maritime surveillance projects. In 2013, he became Head of Innovation for Airbus Cybersecurity. In this role, he won several Awards of Innovation with projects in cryptography, cyber-defence, and industrial control systems security. From 2028 to 2022, he coordinated the European R&D Project SeCoIIA, dealing with Secure Collaborative Intelligent Industrial Automation, a finalist in the Industry 5.0 Prize organised by the European Commission. In December, he joined Thales to take the AI and Cybersecurity Expert role. He is involved in strategic projects in 5G security, AI-based intrusion detection, adversarial AI and generative AI. He is the Technical Coordinator of the European defence project AIDA, which deals with Artificial Intelligence Deployable Agents for cyber-defence operations. He is a member of several cybersecurity and AI expert groups supporting organisations such as ANR (French National Research Agency), EC (the European Commission), ECSO (the European Cyber-Security Organization), ENISA (European Cybersecurity Agency), EDA (the European Defence Agency) and NATO (The North Atlantic Treaty Organization). As a working student at the University Of Porto, he completes a thesis aiming to assess and quantify the impact of AI in applications to Industry 5.0.

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ABBREVIATIONS

Abbreviation	Meaning
AGI	Artificial General Intelligence
AI	Artificial Intelligence
AIT	Artificial Intelligence Theory
AM	Artificial Intelligence Maturity
AP	Artificial Intelligence Place
AR	Artificial Intelligence Role
AT	Artificial Intelligence Type
BS	Business Strategy
CDT	Creative Destruction Theory
CPS	Cyber-Physical System
CPSS	Cyber-Physical Social System
CSS	Cyber-Social System
GPT	General Purpose Technology
HI	Human Intelligence
I1/2/3/4/5	Industry 1.0/2.0/3.0/4.0/5.0
IAI	Industrial Artificial Intelligence
IC	Innovation Capacity
II	Internal Innovation
IM	Innovation Management
IoT	Internet of Things
IP	Innovation Policy
ML	Machine Learning
MS	Manufacturing Strategy
NS	Network Strategy
OA	Organisation Age
OI	Open Innovation
OP	Organisation Product
OS	Organisation Skills
OT	Organisation Type
PS	Product Strategy
PSS	Product Service System
R&D	Research and Development
RBV	Resource-Based View
RS	Resource Strategy
SET	Social Exchange Theory
TCE	Transaction Cost Economics
TIM	Theories of Intelligent Manufacturing

Table 1 Abbreviations

THESIS ABSTRACT

The classic literature assigns innovation strategy the leading and starting role to generate business growth due to technology development and more effective managerial practices. Industry 5.0, however, reverts this paradigm. The focus is moving from “how innovation fosters AI” to “how AI fosters innovation”. Therefore, our research question can be stated as follows: What factors influence the effect of AI on innovation capacity in the context of Industry 5.0?

This question is addressed in three steps: an exploratory study, a qualitative study, and a quantitative study. The review of 352 works of literature reveals four main factors in Industry 5.0 transformation: Organisation Age, AI maturity, Manufacturing Strategy, and Innovation Capacity. The qualitative analysis of 18 expert interviews yields a conceptual model supporting the assessment of three hypotheses: H1 AI Maturity is associated with Organisation Age, H2 Manufacturing Strategy is associated with AI Maturity, and H3 Innovation Capacity is associated with Manufacturing Strategy. The quantitative analysis of 126 industrial AI use cases through Bayesian network modelling verifies the hypotheses. It predicts emerging Innovation Capacity types such as cognitive, generative and parasitic swarms.

This study makes several important contributions. Theoretically, it provides a conceptual model of AI’s impact on Innovation Capacity. It predicts synergic, competitive and deceptive scenarios in AI-driven industrial transformation, addressing an ongoing debate in the literature. Empirically, the research offers qualitative and quantitative evidence on how Organisation Age, AI Maturity, and Manufacturing Strategy influence Innovation Capacity. The findings offer strategic insights for industrial firms undergoing digital transformation and a decision-support framework for policymakers, aiming to conciliate the objectives of human-centricity, resilience and sustainability with the strategic imperative of establishing a sustainable competitive advantage.

RESUMO DA TESE

A literatura clássica atribui à estratégia de inovação um papel central e inicial no crescimento empresarial, impulsionado pelo desenvolvimento tecnológico e por práticas de gestão mais eficazes. No entanto, a Indústria 5.0 inverte este paradigma. O foco está a mudar de "como a inovação impulsiona a IA" para "como a IA impulsiona a inovação". Assim, a nossa questão de investigação pode ser formulada da seguinte forma: Quais os fatores que influenciam o efeito da IA na capacidade de inovação no contexto da Indústria 5.0?

Esta questão é abordada em três etapas: um estudo exploratório, um estudo qualitativo e um estudo quantitativo. A revisão de 352 trabalhos da literatura identifica quatro fatores principais na transformação da Indústria 5.0: Idade da Organização, Maturidade da IA, Estratégia de Fabrico e Capacidade de Inovação. A análise qualitativa de 18 entrevistas com especialistas resulta num modelo conceptual que suporta a avaliação de três hipóteses: H1) A Maturidade da IA está associada à Idade da Organização; H2) A Estratégia de Fabrico está associada à Maturidade da IA; H3) A Capacidade de Inovação está associada à Estratégia de Fabrico. A análise quantitativa de 126 casos de uso industrial da IA, através da modelação de redes Bayesianas, confirma estas hipóteses e prevê tipos emergentes de Capacidade de Inovação, como enxames cognitivos, generativos e parasitários.

Este estudo faz várias contribuições importantes. Teoricamente, fornece um modelo conceptual do impacto da IA na Capacidade de Inovação. Prediz cenários sinérgicos, competitivos e ilusórios na transformação industrial impulsionada pela IA, abordando um debate em curso na literatura. Do ponto de vista empírico, a investigação oferece evidências qualitativas e quantitativas sobre como a Idade da Organização, a Maturidade da IA e a Estratégia de Fabrico influenciam a Capacidade de Inovação. Os resultados proporcionam insights estratégicos para empresas industriais em processo de transformação digital e um quadro de apoio à decisão para os formuladores de políticas, visando conciliar os objetivos de humanização, resiliência e sustentabilidade com o imperativo estratégico de estabelecer uma vantagem competitiva sustentável.

1. INTRODUCTION

1.1. Research Context

In January 2021, a policy brief from the European Commission stirred up the industrial science community by introducing the concept of Industry 5.0 as a paradigm shift from previous growth-driven industrial transformation concepts to the value-driven quest for a sustainable, human-centric and resilient economy (Breque, De Nul, & Petridis, 2021). Since the early 2010s, European manufacturing professionals have been in a tug of war to accomplish the promises of Industry 4.0, formerly branded by the German government and tasked by the European Union to "drive digital manufacturing forward by increasing digitisation and the interconnection of products, value chains, and business models" (The European Commission, 2017). Xu et al. (2021) assert that Industry 4.0 and Industry 5.0 largely coexist and rely on similar technological baselines, including Additive Manufacturing, Industrial IoT, Digital Twins, and Artificial Intelligence (AI). However, Industry 5.0 requires higher levels of intimacy, interaction, and socialisation between machines and humans, which can only be reached through the development of AI agents with cognitive skills (Bryndin, 2020). Aghion et al. (2017) find that, beyond its effects on operations, AI also has an effect on innovation. This work aims to analyse how AI affects innovation capacity in the context of Industry 5.0.

1.2. Research Question

Russel & Norwig (2021) define AI as a field of research in computer science that enables machines to perceive their environment and use learning and intelligence to take actions that maximise their chances of achieving defined goals. A lively trend of research supports AI as the next General Purpose Technology (GPT) (Trajtenberg, 2018) and assigns Innovation Capacity (IC) the leading and starting role to generate business growth due to technology development and more effective managerial practices (Bodrožić & Adler, 2018). But unlike previous GPTs, AI bears in its very definition the potential for an interplay with Human Intelligence (HI). Prior research provides evidence of AI's positive effect on innovation performance (Aghion, Jones, & Jones, 2017). Yet, there is

little consensus on the effect of AI on Innovation Capacity, which, according to different research streams, is found to be competitive (Shabbir & Anwer, 2018), synergic (Lichtenthaler U. , 2018), deceptive (Sætra, 2020). Therefore, our research question can be stated as follows: “What factors influence AI's effects on innovation capacity (IC) in the context of Industry 5.0?”.

1.3. Contributions to Science

Professional Management practice was born with the Industrial Revolution and evolved by reaction to technological revolutions (Bodrožić & Adler, 2018). In 18th century England, the use of steam power in mines initiated the first industrial revolution, which was shortly followed by the professionalisation of middle management activities made necessary by coupling machines and manpower (Industry 1.0). In the late 19th century, in Europe and North America, the electrification of manufacturing lines drew a vertical integration of corporations and the development of scientific management approaches (Industry 2.0). In the sixties, the deployment of electronics and programmable logic controllers in a globalised economy clustered down the manufacturing industry into multidivisional structures. It supported an increased specialisation of labour along automated supply chains (Industry 3.0). At the dawn of the new millennium, extensive use of computer networks and the introduction of connected automation systems known as Cyber-Physical Systems (CPS) enabled the deployment of worldwide horizontal management structures with real-time scheduling and flexible resource optimisation abilities (Industry 4.0). Innovation policy literature has long analysed these paradigm shifts and established chains of causality between technological and managerial events at play in organisations at each industrial age. However, as the European Commission launches its new program called “Industry 5.0” in 2021, the new paradigm comes with social goals known as “human centricity, resilience and sustainability” rather as a key technology to kickstart this ambitious transformation. With this research, we contribute to understanding the specific role of AI and the factors that influence its effect on Innovation Capacity towards the realisation of the Industry 5.0 paradigm. The figure below illustrates the distinctive characteristics of the five Organisation Ages (OA), defined by contemporary industrial policy literature.

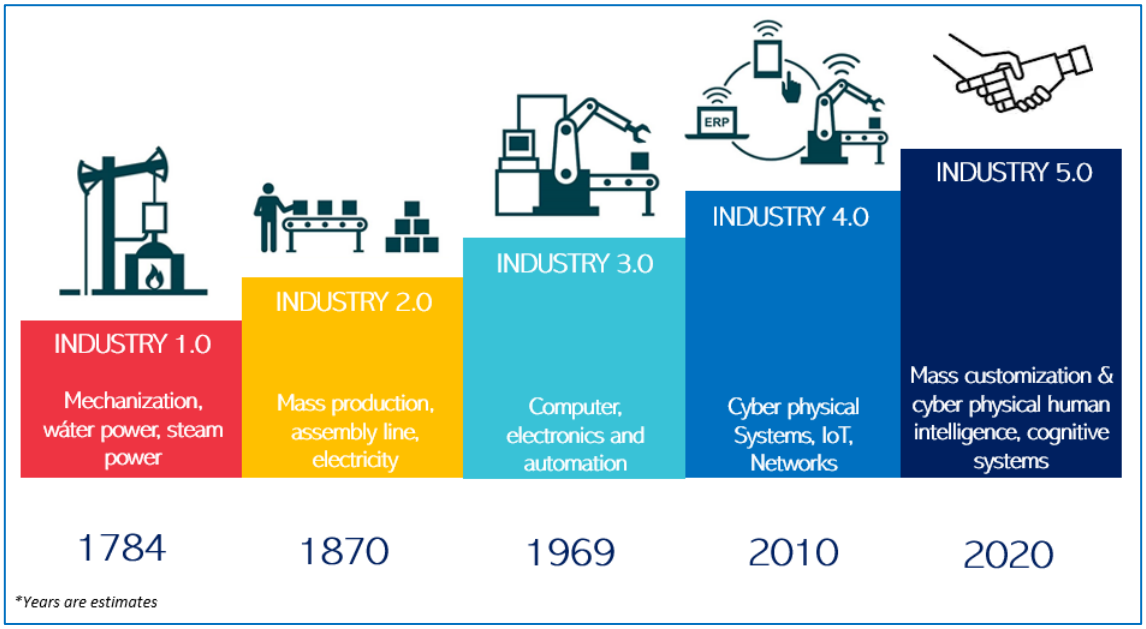


Figure 1: Organisation ages according to the Industry 5.0 paradigm

Abundant engineering literature describes the relationship between technological advancement and organisation age with gradations from Industry 1.0 to 5.0 (Oztemel & Gursev, 2020). While Industry 4.0 embodies artificial intelligence in the concept of Cyber-Physical Systems (CPS), Industry 5.0 requires adopting AI agents with cognitive skills (Bryndin, 2020) and collaborative robotics (Nahavandi, 2019). Economists have also investigated this field, finding AI effects on business models and supply chains. For example, Nicoletti & Appolloni (2023) highlight AI's contribution to the industry's servitisation. Finally, the innovation management literature questions the interplay of AI and human intelligence (HI) and its effect on innovation capacity. For example, Lichtenthaler (2018) finds advanced manufacturing strategies to leverage human and machine intelligence synergies. Trajtenberg (2018) suggests that AI will be the next General Purpose Technology (GPT), which, like steam power, electricity, electronics, and computer networks, would transform production techniques, business strategy, and management practice. Yet, there is a lack of literature analysing the interplay of technological, economic, and managerial factors. This work aims to address this gap by identifying the factors influencing the effects of AI on IC, estimating their effects, and

predicting the impact of AI on firm innovation capacity in the context of Industry 5.0. It helps assess the specific contributions of technological advancement and strategic management to the advent of Industry 5.0. It provides researchers with a new understanding of the interplay between AI and HI, highlighting the moderating role of Manufacturing Strategy. It also gives practitioners strategies and decision metrics for a successful innovation management approach.

1.4.Structure of the dissertation

The concept of Industry 5.0 is emergent and calls for a stepped approach, giving it time for the 2021-born concept to materialise in the economy. Consequently, we have decided on a rolling waves planning approach that starts with a focus on qualitative research and then incrementally grows quantitative. The research work has been structured as follows:

- Phase 1: **Exploratory Study (2022)**: this study aimed to identify model variables by systematically reviewing the literature.
- Phase 2: **Qualitative Study (2023)**: this study aimed to identify the main effects between variables and build a conceptual model by analysing expert interviews.
- Phase 3: **Quantitative Study (2024)**: this study aimed to train and validate the conceptual model against a dataset of real-life Industrial AI use cases.

Consistently with the study plan, the dissertation is structured in 5 chapters. Following this introduction (chapter 1), chapter 2 provides the outcomes of the exploratory study, which contains the state of the literature addressing the research question and helps identify the variables at play. Chapter 3 describes the outcomes of the qualitative study that was conducted based on expert interviews and led to elaborating the conceptual model. Chapter 4 describes the outcomes of the quantitative study that relied on Bayesian Network modelling and answers the research question. Chapter 5 discusses the study outcomes, critically comparing theoretical developments and empirical evidence, and examining residual gaps. The conclusions follow with a summary of the findings and an assessment of study limitations. It suggested avenues for future research.

2. EXPLORATORY STUDY

The exploratory study aims to identify model variables by systematically reviewing the literature. Consistently with the methodology introduced in § 2.2, we proceed to a literature review structured by the main body of literature: Engineering, Humanities and Management. This review is followed by a summary of the findings in which we resume the extracted variables and discuss research gaps.

2.1. Exploratory Study Introduction

The classical literature on innovation attributes to innovation strategy the role of generating business growth, technological development, and deploying more effective management practices. However, the advent of Artificial Intelligence (AI) reverts this paradigm in the context of Industry 5.0. The focus is moving from "how innovation fosters AI" to "how AI fosters innovation". Therefore, our research question can be stated as follows: "What factors influence the effect of AI on Innovation Capacity in the context of Industry 5.0?"

We conduct a systematic literature review on engineering, humanities, and management sciences to address this question. We conduct a keyword-based literature search completed by bibliographic analysis, then classified the resulting 406 works into 3 classes and 15 clusters, which we critically analyse. We extract 3 propositions setting associations between 4 factors: company age, AI maturity, manufacturing strategy, and innovation capacity. Moreover, we identify 12 indicators enabling us to infer these factors and predict AI's effect on Innovation Capacity in the context of Industry 5.0.

In § 2.2 we provide the exploratory study methodology. In §2.3 we review the Engineering literature. In § 2.4 w review the Humanities literature. In § 2.5 we review the Management literature. §**Error! Reference source not found.** provides the result of the literature review. §2.7 summarises the exploratory study. The study uncovers several debates and research gaps. In particular, it confronts engineering theories on AI Maturity and trustworthiness. It explores innovative Manufacturing Strategies such as social manufacturing or mass customisation. Finally, it discusses AI effect on Innovation

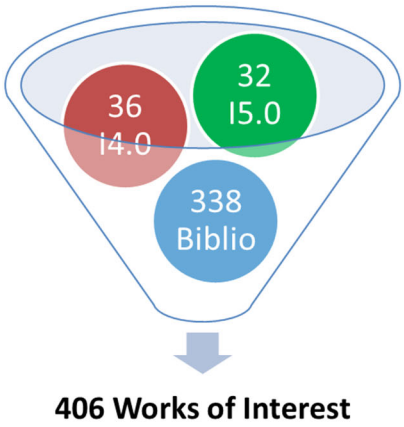
Capacity in different policy settings. These findings give researchers a new understanding of the interplay between artificial intelligence and human intelligence in the context of Industry 5.0.

2.2. Exploratory Study Methods

This study phase aims to identify model variables by systematically reviewing the literature. The research question opens broad research areas from different disciplines, allowing for many possible study designs. Therefore, we have decided to conduct a scoping review. This type of knowledge synthesis follows a systematic approach to map evidence on a topic and identify main concepts, theories, sources, and knowledge gaps (Tricco, 2018).

2.2.1. Literature Search

We aim to retrieve works informing about the effect of AI on [IC] in the context of Industry 5.0, thus ideally combining these three concepts in their title or abstract. Therefore, we conducted a systematic literature search using the following keywords: “Industry 5.0” AND “Artificial Intelligence” OR “Manufacturing Strategy” OR “Innovation Capacity”. A Scopus search (S1) on 04/12/2022 gave 48 results. After reviewing all abstracts, 32 were found relevant, meaning they effectively addressed the research question or any related research question. Acknowledging the common technological baseline between Industry 4.0 and Industry 5.0 (Xu X. , Lu, Vogel-Heuser, & Wang, 2021), we expand the search by replacing 5.0 with 4.0, obtaining 479 results (S2). Yet, reviewing all abstracts gives evidence of no more than 46 works of literature discussing key concepts of the research question. Adding both search results provides a total of 68 relevant works. From this set, a bibliographic analysis aiming to identify works of interest potentially ruled out by a strict semantic search and a systematic refresh of the initial search bring up 338 additional works (S3). The figure below gives an overview of the literature search and selection procedure.



Search tool: Scopus
Initial search: 04/12/2022
Last update: 24/03/2025

-S1: "Industry 5.0" and "Artificial Intelligence" and "Innovation Capacity" > **32** works selected from 48 results

-S2: "Industry 4.0" and "Artificial Intelligence" and "Innovation Capacity" > **36** works selected from 479 results

-S3: Bibliographic analysis & refresh of S1 and S2 results > **338** additional works

Full bibliography: 406 works of interest

Figure 2: Literature search and selection procedure

The initial literature search was updated continuously. In total, 406 works were methodically studied. ANNEX2 provides the comprehensive literature dataset.

2.2.2. Literature Data

The collected works belong to 3 distinct bodies of literature, which we call "classes" in the following lines:

- the Engineering class (ENG) includes works of science and technology concerned with engines, machines, and structures;

- the Humanities class (HUM) includes works of economics, sociology, and industrial Organisation

-the Management class (MGT) includes works on business strategy, industrial policy, and innovation management

The following key concepts appear from a first overview of the literature:

- **Organisation Age [OA],** defined as the level of industrial advancement of a company according to Industry 5.0 maturity framework (from Industry 1.0 to Industry 5.0);

- **AI maturity [AM],** defined as a level of technological advancement according to the properties of AI assets (learning ability, embeddedness, anthropomorphism);

- **Manufacturing Strategy [MS]**, defined as the adopted business strategy according to product/service mix and supply chain structuration;

- **Innovation Capacity [IC]**, defined as the Organisational potential to innovate, determined by the skills and strengths in research and technology.

we assess each literature work's coverage of the above concepts to structure the review process. The result is a dataset of 406 items with four binary variables: [OA], [AM], [MS], [IC]. We look for a statistical technique to retrieve patterns and trends within this literature. We consider factor analysis or cluster analysis relevant for this investigation. However, the distribution of data is slightly positively skewed for [AM], [MS] and [IC]. Therefore, we opt for the cluster analysis technique, for which requirements of normality do not apply (Hair, 2009).

2.2.3. Literature Cluster Analysis

We aim to answer the research question by consigning findings from literature content analysis, not by interpreting bibliometric figures. However, each literature class is sub-split into clusters corresponding to influential trends or theories to describe their respective contributions. In the following lines, we call each theory a "cluster". For conciseness, we set to 4 the maximum number of clusters per class and consigned outliers into a fifth cluster called "miscellaneous". Based on a complete critical review, the cluster assignment decision is made, controlled by a keyword frequency check and a consistency check with the journal editorial line. Clusters are mapped to the fundamental concepts identified by a scoring system. Scores are computed by summing the number of works that effectively address the considered factor within the cluster. **Error! Reference source not found.Error! Reference source not found.** provides the distribution of the selected literature by cluster and their scoring by crucial factor.

		Counts					
Category	Theory	Count	MY	[OA]	[AM]	[MS]	[IC]
All	**All**	**406**	**34**	**292**	**254**	**192**	**171**
ENG	**Engineering**	**132**	**9**	**114**	**118**	**18**	**21**
ENG	Engineering, miscelaneous	7	0	7	5	1	4
AIT	Artificial Intelligence Theories	48	6	31	43	5	12
MFG	Manufacturing Automation	16	0	16	15	1	1
SMT	Smart Manufacturing Theories	19	1	19	14	7	2
CPS	Cyber-Physical Systems	42	2	41	41	4	2
HUM	**Humanities**	**138**	**13**	**96**	**75**	**94**	**40**
HUM	Humanities, miscelaneous	39	12	21	16	13	12
CDT	Creative Destruction Theory	50	0	33	43	33	19
TCE	Transaction Cost Economics	13	0	6	5	13	3
TIM	Theories of Intelligent Manufacturing	21	0	21	6	20	4
SET	Social Exchange Theories	16	1	16	6	15	3
MGT	**Management**	**136**	**12**	**82**	**61**	**80**	**110**
MGT	Management, Miscelaneous	25	4	11	13	22	5
RBV	Resource-Based View	20	0	12	10	12	18
OIT	Open Innovation Theory	37	3	20	7	19	37
IPL	Innovation Policy Literature	30	2	20	17	13	27
IMT	Innovation Management Theory	23	3	18	13	14	22

Table 2 Literature Review Statistics

The above statistics are updated with the latest literature set at writing time. They provide evidence of good coverage of the key concepts at play and a balanced distribution of research work across the three bodies of literature. These statistics justify the structuration of the review scope into three parts. The engineering literature scores high in AI maturity [AM] (118 out of 132 works). The humanities literature scores high in Manufacturing Strategy [MS] (94/138). The management literature scores high in Innovation Capacity [IC] (110 out of 136 works). Expectedly, all literature classes substantially cover Organisation Age [OA] imposed by the context of Industry 4/5.0 (292 out of 406 works). A few works supporting the investigation methodology are marked [MY] (34 out of 406).

2.2.4. Literature Cluster Specification

The Engineering class contains 132 works highlighting AI's role in the industry's transformation. This class of the literature splits into the following clusters:

-Artificial intelligence theories cluster (AIT): consigning works about AI techniques, algorithms, and implementations; helping to characterise AI agents in the context of Industry 5.0;

-Manufacturing automation cluster (MFG): consigning works about industrial processes and operations, helping to define the place of AI in the manufacturing lifecycle;

-Smart manufacturing cluster (SMT): consigning works about ICT integration in manufacturing operations, providing insights into the role of AI in manufacturing use cases;

-Cyber-physical systems cluster (CPS): consigning works of system engineering, defining characteristics of Industry 5.0 systems relative to anterior technology, inferring [OA] from [AM].

The bivariate scatter chart below casts the cluster class centroids on a standardised bidimensional chart with [OA] in abscissas and [AM] in ordinates.

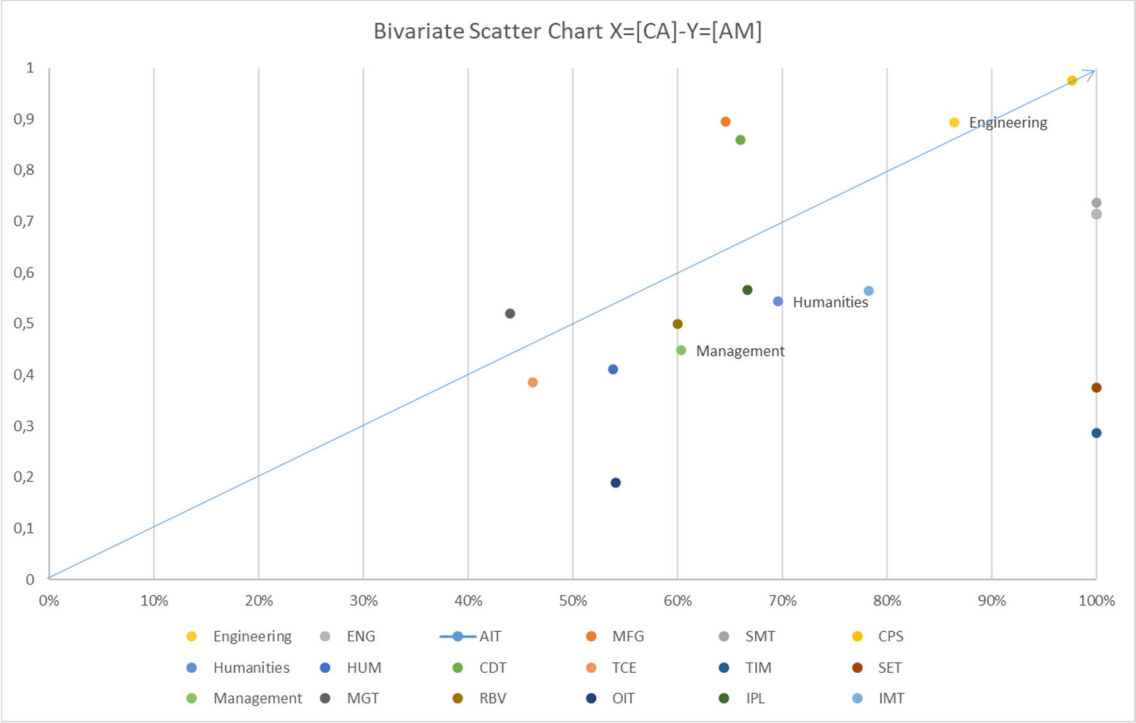


Figure 3: Bivariate Scatter Chart X = [OA]; Y=[AM]

The position of "Engineering" at the upper right corner of the graph with very high scores in [OA] and [AM] suggests the association of Organisation Age with AI maturity in this class of the literature. For example, Yilma et al (2020) introduce a metamodel that characterises Cyber-Physical Social Systems (CPSS) as the ultimate evolutionary step of industrial systems. The average within-class distance is 0,19, while the average between-class distance is 0,39, showing acceptable class homogeneity. In other words, the above-identified clusters of Engineering literature consistently associate Organisation Age and AI maturity.

The Humanities class contains 138 works that suggest novel corporate strategies enabled by the adoption of AI in manufacturing. This class of the literature splits into the following clusters:

-Creative destruction theory cluster (CDT): consigning works of economics inspired by the theory of Schumpeter (1942), discussing the AI effects on firm resources;

-Transaction cost economics cluster (TCE): consigning works of industrial Organisation inspired by the theory of Williamson (1981), helping to assess AI effects on firm boundaries;

-Theories of intelligent manufacturing cluster(TIM): consigning works focusing on the effects of digital transformation on industrial strategy, helping to assess AI impact on the marketing mix;

-Social exchange theories (SET): consigning works of economics and sociology inspired by McNeil (1974), help predict AI effects on manufacturing strategy [MS].

The bivariate scatter chart below casts the cluster class centroids on a standardised bidimensional chart with [AM] in abscissas and [MS] in ordinates.

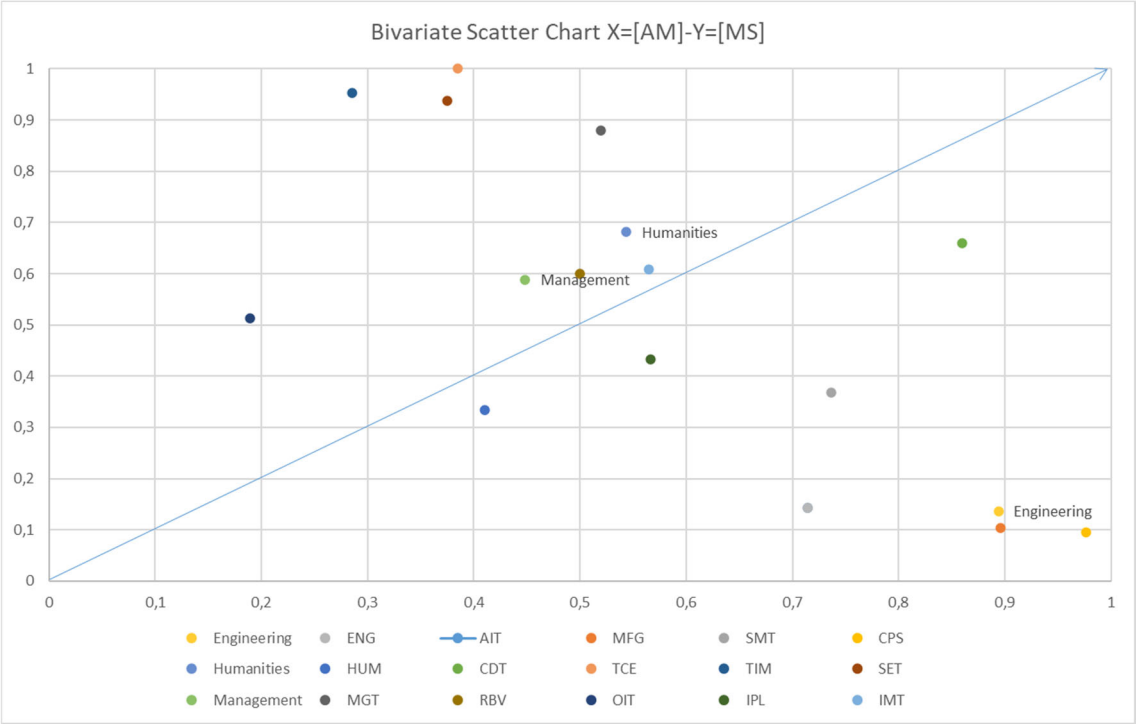


Figure 4: Bivariate Scatter Chart X = [AM]; Y=[MS]

The position of "Humanities" at the upper right corner of the graph with high scores in [AM] and [MS] suggests the association of manufacturing strategy with AI maturity in this class of the literature. For example, Pech & Vrchota (2022). illustrate the contribution of artificial intelligence to the deployment of "mass customisation" strategies. The average within-class distance is 0,26, while the average between-class distance is 0,47, showing acceptable class homogeneity. In other words, the above-identified clusters of Humanities literature consistently associate AI maturity with manufacturing strategy.

The Management class contains 124 works that discuss the interplay of AI and HI in novel manufacturing strategies and their effect on innovation performance. This class of the literature splits into the following clusters:

-Resource-based view cluster (RBV): consigning works of management science influenced by the theory of Barney (1991), helping to assess the effect of AI on internal innovation;

-Open innovation theory cluster (OIT): consigning works of innovation management influenced by Chesbrough (2014), helping to assess AI's effect on collaborative innovation strategies;

-Innovation policy literature cluster (IPL): consigning works of political science addressing innovation policy decisions, helping to assess the effect of innovation policy on AI adoption;

-Innovation management theory cluster (IMT): consigning works of management addressing effects of innovation on firm performance, helping to predict the AI effect on innovation capacity.

The bivariate scatter chart below casts the cluster class centroids on a standardised bidimensional chart with [MS] in abscissas and [IC] in ordinates.

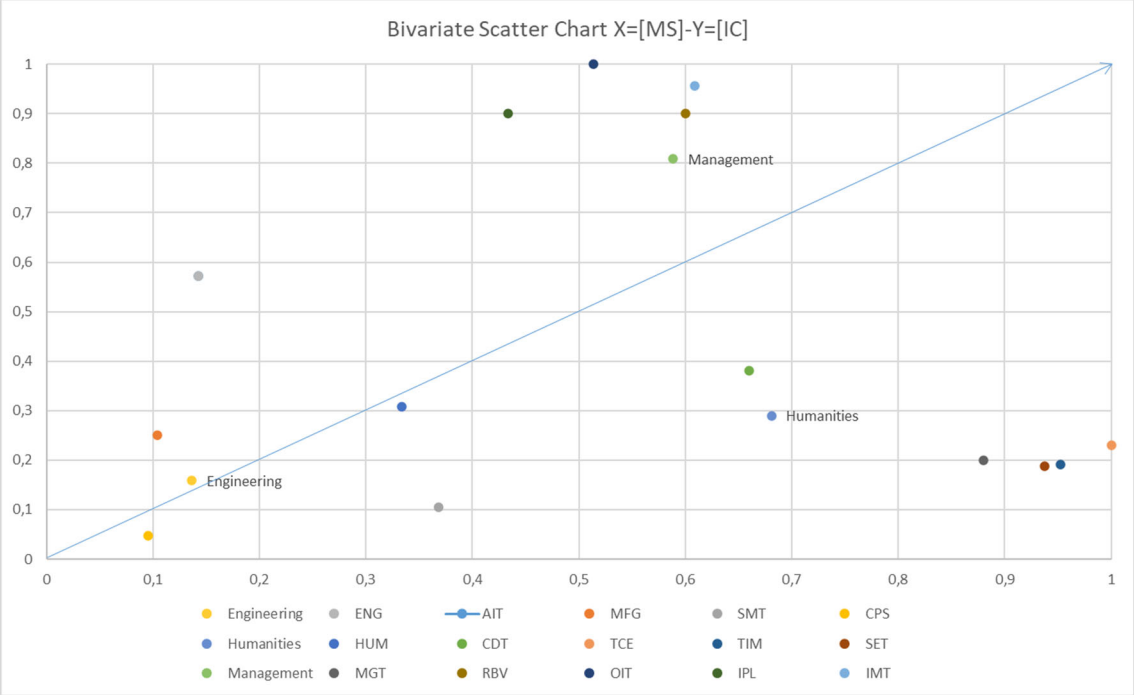


Figure 5: Bivariate Scatter Chart X = [MS]; Y=[IC]

The position of "Management" at the upper right corner of the graph with high scores in [IC] and [MS] suggests the association of innovation capacity with manufacturing strategy in this class of literature. For example, Liu et al. (2020) remote working enables

a more efficient division of labour with a positive effect on technology development. The average within-class distance is 0,26, while the average between-class distance is 0,56, showing good class homogeneity. In other words, the above-identified clusters of Management literature consistently associate manufacturing strategy and innovation capacity.

2.3. Review Part I: Review of the Engineering Literature

This section aims to collect insights from the Engineering literature addressing the research question with a particular focus on extracting indicators of AI maturity and assessing P1: "AI Maturity [AM] is associated with Organisation Age [OA]".

2.3.1. AI Theories and the characterisation of AI agents

With Artificial Intelligence Theories (AIT), we characterise AI agents, aiming to determine if these characteristics reflect a particular AI maturity level. The AI engineering literature defines several types of AI agents with different abilities and consecutively different applications in the context of Industry 5.0. Symbolic AI handles discrete symbols, such as rule-based or logic-based systems (Bunte, et al., 2019). Machine learning (ML) gives computers the ability to learn without being explicitly programmed (Samuel, 1959). Deep learning (DL) further extends the ability of machines to perform human tasks that can be learned through observation and experience (Wason, 2018). Bryndin (2020) highlights the need for substantial improvements in cognitive systems to achieve the Industry 5.0 promise for human centricity. A debate, however, remains on whether AI should aim at thinking humanly, acting humanly, thinking rationally, or acting rationally (Russell & Norvig, 2021).

Duan et al. (2022) discuss the ability of embodied AI to perform tasks in the physical space, similarly to humans. Kaur et al (2023) note that AI agents can also be involved in virtual worlds. An important obstacle to AI adoption is the limited human confidence in AI (Hutson & Plate, 2024). Troshani et al (2021) demonstrate that anthropomorphism helps develop trust in user relationships. However, Zang et al (2020) remind us that a nonlinear relationship between a robot's degree of anthropomorphism and likeability was

formalised with the uncanny valley theory (Mori, 1970). Additionally, Thellman et al. (2022) highlight that humans tend to attribute intentions even to nonhumanoid robots.

Trajtenberg (Trajtenberg, 2018) considers AI to be the next general-purpose technology (GPT), characterised by its pervasive use across a wide variety of sectors and technical dynamism. But Agrawal et al. (2019) deny ML's claim for true "Artificial General Intelligence" (AGI). The EFFRA documents in their project knowledge base 470 industrial innovation projects[1]. Among them, 17 explicitly set in the context of Industry 5.0 develop a broad set of industrial use cases involving symbolic AI or machine learning techniques, embodied or virtual agents, and humanoid or non-humanoid robots. Building on this literature, we can characterise AI agents in the context of Industry 5.0 as follows.

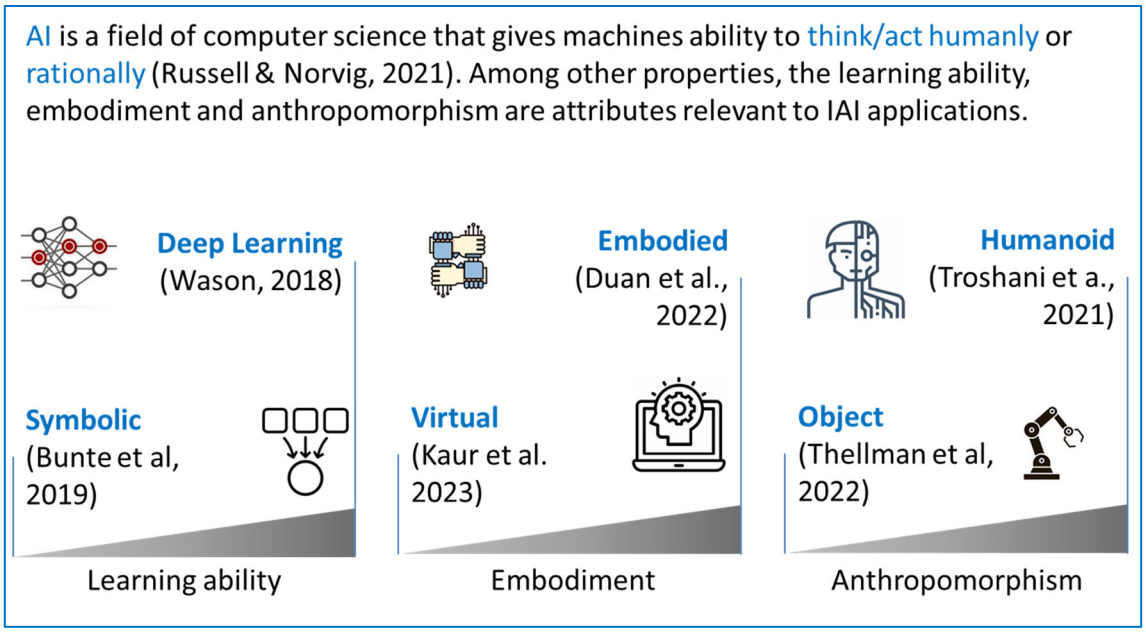


Figure 6: Characterization of AI agents

The AI engineering literature defines different types of AI agents with different levels of learning ability, embodiment, and anthropomorphism (Russell & Norvig, 2021). Therefore, AI type [AT] is a possible indicator of AI Maturity [AM].

[1] https://portal.effra.eu/projects

2.3.2. Manufacturing Automation and AI Place in Manufacturing Lifecycle

With the Manufacturing Automation literature (MFG), we examine AI's place in the manufacturing lifecycle to determine if this place reflects a particular AI maturity level. Industrial AI (IAI) can be broadly defined as any application of AI relating to the physical operations of an enterprise (Lee, Davari, Singh, & Pandhare, 2018). The manufacturing literature provides evidence of IAI implementation at all steps of the lifecycle.

Regenwetter et al (2022) document the growing use of AI in generative design, while Balu et al. (2016) discuss its use in design to production. Del Gallo et al. (2023) provide an overview of its use to solve production scheduling problems. IAI is also found in product inspection (Sundaram & Zeid, 2023), commissioning (Jonsson, 2024) yield management (Ghelani, 2024), operations sequencing (Chen T. , 2023). Baryannis et al. (2018) report AI contribution in supply chain management, Milazzo et al. (2020) in fault prevention and Ucar et al. (2024) in predictive maintenance. Finally, Gupta et al. (2019) address the use of AI in waste management and recycling, while Yin & Yu (2022) demonstrate its contribution to green innovation in manufacturing.

The European Project BOOST 4.0[2] provides insightful examples of industrial AI applications in different stages of the manufacturing lifecycle. For example, at FILL, Austria, a simulation-based release process reduces the commissioning time of machine tools by 10%. At BENTELER, Germany, predictive maintenance techniques help reduce machine downtime by 25%. Building on this literature, we can describe the place of AI in the manufacturing lifecycle as follows.

[2] H2020-780732-BOOST 4.0 (https://cordis.europa.eu/project/id/780732)

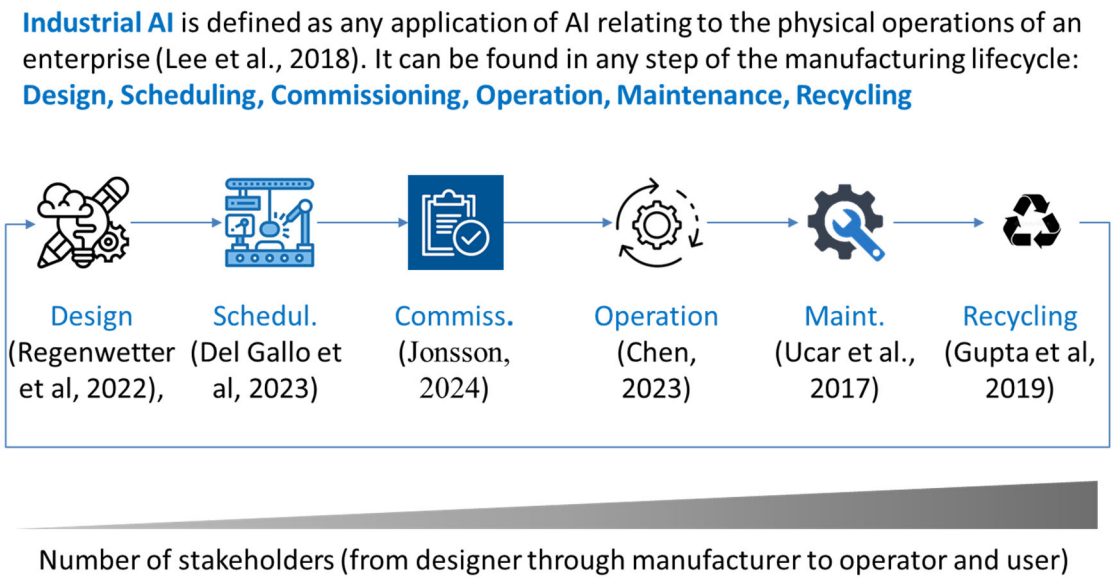


Figure 7: AI in Manufacturing Lifecycle

Manufacturing automation research specifies AI place [AP] in the manufacturing lifecycle as an observable indicator of AI Maturity [AM] (Solanki, Makkar, & Devi, 2020). A broader application of AI along the manufacturing lifecycle reveals a greater level of AI Maturity [AM].

2.3.3. Smart Manufacturing and AI role in manufacturing use cases

With Smart Manufacturing Theories (SMT) we examine AI's role in manufacturing use cases, aiming to determine if this role reflects a particular AI maturity level. Within Industry 4.0, AI's primary role is to enhance industrial processes. Zhao (2022) demonstrates AI use in process monitoring. He et al. (2023) highlight the potential for process optimisation. Wang (2019) leverages AI for process control and automation.

The Industry 5.0 paradigm brings extended requirements. El Zaataria et al. (2019) report AI-based learning from demonstrations. Borboni et al. (2023) discuss their collaborative learning capacity. Seeber et al. (2020) demonstrate AI agents' social behaviour. Koch and Oulasvirta (2018) discuss their cognition and negotiation abilities. Dong et al (2023) demonstrate AI's contribution to digital green innovation. Bécue et al. (2020) highlight AI's impact on industrial system resilience to cyber threats.

The European project STAR provides three insightful industrial AI use cases illustrating the diverse possible roles of AI in manufacturing. The cobotics use case involves active learning systems in quality inspection tasks at Philips, Netherlands. The AI security pilot applies explainable AI techniques to customise automotive air vents at IBER-OLEFF, Portugal. The AI safety pilot demonstrates safe human-robot collaboration in non-segregated spaces at the German Research Centre for Artificial Intelligence (DFKI). Based on this literature, we can describe the possible roles of AI in Industry 5.0 as follows.

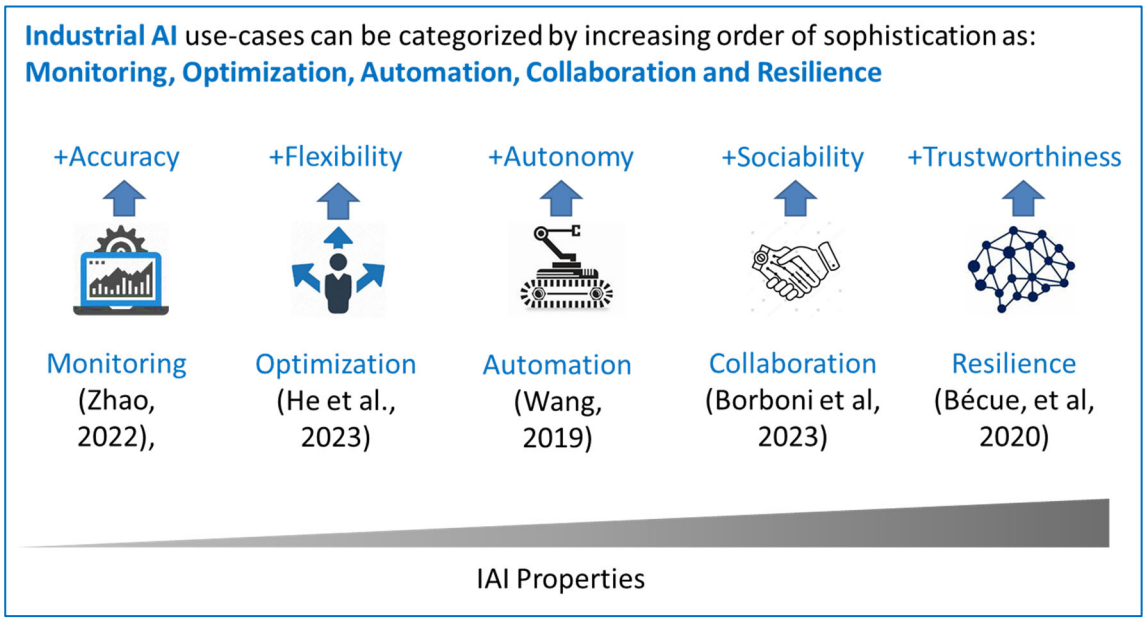


Figure 8: IAI roles in manufacturing use cases

The smart manufacturing literature highlights the AI role [AR] as an observable indicator of AI Maturity [AM] (My, 2021). While Industry 4.0 exhibits early uses of AI in process monitoring, optimisation and automation, Industry 5.0 brings enhanced human-machine collaboration abilities and greater consideration for sustainability and resilience aspects.

2.3.4. Cyber-Physical Systems and AI Association with Organisation Age

With Cyber-Physical Systems engineering (CPS), we examine how industrial systems evolve through different industrial ages and determine corresponding AI maturity levels.

[3] H2020- 956573- STAR Project (https://cordis.europa.eu/project/id/956573)

The system engineering literature provides a classification of manufacturing systems according to AI maturity levels. A system is a complex set of interacting elements with properties richer than the sum of its parts (Bertalanffy, 1969).

Yilma et al. (2020) define elementary systems as cyber (C), physical (P), or social (S). Their combination forms physical-social systems (PSS), cyber-social systems (CSS), cyber-physical systems (CPS), and cyber-physical social systems (CPSS). PSS are compositions of physical and social elements, where the social part is materialised through the physical part (e.g., a worker). CSSs are systems comprising a cyber and a social component where the social element is expressed through cyberspace (e.g., social networks). CPS integrate computing elements with physical components and processes (e.g., industrial robots). Finally, CPSS comprises cyber, physical, and social components. CPSS spaces are metasystems where humans and CPS cohabit (e.g., smart factories). A CPSS object is enhanced with social capabilities (e.g., a collaborative robot).

Hozdić & Jurković (2023) further demonstrate the contribution of AI to the realisation of cognitive cyber-physical production systems, which Industry 5.0 demands They correspond to the highest level of AI development that makes human-machine interaction intuitive and efficient (Radanliev, De Roure, Van Kleek, Santos, & Ani, 2021). The European Project DIH4CPS[4] provides a large set of industrial use cases for Cyber-Physical Systems, demonstrating AI-based advanced human-machine interactions in the physical, cyber and social domains. Based on this literature, we classify the different levels of industrial AI maturity [AM] and the corresponding Organisation Ages [OA] as follows.

[4] H2020-872548-DIH4CPS (https://cordis.europa.eu/project/id/872548)

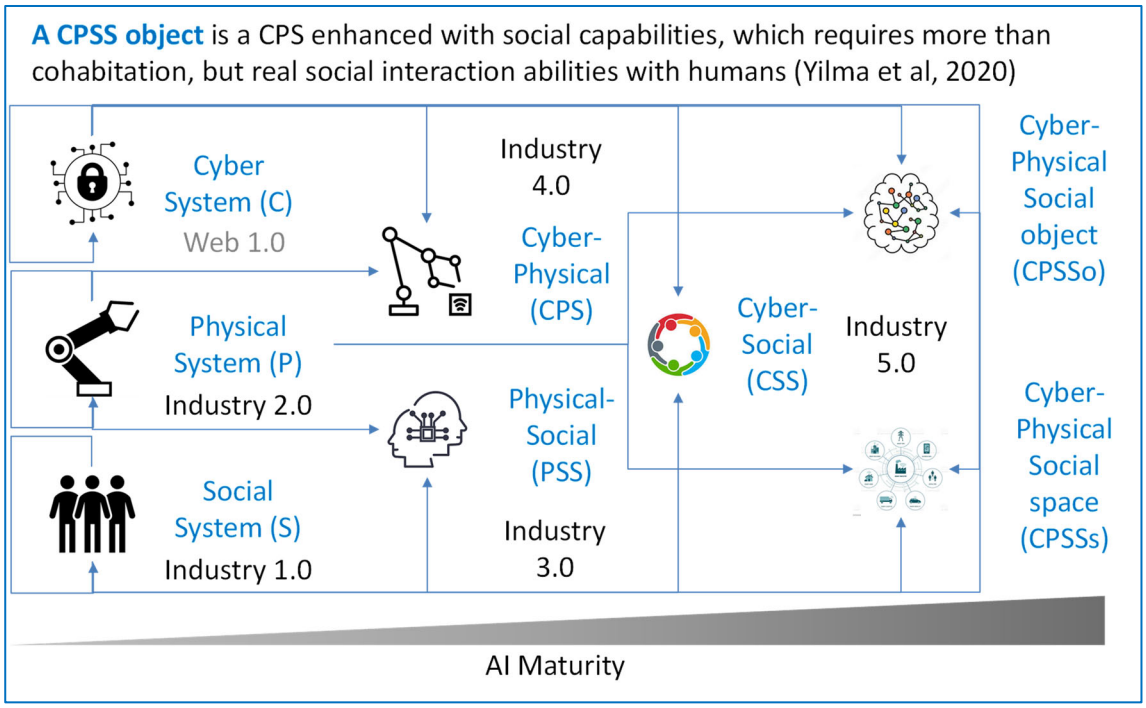


Figure 9: AI Maturity in System Engineering

The systems characterising Industry 5.0 belong to the class defined by the system engineering literature as cyber-physical social systems (Yilma, Naudet, & Panetto, 2020). According to Randliev et al (2021), they correspond to the highest level of AI development. Therefore, we substantiate ***P1):*** *AI Maturity [AM] is positively associated with Organisation Age [OA]*.

2.4.Review Part II: Review of the Humanities Literature

This section aims to collect insights from the humanities literature addressing the research question with a particular focus on extracting indicators of manufacturing strategy and assessing P2: "Manufacturing Strategy [MS] is associated with AI Maturity [AM]".

2.4.1. Creative Destruction Theory and AI Effect on firm resources

With the Creative Destruction Theories (CDT), we characterise firm resource management approaches to determine if these approaches reflect a particular manufacturing strategy. Creative destruction is the process of industrial mutation that incessantly revolutionises the economic structure from within, destroying the old one and

creating a new one (Schumpeter, 1942). However, while innovation has been known to affect lower-qualification jobs, the advent of AI now increasingly exposes the management level (Frank, 2019). Pessimistic views generally claim i) that AI kills jobs and ii) that AI has a limited impact on society. Mokyr (2017) notes that these views cannot both be right. He proves that they can very well be both wrong. Acemoglu & Restrepo (2018) expect the mismatch between skills and technology to widen by the combined effects of "displacement", whereby machines take over human tasks, and "expansion", whereby growth leads to the creation of new tasks for humans.

Furman (2018) forecasts that low wages and skills are more exposed to job losses and that inequitable educational systems amplify this effect. Agrawal et al. (2019) reply that downskilling is equally likely in specific domains and would potentially reduce inequalities. Existing theories mostly diverge between supporters of "replacement" or "augmentation" (Noponen, 2019). Theories of "replacement" postulate that AI will gradually replace humans at work (Eng & Liu, 2024) and that the "embodied leader" will be blown by digital platforms (Auvinen, et al., 2019). Algorithmic management is meant to replace human management in an increasing number of tasks (Parent-Rocheleau & Parker, 2022). Benlian et al. (2022) even report its role in creating information asymmetries that fuel exploitative strategies.

Conversely, Jarrahi (2018) demonstrates the potential for a symbiotic relationship between humans and AI, while Paul et al. (2022) suggest that the distinct capabilities of each can yield an augmentation effect. Dolev and Itzkovich (2020) suggest the resistance of human prevalence in economic activities based on soft skills. Yet, Miraz et al. (2024) report a proliferation of chatbots in customer relationship management. Kinkel et al. (2022) highlight the prerequisite for digital skills to ensure the fruitful adoption of AI in manufacturing. Eventually, these diverse trends of CDT literature converge to acknowledge the possible mitigation of AI effect on employment by revising manufacturing strategies. Based on this literature we can represent the possible effects of AI on firm resources as follows.

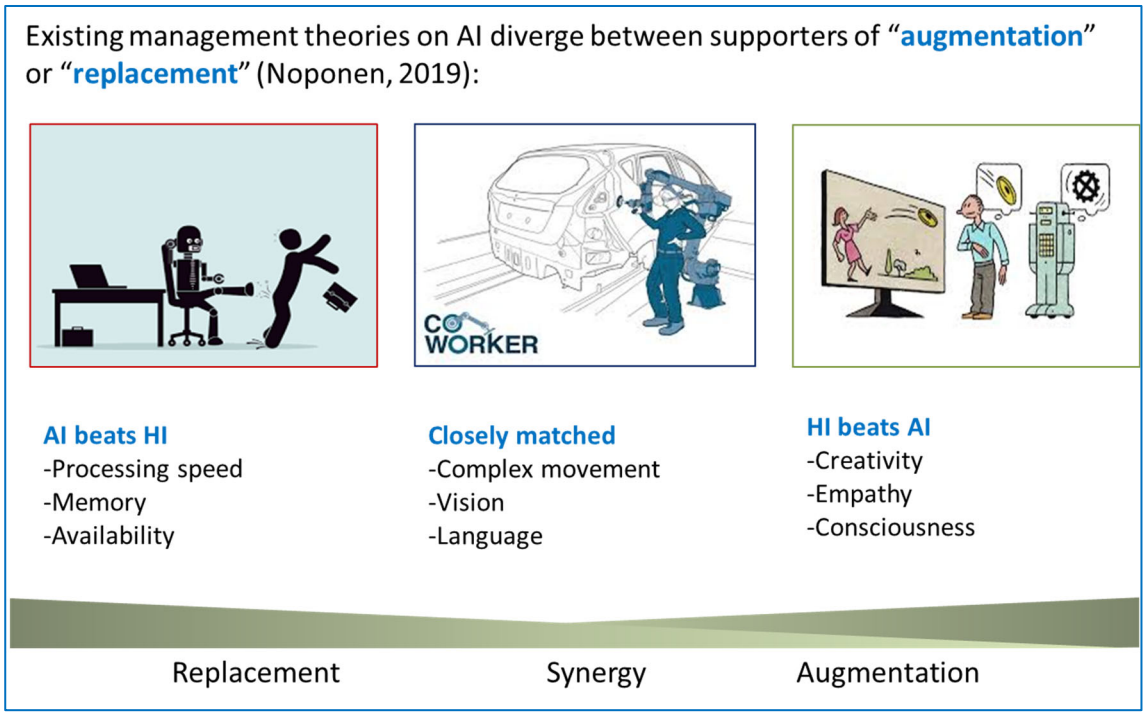


Figure 10: IAI effect on firm resources

Creative destruction theories highlight the relevance of Organisation Skills [OS] as an observable indicator of Organisation Age [OA] (Kinkel, Baumgartner, & Cherubini, 2022) . Furthermore, they provide resource strategy [RS] as an observable indicator of a manufacturing strategy [MS] (Noponen, 2019).

2.4.2. Transaction Cost Economics and AI Effect on firm boundaries

Transaction cost economics (TCE) posits that an organisation's success hinges on its ability to make rational decisions between relying on market mechanisms or hierarchical structures (Williamson, 1981). In this framework, factors such as asset specificity, transaction costs, uncertainty, and governance expenses shape the optimal delineation of firm boundaries. With TCE, we can analyse firm boundary management approaches to determine whether they align with specific manufacturing strategies.

The ICT economy has simultaneously triggered a reduction in the site specificity of industrial assets, a reduction in transaction costs, and, consequently, a preference for the market against hierarchy (Kasper & Streit, 2000). TCE-based studies have found that AI

helps further reduce negotiation time (Patil, et al., 2024), and costs (Plichta & Plichta, 2023). Cuypers et al. (2021) highlight the reduction of coordination complexity. Meng and Gong (2024) demonstrate the reduction of internal transaction costs and the enhancement of external transaction efficiency. Davenport et al. (2020) show that customer interaction, sales platforms, and marketing are among the most common uses of AI, which contributes to further reducing transaction costs.

However, there is a debate about the specific effect of industrial AI on organisation boundaries when it comes to applications in manufacturing. Mateos-Garcia (2018) found AI to trigger Organisational complexity, increased market asymmetry, uncertainty, and decisional inertia. Lu et al. (2024) find that larger firms benefit from AI, experiencing reduced exit rates and increased market concentration. De Moura et al. (2024) report the over-concentration of AI knowledge in a few world-leading companies.

The European project iPRODUCE[5] provides a reference model and several implementations of distributed manufacturing practices, challenging the traditional centralisation of manufacturing activities by leveraging additive manufacturing techniques and collaborative business models. Based on this literature, we can predict the effects of AI on firm boundaries.

[5] H2020-870037- iPRODUCE (https://cordis.europa.eu/project/id/870037)

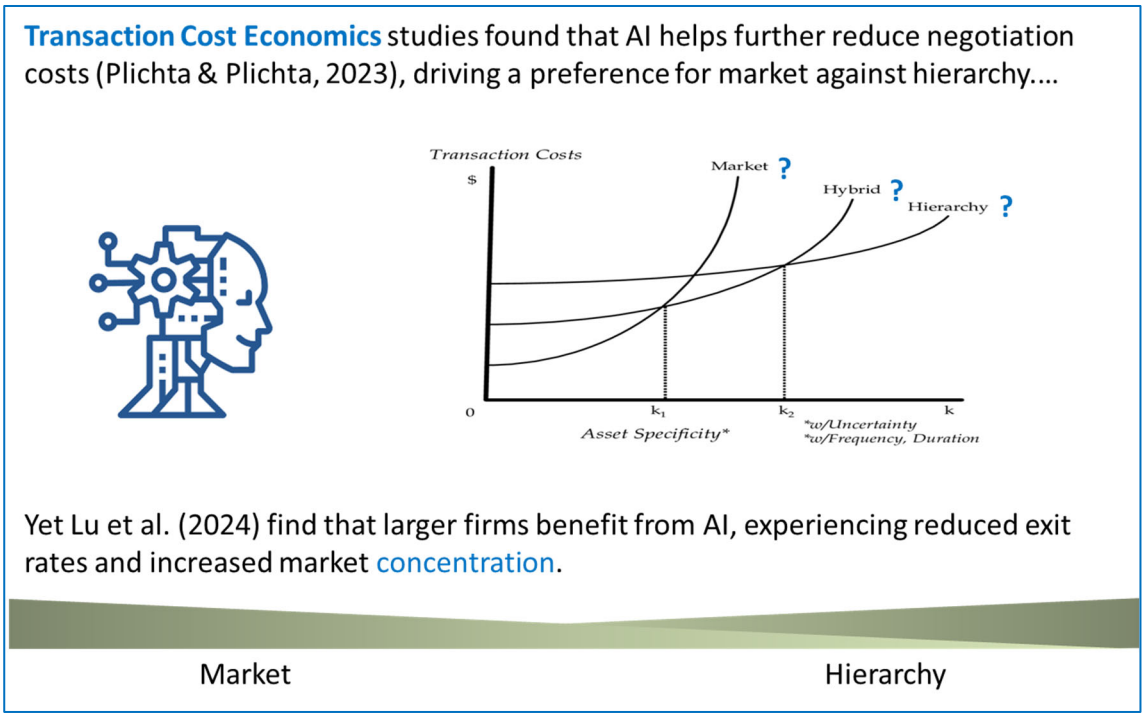


Figure 11: IAI effect on Firm Boundary

Whether IAI plays for market or hierarchy, we retain network strategy [NS] as an observable indicator of a manufacturing strategy [MS] from a TCE perspective (Mateos-Garcia, 2018).

2.4.3. Intelligent Manufacturing and AI Effect on the Product Mix

Computerisation is among the acknowledged factors of the dematerialisation of the industry and the emergence of a service economy (Roy, 2000). To explain this transformation, Theories of Intelligent Manufacturing (TIM) have introduced the concept of "Service-Oriented Manufacturing (SOM)" (Jiang, Feng, Yi, & Guo, 2022). According to Gaiardelli et al. (2021), enhanced digitalisation and connectivity contribute to the successful development of Product Service Systems (PSS) in the context of Industry 4.0. Theories of Intelligent Manufacturing (TIM) associate the digitisation of industry with higher degrees of service integration in firms' product strategy.

Kharub et al. (2022) predict a polarisation of corporate strategies, with firms opting for either cost leadership or differentiation. Meng et al. (2024) illustrate this phenomenon

using Shih's "smiling curve", while Baines et al. (2024) demonstrate that innovative business models can elevate both ends of the value curve, enabling companies to capture greater value. Frank et al. (2019) further argue that digitisation accelerates servitisation. They propose a framework model that connects Servitisation and Industry 4.0 from a business model innovation perspective. Additionally, Sjödin et al. (2023) show how AI can drive circularity and foster sustainable innovation in the realm of industrial digital servitisation.

The ITEA3 project CYBERFACTORY#1[6] provides insightful examples of industrial AI use cases involving revisions of companies' marketing mix. For example, ORG.2, Finland, aims to shift its business model for cheese-making machines from product sales to custom PSS to retain ownership of process data. Based on this literature we can describe AI's effect on the marketing mix as follows.

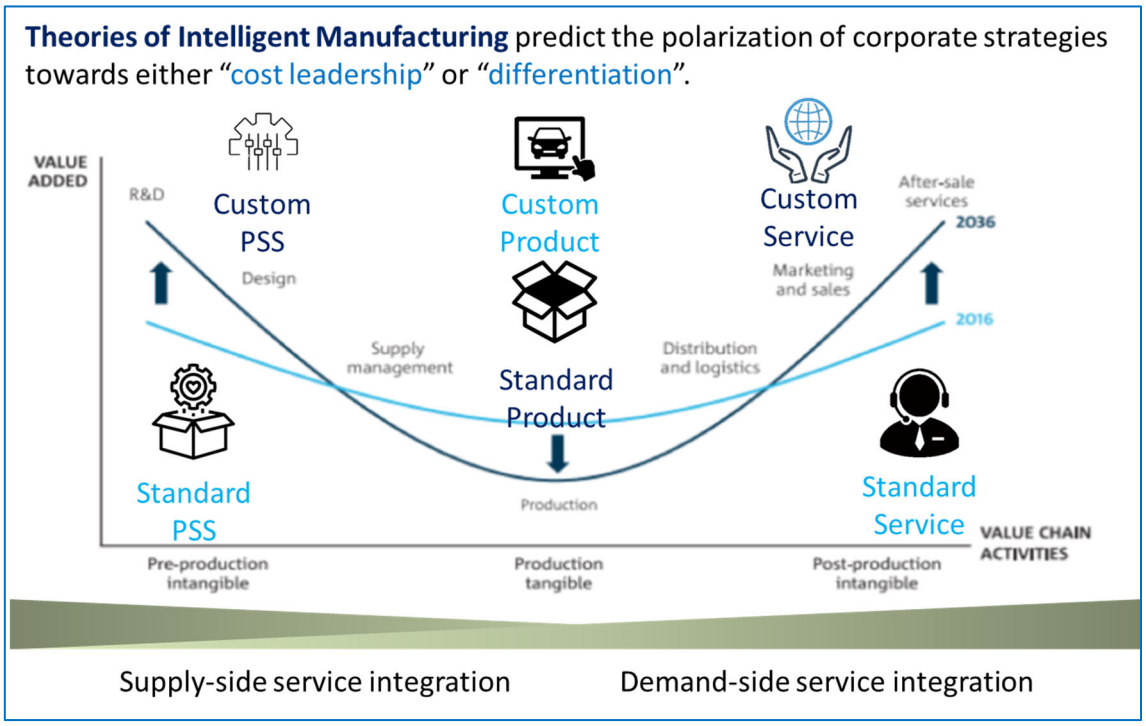


Figure 12: IAI Impact on Marketing Mix

[6] ITEA3-12022-CYBERFACTORY#1 (https://www.cyberfactory-1.org/home/)

TIM literature reveals Organisation Product [OP] as an observable indicator of Organisation Age [OA] and Product/Service Strategy [PS] as an observable indicator of Manufacturing Strategy [MS] (Frank, Mendes, Ayala, & Ghezzi, 2019).

2.4.4. Social Exchange Theory and AI effect on Manufacturing Strategy

According to Chen et al. (2017), services are inherently relational. Therefore, the servitisation of the industry should be examined from a relational perspective. In the mid-seventies, Ian R. McNeil (1974) inspired the Social Exchange Theory (SET) movement that views interactions as reciprocal exchanges where individuals or groups seek to maximise benefits while minimising costs. Farhana (2021) highlights the strategic importance of nurturing trust and satisfaction to stimulate customer involvement in co-creating value and enhancing customer loyalty. With contemporary SET, we examine how AI reshapes manufacturing strategies towards social manufacturing practices.

The social manufacturing literature finds digitisation to help manage complex manufacturing communities where the vertical buyer-seller relationship is replaced by a horizontal relationship between active "prosumers" (Xiong, et al., 2022). Recent literature highlights the potential for enhanced human-AI collaboration, value co-creation and sustainable practices in the realm of Industry 5.0 (Leng, et al., 2024). Other studies claim that industrial digitisation makes product personalisation compatible with large-scale production, leading to the concept of "mass customisation" (Pech & Vrchota, 2022).

Some insightful case studies were presented in the 24th IFIP WG 5.5 Working Conference on Virtual Enterprises[7]. For example, TNO, Netherlands, introduced a maturity model for collaborative agents in human-AI ecosystems that illustrates the concept of social manufacturing. In the same conference, TEC, Mexico, introduced emerging approaches for enterprises and human integration towards Industry 5.0 with an example of a mass-customization strategy. Based on this literature we can forecast an evolution of manufacturing strategies as described hereunder.

[7] 24th IFIP WG 5.5 Working Conference on Virtual Enterprises (https://link.springer.com/book/10.1007/978-3-031-42622-3)

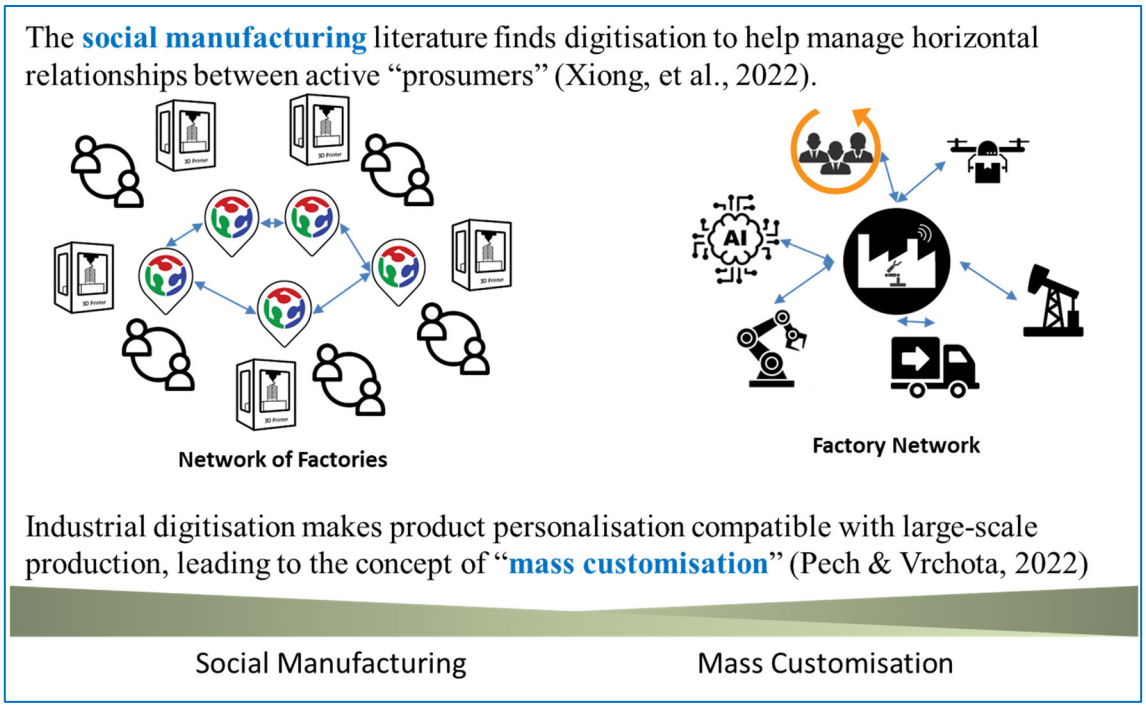


Figure 13: IAI Effect on Manufacturing Strategy

The SET literature suggests an evolution of manufacturing strategies towards AI-powered social manufacturing and/or mass customisation approaches (Gu & Koren, 2022). Therefore, we substantiate ***P2)***: Manufacturing Strategy [MS] is associated with AI Maturity [AM].

2.5. Review Part III: Review of the Management Literature

This section aims to collect insights from the management literature addressing the research question with a particular focus on extracting indicators of innovation capacity and assessing P3: "Innovation Capacity [IC] is associated with Manufacturing Strategy [MS]".

2.5.1. Resource-Based View and AI Effect on Internal Innovation

The resource-based view (RBV) postulates that the acquisition of a sustainable competitive advantage relies on resources gathering singular attributes: 1) value, 2) rareness, 3) imperfect imitability, and 4) non-substitutability (Barney, 1991). Teece et al. (1997) claim that substantial performance gains can only be drawn from investment in a

company-wide “capability” encompassing tangible, intangible, and human resources. Relying on the Resource-Based View (RBV), we examine internal innovation management approaches to determine whether they inform about Innovation Capacity.

Contemporary RBV studies prove that IT is a reliable source of sustainable competitive advantage (Alalie, Harada, & Mdnoor, 2018). Daugherty & Wilson (2018) propose exploiting the synergy between AI and HI. A systematic analysis of interdependencies between them would enhance a firm’s ability to profit from AI (Davenport & Ronanki, 2018). Lichtenhaler (2019) shows that integrating AI applications with specific human expertise is likely to complicate imitation by competitors. However, Pokrovskaya (2024) reports that AI algorithms can also generate highly convincing counterfeit products.

A common trait between different variants of RBV is the assumption that only endogenous characteristics can form the basis of a sustainable competitive advantage. Therefore, these theories emphasize on the prevalent role of AI as a means and an end of internal innovation capacity, suitable to companies adopting product or service specialization strategies. Based on this literature, we set the following properties for AI to form a strategic key capability in the context of Industry 5.0.

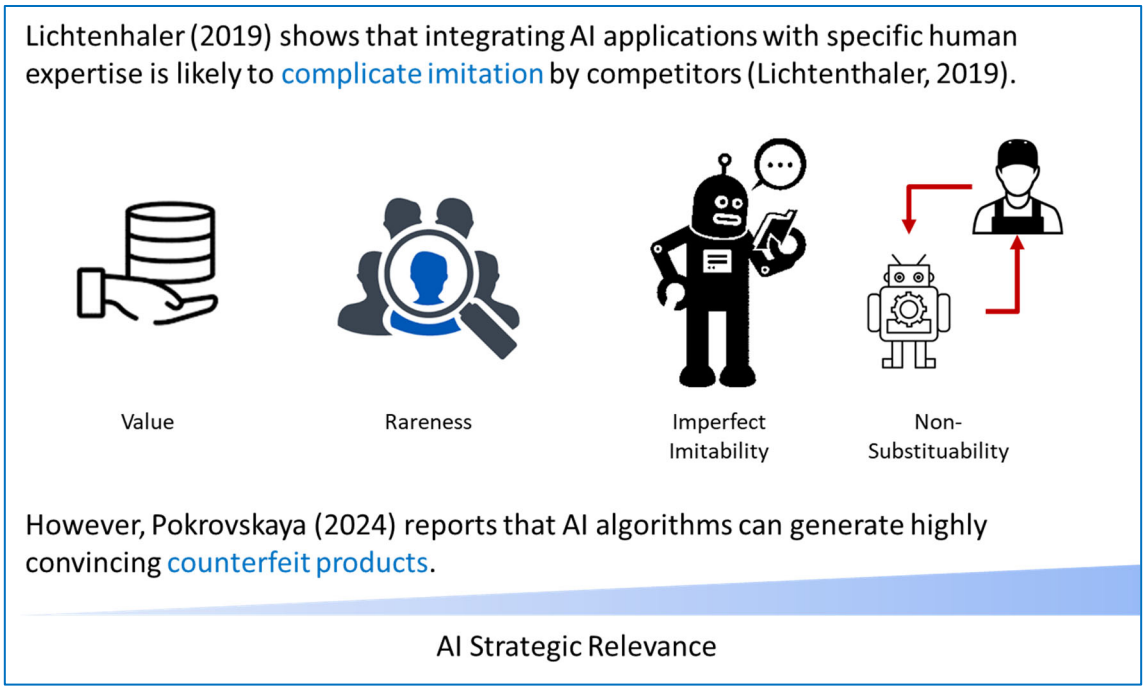


Figure 14: IAI as a Strategic Key Capability

The RBV literature highlights internal innovation [II] primarily as an observable indicator of innovation capacity [IC] and suggests AI innovation as a strategic key capability for Organisations adopting product or service specialisation strategies (Lichtenthaler, 2019).

2.5.2. Open Innovation and AI Effect on Innovation Networks

Open innovation (OI) is defined as a distributed innovation process based on purposively managed knowledge flows across Organisational boundaries (Chesbrough H. &., 2014). We et al. (2022) demonstrate the positive effect of digitisation on open innovation in manufacturing. It is noteworthy that OIT breaks the primary assumption of RBV by assuming a free flow of knowledge across organisational boundaries. With Open Innovation Theories (OIT), we characterise the effect of AI on innovation network strategies, aiming to determine if these strategies reflect a particular Innovation Capacity.

Goldfarb (2018) finds that the development of AI contributes to reducing boundaries of knowledge within and between companies, consequently supporting faster diffusion of knowledge and new knowledge generation by exchange and integration. Liu et al. (2020) demonstrate the spillover effect whereby intelligent technology drives interdivisional

innovation, resulting in profit growth and renewed demand for AI integration. Vlačić (2019) demonstrates that absorptive capacity is a highly effective mechanism for acquiring and sustaining a competitive advantage. Liu et al. (2020) further prove that AI improves the firm's absorptive capacity, preventing errors in technology choices and innovation investment decisions.

Big data platforms facilitate open innovation by enabling companies to collaborate in AI technology development. A noticeable initiative in this direction is the Common European Data Space for Manufacturing (European Commission, 2020). However, Kazantsev et al. (2022) identify major barriers such as partner mistrust, resistance to data sharing and market opacity. Mubarak et al (2021) find that Industry 4.0 positively impacts open innovation, leading to green innovation behaviours. But the environmental impact of AI remains a concern (Alzoubi & Mishra, 2024). Drawing on the existing literature, we envision several distinct modalities for open innovation in Industry 5.0.

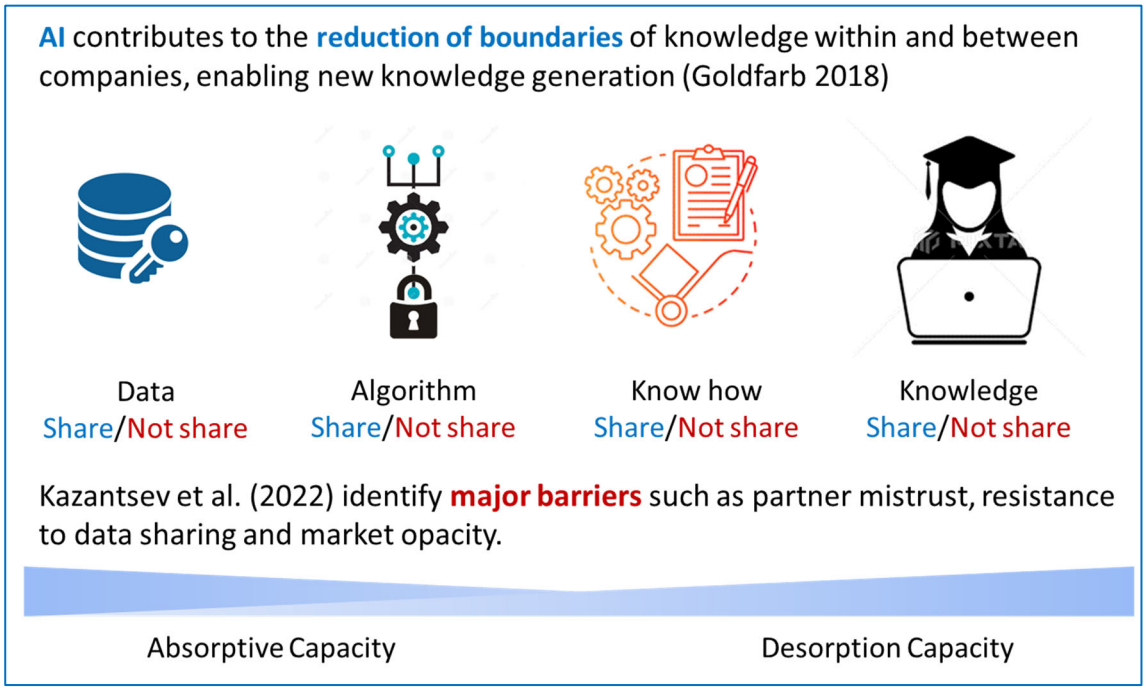


Figure 15: IAI and Open Innovation

OI literature holds Open Innovation [OI] as a relevant indicator of Innovation Capacity [IC] in AI-enhanced manufacturing activities (Goldfarb & Trefler, 2018).

2.5.3. Innovation Policy Literature and AI as a matter of innovation policy

The Innovation Policy Literature (IPL) is the body of research that examines how government interventions, such as R&D support, regulatory reforms, and institutional arrangements, are designed and implemented to foster technological innovation and drive economic growth (Mazzucato, 2021). Agrawal et al. (2019) believe that research support policies will accelerate AI progress. They call "race to the bottom" the temptation for governments to set privacy obligations to a strict minimum. Tucker (2018) highlights the moderating influence of privacy protection policy on the rate and impact of AI innovation. With Innovation Policy Literature (IPL) we characterise innovation policies, aiming to determine if these reflect a particular Innovation Capacity.

Patent protection laws affect the direction and speed of innovation (Mezzanotti, 2021). Tort laws are also likely to have an impact on IAI adoption. Galasso and Luo (2018) state that finding the right balance on liability will be important for the industrial diffusion of AI. Agrawal et al. (2019) suggest policies to care for synchronising business and educational cycles. China now fosters AI education at schools (Xinhua, 2018), and analysts fear the deepening of an "AI divide" that would reinforce world inequalities. Sachs (2018) predicts that AI will rise at the expense of the labour share of GDP. Korinek & Stiglitz (2018) thus recommend taxation of capital. Furman (2018) fears that a universal income would not be spent on education.

The European Commission regularly accuses AI of reinforcing the hegemony of large monopolistic firms. Bajari et al. (2018) counter this argument by showing that big data have a decreasing return to scale. Coercive policies will likely inhibit AI innovation by rendering data sharing costly and reducing the potential to implement mass personalisation strategies. Yet this prejudice can be compensated by incentive policies that proactively support AI-driven innovation. For example the framework DEFACT[8], resulting from the Chinese incentive in Generative AI for Manufacturing 5.0, supports the deployment of social manufacturing strategies in several application cases, such as

[8] DEFACT (https://ieeexplore.ieee.org/abstract/document/10416760)

automated optical inspection, user-friendly human-machine Interaction, and decentralised multi-robot task allocation.

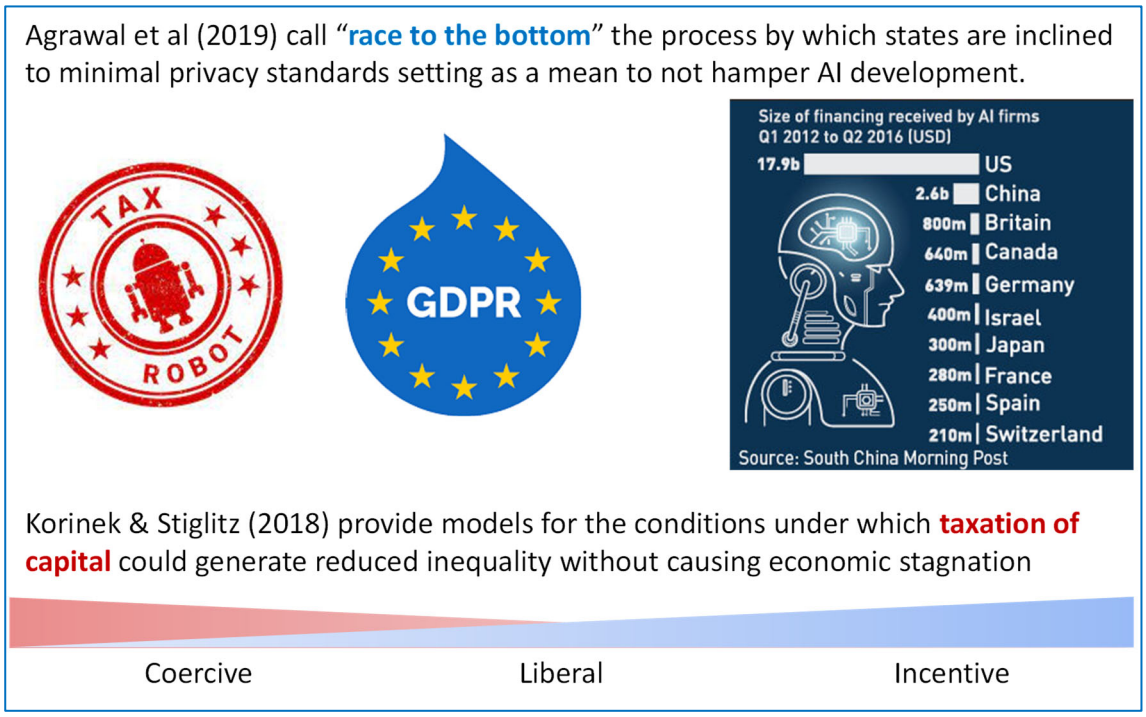


Figure 16: IAI as a matter of innovation policy

The innovation policy literature suggests that Organisation Type [OT] is an observable indicator of Organisation Age [OA] (Bajari, Chernozhukov, Hortaçsu, & Suzuki, 2018). Furthermore, it provides innovation policies [IP] as an observable indicator of innovation capacity [IC] wherever these policies align with the selected manufacturing strategy.

2.5.4. Innovation Management Literature and AI Effect on Innovation Capacity

With Innovation Management Theories (IMT), we examine how manufacturing strategy mediates AI's effects on innovation capacity. O'Leary (2013) reports that AI accelerates knowledge creation with a combined impact on data collection, structuration, analysis, exploration, and integration. Aghion et al. (2017) assert that AI has a positive effect on innovation. Zhou (2012) suggests that AI integration in manufacturing provides not only a common enabling technology for mechanical product innovations but also one for

manufacturing technology innovations. Liu et al. (2020) add that AI-enabled practices such as remote manufacturing, computer-integrated business systems, and data platforms relieve companies from geographical constraints, enabling a more efficient division of labour, information sharing, and resource integration with a direct positive effect on technology development.

Du et al. (Du, Hu, & Chen, 2018) claim that technologies such as deep learning can help industrial robots form independent judgments and take corresponding actions, relieving employees from low-value-added activities and helping them make better-informed decisions. Liu et al. (2020) demonstrate that AI promotes technological innovation by i) quickening knowledge creation, ii) accelerating the spillover of knowledge and technology, iii) improving the capability of learning and absorption, and iv) boosting investment in R&D and talent.

Agrawal et al. (2018) highlight the contribution of AI to the process of knowledge creation, retrieval, and combination. Theben et al. (2021) suggest open-source artificial intelligence (AI) to boost innovation capacity in both the public and private sectors. However, Sætra (2020) warns about the parasitic nature of AI interaction with humans and fears that "Sharing minds with the mindless" might diminish humans' whole learning ability. Based on this literature, we can draw the following possible effects of AI on Innovation Capacity.

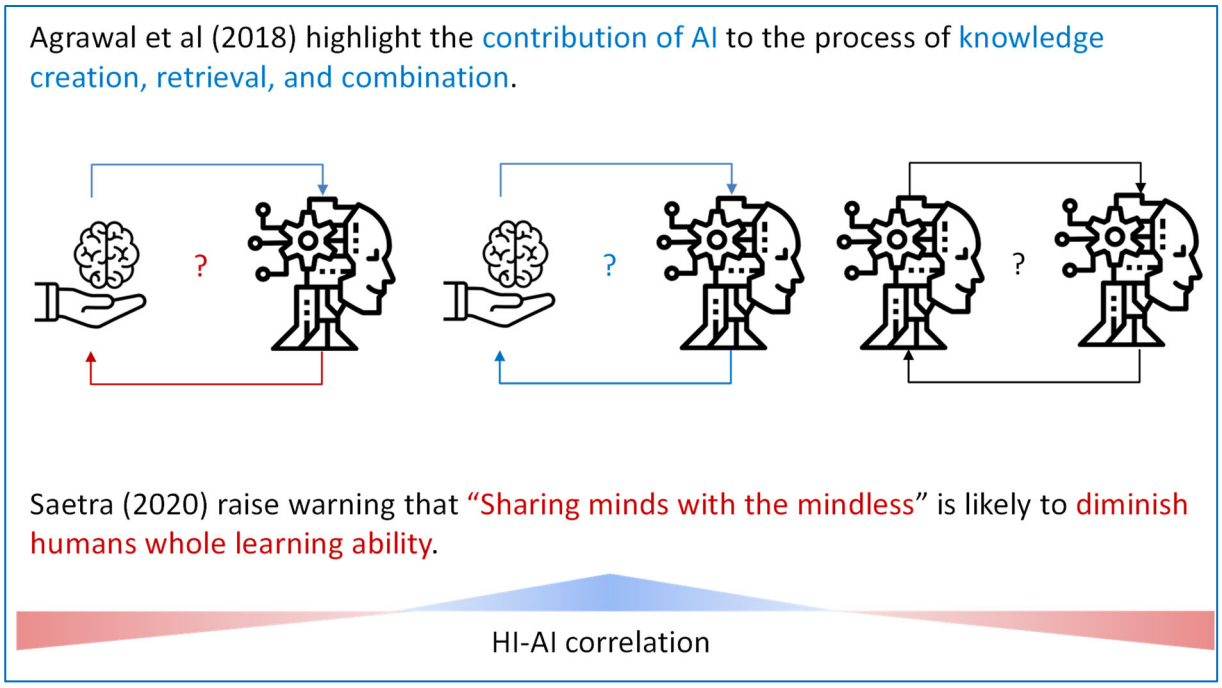


Figure 17: IAI Effect on Innovation Capacity

The innovation management literature suggests that AI-enabled practices such as remote manufacturing positively affect innovation capacity (Liu, Chang, Forrest, & Yang, 2020). Therefore, we substantiate ***P3***: Innovation Capacity [IC] is associated with Manufacturing Strategy [MS].

2.6.Results of the exploratory study

This section aims to provide the exploratory study's outcomes, extract variables at play in the effect of AI on Innovation Capacity, identify the main factors, formulate propositions and identify literature gaps and debates.

2.6.1. Extraction of variables

The literature review provides 16 variables at play in the effect of AI on Innovation Capacity in the context of Industry 5.0. These variables are listed below in relation to the clusters of literature from which they are extracted.

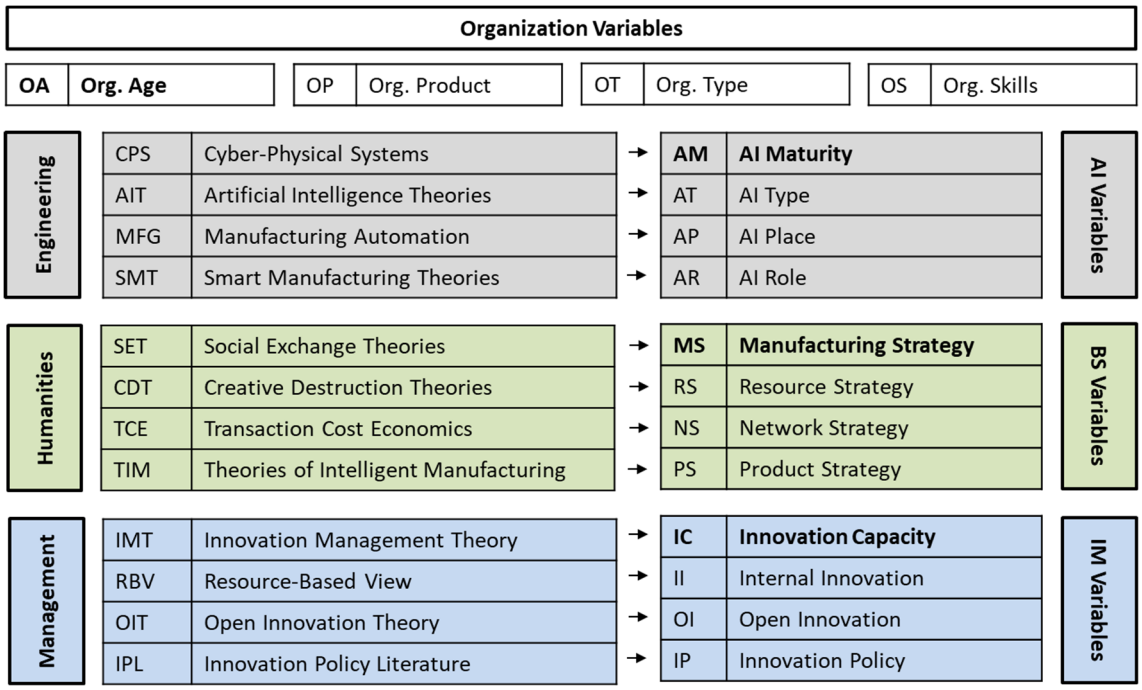


Figure 18: List of variables

In the above figure, the main factors assumed to influence the effect of AI on Innovation Capacity are marked in bold, while their indicators are in light letters. In the following chapter, we discuss the relationship between them.

2.6.2. Factor definition

The literature provides insights into factors' effects on indicators, which, in turn, may help define factors based on observable properties.

Organisation Age [OA]: From the review of all literature bodies, we conclude that specific properties like organisation product (Frank, Mendes, Ayala, & Ghezzi, 2019), organisation type (Bajari, Chernozhukov, Hortaçsu, & Suzuki, 2018), and organisation skills (Acemoglu & Restrepo, 2018) are indicators of [OA]. For example, TIM predicts that AI adoption will drive further service integration in manufacturing products. CDT suggests that AI automation will make smaller-scale production units fit for business. RBV predicts a battle for strategic AI skills and expertise to build a sustainable competitive advantage. The CPS literature defines a maturity model of manufacturing

systems that matches Organisation Ages [OA} from Industry 1.0 to Industry 5.0. Therefore, [OA] can be measured by observable variables such as organisation product [OP] type [OT] and skills [OS].

AI Maturity [AM]: From the review of the engineering literature body, we conclude that the type, the place, and the role of AI in use, are indicators of AI Maturity [AM] in the transition to Industry 5.0. For example, AIT shows that self-learning agents are capable of interacting more naturally with human workers (Bryndin, 2020). MFG shows that the most advanced companies employ AI at all steps of the life cycle with direct positive effects on the environment (Yin & Yuanyuan Yu, 2022). SMT demonstrates that advanced industries assign AI a greater diversity of roles, with growing considerations for collaboration and resilience functions (Solanki, Makkar, & Devi, 2020). The CPS literature suggests AI Maturity [AM] as a predictor of industrial transformation (Yilma, Naudet, & Panetto, 2020). Therefore, [AM] can be measured by a construct of observable variables such as AI type [AT] AI place [AP] and AI role [AR].

Manufacturing Strategy [MS]: From the review of the humanities literature, we conclude that the resource, network, and product strategies of Industry 5.0 companies will differ markedly from those of companies with lower maturity in AI. For example, CDT shows that AI unlike previous general-purpose technologies does not only affect manual jobs but also intellectual ones (Noponen, 2019). TCE highlights that there can be a greater asset-specificity in industrial AI, that revives vertical integration against horizontal networking strategies (Mateos-Garcia, 2018). TIM shows that AI is likely to accelerate the servitisation of the economy and the polarisation of product strategies (Kharub, Mor, & Rana, 2022). SET predicts the development of new manufacturing strategies such as social manufacturing and mass customisation (Pech & Vrchota, 2022). Therefore [MS] can be measured by a construct of observable variables such as Resource Strategy [RS], Network Strategy [NS], and Product Strategy [PS].

Innovation Capacity [IC]: The management literature provides evidence of distinctive attributes of an Industry 5.0 innovation capacity boosted by AI (Liu, Chang, Forrest, & Yang, 2020). For example, RBV forecasts a battle for AI skills and technology considered as strategic key capabilities for realising internal innovation strategies (Lichtenthaler,

2019). OIT suggests a faster diffusion of knowledge across company boundaries through the advent of AI, fostering an increased preference for open innovation strategies (Goldfarb & Trefler, 2018). IPL highlights the moderating effect of coercive policies on AI adoption (Agrawal, Gans, & Goldfarb, 2019). IMT predicts contradictory effects of AI on innovation capacity through a complex interplay with HI (Sætra, 2020). Therefore, [IC] can be measured by a construct of observable variables such as Internal Innovation [II], Open Innovation [OI], and Innovation Policy [IP].

2.6.3. Extraction of Propositions

The figure below shows how the main factors identified above are associated with each other by propositions that the review of the literature reveals:

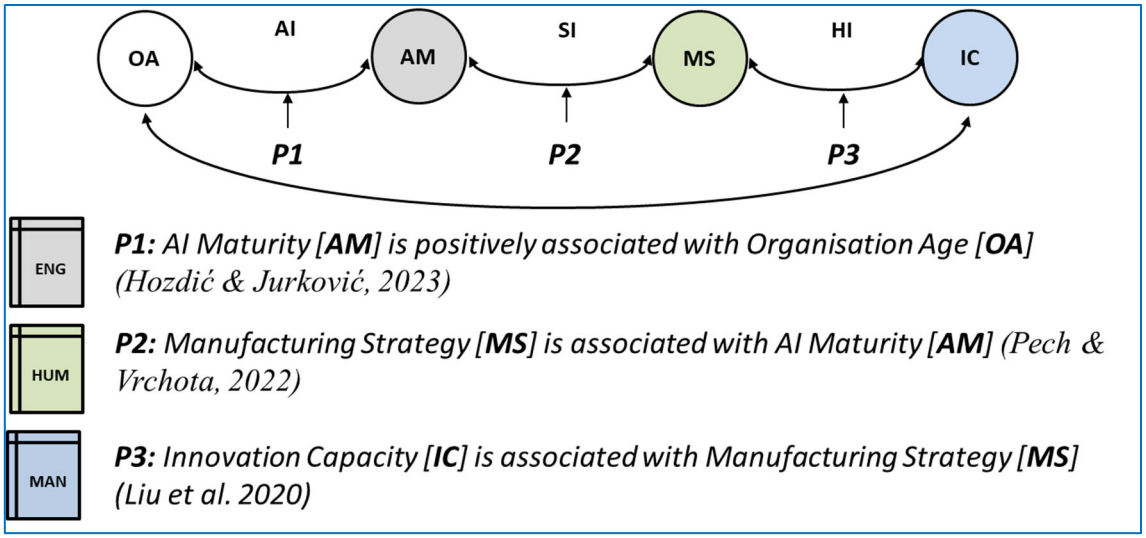


Figure 19: Extraction of Propositions

A summary of how the literature substantiates these propositions follows:

- **P1: AI Maturity is associated with Organisation Age (§2.3):** The systems characterising Industry 5.0 belong to the class defined by system engineering literature as cyber-physical social systems (CPSS) (Yilma, Naudet, & Panetto, 2020). They correspond to the highest level of AI development that makes human-machine interaction intuitive and efficient (Hozdić & Jurković, 2023).

- **P2: Manufacturing Strategy is associated with AI Maturity (§2.4):** Theories of Intelligent Manufacturing (TIM) reveal the contribution of AI to service integration in Product Strategies (PS) (Frank, Mendes, Ayala, & Ghezzi, 2019). Social Exchange Theories (SET) suggest an evolution of manufacturing strategies towards AI-powered social manufacturing and mass customisation. (Pech & Vrchota, 2022).
- **P3: Innovation Capacity is associated with Manufacturing Strategy (§2.5):** The innovation management literature finds that AI-enabled practices, such as remote manufacturing, positively affect Innovation Capacity (Liu, Chang, Forrest, & Yang, 2020). However, this effect may be compromised by a negative effect o AI on Human Intelligence (HI) (Sætra, 2020).

The literature review does not reveal the strength and directionality of these associations. Further qualitative and quantitative research must assess them.

2.6.4. Gaps and Debates

The literature review enables us to extract the following unsolved gaps and debates, which may be addressed by targeted research.

From Engineering (§2.3):

The lack of methodologies and techniques to provide cyber-security assurance on AI-powered industrial systems (Bécue, Gama, & Praça, 2020): while resilience is claimed one of the three main societal objectives of Industry 5.0 (Breque, De Nul, & Petridis, 2021), the very nature of ML within the broader field of AI, makes it less deterministic than conventional technology and thereby vulnerable to adversarial AI threats. This vulnerability potentially limits the potential for successful adoption in manufacturing.

The lack of confidence in AI technology and its effective impact on adoption (Hutson & Plate, 2024): relating with both resilience and human centricity objectives, a distrust in AI is often reported from research in areas of robotics and automation. The manufacturing sector, being known for resistance to change, is likely to meet exacerbated distrust versus

a technology that involves more than technical reliability, raising issues of transparency, explainability, and privacy protection.

The debate whether anthropomorphism affects AI likeability positively, negatively or negligibly (Zhang, et al., 2020): about the human centricity objective, the finding that machines entering the uncanny valley of extreme resemblance to humans tend to trigger sensations of eeriness in humans potentially limits the effective adoption of collaborative robots and other AI artefacts that are core to the Industry 5.0 vision.

The debate about whether AI can be the next GPT (Trajtenberg, 2018) and ML achieve real AGI (Russell & Norvig, 2021): a controversy among economists and engineers about the transformational power of AI, which is potentially overstated by some as equal to or even superhuman and understated by others as merely capable of Pavlovian reactions

From Humanities (§2.4):

The debate between theories of replacement (Noponen, 2019) and theories of augmentation (Paul, et al., 2022) : an unsettled conflict between distopists, who postulate that AI will disqualify humans from a wide range of professional activities, and utopists, who postulate that AI will help improve human performance while reaffirming their sense of usefulness

The debate whether AI will drive enhanced preference for the market (Davenport, Guha, Grewal, & Bressgott, 2020) or for hierarchy (Mateos-Garcia, 2018): contradictory forecasts derived from transaction cost economics about the future trends of either concentration or distribution of industrial supply chains that essentially depend on AI effect on asset specificity versus transaction costs

The question of whether AI will reduce or further enhance the polarisation of industrial strategies towards either “cost leadership” or “differentiation” (Kharub, Mor, & Rana, 2022): an unsolved issue from Theories of Intelligent Manufacturing that simultaneously predict exacerbated standardisation of products to meet low-cost demand on one side of Shih’s “smiling curve” and enhanced product personalisation on the other side of it.

The question of whether AI will drive the industry towards social manufacturing or mass customisation (Pech & Vrchota, 2022): Alternative visions of future supply chains are either allowing centralised production of highly personalised goods by a limited set of highly concentrated firms or local production of individual products by self-employed prosumers

From Management Sciences (§2.5):

The question of whether Industrial AI complicates imitation by competitors (Lichtenthaler, 2019) or helps generate convincing counterfeit products (Pokrovskaya, 2024): how much does AI fluidify the job market, respective to how much it widens the gaps between leading firms that can afford the required talents, from followers that are bound to see their competitiveness weaken.

The conflict between OIT and RBV approaches on the transferability of skills (Goldfarb & Trefler, 2018): a complex arbitration between open innovation, which lowers the cost of technology acquisition but also its market value, and internal innovation, which is costly but potentially gives a long-lasting competitive edge.

The lack of consensus on the role and effect of coercive, liberal or incentive innovation policies on AI with application to manufacturing (Agrawal, Gans, & Goldfarb, 2019): the opposition between liberal policies that urge innovation before regulation (AI in the US) and regulatory policies that urge regulation before innovation (AI in the EU).

The debate about whether the Industrial AI effect on [IC] is synergic (Lichtenthaler U. , 2018), competitive (Shabbir & Anwer, 2018), or deceptive (Sætra, 2020): a theoretical conflict between diverging branches of the engineering, humanities and management literature about the net effect of AI on innovation through antagonist effects on human intelligence, creativity, occupational focus and utility

These open questions are extensively addressed in the following qualitative and quantitative studies.

2.7.Summary of the exploratory study

The exploratory study systematically reviews engineering, humanities, and management literature to understand how Artificial Intelligence (AI) influences innovation capacity.

The study identifies four main factors:

1. **Organisation Age (OA)**, reflecting the maturity level of organisations transitioning to Industry 5.0 (Hozdić & Jurković, 2023).
2. **AI Maturity (AM)**, indicated by AI systems' learning capability, embeddedness, and human-like characteristics (Russell & Norvig, 2021)
3. **Manufacturing Strategy (MS)**, encompassing strategic choices regarding products, services, and supply chain management (Xiong, et al., 2022).
4. **Innovation Capacity (IC)**, which describes an organisation's potential to innovate based on internal skills and research strengths (Liu, Chang, Forrest, & Yang, 2020)

Three propositions emerge clearly from the literature:

- ***P1: AI Maturity is associated with Organisation Age (§2.3)***: The system engineering literature defines AI development as critical for Industry 5.0 realisation (Hozdić & Jurković, 2023).
- ***P2: Manufacturing Strategy is associated with AI Maturity (§2.4)***: Manufacturing Strategy depends significantly on AI Maturity, influencing how resources are managed and products are differentiated (Pech & Vrchota, 2022).
- ***P3: Innovation Capacity is associated with Manufacturing Strategy (§2.5)***: Innovation Capacity is closely linked to Manufacturing Strategy, especially through strategic uses of advanced AI technologies (Goldfarb & Trefler, 2018).

The study highlights key debates and research gaps, such as cybersecurity concerns with AI systems, the controversial role of AI in either augmenting or replacing humans, AI's impact on organisational boundaries, and AI's overall effect on innovation capacity.

3. QUALITATIVE STUDY

The qualitative study aims to identify the main effects between variables and build a conceptual model by analysing expert interviews. Consistently with the methodology introduced in §3.1, we analyse interviews of professionals involved in Industry4/ 5.0 initiatives, with profiles of engineers, researchers, and managers. From this analysis, we extract data that help populate a conceptual model of the effect of AI on IC in the context of I5.0.

3.1. Qualitative Study Introduction

The classical literature on innovation attributes to innovation strategy the role of generating business growth, technological development, and deploying more effective management practices. However, the advent of Artificial Intelligence (AI) reverts this paradigm in the context of Industry 5.0. The focus is moving from "how innovation fosters AI" to "how AI fosters innovation". Therefore, our research question can be stated as follows: "What factors influence the effect of AI on Innovation Capacity in the context of Industry 5.0?"

In the previous part, we conducted an exploratory study to examine this research question based on a review of the literature. Based on this study, we have formulated 3 propositions about the factors at play in the observed phenomenon, suggesting that: *P1 AI Maturity is associated with Organisation Age*, *P2 Manufacturing Strategy is associated with AI Maturity*, and *P3 Innovation Capacity is associated with Manufacturing Strategy*. In this part, we conduct a qualitative study to fill the uncovered research gaps and debates, elaborate a qualitative model and formulate hypotheses to be tested by quantitative means.

In part 3.2 we introduce the qualitative study methods. In §3.3 we collect qualitative data. In §3.4 we provide an analysis of expert interviews. In § 3.5 we design a conceptual model. §3.6 provides a summary of the qualitative study. The contribution to science is substantial, with a qualitative examination of prior theories devising the role of AI in the fifth industrial revolution. This result also supports management practitioners with a conceptual model formalising the causal effects of alternative innovation policies.

3.2. Qualitative Study Methods

This study phase aims to identify the main effects between variables and build a conceptual model by analysing expert interviews. We aim to research a phenomenon at play in the manufacturing industry, with long-lasting effects that partially stand in the future and thus cannot be measured by analysing existing quantitative data. Therefore, we have conducted an explanatory case study to identify the factors influencing the effects of AI on [IC] in the context of Industry 5.0. Following the methodology of Naz, Gulab & Aslam (2022) and (Glesne, 2016), we use in-depth semi-structured interviews to collect the data for this case study.

3.2.1. Qualitative data collection method

We aim to interview professionals from engineering, research, and management backgrounds involved in industrial transformation activities. As the Industry 5.0 transformation is assumed to be a fact of humans, it is appropriate to seek people's opinions and perceptions (Barriball & While, 1994). This is particularly relevant, taking into account the requirement for human-centricity inherent to the definition of Industry 5.0 (Breque, De Nul, & Petridis, 2021). Moreover, our research question has implications for engineering, humanities, and management sciences. Therefore, we aim to interview professionals with these backgrounds.

The Industry 5.0 concept is relatively new, and there is little awareness of it, even among the target population still at hand with Industry 4.0. Therefore, we will conduct in-depth semi-structured interviews. A pool of experts meeting the study requirements has been assembled based on public records. Their profiles are provided in ANNEX 4: List of Experts. Interviews were held until the saturation of the study subject, totalising the interview of 18 experts, among which were 8 engineers, 4 researchers, and 6 managers. While the first interviews yielded novel insights into involved variables and effects, the marginal knowledge gain vanished as we approached the last interview.

The interviewees come from 11 different Organisations, of which 1 is a Non-Profit Organisation (NPO), 2 are Research & Technology Offices (RTO), 3 are Large

Enterprises (LE), and 5 are Small or Medium Enterprises (SME)[9] They belong to 9 industries, ranging from textile to robotics, and nine countries, predominantly in Europe. This is consistent with the geographical scope of the investigation focusing on Europe and Associated Countries according to Regulation (EU) 2021/695[10] where the Industry 5.0 paradigm has been fostered through public innovation policy.

3.2.2. Design and testing of the interview guide

The interview guide has been developed according to the methodology of Naz, Gulab & Aslam (2022) and (Glesne, 2016) as a list of main theme questions, refined with follow-up questions. The first question block assesses the interviewee's profile to calibrate the depth of interview exchange on each key concept and relationship. Then, the main theme questions are open-ended questions that map the four key factors extracted from the literature: Organisation Age [OA], AI Maturity [AM], Manufacturing Strategy [MS} and Innovation Capacity [IC]. The follow-up questions are directed. They aim to keep the interviewee engaged while verifying the validity of indicators proposed by the literature. The interview guide leaves, however, a vast place for interview personalisation and natural interaction, as recommended by Glesne (2016). It can be found in ANNEX 3: Interview Guide.

The interview guide has passed internal testing, expert assessment and field testing. The internal test was carried out by a research team that included three experienced engineering, humanities, and management researchers. The guide has been reviewed following roleplays where each team member acted once as interviewer and once as interviewee. The expert assessment was done by inviting three researchers external to the study team to review the interview guide and provide feedback and recommendations. Finally, three professionals representative of the target population have been interviewed to test the interview guide. This field test has led to simplifying the guide and setting an

[10] Regulation (EU) 2021/695 establishing Horizon Europe (https://eur-lex.europa.eu/eli/reg/2021/695/oj/eng)

interview time of 45 minutes, which is considered adequate to explore all dimensions of the research question without losing the interviewee's attention.

3.2.3. Interview procedure and analysis techniques

Interviewees have been invited by email to interview sessions held on the Google Meet web conferencing application in a period lasting from January 2022 to December 2023. All interviews were carried out and transcribed in English. Interviews have been held following interview protocols suggested by Rabionet (2011). The interviewer introduces himself and the research objectives. Interviewees are asked for consent to be recorded, given the option to withdraw, informed about the use and publication of the results, and invited to remain in contact to benefit from the results. To respect the requirements expressed by the interviewees, the results of these interviews have been anonymised. Experts and organisations are therefore introduced under pseudonyms.

Following each interview, the recordings were analysed and automatically transcribed using the Otter.ai application to avoid researcher bias. Video records have also been analysed for non-verbal signals as recommended by Glesne (2016). The transcripts and an interview analysis were inserted in an interview report, sent for review by the interviewee and for analysis by co-researchers. The analysis of interview transcripts has helped refine the variables extracted from the literature, analyse the effects among them, and evaluate them qualitatively in an inductive approach. Moreover, they have supported the development of a conceptual model for the impact of [AI] on [IC]. The industrial AI use cases proposed by the interviewees have been extracted to form the first 21 rows of ANNEX 7: Use-cases List to be analysed by quantitative means (§4).

3.3. Data Collection

This section aims to extract qualitative data from the analysis of the interviews, enabling the derivation of a conceptual model that can be functionally tested with a preliminary dataset. We record and classify four datasets: i) a list of experts, ii) a list of organisations, iii) a list of projects, and iv) a list of use cases.

3.3.1. Experts

ANNEX 4: List of Experts contains the list of experts involved in the thesis work. The table collects and classifies the profiles of 79 experts. From this list, the 18 first rows are the experts interviewed as part of the qualitative study. The other rows are experts involved in the subsequent quantitative study (§624). The qualitative study data includes eight professionals from an engineering background, four from a research background, and six from a management background. This distribution of competencies is appropriate to the background requirements established in §3.2.

3.3.2. Organisations

ANNEX 5: Organisations List contains the list of organisations involved in the thesis work. The table collects and classifies the profiles of 92 organisations. The first 11 rows from this list are the organisations to which the interviewed experts belong. The other rows are organisations involved in the subsequent quantitative study (§624). The qualitative study data includes one non-profit organisation, two research and technology offices, five small or medium enterprises, and three large industrial companies. The dominant section within NACE[11] activity nomenclature is section C (NACE codes from 10.nn to 33.nn). Expectedly, this section contains manufacturing activities.

3.3.3. Projects

ANNEX 6: Projects List contains the list of projects identified in the thesis work. That table collects and classifies 39 projects, from which 7 are reported by the interviewed experts. The other rows are projects involved in the subsequent quantitative study (§624). Within the qualitative study data, one project belongs to the ITEA4 framework, a European program for collaborative research and development activities in software. Three projects belong to the Horizon 2020 framework, a European program for research and innovation. Three projects belong to the Horizon Europe framework, which is the

[11] NACE-The statistical classification of economic activities in the European Community (https://ec.europa.eu/eurostat/web/nace)

follow-up of Horizon 2020. This setup satisfies the target geography and temporality of the study.

3.3.1. Use-cases

Annex 7 contains the list of use cases identified in the study. The table collects and classifies a total of 126 use cases. From this list, the first 21 rows are the use cases reported by the interviewed experts. The other rows are use cases involved in the subsequent quantitative study (§624). Within the qualitative study data, one use-case is reported from an organisation of age "Industry 1.0". Two are reported from organisations of age "Industry 2.0". Nine are reported from organisations of age "Industry 3.0". Six are reported from organisations of age "Industry 4.0". And three are reported from organisations of age 'Industry 5.0'. Therefore, we can qualitatively assess all Organisation Ages with the interviewed experts.

3.4. Interview Analysis

A summary of the interviews structured by organisation is provided in ANNEX 8: Summary of Interviews. In this chapter, we analyse interview outcomes for each of the four groups of variables extracted from the literature: Organisation Characteristics, Artificial Intelligence, Business Strategy and Innovation Management. The interviewees are introduced as (**EXP.n**) according to the pseudonyms defined in ANNEX 4: List of Experts. The organisations are introduced as (**ORG.n**) according to the pseudonyms defined in ANNEX 5: Organisations List. Projects are identified as (PROJ.n) according to the pseudonyms defined in ANNEX 6: Projects List. Use cases are identified as (**UC.n**) according to the Pseudonyms defined in ANNEX 7: Use-cases List. Observable variables of interest are marked as (Variable = Observed Value). When the interviews inform about one of the propositions extracted from the exploratory study, the related sentence is marketed with (***Pn***).

3.4.1. Organization Characteristics

The interviews reveal that Organisation Age [OA], defined by the Industry 5.0 maturity model (§1.3), is subject to interpretation and is not readily observable. However,

characteristics such as Organisation Product [OP], Organisation Type [OT] and Organisation Skills [OS] are observable at the use-case level, and consistent patterns emerge during the interview analysis.

Industry 1.0 (OA = Industry 1.0) is represented in a single use case (UC.2), which is also the only one delivering materials as a product (OP = Materials). It is proposed by a small enterprise (OT = SME) whose dominant skill is mechanics (OS = Mechanics).

Industry 2.0 (OA = Industry 2.0) is represented in 2 use cases (UC.1 & UC.14), which both focus on producing goods (OP = Goods). While UC.1 is reported by a small company (OT = SME), UC.14 is reported by a non-profit organisation (OT = NPO). Both use cases leverage mechanics as the dominant skill (OS = Mechanics).

Industry 3.0 (OA = Industry 3.0) is represented in 9 use cases (UC.4, 5, 6, 7, 8, 9, 13, 16, 17), of which four deal with hardware manufacturing (OP = Hardware) and five deal with system integration (OP = System). Except for UC.13, they are all reported by large enterprises (OT = IND). The dominant skills are electrical engineering (OS = Electrical Engineering) and mechanics (OS = Mechanics).

Industry 4.0 (OA = Industry 4.0) is represented in 6 use cases (UC.11,12,19,21), of which 2 deliver software (OP = Software), 2 deliver services (OP = Services), and 2 deliver systems (OP = Systems). Large organisations are dominant (OT = IND), but non-profit (OT = NPO) and smaller businesses (OT = SME) are also represented. The dominant skill is system engineering (OS = System Engineering).

Industry 5.0 (OA = Industry 5.0) is represented in 3 use cases (UC.8,11,14), of which 2 deliver systems (OP = Systems) and 1 deliver software (OP = Software). Large enterprises are not represented; only UC.10 is for profit (OT = SME). There is no clear dominant skill, although computing appears for the first time in UC.15 (OS = Computing).

In contrast with the literature in §3.1, we note that Industry 5.0 organisations deliver systems rather than services. Consistently with §3.2 Industry 5.0 is compatible with small organisation types and non-profit motivations. Consistently with §3.3 we find system engineering dominant in Industry 4.0.

3.4.2. Artificial Intelligence

The interviews reveal that AI Maturity [AM], defined according to CPS Engineering theory (§2.3.4), is difficult to assess by expert judgment. However, characteristics such as AI Type [AT], AI Place [AP] and AI Role [AR] are observable at the use-case level, and consistent patterns emerge during the interview analysis. An association between AI Maturity [AM] and Organisation Age [OA] also emerges, supporting ***P1***.

Single maturity levels are represented in 8 use cases, among which Cyber is dominant (AM = Cyber) while only UC.1 involves physical systems (AM = Physical) and UC.2 involves social systems (AM = Social). The dominant type of AI is machine learning, with four use cases involving virtual non-humanoid agents (AT = Machine Learning Virtual Object). It is predominantly deployed in operations (AP = Operation) to optimise processes (AP = Optimisation). It is loosely associated with Industry 3.0 (OA = Industry 3.0) (***P1***).

Double maturity levels are represented in 10 use cases, among which Cyber-Physical systems are largely dominant (AM = Cyber-Physical). In comparison, only two use cases involve cyber-social systems (AM = Cyber-Social). The dominant type of AI is machine learning, but this time with embodied non-humanoid agents (AT = Machine Learning Embodied Object). It is most often deployed in manufacturing activities (AP = Manufacturing) to automate processes (AP = Automation). It is strongly associated with Industry 3.0 (OMA = Industry 3.0) (***P1***).

Triple maturity levels (AM = Cyber-Physical-Social) are found in 3 use cases (UC.10,15,18). They involve machine learning in embodied systems (AT = Machine Learning Embodied), humanoid in the case of UC.10 and UC15. They are deployed in operations (AP = Operations) to support human-machine collaboration (AR = Collaboration). All 3 use cases are reported by Industry 5.0 organisations (OA = Industry 5.0), which verifies the association between AI maturity and Organisation Age (***P1***).

Consistently with §2.3.4 We note that Cyber-physical Systems (CPS) predominantly leverage embodied ML algorithms, and Cyber-physical Social Systems (CPSS)

additionally tend to adopt humanoid features. Enriching the findings from §2.3.1, Generative AI appears within the playable AI types in UC.19 (Generative Design of Mechanical Parts). Consistently with §2.3.2 the experts place AI in various stages of the manufacturing lifecycle with design, manufacturing, testing, commissioning, operation, and maintenance stages appearing in the qualitative data. Consistently with §2.3.3 Collaboration appears as the main differentiating role of CPSS. While single maturity level use cases belong to a wide range of organisation ages, cyber-physical social systems are tightly bound to Industry 5.0, which supports ***P1***.

3.4.3. Business Strategy

The interviews reveal that Manufacturing Strategy [MS], defined according to Social Exchange Theory (§2.4.4), is difficult to assess by expert judgment. However, characteristics such as Resources Strategy [RS], Network Strategy [NS] and Product Strategy [PS] are observable at the use-case level, and consistent patterns emerge during the interview analysis. An association between Manufacturing Strategy [MS] and AI Maturity [AM] also emerges, supporting ***P2***.

Product-oriented businesses are found in 12 use cases, among which 8 rely primarily on specialisation strategies (MS = Product Specialisation). Their dominant resource strategy is to replace or augment operators (RS = Replace / Augment Operators), although augmenting managers and engineers also appears in a few cases. The dominant network strategy is develop AI internally (NS = Develop) but other approaches like purchasing AI also appear. Delivering standard products is the dominant product strategy (PS = Standard product) although custom product-systems also appear. Product oriented businesses tend to leverage cyber-physical systems (AM = Cyber-Physical) (***P2***).

Process-oriented businesses are found in 9 use cases which 5 rely primarily on specialisation strategies (MS = Process Specialisation). Their dominant resource strategy is to augment operators (RS = Augment Operators) although replacing operators and augmenting managers is also reported. AI specification is the dominant network strategy (NS = Network Specification) while crowdsourcing and customisation of standard AI supplies is also reported. Custom services are the dominant product strategy (PS =

Custom Service) although custom products are also reported in a few cases. These use cases mostly leverage AI at the cybernetic level (AM = Cyber) (***P2***).

Specialisation strategies are found in 13 use-cases among which a majority of 8 is for product businesses (MS = Product Specialisation). Both replacement and augmentation strategies are found with a focus on operators (RS = Replace/Augment Operators). In most cases, users specify AI tools to be deployed (NS = Specify). Standard products are the dominant product strategy (PS = Standard Product). The cybernetic element is dominant in AI maturity levels with the physical element adding in the case of product-oriented businesses (AM = Cyber(-physical)) (***P2***).

Servitisation and customisation strategies are found in 8 use-cases evenly distributed among product-oriented (MS = Product Servitisation) and process-oriented businesses (MS = Process Servitisation). They demonstrate a preference for augmentation against replacement of human resources (RS = Augment Operators/Managers). AI customisation is the dominant network approach although other approaches are also reported (NS = Customise). Product service integration appears highly represented here (PS = Custom/Standard PSS). The social element appears more prevalent in these use cases (AM = Cyber-(Physical)-Social) (***P2***).

Consistently with §2.4.1, we find specialisation strategies more prone to resource replacement than servitisation and customisation strategies, which aim at resource augmentation. Customisation strategies appear much less in this dataset than in the literature. The operator level remains the focus of resource optimisation tactics, although managers come in with servitisation and customisation strategies. In addition, the interview analysis yields “customers” and “engineers” among the affected resources. Consistently with §2.4.2, specialisation strategies involve binary make-or-buy decisions, although the buy decision seems to come with user specifications. Crowdsourcing appears as a novelty unaddressed by the study's body of literature. Consistently with § 2.4.3 we note the blending of product and services in PSSs in use-cases applying product servitisation strategies. Overall, the cyber component seems prevalent in transforming process-oriented businesses, while the physical component is core to product-oriented businesses. The integration of the social component enables customisation strategies (***P2***).

3.4.4. Innovation Management

The interviews reveal that Innovation Capacity [IC], defined according to the Innovation Management literature, is difficult to assess by expert judgment. However, characteristics such as Internal Innovation [II], Open Innovation [OI] and Innovation Policy [IP] are observable at the use-case level, and consistent patterns emerge during the interview analysis. An association between Innovation Capacity [IC] and Manufacturing Strategy [MS] also emerges, supporting ***P3***.

Analytic capacities appear in 13 use cases with a majority of 8 singletons (IC = Analytic Singleton). In most cases, internal innovation is led by engineers or operations (II = Engineering/Operations). Open innovation is used systematically to expand the customer base (OI = Systematic Outbound). Private policies drive these use cases with a focus on incremental innovation (IP = Private Incremental). They associate with product specialisation strategies (MS = Product Specialisation) (***P3***).

Cognitive capacities appear in 6 use cases, among which 5 swarms (IC = Cognitive Swarm) and only one singleton (UC.9). In most cases, they are initiated by engineers or experts (II = Engineering/Expertise). Open innovation is usual but not systematic (OI = Regular). Private policies dominate again, while the ambitioned innovation is disruptive here (IP = Private Disruptive). These innovation capacities are associated with process specialisation strategies (PS = Process Specialisation) (***P3***).

Generative capacities appear only in UC. 19 (Generative Design of Mechanical Parts) in the form of cloud-based software (Generative Singleton). It is led by mechanical engineers (II = Engineering Driven) and supported by regular outbound innovation initiatives (OI = Regular Outbound). It is a private initiative of disruptive nature (IS = Private Disruptive) sponsored by a product specialisation strategy (MS = Product Specialisation) (***P3***).

Parasitic capacities appear only in UC.6 (Intelligent media recommendation) as a centrally controlled software (IC = Parasitic Singleton). The initiative is driven by corporate strategy level (II = Strategy-driven) and supported by systematic open

innovation projects (OI = Systematic Outbound). It is a private initiative that disrupts the market (IP = Private Disruptive) by shifting revenue streams from the sales of consumer electronics to media channel subscriptions (MS = Product Servitisation) (***P3***).

Consistently with §2.5.1 we note AI tends to take over analytical tasks in operation-driven and management-driven innovation approaches, while it may take more cognitive tasks in engineering and expertise-driven activities. Consistently with § 2.5.2 we find organisations involved in open innovation more prone to adopt swarm intelligence while others tend to forge singletons. Consistently with §2.5.3, analytic innovation capacities are usually associated with defensive or incremental innovation policies, while cognitive innovation capacities tend to match more disruptive Innovation Policies. Product specialisation drives analytic AI capacity, while process specialisation drives cognitive AI capacity (***P3***).

3.5. Conceptual Model Design

The conceptual model is designed underneath consistently with the findings from the interview analysis (§3.4). In the following graphs, hidden factors are represented in circles; observable indicators are represented in squares; and effects are represented with arrows from cause to effect variable.

3.5.1. Organisation Age Inference System

We acknowledge from the interview analysis that [OA] is a variable difficult to observe, which we call a hidden factor. However, this factor can be inferred by its direct effects on observable indicators, as demonstrated below:

- Organisation Product is an indicator of Organisation Age: for example, we found Industry 5.0 organisations more likely to deliver systems as a main product. We can, therefore, assume a direct effect between [OA] and [OP].
- Organisation Type is an indicator of Organisation Age: for example, we found Industry 5.0 organisations more likely to be small enterprises or non-profit organisations. We can, therefore, assume a direct effect between [OA] and [OT].

- Organisation Skills is an indicator of Organisation Age: for example, we found computing skills more likely dominant in Industry 5.0 organisations. We can, therefore, assume a direct effect between [OA] and [OS].

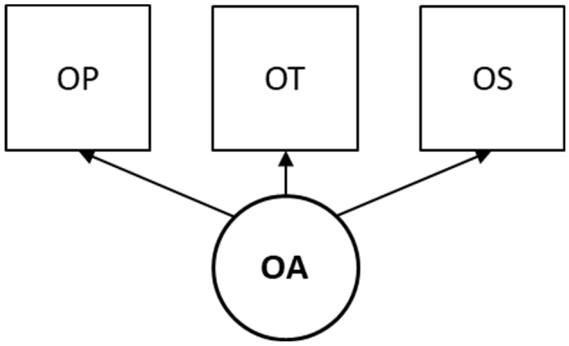


Figure 20: Organisation Age Inference System

This figure describes the structure of effects from the factor Organisation Age [OA] to its indicators: Organisation Product [OP], Organisation Type [OT] and Organisation Skills [OS].

3.5.1. AI Maturity Inference System

Measuring AI Maturity (§3.4.2): We acknowledge from the interview analysis that [AM] is a variable difficult to observe, which we call a hidden factor. However, this factor can be measured by its direct effects on observable indicators as demonstrated below:

- AI Type is an indicator of AI Maturity: for example, we found humanoid features more likely in cyber-physical-social systems. We can, therefore, assume a direct effect from [AM] to [AT].
- AI Place is an indicator of AI Maturity: for example, we found cyber-physical social systems more likely to be deployed in operations than others. We can, therefore, assume a direct effect from [AM] to |AP]
- AI Role is an indicator of AI Maturity: for example, we found cyber-physical-social systems more likely involved in human-machine collaboration. We can, therefore, assume a direct effect from [AM] to [AR].

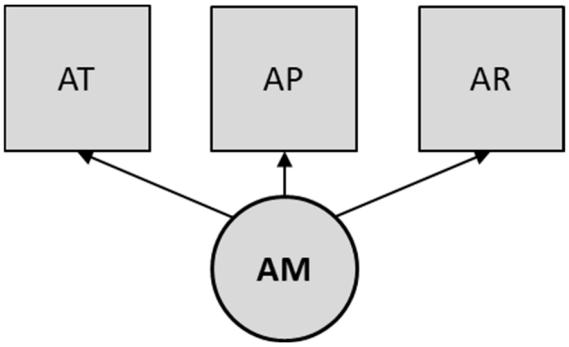


Figure 21: AI Maturity Inference System

This figure describes the structure of effects from the factor AI Maturity [AM] to its indicators: AI Type [AT], AI Place [AP] AI Role[AR].

3.5.2. Manufacturing Strategy Inference System

We acknowledge from the interview analysis that [MS] is a variable difficult to observe, which we call a hidden factor. However, this factor can be measured by its direct effects on observable indicators, as demonstrated below:

- Resource Strategy is an indicator of Manufacturing Strategy: for example, we found customisation strategies leveraging AI to augment human operators rather than replace them. We can, therefore, assume a direct effect from [MS] to [RS].
- Network Strategy is an indicator of Manufacturing Strategy: for example, we found product-oriented businesses more likely to develop AI internally than to purchase it. We can, therefore, assume a direct effect from [MS] to [NS].
- Product Strategy is an indicator of Manufacturing Strategy: for example, we found process-oriented strategies more prone to customisation than product-oriented strategies. We can, therefore, assume a direct effect from [MS] to [PS]

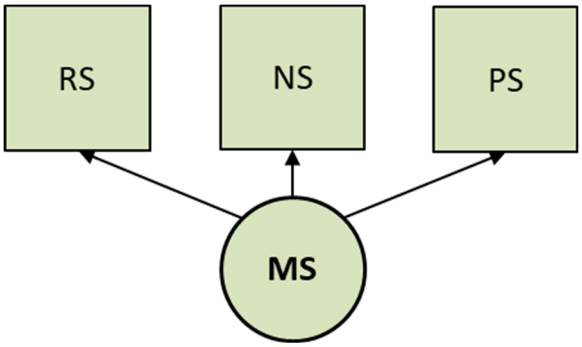


Figure 22: Manufacturing Strategy Inference System

This figure describes the structure of effects from the factor Manufacturing Strategy [MS] to its indicators: Resource Strategy [RS], Network Strategy [NS] and Product Strategy [PS].

3.5.3. Innovation Capacity Inference System

We acknowledge from the interview analysis that [IC] is a variable difficult to observe, which we call a hidden factor. However, this factor can be measured by its direct effects on observable indicators, as demonstrated below:

- Internal Innovation is an indicator of Innovation Capacity: For example, cognitive AI capacities are more likely to be driven by experts than by operations or strategy. Therefore, we can assume a direct effect from [IC] to [II].
- Open Innovation is an indicator of Innovation Capacity: For example, we found open innovation more systematic in use-cases leveraging swarm intelligence. Therefore, we can assume a direct effect from [IC] to [OI].
- Innovation Policy is an indicator of Innovation Capacity: For example, cognitive AI is more likely in use cases driven by disruptive innovation policies. Therefore, we can assume a direct effect from [IC] to [IP].

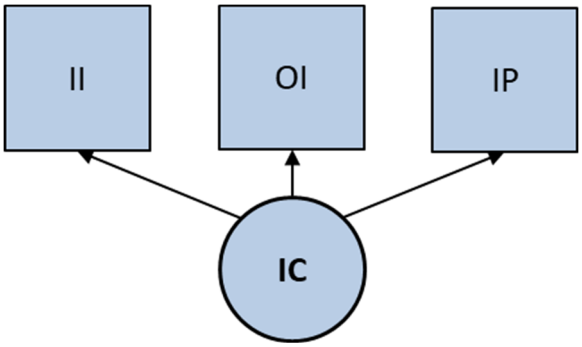


Figure 23: [IC] factor inference system

This figure describes the structure of the effects of the factor Innovation Capacity [IC] on its indicators: Internal Innovation [II], Open Innovation [OI] and Innovation Policy [IP].

3.5.4. Model Path Effects

The model path effects correspond to the 3 proposed associations extracted from the literature in §3.4.1 which the qualitative study now allows to refine as hypotheses:

- ***H1: Organisation Age has an effect on AI Maturity***: For example, we found that cyber-physical social systems were tightly bound to Industry 5.0. In contrast, cyber-physical systems are predominant in Industry 4.0 and Industry 3.0 organisations. Earlier ages tend to be associated with physical or social systems as single-level AI maturity levels (§3.4.2).

- ***H2: AI Maturity has an effect on Manufacturing Strategy***: For example, we found that overall, the cyber component seems prevalent in process-oriented businesses. In contrast, the physical component is core to the product-oriented businesses. The integration of the social component enables customisation strategies(3.4.3).

- ***H3: Manufacturing Strategy has an effect on Innovation Capacity***: For example, we found that Product specialisation drives analytic AI capacity, while process specialisation drives cognitive AI capacity. The interview set does not

allow for predicting generative or parasitic AI capacities, as only one use case of each type is provided (§3.4.4).

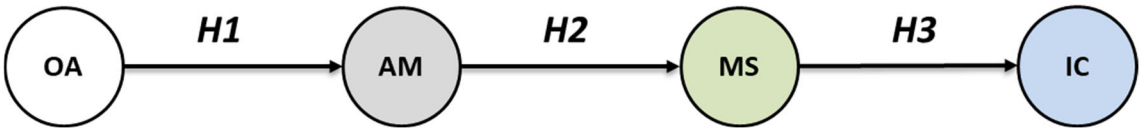


Figure 24: Model Path Effects

This figure describes the path through the main factors influencing AI's effects on innovation capacity in the context of Industry 5.0.

3.5.5. Model Graph

Acknowledging the patterns learned from the interview analysis, we proceed with constructing a conceptual model that formalises the structure of the uncovered effects. For this, we assemble the factor inference systems along the model path.

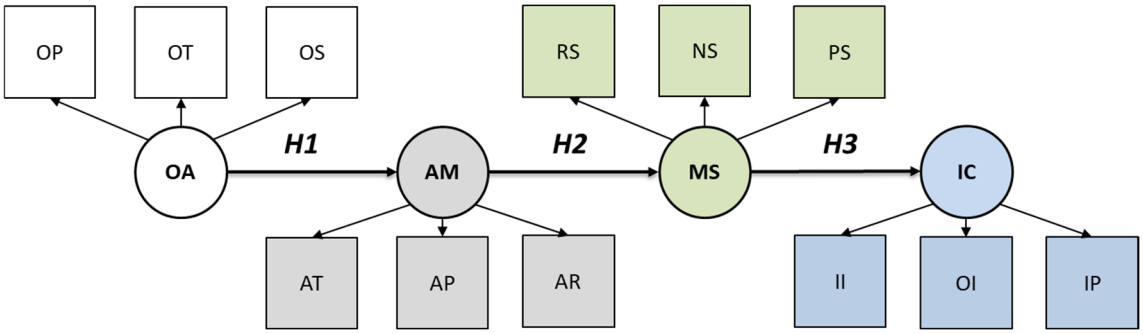


Figure 25 Conceptual model

The graph is structured around the four main factors: Organisation Age [OA], AI Maturity [AM], Manufacturing Strategy [MS], and Innovation Capacity [IC]. The path effects between them are now formulated as hypotheses to be tested (H1, H2, H3).

3.6. Summary of the Qualitative Study

This study gives a preliminary answer to the question: "What factors influence the effect of AI on IC in the context of Industry 5.0?". We examine the factors extracted from the literature in §2, provide evidence of their effects, and propose an inference technique to assign factor values. Further, we build a conceptual model that can be tested against more extensive data. We conclude that Company Age influences AI Maturity toward greater integration of human, physical, and cyber components in the age of Industry 5.0, as suggested by Yilma et al. (2020). We demonstrate that higher levels of AI maturity contribute to the enhanced polarisation of manufacturing strategies and drive further service integration, as suggested by Frank et al. (2019).

We find that manufacturing strategies mediate the effect of AI on IC, leading to scenarios of synergy (Lichtenthaler U. , 2019), competition (Shabbir & Anwer, 2018), or deception (Sætra, 2020). The scenario of synergy is exemplified by reported cognitive use cases such as collaborative robotics (UC.10), where humans and artificial intelligence combine to benefit both. The competition scenario is exemplified by the generative design of mechanical parts (UC.19) where AI demonstrates creative abilities previously undisputed to humans. The deception scenario is exemplified by the intelligent media recommendation use case (UC.6), where a centrally managed AI agent orients customers towards manufacturer-specified media consumption.

This work contributes to a better understanding of AI effects on IC in the context of Industry 5.0. It provides qualitative insights on possible futures for industries involved in digital transformation projects. In particular, it proposes a conceptual model and a factor inference system readily available for quantitative analysis. It also contributes to practice by suggesting context-aware innovation management strategies. The initial set of use cases is diverse enough to elaborate a sound conceptual model. It is, however, not broad and representative enough to draw definitive conclusions. A quantitative study needs to be conducted to verify this model's prediction accuracy.

4. QUANTITATIVE STUDY

The quantitative study aims to train and validate the conceptual model against a dataset of real-life Industrial AI use cases to verify the generalisability of the findings from previous research phases.

4.1. Quantitative Study Introduction

The classical literature on innovation attributes to innovation strategy the role of generating business growth, technological development, and deploying more effective management practices. However, the advent of Artificial Intelligence (AI) reverts this paradigm in the context of Industry 5.0. The focus is moving from "how innovation fosters AI" to "how AI fosters innovation". Therefore, our research question can be stated as follows: "What factors influence the effect of AI on Innovation Capacity in the context of Industry 5.0?"

In the previous parts, we have conducted an exploratory study to identify key factors based on a review of the literature (§2) and a qualitative study to assess the chain of effects at play (§3). Based on this study, we have formulated 3 hypotheses, suggesting that ***H1 AI Maturity is associated with Organisation Age***, ***H2 Manufacturing Strategy is associated with AI Maturity***, and ***P3 Innovation Capacity is associated with Manufacturing Strategy***. In this part, we conduct a quantitative study to train a Bayesian model and test the hypotheses against real-world data.

In §4.2 we introduce the quantitative study methods. In §4.3 we define variable categories. In §4.4 we conduct a Bayesian analysis. In § 4.5 we test the model. In §4.6 we test the hypotheses. § 4.7 provides a summary of the quantitative study. We conclude that Industry 5.0 organisations use Cyber-Physical-Social Systems de develop Social Manufacturing strategies, leading to the elaboration of a distributed AI-driven innovation capacity that we call "Cognitive Swarms". These findings give researchers a new understanding of the interplay between artificial intelligence and human intelligence. They provide practitioners with decision metrics for a successful transition to Industry 5.0.

4.2. Quantitative Study Methods

This study phase aims to train and validate the conceptual model against a real-life Industrial AI use case dataset. We need to verify if the patterns of effects extracted from the qualitative study are generalisable to a larger population of interest. We use a Total Survey Error (TSE) approach, following the methodology of Wolf et al (2016). With this choice, we aim to minimise sampling, coverage, and non-response errors while mitigating response accuracy and survey administration issues.

4.2.1. Quantitative data sampling and collection method

The geographical scope of the investigation is Europe and Associated Countries according to Regulation (EU) 2021/695. Within this territory, the target population will be organisations of any size and type involved in the Industry 4/5.0 transformation programs. To identify this population, we explore the public records of 39 projects, of which the list is provided in ANNEX 6: Projects List. We record the organisations in the lead of IAI use cases, expanding the organisations list to 92 records provided in ANNEX 5: Organisations List. Within these organisations, we further expand our list of experts, reaching 79 records provided in ANNEX 4: List of Experts. To automate the use-case collection procedure, we design an online survey questionnaire. The questionnaire is relayed by the European Factories of the Future Research Association (EFFRA) in their newsletter on 5th March 2024 [12]. This dissemination channel is complemented by direct requests for contributions by the identified experts and by a systematic review of published IAI use cases.

The resulting dataset includes 126 records, among which 21 were collected from experts' interviews, 36 from a review of published use cases, and 69 from respondents to the online survey. The unit of analysis is the industrial AI use case, a record of 27 fields encoding

11 textboxes and 16 model variables. Among the 92 Organisations involved in this quantitative study are 3 Non-Profit Organisations (NPOs), 12 Research and Technology Offices (RTOs), 18 academic research organisations (ACAs), 28 Small or Medium Enterprises (SMEs), and 31 large enterprises (INDs). 33 NACE2. classes are represented, the dominant classes (apart from academic and research) being class 28.99, "Manufacture of other special-purpose machinery", class 62.01 ", Computer programming activities", and class 82.92, Packaging activities. The data sample is, therefore, adequate in size and diversity for this study. The combination of different collection procedures ensures robustness against bias.

4.2.2. Design and testing of an online questionnaire

The questionnaire has been designed according to the guidelines and the six methodological components of Regmi et al. (2016):

- 1) A user-friendly layout: This requirement has been addressed through the structuring of 4 sections corresponding to the four factors of interest, the limitation to a maximum of 30 questions and the "admin" and "interface" scoring of candidate online survey tools in Table 2.
- 2) Selecting survey participants: The collection and dissemination medium have been selected adequately to reach the population of interest, and the EFFRA newsletter is being read by the largest community of researchers, engineers, and managers involved in manufacturing digitisation. This population is, by definition, familiar with the Internet and online surveys.
- 3) Avoiding multiple responses: The absence of financial incentives makes the risk of redundant responses very low in our case. Accidental doubloons have been detected and deleted before data analysis. Respondents were invited to submit several IAI use cases if they wanted, as the unit of study is not the respondent himself but the use case.
- 4) Data management: The predominant use of closed-ended questions with formatted choice lists and an open textbox for respondent comments or questions gives exploitable data for model training and the opportunity to enrich the model

wherever needed. Ease of data export and embedded statistics were scored in "data" and "analytics" criteria in Table 2.

- 5) Ethical issues: The questionnaire applies all good practices in survey ethics: informed consent, privacy and confidentiality terms, and withdrawal rights. By nature, the subject does not involve any particular gender issue nor requires the respondent to expose personal information. Anonymisation procedures protect information relating to corporate strategy.
- 6) Piloting: The first version of the questionnaire was deployed for a test by 18 preselected experts (the interviewees of phase 2) to capture feedback and recommendations for improvement. The introductory words and some complex questions were rephrased following that test.

4.2.3. Survey procedure and analysis techniques

The survey administration procedure is carried out according to the methodology of Wolf et al. (2016) and the guidelines of Regmi et al. (2016). A set of online survey tools has been preselected based on a benchmark from PC MAG[13]. After some investigations and trials, a subset of this panel has been evaluated based on the following criteria: cost of use, interoperability, administration functions, interface ergonomics, analytic functions, and languages supported. ZohoSurvey has been selected and used to deploy the online questionnaire that is accessible at: https://survey.zohopublic.eu/zs/YkTzHN.

For proper integration with the data collected by direct interview or review of published materials, the survey answers were extracted from a CSV file and converted by simple computation functions to the tabular use-case description format enclosed in ANNEX 7: Use-cases List. A few text-field comments have been retrieved. They have been used to enrich variable categories wherever applicable, resulting in the 122 current categories. However, the number of categories for one variable has been limited to 10 to avoid model overfitting and degraded generalisability.

[13] https://www.pcmag.com/picks/the-best-online-survey-tools

4.2.1. Bayesian model training and testing

The analysis of survey answers and the aggregation of the use-case dataset give clear insights into the validity of the structure of effects extracted from the qualitative study procedure. However, the size and distribution of data do not match the requirements for conventional statistical analysis techniques. Indeed, The major assumptions associated with these techniques include multivariate normality, no systematic missing data, and a large sample size. Therefore, a more flexible approach is needed. We need a technique that can be used to predict the consequences of intervention, acknowledging that direct observation of the phenomenon is not guaranteed.

A Bayesian network consists of a set of variables and a set of directed links (or edges) between these variables (Heckerman, 2022). Mathematically, the structure is called a directed acyclic graph (DAG), G = (V,E), where V is a set of random variables X = (X1, X2, ..., Xn), also known as nodes and E is a set of edges that represent conditional dependencies between nodes. If there is a link from X1 to X2, we say that X2 is a child of X1, and X1 is apparent of X2. For each node Xi the corresponding probability distribution can be written as: P(Xi) = P(Xi | pa(Xi)), where pa(Xi) denotes the set of parents of Xi in G. Using the chain rule for Bayesian networks, we can write the joint probability distribution over all variables as follows:

$$P(X1, X2, \dots, Xn) = \prod P(Xi \mid pa(Xi))$$

Equation 1 : Joint probability distribution

Conditional Probability Tables (CPTs) quantify the strength of probabilistic dependencies between variables (Koller & Friedman, 2009). CPTs provide the "weights" of these edges by specifying how the probability of the child node changes based on different configurations of its parent nodes. In the following example, the joint probability distribution of [IC] can be expressed as:

$$P(IC, MS, AM, OA) = P(IC \mid MS) * \text{P(MS |AM)} * \text{P(AM | OA)} * \text{P(OA)}$$

Equation 2 : Bayesian network factorisation

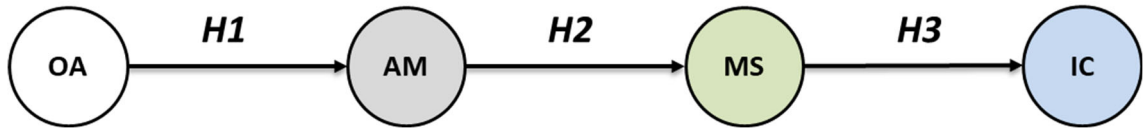


Figure 26: Bayesian Network Model Path

Bayesian Networks present the following advantages for this research: i) they can handle situations where some data entries are missing, ii)-they have both causal and probabilistic semantics, iii) they allow to represent expert knowledge in a probabilistic manner, iv) they can equally infer the state of a non-observable variable or predict the probable cause of an observation. The ability of Bayesian networks to accommodate domain knowledge has been leveraged to verify the model effects extracted from the qualitative analysis. Their flexibility of use with small or incomplete data fits our constraints.

We use GenIE software from Bayes Fusion[14] to elaborate a Bayesian network replicating the model extracted from the qualitative study phase. We train this network with the data collected in the quantitative study phase. We use the "leave one out" testing procedure to validate the Bayesian network. This procedure introduces randomness in the testing sample selection so that the measures of model fit can be trusted and consistent over time. Finally, we test the hypotheses extracted from the qualitative review against the trained Bayesian network by analysing the learned conditional probabilities.

4.3. Variable Categories setting

The conduct of expert interviews, combined with the systematic literature review, allows the definition of 122 categories for the identified set of 16 variables. These categories are justified below and listed in ANNEX 9: Variable Categories.

4.3.1. Organisation Characteristics

Organisation Product: The variable categories for Organisation Products have been extracted from the interview analysis and matched against NACE Rev. 2 Statistical

[14] https://www.bayesfusion.com/2024/10/10/genie-5-0/

classification of economic activities in the European Community from EUROSTAT. Goods and materials, as well as software and services, are included.

Organisation Type: The variable categories for Organisation Type are adapted from European Commission Recommendation 2003/361, which defines micro, small and medium-sized enterprises and Information Report SOC/639-EESC-2020, which defines Non-Profit Organisations. Different sizes and purposes (profit/non-profit) are covered.

Organisation Skills: The variable categories for Organisation Skills have been extracted from the interview analysis and matched against NACE Rev. 2 Statistical classification of economic activities in the European Community from EUROSTAT. Skills range from core industrial mechanics to electricity, electronics and computing.

Organisation Age: The variable categories for Organisation Age are defined according to Industry 5.0 communication from the European Commission (2022) and contemporary innovation policy literature (§2). They range from Industry 1.0 to Industry 5.0, matching characteristics of the corresponding industrial revolutions.

4.3.2. Artificial Intelligence

AI Type: The variable categories for AI Type are defined according to a modern approach to AI from Russel & Norvig (2021) and contemporary data science literature (§2.3.1). They help determine whether symbolic, machine learning or generative techniques are used and specify AI agents' embodiment and anthropomorphism levels.

AI Place: The variable categories for AI Place are defined according to contemporary manufacturing automation literature (§2.3.2) in 7 places covering the full product lifecycle from early design to recycling. The commissioning stage marks the transfer of product ownership from supplier to user in product-oriented businesses. In service-oriented businesses, this transfer of ownership does not necessarily happen.

AI Role: The variable categories for AI Role have been defined based on contemporary smart manufacturing literature (§2.3.3) and refined based on interview analysis (§3.4). They cover a broad range of passive (e.g. monitoring), active (e.g. automation) and

interactive (collaboration) roles of AI which have implications on the required properties of the employed AI models.

AI Maturity: The variable categories for AI Maturity have been defined based on the system engineering taxonomy from Yilma et al. (2020) and contemporary CPS engineering literature (§2.3.4). They describe the integration of cyber, physical and social elements in single, double or triple levels of integration. Eventually, this variable encodes the deployed AI assets' analytical, cognitive and social abilities.

4.3.3. Business Strategy

Resources Strategy: The variable categories for Resource Strategy have been defined based on theories of replacement and augmentation (Noponen, 2019), creative destruction theories (§2.4.1) and interview analysis (§3.4.3). They cover alternative replacement or augmentation of human resources of different kinds, namely operators, managers, engineers and customers.

Network Strategy: The variable categories for Network Strategy have been defined according to transaction cost economics theories (§2.4.2) and further expanded by interview analysis (§3.4.3). They enrich the classic make-or-buy strategy with finer options found in practice, such as customising standard solutions, development by a third party upon specification, integration by merger and acquisition, and crowdsourcing.

Product Strategy: The variable categories for Product Strategy have been defined according to circular economics and intelligent manufacturing literature (§2.4.3). They cover various product- or service-focused marketing mixes with the option of combined product service systems (PSS). They encode the alternative for standard or custom solutions.

Manufacturing Strategy: The variable categories for Manufacturing Strategy are inspired by contemporary social manufacturing approaches (§ 2.4.4). They cover product- or process-oriented businesses. Specialisation strategies aim at cost leadership, while customisation strategies aim at differentiating by enhanced product personalisation. Mass

customisation aims to personalise at a large scale, while social manufacturing aims to scale by networking production agents.

4.3.4. Innovation Management

Internal Innovation: The variable categories for Internal Innovation are inspired by the resource-based view (§2.5.1) and enriched based on the interview analysis (§3.4). Operation-driven initiatives are led by production and governed by needs. Engineering-driven initiatives aim to leverage a novel technology opportunistically. Qualitative demand shifts may trigger business-driven innovation, while quantitative demand shifts trigger demand-driven innovation. Strategy-driven approaches leverage innovation to establish a sustainable competitive advantage, while expertise-driven approaches result from advanced technology foresight.

Open Innovation: The variable categories for Open Innovation are derived from contemporary open innovation literature (§2.5.2). Inbound open innovation aims to maximise knowledge extraction from an ecosystem of research and technology partners. In contrast, outbound open innovation aims to maximise innovation adoption by an ecosystem of economic partners and lead customers. Different gradations encode the appetite for open innovation from weak to systematic.

Innovation Policy: The variable categories of Innovation Policy are inspired by the innovation policy literature (§2.5.3) and enriched by the interview analysis (§3.4.4). Private innovation policies are established by corporate strategy to optimise innovation capture and exploitation. In contrast, public innovation policies are established by states or institutions to augment innovation generation or improve its diffusion to society. Reactive competitiveness measures characterise defensive policies, while proactive technology upgrades characterise incremental policies. Long-lasting structural impacts characterise disruptive innovation policies.

Innovation Capacity: The variable categories of "Innovation Capacity" are inspired by contemporary innovation management literature and works of AI technology foresight (§2.5.4). This variable encodes different possible futures of AI with humans: analytic AI

can think rationally, cognitive AI can behave humanly, generative AI can fake human creativity, and parasitic AI can exploit human vulnerabilities. It also differentiates singletons, which centralise innovation capacity into a unique AI agent, from swarms, which distribute intelligence over a multiagent system.

4.4. Bayesian Network Analysis

4.4.1. Training Dataset

As explained in §4.2 we combine different collection procedures to gather the dataset supporting the training and testing of our model:

- Interview-based data collection: The interviews carried out in phase 2 provide a baseline of 21 fully described use cases, thanks to a qualitative analysis study developed in §3.
- Survey-based data collection: The main quantitative data source is the answers to the online questionnaire and the survey conducted according to §4.2. This procedure gives 69 entries.
- Literature-based data collection: Finally, 36 entries incorporate the use cases found in the literature through a continuous literature review.

The resulting dataset counts 126 entries, which are described in ANNEX 7: Use-cases List. It is relatively small but comprehensive, with only 21 missing variable values (1%). This dataset is sufficient to train a Bayesian Network. Therefore, we proceed to a Bayesian Network analysis as specified in §4.2.1.

4.4.1. Descriptive Statistics

The following diagrams show the categorical distribution for each of the four factors.



Figure 27: Use case distribution for each factor

Note that some survey respondents missed assigning categories for AI Maturity (2 cases), Manufacturing Strategy (2 cases), and Innovation Capacity (3 cases). The complete distribution of all 16 variables can be found in ANNEX 12: Descriptive Statistics.

4.4.2. Network Design

Bayesian Networks need a directed acyclic graph structure. This is compatible with the structure of the conceptual model introduced in §3.5. The model structure is replicated in GeNIe Academic software as follows.

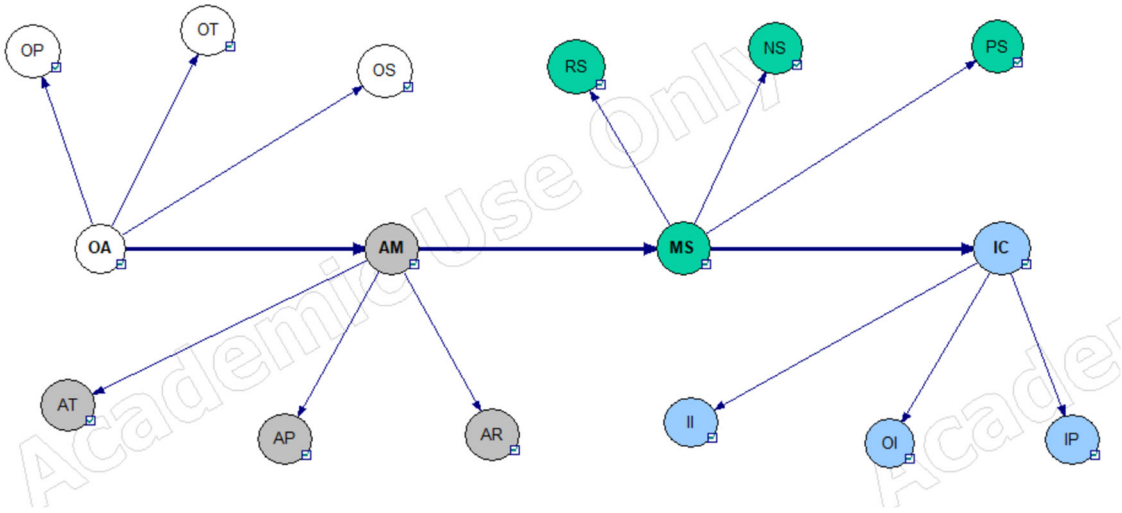


Figure 28: Bayesian Network

Consistently with §3.5, this network has four main factors, 12 indicators, and 15 direct effects. The main factors and the path effects are represented in bold.

4.4.3. Network Training

We train this model against the dataset provided in ANNEX 7: Use-cases List. The software computes conditional probabilities that quantify the effects between variables.

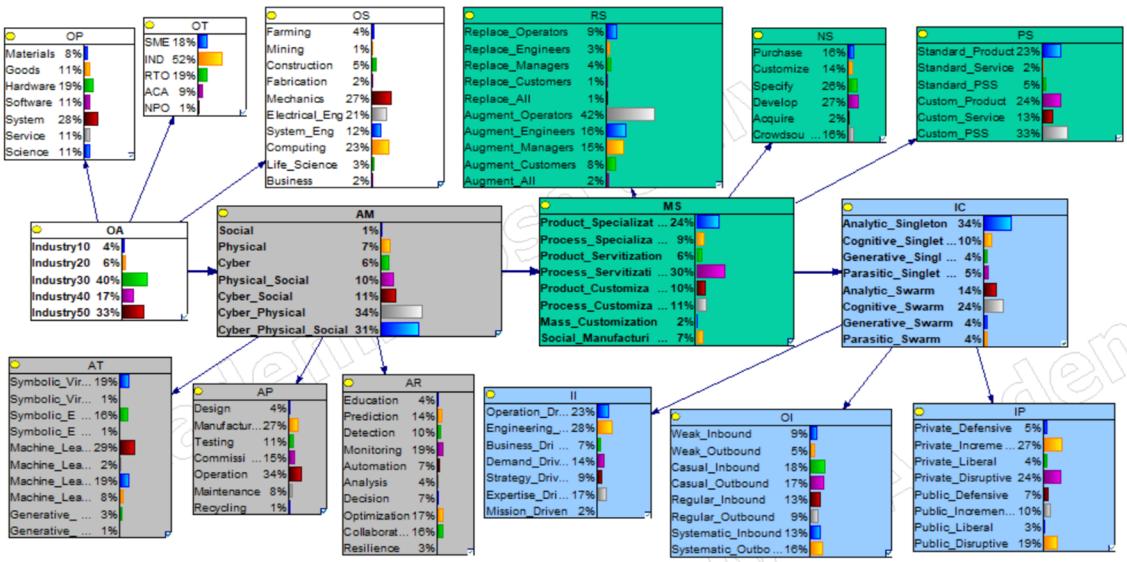


Figure 29: Bayesian Network Training

This figure displays the 122 initial probabilities learned from the dataset provided in ANNEX 7: Use-cases List. The individual conditional probabilities of each variable class are provided in Annex 11: Conditional Probabilities.

4.4.1. Diagnosis Example

In Bayesian Network Analysis, diagnosis refers to inferring the most probable causes (hidden variables or faults) given observed evidence (symptoms or effects) using Bayesian inference. To demonstrate the use of Bayesian Networks for diagnosis, we aim to determine the most likely cause for an organisation to exhibit a "public disruptive" Innovation Policy ([IP]=Public Disruptive).

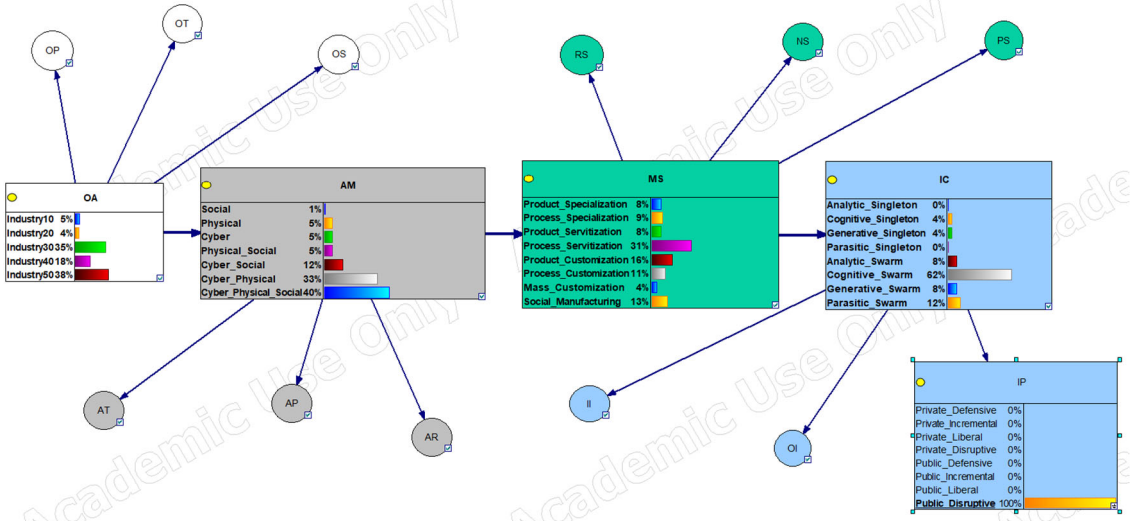


Figure 30: Diagnosis of public disruptive IP

By setting "Public Disruptive" as evidence and recomputing the conditional probabilities of the model, we find that the most probable cause is the adoption of a cognitive swarm. Indeed, P(IC = Cognitive Swarm) jumps from 24% to 62% with this evidence. Furthermore, social manufacturing, a rare Manufacturing Strategy, jumps from 7% to 13% probability. Cyber-physical social systems jump from 31% to 40%, becoming the most probable type of AI Maturity. Simultaneously, Industry 5.0 jumps from 33% to 38%, becoming the most likely Organisation Age. We can conclude that Industry 5.0 is the most likely cause of a public disruptive Innovation Policy.

4.4.1. Prediction Example

In Bayesian Network Analysis, prediction refers to estimating the probability of future or unobserved events (effects) given known causes (inputs or prior observations) using Bayesian inference. It involves computing the probability distribution of target variables based on given evidence and the structure of the Bayesian network. To demonstrate the Bayesian network's prediction ability, we aim to predict the Innovation Capacity of a computing organisation ([OS] = Computing) that works on collaborative robotics ([AR] = Collaboration) while exhibiting a customisation network strategy ([NS] = Customise).

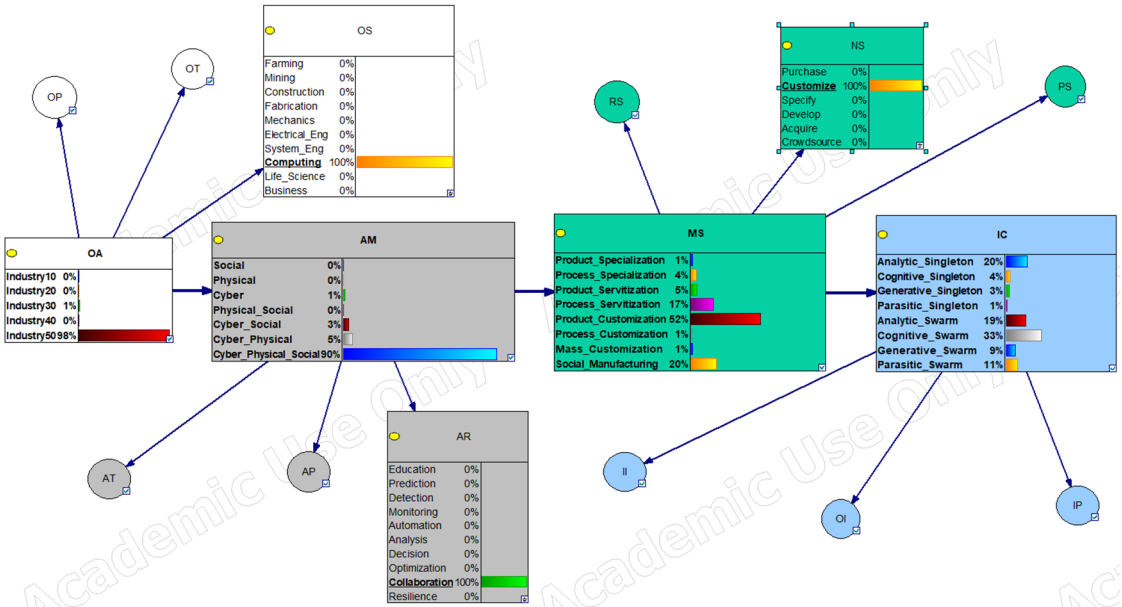


Figure 31: Predict Innovation

The variables influencing Innovation Capacity ([MS], [AM], [OA]) are hidden variables. Therefore, we need to infer their states prior to predicting IC. Competence in computing is strong evidence that the Organisation Age is Industry 5.0 as we find P([OA]=Industry 5.0) = 98%. The use of AI in a human-machine collaboration is strong evidence that AI Maturity is of cyber-physical social type as we find P([AM]=Cyber-Physical Social)=90%. A customisation Network Strategy indicates a preference for product customisation as P([MS]=Product Customisation) = 52%. The chain of effects from [OA] to [IC] helps predict Cognitive Swarm as the most likely Innovation Capacity, with a jump from 24% to 33%.

4.5.Model testing

Within GenIe software, the validation by the "leave one out" procedure gives an overall accuracy for all four factors of 60% (300/504). Knowing that the four factors account for 28 categories, this is to be compared with an accuracy of 17% at random.

4.5.1. Organization Age

The prediction accuracy for Organisation Age is 75% (94/126). Knowing that the variable has 5 categories, this is to be compared with 20% at random.

Class node: L_Organization_Age_OA

		Predicted				
		Industry10	Industry20	Industry30	Industry40	Industry50
Actual	Industry10	**3**	0	0	2	0
	Industry20	1	**0**	4	1	1
	Industry30	0	0	**40**	9	1
	Industry40	1	0	2	**15**	4
	Industry50	3	1	2	0	**36**

Figure 32: Confusion Matrix of Organisation Age

The confusion matrix shows weak classification accuracy of Industry 2.0 Organisations. This is possibly due to respondents confusing initial Organisation age with ambitioned maturity according to the Industry 5.0 taxonomy.

4.5.2. AI Maturity

The prediction accuracy for AI Maturity is 63% (79/126). Knowing that this factor has 7 categories, this is to be compared with 14% at random.

Class node: L_AI_Maturity_AM

		Predicted						
		Social	Physical	Cyber	Physical_So...	Cyber_Social	Cyber_Physi...	Cyber_Physi...
Actual	Social	**0**	0	0	0	0	0	0
	Physical	0	**3**	0	2	0	3	0
	Cyber	0	0	**0**	3	1	3	0
	Physical_Social	0	0	2	**10**	0	1	0
	Cyber_Social	1	1	2	0	**6**	4	0
	Cyber_Physical	1	3	1	0	3	**28**	8
	Cyber_Physical_Social	0	0	0	0	1	7	**32**

Figure 33: Confusion Matrix of AI Maturity

The confusion matrix shows weak classification accuracy in Social Systems and Cyber Systems. The population of interest predominantly works in the industrial automation domain and, therefore, might be biased towards physical processes.

4.5.3. Manufacturing Strategy

The prediction accuracy for Manufacturing Strategy is 50% (63/126). Knowing that this factor has 8 categories, this is to be compared with 12% at random.

Class node: L_BS_Manufacturing_Strategy_MS

		Predicted							
		Product_Sp...	Process_Sp...	Product_Se...	Process_Se...	Product_Cu...	Process_Cu...	Mass_Custo...	Social_Man...
Actual	Product_Specialization	**26**	2	0	4	0	0	0	0
	Process_Specialization	2	**3**	0	2	1	1	0	2
	Product_Servitization	0	0	**3**	2	0	1	0	1
	Process_Servitization	5	2	2	**19**	3	5	0	2
	Product_Customization	2	0	1	2	**8**	0	0	0
	Process_Customization	1	1	2	7	0	**3**	0	0
	Mass_Customization	0	0	0	1	0	0	**0**	1
	Social_Manufacturing	0	0	1	5	1	1	0	**1**

Figure 34: Confusion Matrix of Manufacturing Strategy

The confusion matrix shows weak classification performance on Mass Customization and Social Manufacturing, which are rare emerging manufacturing strategies primarily found in the literature.

4.5.4. Innovation capacity

The prediction accuracy for Innovation Capacity is 51% (64/126). Knowing that this factor holds 8 categories, this is to be compared with 12% at random.

Class node: L_IM_Innovation_Capacity_IC

		Predicted							
		Analytic_Sin...	Cognitive_S...	Generative_...	Parasitic_Si...	Analytic_Sw...	Cognitive_S...	Generative_...	Parasitic_S...
Actual	Analytic_Singleton	**28**	1	3	1	9	2	0	0
	Cognitive_Singleton	4	**3**	0	1	2	2	0	0
	Generative_Singleton	1	0	**2**	1	0	0	1	0
	Parasitic_Singleton	4	1	0	**0**	1	0	0	0
	Analytic_Swarm	4	0	1	1	**6**	6	0	0
	Cognitive_Swarm	1	3	0	0	1	**25**	1	0
	Generative_Swarm	1	0	0	0	0	2	**0**	2
	Parasitic_Swarm	0	1	0	0	0	3	1	**0**

Figure 35: Confusion Matrix of Innovation Capacity

The confusion matrix exhibits a weak classification performance on Analytic Swarms. They appear to be a choice of organisations that the model may not efficiently predict.

4.6. Hypotheses testing

The quantitative study results enable us to assess the three hypotheses extracted from the literature about the interplays of Industry Age, AI Maturity, Manufacturing Strategy and Innovation Capacity.

4.6.1. Assessing H1: [AM] is associated with [OA]

To assess H1, we set each target class of [OA] as evidence, examine the corresponding indicators, and note the major effects on [AM] by comparing the resulting conditional probabilities with the initial probabilities observed in §4.4.3. The study findings are partially consistent with system engineering literature establishing ***H1: AI Maturity [AM] is associated with Organisation Age [OA].***

- **Industry 1.0 (5%)** involves service companies (36%), predominantly SMEs (70%) with core skills in farming (68%). They adopt Cyber-Physical Social systems (69%) using Machine Learning techniques (77%), with most applications in operations (46%) and a preference for collaboration tasks (28%).
- **Industry 2.0** (6%) involves hardware producers (39%), primarily SMEs (53%) with core skills in mechanics (39%). They adopt Cyber-Physical Systems (39%), using Symbolic AI techniques (56%), with most applications in manufacturing (34%) and a preference for optimisation tasks (23%).

- **Industry 3.0** (34%) involves hardware producers (36%), primarily large companies (81%), with mechanics as the primary skill (49%). They adopt Cyber-Physical systems (38%), using virtual agents of either symbolic (26%) or machine learning type (32%). They have AI in manufacturing (30%) and operations (28%) and a very broad set of tasks from prediction (16%) to optimisation (20%).
- **Industry 4.0** (20%) involves system builders (75%) of large size (66%) with Electrical Engineering at their core (48%). They adopt Cyber-Physical Systems (53%) with embodied AI (42%) in operations (36%) for a very broad set of tasks, from Monitoring (21%) to collaboration (15%).
- **Industry 5.0** (31%) involves science service providers (54%), predominantly RTOs (45%), with computing as their core expertise (65%). They deploy Cyber-Physical-Social Systems (54%), implementing primarily machine learning algorithms (74%) in operations (41%) with a focus on collaboration tasks (23%)

In summary, the use of Cyber-Physical-Social Systems is a characteristic of Industry 5.0 that distinguishes it from Industry 4.0, where the social component is less involved. It is noteworthy that Industry 1.0 also exhibits high traction for CPSS, potentially skipping several stages of development to modernise labour-intensive activities.

4.6.2. Assessing H2: [MS] is associated with [AM]

To assess H2, we set each target class of [AM] as evidence, examine the corresponding indicators, and note the major effects on [MS] by comparing the resulting conditional probabilities with the initial probabilities observed in §4.4.3. The study findings are partially consistent with the humanities literature establishing ***H2: Manufacturing Strategy [MS] is associated with AI Maturity [AM].***

- **Social Systems** (1%) cannot be assessed quantitatively with a population of 1 use case in the training dataset. Although many organisations maintain intensive manpower-based operations, the surveyed population does not recognise this maturity level as theirs.
- **Physical Systems** (6%) involve Symbolic Embodied AI (58%) in maintenance activities (35%) with a focus on Prediction tasks (46%). They deploy product

specialisation strategies (57%) to augment operators (35%). They purchase AI technology (35%) and sell standard products (43%).

- **Cyber Systems** (7%) involve virtual AI agents (78%) in commissioning activities (27%) with a focus on monitoring tasks (39%). They match process-focused strategies (94%) aiming to augment operators (41%) and use specific AI (55%) to manufacture standard products (34%).
- **Physical-Social Systems** (5%) involve Symbolic virtual objects (58%) in manufacturing activities (80%) with a focus on optimisation tasks (36%). They match product specialisation strategies (87%) aiming to augment operators (31%) but also Managers (30%) and Engineers (19%). They use standard AI technology (43%) to manufacture standard products (59%).
- **Cyber-Social Systems** (12%) involve Machine Learning virtual agents (55%) deployed in Commissioning activities (48%) with a focus on monitoring tasks (21%). They match process servitisation strategies (28%) aiming to augment operators (42%). They implement internal AI developments (29%) supporting the delivery of custom Product Service Systems (39%)
- **Cyber-Physical Systems** (39%) involve a mix of Machine Learning (51%) and Symbolic AI (47%) deployed in Operations (36%) with a broad set of tasks such as monitoring (25%), prediction (20%) and optimisation (18%). They match servitisation strategies (41%) that rely on the augmentation of operators (46%). They use specific AI (56%) that is either developed in-house (30%) or outsourced (26%). They enable custom product and service delivery (69%).
- **Cyber-Physical Social** (28%) involve Machine Learning Embodied AI agents (75%) including Humanoids (25%) deployed in Operations (54%) with a focus on Collaboration tasks (37%). They match Servitisation (42%) but also Customisation strategies (35%) relying on the augmentation of operators (46%) and Engineers (16%). They involve specific developments (32%) and crowdsourced AI/data (22%). They support the delivery of Custom Product Service Systems (44%).

Product-focused strategies work with cyber-physical systems, while process-focused strategies work with cyber-social systems. Servitisation starts with integrating the cyber component, and customisation requires all three components of [AM] (Cyber, Physical, Social).

4.6.3. Assessing H3: [IC] is associated with [MS]

To assess H3, we set each target class of [MS] as evidence, examine the corresponding indicators, and note the major effects on [IC] by comparing the resulting conditional probabilities with the initial probabilities observed in §4.4.3. The study findings are partially consistent with the management literature establishing ***H3: Innovation Capacity [IC] is associated with Manufacturing Strategy [MS]***.

- **Product Specialisation** (23%) is a strategy that drives augmentation of the management level (34%), relies on standard AI from the market (49%) and delivers standard products as well (67%). It combines with Analytic Singletons (52%) in innovation approaches driven by internal operations (33%) and casual inbound collaborative projects (24%). It fits with private incremental innovation policies (39%).
- **Process Specialisation** (10%) is a strategy that employs AI to augment or replace operators (60%). It relies on specific AI that is either developed in-house (26%) or specified for third-party development (26%). It leads to sales of Product-Service Systems (PSS) (53%). This strategy is compatible with innovation in swarms (62%), engineering or expertise-driven (51%), and predominantly outbound (51%). It is mostly driven by private innovation policies (58%).
- **Product Servitisation** (7%) is a strategy that employs AI to augment customers (51%), with crowdsourcing as the dominant network strategy (40%). It is suitable for delivering custom Product-Service Systems (40%). This strategy matches Cognitive Innovation Capacity (78%), is engineering or operation-driven (45%), and is compatible with systematic open innovation approaches (32%). It fulfils private disruptive innovation policies (37%).

- **Process Servitisation** (29%) is a strategy that tends to augment operators (54%) by internal development of specific AI (47%), enabling the sale of custom Product-Service Systems (47%). It tends to go along with analytic singletons (46), driven by operations or engineering (54%), compatible with casual open innovation and private innovation policies (59%)
- **Product Customization** (9%) is a strategy that relies on operator augmentation (51%) by customising generic AI technology (58%) and marketing custom products (73%). It matches cognitive swarm innovation capacity (37%) and engineering-driven programs (32%). It accompanies systematic open innovation approaches (37%) and disruptive innovation policies (58%).
- **Process Customisation** (11%) is a strategy that predominantly augments operators (54%) by the subcontracting of specific AI technology (41%) that leads to custom Product Service System offerings (41%). It involves analytics innovation capacities (49%), engineering or expertise-driven (50%), casual open innovation 38% and disruptive innovation policies (43%).
- **Mass Customisation** (2%) is a strategy that replaces operators (37%) with the help of crowdsourced AI/data (39%), leading to the delivery of customer Product Service Systems (39%). It goes along with cognitive swarms (71%) that involve engineering-driven (35%) and systematic outbound innovation approaches (32%). It is compatible with public disruptive innovation policies (41%).
- **Social Manufacturing** (7%) is a strategy that augments operators and engineers (52%) with developed or crowdsource AI/data (64%), leading to the marketing of custom Product Service Systems (62%). It works with generative swarms (41%), involving engineering-driven (42%) but also outbound open innovation (66%). It is compatible with public disruptive innovation policies (34%).

In summary, singletons form with cost-driven strategies such as “product specialisation” and “process servitisation”. Differentiation strategies allow more distributed (Swarm) [IC] setups. Cognitive and generative [IC] only appear with intelligent manufacturing strategies.

4.7. Summary of the Quantitative Study

This study gives a final answer to the question: “What factors influence the effect of AI on IC in the context of Industry 5.0?”. We defined the categories of variables extracted from previous exploratory study and designed a Bayesian Network based on the conceptual model extracted from the qualitative study. Further, we launched an online survey to collect a dataset of 126 industrial AI use cases. We trained the Bayesian Network with this dataset and validated it with a “leave one out” procedure. We then tested the hypotheses extracted from the previous qualitative study. The study outlines the characteristics of AI-driven Industry 5.0 manufacturing strategies.

As the qualitative study suggested, cyber-Physical-Social Systems is a characteristic of Industry 5.0. Moreover, we find that servitisation starts with integrating the cyber component, and customisation requires all three components of AI Maturity (Cyber, Physical, Social). We prove that singletons form with cost-driven strategies like product specialisation and process servitisation while differentiation strategies allow more distributed Innovation Capacity types (Swarms). We also find that cognitive and generative Innovation Capacities only appear with intelligent manufacturing strategies.

This work contributes to a better understanding of AI effects on IC in the context of Industry 5.0 by testing hypotheses extracted from contemporary research in engineering, humanities, and management. It provides qualitative insights on possible futures for industries involved in digital transformation projects. In particular, it proposes a prediction model that helps assess the respective likelihoods of synergy, competition, and deception scenarios. It also contributes to practice by suggesting adapted technology, manufacturing, and innovation management strategies considering specific characteristics of the firm and its environment.

5. DISCUSSION

The discussion aims to assess the overall thesis results critically, compare the findings from exploratory, qualitative, and quantitative studies, identify limitations, and suggest future works.

5.1. Discussion Introduction

The classical literature on innovation attributes to innovation strategy the role of generating business growth, technological development, and deploying more effective management practices. However, the advent of Artificial Intelligence (AI) reverts this paradigm in the context of Industry 5.0. The focus is moving from "how innovation fosters AI" to "how AI fosters innovation". Therefore, our research question can be stated as follows: "What factors influence the effect of AI on Innovation Capacity in the context of Industry 5.0?"

In the previous parts, we have conducted an exploratory study to identify key factors based on a review of the literature (§2), a qualitative study to model the chain of effects at play (§3), a quantitative study to test this model against real-life data and extract quantitative parameters (§4). Cognitive Swarms, characterised by expertise-driven innovation and Systematic Outbound Collaboration, appear more prominent in Industry 5.0 contexts. The study also identifies Generative Swarms and Parasitic Swarms as emerging but less prevalent IC types. In this discussion part, we critically assess the results of the thesis work, highlighting the potential conflicts between theoretical and empirical findings.

In § 5.2 we answer the research question by predicting Innovation Capacity according to the conditional probabilities learned from the quantitative study. In §5.3 we critically examine the theoretical and empirical alignment of these predictions, comparing insights from exploratory, qualitative, and quantitative analyses. In §5.4 we assess the residual gaps and debates. In §5.5 we discuss limitations and provide suggestions for future work. This discussion section assesses the accuracy of predicted outcomes. It evaluates

discrepancies between theoretical expectations and real-world findings, challenging prior assumptions of a shared technological foundation.

5.2. Predicting Innovation Capacity

The following types of Innovation Capacity [IC] can be predicted based on Organisation Age [OA], AI Maturity [AM] and Manufacturing Strategy [MS]:

- **Analytic Singleton** (35%) is a likely development for Industry 3.0 organisations (43%) that adopt Cyber-Physical Systems (35%) while deploying a process servitisation strategy (41%). This Innovation Capacity is characterised by a strong focus on operations (52%), casual inbound research collaborations (32%) and a private incremental innovation policy (49%).
- **Cognitive Singleton** (9%) is a possible development for Industry 3.0 organisations (45%), adopting Cyber-Physical Systems (33%) with a Product Specialisation strategy (39%). This type of Innovation Capacity is characterised by a focus on demand-driven innovations (32%), well served by regular inbound collaborative research and compatible with private disruptive innovation policies (47%).
- **Generative Singleton** (2%) is a possible development for Industry 3.0 organisations (44%), adopting Cyber-Physical-Social systems (27%) with a product specialisation strategy (52%). This type of Innovation Capacity is characterised by engineering-driven innovation (52%), regular inbound collaborative research (35%) and a private defensive innovation strategy (52%).
- **Parasitic Singleton** (5%) is a possible development for Industry 3.0 organisations (46%) adopting Cyber-Physical Systems (36%) and a product specialisation strategy (45%). It is characterised by demand-driven (45%) and casual inbound innovation approaches (30%) with private incremental Innovation Policies (45%).
- **Analytic Swarm** (18%) is a likely development for Industry 3.0 organisations (40%) adopting Cyber-Physical Systems (41%) with customisation manufacturing strategies (45%). It is characterised by engineering and expertise-

driven innovation (59%), casual outbound open innovation and incremental innovation policies (44%).

- **Cognitive Swarm** (22%) is a likely development for Industry 5.0 organisations (39%) adopting Cyber-Physical Social Systems (41%) to deploy process servitisation strategies (42%). This Innovation Capacity is characterised by expertise-driven innovation (35%), systematic outbound research (41%) and public disruptive policies (50%).
- **Generative Swarm** (4%) is a possible development for Industry 5.0 organisations (46%) adopting Cyber-Physical Social Systems (55%) in Social Manufacturing strategies (69%). This Innovation Capacity is characterised by engineering-driven innovation (52%), outbound collaborative research (91%) and a public disruptive policy (35%).
- **Parasitic Swarm** (3%) is a possible development for Industry 5.0 organisations (42%) adopting Cyber-Physical Social systems (48%) in product customisation strategies (35%). This Innovation Capacity is characterised by engineering-driven internal innovation (36%), casual outbound open innovation (35%), and a public disruptive innovation policy (52%).

In summary, parasitic [IC] types are unlikely to appear in Industry 5.0. But analytic singletons are very likely, and their development will deprive humans of analytical tasks that will be largely automated. Cognitive [IC] can potentially disrupt the industry, while generative [ICs] appear more anecdotic in this study sample.

5.3. Discussing theoretical and empirical results

The combination of approaches in this research enables a comparison of theoretical and empirical findings about the effect of AI on IC in the context of Industry 5.0. We compare here the exploratory, qualitative, and quantitative study outcomes for each of the 4 main factors.

5.3.1. About Organisation Age [OA]

Here, We compare the exploratory, qualitative, and quantitative study outcomes for the Organisation Age factor.

Exploratory study result	Qualitative study result	Quantitative study result
TIM predicts that AI adoption will drive further service integration in manufacturing products.	In contrast with the literature in §3.1, we note that Industry 5.0 organisations tend to deliver systems rather than services.	Service accounts for 26% of the organisation product type for Industry 5.0 organisations, which is significant, yet only 1% of Industry 4.0 organisations.
CDT suggest automation by AI will make smaller-scale production units fit for business.	Consistently with §3.2, we find that it is compatible with small or large organisation types.	SMEs account for 21% of Industry 5.0 Organisations, which is significant. Large enterprises only account for 11%. However, this is reversed for Industry 4.0.
RBV predicts a battle for strategic AI skills and expertise required to build a sustainable competitive advantage.	Consistently with §3.3, we find System Engineering and Computing dominant among Industry 5.0 organisations.	Computing specifically accounts for 65% of Industry 5.0 organisations. Paradoxically 0% of Industry 4.0
The CPS literature defines observable attributes of manufacturing system characteristics in each industrial age, from Industry 1.0 to Industry 5.0.	The interview sample provides 21 use cases with examples for each of these 5 classes: 1 Industry 1.0, 2 Industry 2.0, 9 Industry 3.0, 6 Industry 4.0, and 3 Industry 5.0.	The overall accuracy of the prediction of Organisation Age is 0.75, which is very good, acknowledging that this variable has 5 categories.

Table 3 Comparing theoretical and empirical results on [OA]

This comparison of outcomes gives an interesting paradox. While many authors, such as Xu et al. (2021), assumed that Industry 4.0 and Industry 5.0 had the same technological baseline, the set of skills and other characteristics of Industry 5.0 organisations seem highly distinctive from those of Industry 4.0 organisations.

5.3.2. About AI Maturity [AM]

Here, We compare the exploratory, qualitative, and quantitative study outcomes for the AI Maturity factor.

Exploratory study result	Qualitative study result	Quantitative study result
AIT shows that self-learning agents can interact more naturally with human workers (Bryndin, 2020).	Cyber-Physical Systems predominantly leverage embodied ML algorithms and Cyber-Physical Social systems additionally tend to adopt humanoid features. A novelty here is the appearance of generative AI within the playable AI types.	Cyber-Physical Social Systems use embodied Machine-Learning at 74% among which humanoids at 25%. Humanoids only appear in this [AM] category. Generative unimodal AI is rare and loosely related to CPSS (2%). But Generative multimodal AI is strongly CPSS [AM] (66%)
MFG shows that the most advanced companies employ AI at all steps of the life cycle with direct positive effects on the environment (Yin & Yuanyuan Yu, 2022).	Consistent with § 3.1.2, we note the expansion of AI beyond the strict boundary of manufacturing, with applications from design to Maintenance stages.	Few examples of design or recycling-focused use cases have been collected (5). Quantitatively, the survey results do not allow verification of this assertion.
SMT demonstrates that advanced industries assign AI a greater diversity of roles, with growing considerations for collaboration and resilience functions (Solanki, Makkar, & Devi, 2020).	Cyber systems involve AI in passive roles such as prediction, detection, and monitoring, while Cyber-Physical Systems involve AI in active roles such as automation or optimisation. Cyber-physical social systems involve interactive AI with collaboration as a predominant role.	The quantitative study confirms the strong contribution of [AM] to collaboration tasks, with 37% of CPSS use cases focusing on this role. The impact on resilience is much less obvious (2%), and too few cases (3) have been collected to verify this assertion.
CPS literature suggests AI maturity as the main predictor of industrial transformation in the frame of Industry 5.0 (Yilma, Naudet, & Panetto, 2020).	The 3 examples of Cyber-Physical Social Systems provided by the interviewees land clearly in Industry 5.0 organisations.	CPSS [AM] is a very strong predictor for Industry 5.0 [OA] (58%). The accuracy of prediction of AI Maturity overall is 63% (79/126) which is good, knowing that this factor has 7 categories

Table 4 Comparing theoretical and empirical results on [AM]

The empirical study generally confirms [AM] 's influence but orients on human-machine collaboration more than on the other ambitions of Industry 5.0, like sustainability and resilience. The breadth of AI places and roles also seems much less than what the

literature suggests. The emergence of generative AI between the timing of the original literature review and that of the survey calls for further analysis of the potential impacts of this AI type.

5.3.3. About Manufacturing Strategy [MS]

Here, We compare the exploratory, qualitative, and quantitative study outcomes for the Manufacturing Strategy factor.

Exploratory study result	Qualitative study result	Quantitative study result
CDT shows that AI, unlike previous general-purpose technologies, affects operators and managers (Noponen, 2019).	Operators, managers, customers, and engineers appear among the affected resources. Specialisation strategies are more prone to resource replacement, while customisation strategies tend to work with resource augmentation.	The dominant effect on resources across all strategies is the augmentation of operators (42%). Overall, augmentation (82%) is more trendy than replacement (18%). An unexpected exception is that of Mass Customization strategies, which seem to replace operators (37%). Product Servitisation is a strategy that employs AI to augment customers (51%), a strategy unseen in the literature.
TCE highlights there can be a greater asset-specificity in industrial AI, that revives vertical integration against horizontal networking strategies (Mateos-Garcia, 2018).	Specialisation strategies involve binary make-or-buy decisions, with develop-or-purchase as the dominant NS. Servitisation strategies tend to complement more collaborative manufacturing approaches, with AI specification and customisation as the dominant NS. Crowdsourcing appears as a novelty unaddressed by the study's body of literature.	The quantitative data in this study do not support vertical integration as a major trend. This is reflected by 2% of use cases marking acquisition as a network strategy. Only process servitisation appears to match acquisition strategies (51%). Crowdsourcing also works with process servitisation (39%), which makes it a quite unique strategy in this population.

Exploratory study result	Qualitative study result	Quantitative study result
TIM shows that AI is likely to accelerate the servitisation of the economy and the polarization of product strategies (Tukker, 2015.).	Consistent with § 3.2.3, we note the blending of products and services in PSSs in use cases applying product servitisation strategies.	Custom Product Service Systems appear the most consensual product strategy in this dataset (33%). It is the dominant product strategy for product servitisation (40%) and process servitisation (45%)
SET predicts the development of new manufacturing strategies such as social manufacturing and mass customisation (Jiang, Leng, Ding, Gu, & Koren, 2016).	The interviewees provide use cases applying product specialisation (8), process specialisation (5), product servitisation (3), process servitisation (4), and product customisation (1). Mass Customization and Social Manufacturing are absent from the interview sample.	Mass Customisation appears in 2 occurrences (2%) which does not make it a trend. Social Manufacturing comes in 7 use cases (9%). It is very Industry 5.0 (56%), leverages CPSS (73%) and leads to generative swarms (41%). The accuracy of the prediction of Manufacturing Strategy is 50% (63/126) which is acceptable, knowing that this factor has 8 categories

Table 5 Comparing theoretical and empirical results on [MS]

The empirical study generally confirms [MS] as an influential factor but moderates the trends identified in the humanities literature. In particular, Mass Customization appears in very few cases (2). Yet the strong connection to Industry 5.0, Cyber-Social Systems, and cognitive or generative swarms for these novel strategies lets us expect that they are indeed promised further development in the context of Industry 5.0.

5.3.4. About Capacity [IC]

Here, We compare the exploratory, qualitative, and quantitative study outcomes for the Manufacturing Strategy factor.

Exploratory study result	Qualitative study result	Quantitative study result
RBV forecasts a battle for AI skills and technology, which are considered	AI tends to take over analytical tasks in operation-driven and	Engineers lead internal innovation for AI (28%), followed by Operations

Exploratory study result	Qualitative study result	Quantitative study result
strategic key capabilities for realising internal innovation strategies (Lichtenthaler, 2019).	management-driven innovation approaches, while it may take more cognitive tasks in engineering and expertise-driven activities.	(23%). This order is reverted in the case of Analytic Singletons. Generative swarms are strongly engineering-driven (52%), while Parasitic swarms are more likely demand-driven (19%).
OIT suggests a faster diffusion of knowledge across company boundaries through the advent of AI, fostering an increased preference for open innovation strategies (Goldfarb & Trefler, 2018).	Consistent with § 3.3.2, we find organisations involved in open innovation more prone to adopt swarm intelligence while others tend to forge singletons.	The dominant OI strategies are casual inbound (18%) and casual outbound (17%). Analytic Singletons have casual inbound [OI] (32%). Cognitive Swarms seem well supported by Systematic Outbound open innovation (41%).
IPL highlights the moderating effect of coercive policies on AI adoption (Agrawal, Gans, & Goldfarb, 2019).	Consistently with §3.3.3, analytic ICs usually match defensive or incremental IPs, while cognitive ICs tend to match more disruptive IPs. Counterintuitively, private IPs tend to coincide with swarm ICs while public IPs match with singletons.	Private incremental policies are dominant (27%), followed by private disruptive (26%) and public disruptive (19%). But Cognitive Swarms [IC] are strongly supported by public disruptive [IP] (50%), which tends to justify the role of public investment in AI.
IMT predicts contradictory effects of AI on innovation capacity through a complex interplay with HI (Sætra, 2020).	Generative Swarm or Parasitic Swarm do not appear in the interview sample. Only one use case involves parasitic effects of AI adoption, namely in media recommendation.	Analytic Singleton is the dominant [IC] overall (34%). Cognitive Swarms follow (24%) with a strong connection to Expertise [II] (35%), systematic outbound [OI] (41%) and public disruptive [IP] (50%). The survey reveals 6 Parasitic Singletons (5%) and 4 Parasitic Swarms (3%). They are associated with the Social component in

Exploratory study result	Qualitative study result	Quantitative study result
		[AM] and Demand Driven [II].

Table 6 Comparing theoretical and empirical results on [IC]

The empirical study generally confirms that the effect of AI on IC can be synergic (Lichtenthaler U. , 2018) with cognitive [IC] (34%), deceptive (Sætra, 2020) with parasitic [IC] (9%), competitive (Shabbir & Anwer, 2018) with generative [IC] (8%).

5.4. Assessing residual gaps and debates

This research work enables us to fill some of the gaps and contradictions extracted from the literature.

5.4.1. From Engineering

The lack of methodologies and techniques to provide cyber-security assurance on AI-powered industrial systems (Bécue, Gama, & Praça, 2020): 11 of the collected use cases explicitly focus on security or safety. Safe human-robot interaction is the dominant topic, with information security and adversarial AI as secondary topics. This field of research has progressed quite a lot during the study time.

The lack of confidence in AI technology and its effective impact on adoption (Hutson & Plate, 2024): 28 collected use cases address trust-enabling AI techniques, including AI use cases in education, healthcare, language, robotics and cybersecurity. The diffusion of Large Language Models (LLM) between the early exploratory and the final quantitative study phases significantly boosted AI trust and adoption. However, we may now face the opposite issue of overconfidence in AI in some application areas.

The debate whether anthropomorphism affects AI likeability positively, negatively or negligibly (Zhang, et al., 2020): 14 use cases involve humanoid AI, including 4 virtual agents and 10 embedded agents. This tends to support the validity of anthropomorphic AI approaches for manufacturing applications. Practitioners do not report discomfort in the presence of humanoids. They, however, take a resemblance as a minor adoption criterion in this domain.

The debate whether AI can be the next GPT (Trajtenberg, 2018) and ML achieve real AGI (Russell & Norvig, 2021): 8 use cases involve direct or indirect use of general-purpose AI models. The deployment of generative AI between the initial exploratory study and the final quantitative study phases has been a major change driver in that regard. Although they are essentially a language processing technology, multimodal transformers tend to challenge our broad (said general) intelligence capacity. Further developments are expected to happen within the European call HUMAN-03-0215F15F15 for human-centred and ethical development of digital and industrial technologies.

5.4.2. From Humanities

The debate between theories of replacement (Noponen, 2019) and theories of augmentation (Paul, et al., 2022): 25 out of 126 use cases involve explicit replacement of humans by AI: 18 to replace operators, 3 to replace engineers, 3 to replace managers, and 1 to replace Customers. This makes replacement a non-neglectable minority, particularly if we assume that survey respondents have been politically correct in their answers. In an economy driven by "likes" and "views", replacement of customers comes as a scary novelty.

The debate whether AI will drive enhanced preference for the market (Davenport, Guha, Grewal, & Bressgott, 2020) or for hierarchy (Mateos-Garcia, 2018): 37 organisations choose to develop AI themselves. In one case, they chose to acquire the AI editor. This makes the choice of "hierarchy" a minority against the choice of the "market" (89 cases). They are overrepresented in process servitisation strategies and slightly more frequent in Industry 5.0 organisations (41% against 31% on average). They match engineering and expertise-driven innovation styles.

The question of whether AI will reduce or further enhance the polarisation of industrial strategies towards either "cost leadership" or "differentiation" (Kharub, Mor, & Rana, 2022): 36 organisations chose standard production as their product strategy, which

[15] https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/topic-details/horizon-cl4-2024-human-03-01

indicates a focus on cost leadership. They are over-represented in the population of Industry 3.0 (58% against 39%) and involve Cyber-physical systems more extensively (50% against 39%). They tend to match analytic singletons rather than other types of [IC] (58% against 35%). Industry 5.0 organisations, on the other hand, tend to make the choice of differentiation with greater representation in custom production strategies (99% against 69%).

The question of whether AI will drive the industry towards social manufacturing or mass customisation (Pech & Vrchota, 2022): 9 cases of Social Manufacturing and 2 cases of mass customisation appear in the dataset. This makes social manufacturing quantitatively more likely, yet does not account for how much this strategy leads to successful business. Indeed, RTOs and academics are overrepresented in this population (82% against 24%), indicating that these experimental business models have not yet been marketed.

5.4.3. From Management Sciences

The question of whether Industrial AI complicates imitation by competitors (Lichtenthaler, 2019) or helps generate convincing counterfeit products (Pokrovskaya, 2024): 15 use cases are reported as "strategy-driven", which is relatively few compared to those driven by engineering (38) or operations (25). It may mean that AI is either not a strategic resource or at least not perceived so by the surveyed population. Yet it is important to note that the Industry 4/5.0 organisations are over-represented in this sub-population (60% against 51%).

The conflict between OIT and RBV approaches on the transferability of skills (Goldfarb & Trefler, 2018): 38 use cases are reported by organisations applying systematic open innovation approaches. This population has a higher AI development score than average (37% against 28%) and a higher rate of private disruptive innovation policy (34% against 24%). The data contradict the assumption that open innovation plays against internal innovation and intellectual property generation.

The lack of consensus on the role and effect of coercive, liberal or incentive innovation policies on AI with application to manufacturing (Agrawal, Gans, & Goldfarb, 2019): 49

use cases are reported as driven by public innovation policy. This population shows greater representation in cognitive swarm capacity (33% against 22%), Cyber-Physical Social systems [AM] (43% against 28%) and Industry 5.0 [OA] (57% against 31%). Overall, public policies seem to influence positively the adoption of AI and the transition to Industry 5.0.

The debate about whether the Industrial AI effect on [IC] is synergic (Lichtenthaler U. , 2018), competitive (Shabbir & Anwer, 2018), or deceptive (Sætra, 2020): 10 use cases are reported as "parasitic", suggesting that a negative effect of AI on Innovation Capacity is possible, yet relatively rare. This population has higher rates than average in process customisation (30% against 11%), cyber-social AI (30% against 12%) and Industry 3.0 (60% against 34%). It suggests specific care should be taken with the social component of [AM] to avoid negative side-effects of AI integration on Innovation Capacity.

5.5. Limitations and future works

The results of this work tend to support the validity of the selected approach. While the prediction accuracy of the model is acceptable, there are signs that it could be improved by training with larger data. As the descriptive statistics show (§4.4.1), some categories of the main factors have very few records. For example, the dataset has only 6 examples of Industry1.0 organisations, which makes it difficult to avoid potential bias in the training procedure. Only 1 organisation claims to have a Social AI Maturity level which invalidates predictions for this category. Mass Customisation, as a Manufacturing Strategy, is only reported twice in the whole dataset. It makes it difficult to evaluate the reality of this concept which is dear to the Industry 5.0 literature. Similarly, the category of Generative Singletons, a concept in the hype of AI dystopias, is only found with 3 records in the dataset. It is difficult to assess if these rarities result from inaccurate concepts, misunderstandings from the survey population, or lack of representativeness of the dataset. Growing the dataset would potentially give an answer.

Another possible limitation of this study work relates to the dynamic nature of the observed phenomenon. Noticing the emergence of new concepts and the development of Industry 5.0 vision during the study phases, we have enriched the model and variable

categories accordingly. However, the model has been trained only once with the data collected in study phase 3. This static training procedure does not allow monitoring of the surveyed population's evolutions. For example, we are aware that since the end of 2022, projects revolving around generative AI have been launched in many organisations. While the first wave of generative models primarily affected office work and consumer businesses with unimodal text and image generation tools, more recent developments of multimodal generative AI tools can process tabular data, sensor data, time series, and other artefacts more suitable to industrial applications. Generative AI also dramatically improves the potential for natural interactions between human operators and machines which is core to Industry5.0. It would be interesting to retrain the model in a few months and see if it affects predictions with categories such as Cyber-Physical-Social (CPSS) AI Maturity level or Generative Innovation Capacity types.

Finally, a potential improvement lies in comparing alternative model structures and determining whether the overall model accuracy improves. More complex paths could be considered with theoretical groundings. For example, there could be a direct effect between Organisation Skills and AI Type, assuming that organisations having data science as a core skill are more likely to adopt advanced AI in their manufacturing processes. The same variable could also have a direct effect on Network Strategy as the availability of AI skills would influence the strategy towards developing, rather than purchasing, industrial AI. The Network Strategy itself could have a direct effect on Open Innovation, acknowledging that organisations deciding to “specify “AI would likely opt for “inbound” OI strategies, while those developing AI would rather opt for “outbound” OI strategies. We suggest these developments for future works and provide all the necessary data in this report to support them.

6. CONCLUSIONS

A Significant outcome of this work is the discovery of three types of intelligence at play in the transition to Industry 5.0: Artificial Intelligence (AI), Social Intelligence (SI), and Human Intelligence (HI). The abilities of AI are expanding from analytical to social and creative activities, influencing not only industrial processes but also manufacturing strategy and innovation capacity through a complex interplay with social and human intelligence. This work addresses the question: "What factors influence the effect of AI on Innovation Capacity in the context of Industry 5.0?".

Through an exploratory study, four key factors influencing AI's impact on innovation capacity were identified: Organisation Age (OA), AI Maturity (AM), Manufacturing Strategy (MS), and Innovation Capacity (IC). Twelve observable criteria were defined, leading to three propositions: P1) AI Maturity is associated with Organisation Age; P2) Manufacturing Strategy is associated with AI Maturity; and P3) Innovation Capacity is associated with Manufacturing Strategy. The qualitative study extended these findings by identifying fifteen key effects that shape AI's impact on innovation in Industry 5.0. This study identified the early adoption of generative AI in selected industrial applications, suggesting its growing significance in advanced manufacturing. It supported constructing a conceptual model, turning the initial propositions into hypotheses to be tested quantitatively.

The quantitative study further validated these insights through a dataset of 126 industrial AI use cases. A Bayesian Network model was developed, learning the conditional probabilities of 122 variable categories. Model validation using the leave-one-out approach yielded an overall accuracy of 60% to be compared against 17% at random. The research findings provide empirical support for the initial hypotheses. Cyber-Physical-Social Systems emerge as a defining characteristic of Industry 5.0, which aligns with previous studies. Customisation strategies require integrating cyber, physical and social capabilities in higher AI Maturity levels. Cognitive and generative innovation capacities emerge with social manufacturing strategies. Furthermore, this research reveals novel cognitive, generative and parasitic Innovation Capacity types. We thus accept AI as a

general-purpose technology influencing innovation through synergy, competition, or deception scenarios.

This study makes several important contributions. Theoretically, it provides a conceptual model of AI's impact on Innovation Capacity, bridging insights from engineering, humanities, and management sciences. It introduces an inference system for assessing the likelihood of synergy, competition or deception scenarios in AI-driven industrial transformation, addressing an ongoing debate in the literature. Empirically, the research offers qualitative and quantitative evidence on how Organisation Age, AI Maturity, and Manufacturing Strategy influence Innovation Capacity. The findings offer strategic insights for industrial firms undergoing digital transformation and a decision-support framework for policymakers, technology leaders, and entrepreneurs in Europe and beyond.

The model and dataset have been submitted for publication to encourage further research and potential reuse. Future studies should consider expanding the dataset to refine predictive accuracy, particularly for underrepresented categories such as Mass Customization and Generative Singletons. Longitudinal studies could capture the dynamic evolution of AI adoption in Industry 5.0, while comparative analyses of alternative Bayesian Network structures may optimise prediction accuracy. Additionally, given the rapid evolution of generative AI, further research could examine its industrial applications and its potential to reshape AI's role in manufacturing and innovation ecosystems. By addressing these areas, future research can further enhance our understanding of AI's transformative potential in Industry 5.0, ensuring that human, social, and artificial intelligence work in synergy to drive industrial progress.

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Sundaram, S., & Zeid, A. (2023). Artificial intelligence-based smart quality inspection for manufacturing. *Micromachines, 14(3), 570*.

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Thellman, S., De Graaf, M., & Ziemke, T. (2022). Mental state attribution to robots: A systematic review of conceptions, methods, and findings. . *ACM Transactions on Human-Robot Interaction (THRI), 11(4)*, (pp. 1-51).

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Wang, L. (2019). From Intelligence Science to Intelligent Manufacturing. *Engineering,Volume 5, Issue 4*, 615-618.

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Wolf, C., Joye, D., Smith, T. W., & Fu, Y. C. (2016). *The SAGE handbook of survey methodology.* Sage.

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Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems, 61, 530-535.*

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ANNEX 1: LIST OF PUBLICATIONS

Paper	Status
Bécue, A.; Gama, J.; Quelhas-Brito, P. (2023) AI's effect on Innovation Capacity in the context of Industry 5.0: a quantitative study. Journal to be defined.	In preparation (07/2024)
Bécue, A.; Gama, J.; Quelhas-Brito, P. (2023) AI's effect on Innovation Capacity in the context of Industry 5.0: an qualitative study. Expert systems with Applications.	Submitted (12/2023) under Review
Bécue, A.; Gama, J.; Quelhas-Brito, P. (2023) AI's effect on Innovation Capacity in the context of Industry 5.0: a scoping review. Artificial Intelligence Review	Published
Bécue, A., Praça, I. & Gama, J. (2021) Artificial intelligence, cyber-threats and Industry 4.0: challenges and opportunities. Artif Intell Rev 54, 3849–3886	Published
Bécue, A.; Maia, E.; Feeken, L.; Borchers, P.; Praça, I. (2020) A New Concept of Digital Twin Supporting Optimization and Resilience of Factories of the Future. *Appl. Sci.* **2020**, *10*, 4482.	Published
A. Bécue et al. (2019) "CyberFactory#1 — Securing the industry 4.0 with cyber-ranges and digital twins," 2018 14th IEEE International Workshop on Factory Communication SystBS (WFCS), Imperia, 2018, pp. 1-4, doi: 10.1109/WFCS.2018.8402377	Published

ANNEX 2: LITERATURE DATASET

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2016	Abadi, M., Barham, P., Chen, J., Chen, Z. D., Dean, J., Devin, M., . . . Kudlur, M. (2016). Tensorflow: a system for large-scale machine learning. 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 2016), (pp. 265-283)	ENG	AIT			1		
2018	Acemoglu, D., Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review, 108(6), 1488-1542.	HUM	CDT				1	1
2019	Aghion, P., Jones, B. F., & Jones, C. I. (2019). 9. Artificial Intelligence and Economic Growth (pp. 237-290). University of Chicago Press.	HUM	HUM		1	1		
2018	Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2018. Prediction Machines: The Simple Economics of Artifi cial Intelligence. Boston, MA: Harvard Business Review Press.	HUM	CDT		1	1	1	
2019	Agrawal, Ajay Gans, Joshua S. Goldfarb, Avi, 2019 - Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction Journal of Economic Perspectives 33 2 31-50 2019 10.1257/jep.33.2.31 https://www.aeaweb.org/articles?id=10.1257/jep.33.2.31	HUM	HUM		1	1	1	
2019	Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). The economics of artificial intelligence: an agenda. University of Chicago Press.	HUM	CDT		1	1	1	1
2018	Alalie, H., Harada, Y., & Mdnoor, I. (2018). A Resource-Based View: How Information Technology Creates Sustainable Competitive Advantage to Improve Organizations. Journal of Advance Management Research,, 1-5.	MGT	RBV				1	1
2024	Alzoubi, Y. I., & Mishra, A. (2024). Green artificial intelligence initiatives: Potentials and challenges. Journal of Cleaner Production, 143090	MGT	OIT		1	1	1	1
2020	Ahn, J. M. (2020). The hierarchical relationships between CEO characteristics, innovation strategy and firm performance in open innovation. International Journal of Entrepreneurship and Innovation Management, 24(1), 31-52.	MGT	OIT				1	1
2016	Ahn, J. M., Ju, Y., Moon, T. H., Minshall, T., Probert, D., Sohn, S. Y., & Mortara, L. ; 2016; Beyond absorptive capacity in open innovation process: the relationships between openness, capacities and firm performance. ; Technology Analysis & Strategic Management, 28(9); 1009-1028;	MGT	OIT				1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2017	Ai, Q., Zhang, Y., Bi, K., Chen, X., & Croft, W. B. (2017, August). Learning a hierarchical embedding model for personalized product search. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 645-654).	ENG	AIT		1	1	1	
2001	Aizenberg I., Myasnikova E., Samsonova M., Reinitz J. (2001) Application of the Neural Networks Based on Multi-valued Neurons to Classification of the Images of Gene Expression Patterns. In: Reusch B. (eds) Computational Intelligence. Theory and Applications. Fuzzy Days 2001. Lecture Notes in Computer Science, vol 2206. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-45493-4_33	ENG	AIT			1		
2018	Alalie, H. M., Harada, Y., & Noor, I. M. (2018). A Resource-Based View: How Information Technology Creates Sustainable Competitive Advantage to Improve Organizations. Journal of Advance Management Research, 6(12), 1-5.	MGT	RBV				1	1
2023	Alimam, H., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. (2023, August). Digital Triplet Paradigm for Brownfield Development towards Industry 5.0: A Case Study of Intelligent Retrofitting for Oil and Gas Boosting Plant in the Industrial Internet of Things (IIoT) Context. In 2023 IEEE Smart World Congress (SWC) (pp. 1-10). IEEE.	ENG	CPS		1	1		
2015	Aloini, D., Pellegrini, L., Lazzarotti, V., & Manzini, R. (2015). Technological strategy, open innovation and innovation performance: evidences on the basis of a structural-equation-model approach. *Measuring Business Excellence.*	MGT	OIT				1	1
2011	Alzghoul, A., & Löfstrand, M. (2011). Increasing availability of industrial systems through data stream mining. Computers & Industrial Engineering, 60(2), 195–205. https://doi.org/10.1016/J.CIE.2010.10.008	ENG	CPS		1	1		
1984	Anderson, J. C., & Narus, J. A. (1984). A model of the distributor's perspective of distributor-manufacturer working relationships. Journal of marketing, 48(4), 62-74.	HUM	SET	1	1		1	
2005	Arksey, H., & O'Malley, L. (2005). Scoping studies: towards a methodological framework. International journal of social research methodology, 8(1), 19-32.	HUM	HUM	1				
2002	Asheim, B.T., Isaksen, A. Regional Innovation Systems: The Integration of Local 'Sticky' and Global 'Ubiquitous' Knowledge. The Journal of Technology Transfer 27, 77–86 (2002). https://doi.org/10.1023/A:1013100704794	MGT	OIT		1		1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2015	Autodesk. (2015). autodesk and airbus show the future of aerospace design and manufacture. Récupéré sur Autodesk: https://adsknews.autodesk.com/news/autodesk-and-airbus-show-the-future-of-aerospace-design-and-manufacture-in-pioneering-generatively-d	ENG	SMT		1	1		
2020	Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. The Quarterly Journal of Economics, 135(2), 645-709.	HUM	CDT		1		1	
2015	Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." Journal of Economic Perspectives, 29 (3): 3-30. DOI: 10.1257/jep.29.3.3	HUM	CDT			1	1	
2019	Auvinen, T. (2019). Johtaminen ja Tarinankerronta Organisaatioissa Digitaalisessa Vallankumouksessa. Electronic Journal of Business Ethics and Organization Studies.	HUM	CDT			1	1	
2019	Auvinen, T., Sajasalo, P., Sintonen, T., Pekkala, K., Takala, T., & & Luoma-aho, V. (2019). Evolution of strategy narration and leadership work in the digital era. Leadership, 15(2), , 205–225.	HUM	CDT		1	1	1	
2013	Avolio, Bruce & Sosik, John & Kahai, Simran & Baker, Bradford. (2013). E-leadership: Re-examining transformations in leadership source and transmission. The Leadership Quarterly. 25. 10.1016/j.leaqua.2013.11.003.	HUM	CDT			1	1	
2000	Avolio,B. J. ; Surinder, K. (2000) ; Dodge, G. E. . E-Leadership: Implications for Theory, Research, and Practice. The Leadership Quarterly, Vol. 11, No. 4, 615-668.	HUM	CDT		1	1	1	
2010	Ayitey, W. (2010). A Simple Approach to Strategic Management. Prof. A. H. O Mensah. B. J. Avolio, S. K. (2000). E-Leadership: Implications for Theory, Research, and Practice. The Leadership Quarterly, Vol. 11, No. 4, 615-668.	MGT	MGT			1	1	
2019	Bajari, P., Chernozhukov, V., Hortaçsu, A., & Suzuki, J. (2019, May). The impact of big data on firm performance: An empirical investigation. In AEA Papers and Proceedings (Vol. 109, pp. 33-37).	MGT	IMT		1	1	1	1
1998	Bakos, Yannis 1998. The emerging role of electronic marketplaces on the Internet. Commun. ACM 41, 8 (Aug. 1998), 35–42. DOI:https://doi.org/10.1145/280324.280330	HUM	TCE				1	
2024	Baines, T., Bigdeli, A. Z., & Kapoor, K. (2024). Servitization Strategy. Springer Nature.	HUM	TIM		1		1	1
2018	Bajari, P., Chernozhukov, V., Hortaçsu, A., & Suzuki, J. (2018). The Impact of Big Data on Firm Performance: An Empirical Investigation. Cambridge: NBER.	MGT	IPL		1	1	1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2016	Balu, A., Lore, K. G., Young, G., Krishnamurthy, A., & Sarkar, S. (2016). A deep 3d convolutional neural network based design for manufacturability framework. arXiv preprint arXiv:1612.02141.	ENG	MFG		1	1		
2018	Banerjee, S., Wahl, M. F., & Panigrahi, J. K. (2018). Technology, innovation and knowledge transfer: A value chain perspective. International Journal of Mechanical Engineering and Technology, 9(1), 1145-1161.	MGT	OIT		1			1
1999	Barabási, A. (1999). Emergence of scaling in random networks. Science. 286 (5439), 509–512.	MGT	OIT	1				1
1991	Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management.	MGT	RBV		1			1
2015	Barquet, A. P. B. (2015). Creation of product-service systems (PSS) proposals in the fuzzy front-end (Doctoral dissertation, Universidade de São Paulo).	HUM	TIM		1		1	
1994	Barriball, K. L., & While, A. (1994). Collecting data using a semi-structured interview: a discussion paper. Journal of Advanced Nursing-Institutional Subscription, 19(2), 328-335	HUM	HUM	1				
2018	Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2018). Supply chain risk management and artificial intelligence: State of the art and future research directions. International Journal of Production Research	HUM	TIM		1		1	
2012	Bastl, M., Johnson, M., Lightfoot, H., & Evans, S. (2012). Buyer-supplier relationships in a servitized environment: An examination with Cannon and Perreault's framework. International Journal of Operations & Production Management.	HUM	SET		1		1	
2022	Bhattacharya, P., Obaidat, M. S., Sanghavi, S., Sakariya, V., Tanwar, S., & Hsiao, K. F. (2022, October). Internet-of-explainable-digital-twins: A case study of versatile corn production ecosystem. In 2022 International Conference on Communications, Computing, Cybersecurity, and Informatics (CCCI) (pp. 1-5). IEEE.	ENG	CPS		1	1		
2018	Bauer, A., Wollherr, D., & Buss, M. (2018). Human-robot collaboration: a survey . International Journal of Humanoid Robotics, 47-66	ENG	SMT		1	1		
1967	Baumol, W. J. (1967). Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis. American Economic Review 57, 415–426	HUM	HUM		1		1	
2018	Bécue, A., Fourrastier, Y., Praça, I., Savarit, A., Baron, C., Gradussofs, B., . . . Thomas, C. (2018). CyberFactory#1 — Securing the industry 4.0 with cyber-ranges and digital twins. 14th IEEE International Work-shop on Factory Communication Systems (WFCS), (pp. 1-4). Imperia, Italy	ENG	AIT		1	1		

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2020	Bécue, A., Gama, J., & Praça, I. (2020). Artificial Intelligence, Cyber-threats and Industry 4.0: Challenges and Opportunities. Artificial Intelligence Review (AIRE-D-19-00467R1 under review).	ENG	SMT		1	1		
2020	Bécue, A., Maia, E., Feeken, L., Borchers, P., & Praça, I. (2020). A New Concept of Digital Twin Supporting Optimization and Resilience of Factories of the Future. Applied Sciences.	ENG	AIT		1	1		
2022	Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., ... & Remus, U. (2022). Algorithmic management: bright and dark sides, practical implications, and research opportunities. Business & Information Systems Engineering, 64(6), 825-839.	HUM	CDT		1		1	1
2024	Benmessabih, T., Slama, R., Havard, V., & Baudry, D. (2024). Online human motion analysis in industrial context: A review. Engineering Applications of Artificial Intelligence, 131, 107850.	ENG	AIT		1	1		1
2018	Bernard, M. (2018). The Amazing Ways Chinese Tech Giant Alibaba Uses Artificial Intelligence And Machine Learning. Retreived on Forbes Innovation Enterprise & Cloud.	MGT	RBV		1			1
1969	Bertalanffy, L. V. (1969). General system theory: Foundations, development, applications.	ENG	CPS		1	1		
2007	Berthon, P. R., Pitt, L. F., McCarthy, I., & Kates, S. M. (2007). When customers get clever: Managerial approaches to dealing with creative consumers. Business Horizons. 50 (1), 39–47.	MGT	OIT		1			1
2022	Bezić, H., Mance, D., & Balaž, D. (2022). Panel Evidence from EU Countries on CO2 Emission Indicators during the Fourth Industrial Revolution. Sustainability, 14(19), 12554.	MGT	IPL	1	1			1
2009	Björk, Jennie & Magnusson, Mats. (2009). Where Do Good Innovation Ideas Come From? Exploring the Influence of Network Connectivity on Innovation Idea Quality. Journal of Product Innovation Management. 26. 662 - 670. 10.1111/j.1540-5885.2009.00691.x.	MGT	OIT			1		1
2010	Blake, Anne & Moseley, James. (2010). One hundred years after The Principles of Scientific Management : Frederick Taylor's life and impact on the field of human performance technology. Performance Improvement. 49. 27-34. 10.1002/pfi.20141.	MGT	MGT			1	1	
2017	Bloem, J., Van Doorn, M., Duivestein, S., Excoffier, D., Maas, R., & Van Ommeren, E. (2017). The Fourth Industrial Revolution. Things Tighten. International Journal of Communications, Network and System Sciences, Vol.10 No.3.	ENG	CPS		1	1		
2018	Bodrožić, Z., & Adler, P. S. (2018). The evolution of management models: A neo-Schumpeterian theory. Administrative Science Quarterly, 63(1), 85-129.	MGT	MGT		1		1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
1984	Bouchard Jr, Thomas. (1984). Review of Frames of mind: The theory of multiple intelligences. American Journal of Orthopsychiatry. 54. 506. 10.1111/j.1939-0025.1984.tb01522.x.	HUM	HUM			1		1
2021	Breque, M., De Nul, L., & Petridis, A. (2021). Industry 5.0 : towards a sustainable, human-centric and resilient European industry, Publications Office. European Commission, Directorate-General for Research and Innovation.	HUM	CDT		1	1		
2020	Bryndin, E. (2020). Formation and Management of Industry 5.0 by Systems with Artificial Intelligence and Technological Singularity. American Journal of Mechanical and Industrial Engineering, 5(2), 24-30.	ENG	CPS		1	1		
2014	Brynjolfsson, E., & Mcafee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company	HUM	CDT		1	1	1	
2017	Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications: Profound change is coming, but roles for humans remain. Science, 1530–1534	HUM	CDT		1	1	1	
2019	Bunte, A., Wunderlich, P., Moriz, N., Li, P., Mankowski, A., Rogalla, A., & Niggemann, O. (2019, September). Why symbolic ai is a key technology for self-adaption in the context of cpps. In 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA) (pp. 1701-1704). IEEE.	ENG	CPS		1	1		
2008	Burden, D. J. (2008). Deploying embodied AI into virtual worlds. International Conference on Innovative Techniques and Applications of Artificial Intelligence (pp. 103-115). Springer, London.	ENG	AIT		1	1		
2020	Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2020). Explainable AI in Fintech Risk Management. Frontiers in Artificial Intelligence, Volume 3, 26	ENG	AIT		1	1		
2013	Calis Uslu, S., & Bulkan, B. (2013). A research survey: review of ai solution strategies of job shop scheduling problem. Journal of Intelligent Manufacturing. 26(5)	ENG	AIT		1	1		
2023	Camarinha-Matos, L. M. (2023). Collaborative Networks in Digitalization and Society 5. 0: 24th IFIP WG 5. 5 Working Conference on Virtual Enterprises, PRO-VE 2023, Valencia, Spain, September 27-29, 2023, Proceedings (Vol. 688). Springer Nature.	ENG	ENG		1	1		
1999	Cannon, J. a. (1999). Buyer-supplier relationships in business markets. Journal of Marketing Research, Vol. 36 No. 4 , 439-460.	MGT	MGT		1		1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2016	Caputo, A., Marzi, G., & Pellegrini, M. M. (2016). The internet of things in manufacturing innovation processes: development and application of a conceptual framework. . Business Process Management Journal.	MGT	IMT		1	1	1	1
2017	Camarinha-Matos, L. M., Fornasiero, R., & Afsarmanesh, H. (2017, September). Collaborative networks as a core enabler of industry 4.0. In Working Conference on Virtual Enterprises (pp. 3-17). Springer, Cham.	ENG	ENG		1	1	1	
2023	Cannavacciuolo, Lorella & Ferraro, Giovanna & Ponsiglione, Cristina & Primario, Simonetta & Quinto, Ivana, 2023. "Technological innovation-enabling industry 4.0 paradigm: A systematic literature review," Technovation, Elsevier, vol. 124(C).	MGT	IMT	1	1	1	1	1
2021	Carayannis, E. G., Draper, J., & Bhaneja, B. (2021). Towards fusion energy in the Industry 5.0 and Society 5.0 context: Call for a global commission for urgent action on fusion energy. Journal of the Knowledge Economy, 12(4), 1891-1904.	ENG	ENG		1			1
2014	Carter, C; Ellram, L; KAUFMANN, L; Autry, C; Zhao, X; Callarman, T.E., (2014)- Looking back and moving forwards: 50 years of the journal of Supply Chain Management - Journal of Supply Chain Management	HUM	TIM		1	1	1	
2016	Cassiman, B., & Valentini, G. (2016). Open innovation: are inbound and outbound knowledge flows really complementary?. Strategic Management Journal, 37(6), 1034-1046.	MGT	OIT		1			1
1990	Chandler, A. D. (1990). Strategy and structure: Chapters in the history of the industrial enterprise (Vol. 120). MIT press.	MGT	MGT		1		1	
2007	Chen, J., Zhang, C., Yuan, Y., & Huang, L. (2007). Understanding the emerging C2C electronic market in China: an experience-seeking social marketplace. *Electronic Markets*, *17*(2), 86-100.	HUM	SET		1	1	1	
2023	Chen, L., Xie, J., Zhang, X., Deng, J., Ge, S., & Wang, F. Y. (2023). Mining 5.0: Concept and framework for intelligent mining systems in CPSS. IEEE Transactions on Intelligent Vehicles.	ENG	CPS		1	1		
2024	Chen, M., Wei, Z., Li, L., & Zhang, K. (2024). Edge computing-based proactive control method for industrial product manufacturing quality prediction. Scientific Reports, 14(1), 1288.	ENG	MFG		1	1		
2012	Chen, S. H., & Pollino, C. A. (2012). Good practice in Bayesian network modelling. Environmental Modelling & Software, 37, 134-145.	ENG	AIT	1				

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2014	Chesbrough, H. &. (2014). Explicating open innovation: Clarifying an emerging paradigm for understanding innovation. . New Frontiers in Open Innovation. Oxford: Oxford University Press, Forthcoming, 3-28.	MGT	OIT		1		1	1
2003	Chesbrough, H. W. (2003). Open Innovation: The new imperative for creating and profiting from technology. Boston: Harvard Business School Press. Harvard business school press: Boston, Massachusetts.	MGT	OIT					1
2018	Chesbrough, H., Lettl, C., & Ritter, T. (2018). Value creation and value capture in open innovation. Journal of Product Innovation Management, 35(6), 930-938.	MGT	OIT				1	1
2020	Chew, Dinah; Atkinson, Craig; Herbay, Matthew; Wang, Guohua; Sharma, Ajay; Seth, Amish (2020) - Strategic Recommendation Report - CONSULTONSLEY REPORT	MGT	IPL		1		1	
2021	Chinerawat, V., & Vorapruck, P. (2021). Innovation and Knowledge Management Role in IoT industries of Thailand transformation: A case of Things on Net Thailand: A case of Things on Net Thailand. Nimitmai Review Journal, 4(1), 61-72.	MGT	RBV			1		1
1993	Clemons, Eric K.; Reddi Sashidhar P. , Row, Michael C. . 1993. The impact of information technology on the organization of economic activity: the "Move to the middle" hypothesis. Journal of management information systems 10.2	HUM	TCE				1	
2020	CoalitionForCriticalTechnology. (n.d.). Abolish the TechToPrisonPipeline. Retrieved from https://medium.com/@CoalitionForCriticalTechnology/abolish-the-techtoprisonpipeline-9b5b14366b16	HUM	HUM		1			
2018	Columbus, L. (2018). Roundup of Machine Learning Forecasts and Market Estimates. Forbes.	MGT	RBV		1	1	1	1
2006	Cook, M. B., Bhamra, T. A., & Lemon, M. (2006). The transfer and application of Product Service Systems: from academia to UK manufacturing firms. Journal of cleaner production, 14(17), 1455-1465.	HUM	TIM		1		1	
2002	Dagnino, G. B., & Padula, G. (2002). Coopetition Strategy: Towards a New Kind of Interfirm Dynamics for Value Creation. EURAM 2nd Annual Conference. Stockholm School of Entrepreneurship, Sweden	MGT	OIT		1		1	1
2018	Daugherty, P. R., & Wilson, H. J. (2018). Human + machine: Reimagining work in the age of AI. Boston: Harvard Business Review Press.	HUM	CDT			1	1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2018	Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. Harvard Business Review, 96, 108–116.	MGT	RBV			1	1	
2020	Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science (2020) 48, 24–42.	HUM	CDT		1	1	1	
2023	Del Gallo, M., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. (2023). Artificial intelligence to solve production scheduling problems in real industrial settings: Systematic Literature Review. Electronics, 12(23), 4732	ENG	MFG		1	1		
2017	Deming, D. (2017). The Growing Importance of Social Skills in the Labor Market. Quarterly Journal of Economics 132(4), 1593–1640	MGT	IPL			1	1	1
2021	Shkarupa, O. V., Kubatko, O. V., Shkarupa, O.V, Яременко, А.Г. (2021), Business Processes Intellectualisation towards Sustainable Development Goals Fulfillment, Сумський державний університет	MGT	IMT		1			1
2012	Davis, K; Christodoulou, J; Seider, S; Gardner, H ; 2012; The Theory of Multiple Intelligences	HUM	HUM			1		1
2016	Ding, K., Jiang, P., Leng, J., & Cao, W. (2016). Modeling and analyzing of an enterprise relationship network in the context of social manufacturing. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 230(4), 752-769.	HUM	SET		1		1	
2008	Dodgson, M., Gann, D. M., & Salter, A. (2008). The management of technological innovation: strategy and practice. Oxford University Press on Demand.	MGT	IMT				1	1
2020	Dolev, N., & Itzkovich, Y. (2020). In the AI era, soft skills are the new hard skills. . Artificial intelligence and its impact on business, 55	HUM	CDT			1	1	1
2023	Dong, Tong, Shi Yin, and Nan Zhang. 2023. New Energy-Driven Construction Industry: Digital Green Innovation Investment Project Selection of Photovoltaic Building Materials Enterprises Using an Integrated Fuzzy Decision Approach" Systems 11, no. 1: 11. https://doi.org/10.3390/systems11010011	MGT	MGT		1		1	1
2023	Dong, Tong, Shi Yin, and Nan Zhang. 2023. "The Interaction Mechanism and Dynamic Evolution of Digital Green Innovation in the Integrated Green Building Supply Chain" Systems 11, no. 3: 122. https://doi.org/10.3390/systems11030122	MGT	IMT		1		1	1

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2019	Doostmohammadian, M., Rabiee, H. R., & Khan, U. A. (2019). Cyber-social systems: modeling, inference, and optimal design. . IEEE Systems Journal, 14(1), 73-83.	ENG	CPS		1	1	1	
2018	Du, C. J., Hu, J., & Chen, W. X. (2018). Development model and countermeasures of china's new generation of artificial intelligence industry. . Economic Review Journal, 4, , 41-47.	MGT	IPL		1	1		1
2022	Duan, J., Yu, S., Tan, H. L., Zhu, H., & Tan, C. (2022). A survey of embodied ai: From simulators to research tasks. . IEEE Transactions on Emerging Topics in Computational Intelligence, 6(2), 230-244	ENG	AIT			1		1
2018	Dubé, L., Du, P., McRae, C., Sharma, N., Jayaraman, S., & Nie, J. Y. (2018). Convergent innovation in food through big data and artificial intelligence for societal-scale inclusive growth. Technology Innovation Management Review, 8(2).	HUM	CDT			1		1
2022	Del Baldo, M., Sitnikov, C., Vasilescu, L., Mandache, L., Ogarcă, R., Băndoi, A., & Ganea, E. (2022). Funding, Turnover, Sustainability and Digital Technologies: A Multicriteria Research Model for SMEs Facing a Challenging Context. Sustainability, 14(7), 3953.	MGT	MGT		1	1	1	
2017	Einstein. (2017). Récupéré sur A Trillion Dollar Boost: Artificial Intelligence in CRM is Driving Growth and Creating Jobs : https://www.salesforce.com/blog/2017/06/trillion-dollar-boost-idc-report.html	HUM	CDT		1	1	1	1
2019	El Zaataria, S., Mareia, M., & Usmanb, Z. (2019). Cobot programming for collaborative industrial tasks: An overview. *Robotics and Autonomous Systems*.	ENG	CPS		1	1		
2008	Ellram, L., Tate, W., & Billington, C. (2008). Offshore outsourcing of professional services: a transaction cost economics perspective",. *Journal of Operations Management, Vol. 26 No. 2,*, 148-163.	HUM	TCE		1		1	
2021	ElFar, O. A., Chang, C. K., Leong, H. Y., Peter, A. P., Chew, K. W., & Show, P. L. (2021). Prospects of Industry 5.0 in algae: Customization of production and new advance technology for clean bioenergy generation. Energy Conversion and Management: X, 10, 100048.	ENG	MFG		1			1
2024	Eng, P. H., & Liu, R. L. (2024). Will Intelligent Technologies Replace Humans in the Future? An Exploratory Study for Likelihood of Intelligent Technologies to Replace Humans in the Future. In M. A. Al-Sharafi, M. Al-Emran, G. Wei-Han Tan, & K.-B. Ooi, Current and Future Trends on Intelligent Technology Adoption:. Springer.	HUM	CDT				1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2020	European Commission. (2020, 02 19). A European strategy for data. Communication from the European Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Brussels.	HUM	HUM		1	1		1
2021	European Commission (2021), Industry 5.0: A Transformative Vision for Europe, ESIR Policy Brief No. 3	HUM	HUM		1	1		1
2016	Ezrachi, A., & Stucke, M. E. (2016). Virtual Competition. Oxford: Oxford University Press.	HUM	HUM		1	1		
2010	Factories of the Future PPP. (2010). STRATEGIC MULTI-ANNUAL ROADMAP. Récupéré sur https://ec.europa.eu/research/industrial_technologies/pdf/ppp-factories-of-the-future-strategic-multiannual-roadmap-info-day_en.pdf	ENG	CPS		1	1		
2021	Farhana, A. (2021). Applying Social Exchange Theory to Value Co-Creation Frame: Does it Leads to Customer Loyalty? Sriwijaya International Journal of Dynamic Economics and Business, 191-206.	HUM	SET		1		1	
2022	Fazal, N., Haleem, A., Bahl, S., Javaid, M., Nandan, D. (2022). Digital Management Systems in Manufacturing Using Industry 5.0 Technologies. In: Verma, P., Samuel, O.D., Verma, T.N., Dwivedi, G. (eds) Advancement in Materials, Manufacturing and Energy Engineering, Vol. II. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-16-8341-1_18	ENG	SMT		1	1		1
2022	Ferrari, A., Mangano, G., Cagliano, A. C., & De Marco, A. (2022). 4.0 technologies in city logistics: an empirical investigation of contextual factors. Operations Management Research, 1-18.	HUM	TIM		1	1		1
2018	Flores, M., Maklin, D., Golob, M., Al-Ashaab, A., & Tucci, C. (2018). Awareness Towards Industry 4.0: Key Enablers and Applications for Internet of Things and Big Data. IFIP Advances in Information and Communication Technology, 377–386. https://doi.org/10.1007/978-3-319-99127-6_32	ENG	SMT	1	1	1	1	
2019	Forrest, J. Y., Lin, C., Mondal, S., & Tucker, R. (2019). Environmental forces underneath the innovativeness of manufacturing firms. . Theoretical Economics Letters, 9(05), 1353.	MGT	IPL		1		1	1
2006	Forsyth, T. (2006) "Moore" to Come for Premature Deindustrialization: A Kaldorian analysis of the role of globalization and computerization on the labour share in emerging market and developing countries, ECONOMICS 490	HUM	HUM		1		1	
2017	Foye, L. (2017). *Chatbot Conversations to deliver $8 billion in Cost savings by 2022*. Récupéré sur Juniper Research.: https://www.juniperresearch.com/analystxpress/july-2017/.	HUM	CDT			1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2019	Frank, A. G., Mendes, G. H., Ayala, N. F., & Ghezzi, A. (2019). Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. Technological Forecasting and Social Change, 141, ., 341-351.	HUM	TIM		1		1	
2019	Frank, M. R. (2019). Toward understanding the impact of artificial intelligence on labor . National Academy of Sciences of the United States of America, (pp. 6531–6539).	HUM	CDT		1	1		
2013	Frey, C. B., & Osborne, M. A. (2013). The future of employment: How susceptible are jobs to computerisation? . Oxford Martin School.	HUM	CDT		1	1		
2018	Furman, J. (2018). Should We Be Reassured If Automation in the Future Looks Like Automation in the Past? In A. Agrawal, J. Gans, & A. Goldfarb, The Economics of Artificial Intelligence: An Agenda. Chicago: Chicago: University Press.	MGT	IPL			1	1	1
2012	Gacek, S. (2012). Cnc machine group scheduling methods in a multitasking system. *Carpathian Logistics Congress 2012.* Jesenik, Czech Republic.	ENG	MFG		1	1		
2017	GahhYi , Ban; Bora, Keskin, N. ; 2017; Personalized Dynamic Pricing with Machine Learning: High-Dimensional Features and Heterogeneous Elasticity; Management Science; ;	ENG	AIT		1	1		
2021	Gaiardelli, P., Pezzotta, G., Rondini, A., Romero, D., Jarrahi, F., Bertoni, M., & Cavalieri, S. (2021). Product-service systems evolution in the era of Industry 4.0. . Service Business, 15, 177-207	HUM	TIM		1		1	1
2018	Galasso, A., & Luo, H. (2018). Punishing Robots: Issues in the Eco nomics of Tort Liability and Innovation in Artificial Intelligence. In A. Agrawal, J. Gans, & A. Goldfarb, The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press	MGT	IPL		1	1		1
2011	Gao, J., Yao, Y., Zhu, V. C., Sun, L., & Lin, L. (2011). Service-oriented manufacturing: a new product pattern and manufacturing paradigm. Journal of Intelligent Manufacturing, 435-436.	HUM	TIM		1		1	
1983	Gardner, H. K. (1983). Frames of mind: The theory of multiple intelligences. New York: BasicBooks.	HUM	HUM		1		1	
2020	Ghadge, A., Kara, M. E., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on supply chains. Journal of Manufacturing Technology Management, 31(4), 669–686. https://doi.org/10.1108/JMTM-10-2019-0368	ENG	SMT		1		1	
2020	Ghahramani, M., Qiao, Y., Zhou, M. C., 'Hagan, A., & Sweeney, J. (2020). AI-based modeling and data-driven evaluation for smart manufacturing processes. IEEE/CAA Journal of Automatica Sinica, 1026-1037.	ENG	SMT		1	1		

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2024	Ghelani, H. (2024). Advanced AI Technologies for Defect Prevention and Yield Optimization in PCB Manufacturing. International Journal Of Engineering And Computer Science, 13(10	ENG	MFG		1	1		
2021	Ghobakhloo, M., Iranmanesh, M., Grybauskas, A., Vilkas, M., & Petraitė, M. (2021). Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation. Business Strategy and the Environment, 30(8), 4237-4257.	MGT	IMT		1			1
2022	Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. (2022). Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: a systematic review and transformation roadmap. Journal of Manufacturing Technology Management, (ahead-of-print).	MGT	IMT		1	1		1
2022	Ghobakhloo, M., Iranmanesh, M., Mubarak, M. F., Mubarik, M., Rejeb, A., & Nilashi, M. (2022). Identifying industry 5.0 contributions to sustainable development: A strategy roadmap for delivering sustainability values. Sustainable Production and Consumption, 33, 716-737.	MGT	IMT		1	1	1	1
2011	Giannantonio, C. &.-H. (2011). Frederick Winslow Taylor: Reflections on the Relevance of The Principles of Scientific Management 100 Years Later. Journal of Business and Management, 17, 7-10.	MGT	MGT			1	1	
2016	Glesne, C. (2016). Becoming qualitative researchers: An introduction. One Lake Street, Upper Saddle River, New Jersey 07458.: Pearson	HUM	HUM	1				
2006	Gloor, P. A. (2006). Swarm creativity: Competitive advantage through collaborative innovation networks. Oxford University Press.	MGT	OIT		1		1	1
2011	Gloor, P. A., Dorsaz, P., & Fuehres, H. (2011). Analyzing success of startup entrepreneurs by measuring their social network distance to a business networking hub. In Proceedings 3rd international conference on collaborative innovation networks coins, Basel. Sept (pp. 8-10).	MGT	OIT			1	1	1
2018	Goldfarb, A., & Trefler, D. (2018). Artificial Intelligence and International Trade. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press.	MGT	OIT			1		1
2018	Goodfellow, I., Bengio, Y., Courville, A. (2016). Deep learning. MIT press.	ENG	AIT		1	1		
2018	Goodwin, T. (2018). Digital Darwinism : Survival of the Fittest in the Age of Business Disruption. Kogan Page Ltd.	MGT	IMT		1	1	1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
1992	Goul, Michael & Henderson, John & Tonge, Fred. (2007). The Emergence of Artificial Intelligence as a Reference Discipline for Decision Support Systems Research. Decision Sciences. 23. 1263 - 1276. 10.1111/j.1540-5915.1992.tb00448.x.	HUM	CDT			1		
2018	Graeber, D. (2018). Bullshit Jobs: A Theory. Journal of Applied Learning & Teaching Vol.1 No.2 , 78-82.	HUM	CDT		1		1	
1991	Grant, R. (1991). The resource-based theory of competitive advantage: implications for strategy formulation. California management review 33, 114-135.	MGT	RBV		1	1		1
2022	Grybauskas, A., Stefanini, A., & Ghobakhloo, M. (2022). Social sustainability in the age of digitalization: A systematic literature review on the social implications of industry 4.0. Technology in Society, 101997.	HUM	HUM		1	1		1
2022	Gu, X., & Koren, Y. (2022). Mass-Individualisation–the twenty first century manufacturing paradigm. International Journal of Production Research, 60(24), 7572-7587	HUM	SET		1		1	1
2022	Guerroum, M., Zegrari, M., & Elmahjoub, A. A. (2022, September). Smart Greasing System in Mining Facilities: Proactive and Predictive Maintenance Case Study. In International Conference on Smart Applications and Data Analysis (pp. 348-362). Cham: Springer International Publishing.	ENG	MFG		1	1		
2019	Gupta, P. K., Shree, V., Hiremath, L., & Rajendran, S. (2019). The use of modern technology in smart waste management and recycling: Artificial intelligence and machine learning. In Recent advances in computational intelligence (pp. 173-188). Springer, Ch.	ENG	MFG		1	1		
2008	Gupta, S., & Kim, H. W. (2008). Linking structural equation modeling to Bayesian networks: Decision support for customer retention in virtual communities. European Journal of Operational Research, 190(3), 818-833.	ENG	AIT	1				
2004	Hackett, S. M., & Dilts, D. M. (2004). A systematic review of business incubation research. The Journal of Technology Transfer, 29(1), 55-82.	MGT	OIT		1			1
2009	Hair, J. F. (2009). Multivariate data analysis	MGT	MGT	1				
2002	Hall, L. A., & Bagchi-Sen, S. (2002). A study of R&D, innovation, and business performance in the Canadian biotechnology industry. Technovation, 22(4), 231-244	MGT	IMT				1	1
2006	Hanusch, H., & Pyka, A. (2006). Principles of neo-Schumpeterian economics. Cambridge Journal of Economics: 31(2), 275-289	HUM	CDT			1	1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
1991	Hart, P. &. (1991). Inter-Organization Networks, Computer Integration, and Shifts in Interdependence: The Case of the Semiconductor Industry . ACM Transactions on Information Systems.	HUM	TCE				1	
2006	Haslam, N. (2006). Dehumanization: an integrative review. . Pers Soc Psychol Rev 10(3), 252–264.	HUM	HUM		1	1		
2019	Hastie, T., Tibshirani, R., & Friedman, J. (2019). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer.	ENG	AIT		1	1		
1985	Haugeland, J. (1985). Artificial intelligence: the very ide. Massachusetts Institute of Technolog.	ENG	AIT		1	1		
2023	He, C., Zhang, C., Bian, T., Jiao, K., Su, W., Wu, K. J., & Su, A. (2023). A review on artificial intelligence enabled design, synthesis, and process optimization of chemical products for industry 4.0. Processes, 11(2), 330.	ENG	SMT		1	1		
1997	Heckerman, D. (1997). Bayesian Networks for Data Mining. Data Mining and Knowledge Discovery 1, 79–119.	ENG	AIT	1		1		
2022	Heckerman, D. (2022). A tutorial on learning with Bayesian networks. Learning in graphical models, 301-354.	**ENG**	**AIT**	1		1		
1999	Hinton, G., & Sejnowski, T. (1999). Unsupervised Learning: Foundations of Neural Computation. MIT Press.	ENG	AIT		1	1		
2018	Hoffman, M., Kahn, L. B., & Li, D. (2018). Discretion in hiring. The Quarterly Journal of Economics, 133(2), 765-800.	MGT	MGT			1	1	
2016	Holmström, J., Holweg, M., Khajavi, S. H., & Partanen, J. (2016). The direct digital manufacturing (r) evolution: definition of a research agenda. . Operations Management Research, 9(1), , 1-10.	ENG	SMT		1		1	
2023	Hozdić, Elvis, and Zoran Jurković. "Cognitive Cyber-Physical Production Systems: A New Concept of Manufacturing Systems on the Route to Industry 5.0." International Conference “New Technologies, Development and Applications”. Cham: Springer Nature Switzerland, 2023.	ENG	CPS		1	1		
2018	Huang, M.-H., & & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2),, 155–172.	HUM	CDT		1	1		
2018	Hugh Boyes, B. H. (2018). The industrial internet of things (IIoT): An analysis framework. Computers in Industry,, 101(doi.org/10.1016/j.compind.2018.04.015), 1-12.	ENG	CPS		1	1		

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2023	Hussain, S., Singh, A. M., Mohanty, P., & Gavinolla, M. R. (2023). Next generation employability and career sustainability in the hospitality industry 5.0. Worldwide Hospitality and Tourism Themes, 15(3), 308-321.	HUM	HUM		1	1	1	
2021	Hutajulu, R. S., Susita, D., & Eliyana, A. (2021). The effect of digitalization and virtual leadership on organizational innovation during the COVID-19 pandemic crisis: A case study in Indonesia. The Journal of Asian Finance, Economics and Business, 8(10), 57-64.	MGT	IMT		1	1		1
2024	Hutson, J., & Plate, D. (2024). The Algorithm of Fear: Unpacking Prejudice Against AI and the Mistrust of Technology. Journal of Innovation and Technology	MGT	IMT		1	1		1
2019	Ibrahim, W. M. R. W., & Hassan, R. (2019). Recruitment trends in the era of industry 4.0 using artificial intelligence: pro and cons. Asian Journal of Research in Business and Management, 1(1), 16-21.	HUM	CDT		1	1	1	
2024	Jácome de Moura Jr, P., dos Santos Junior, C. D., Porto-Bellini, C. G., & Dias Junior, J. J. (2024). The over-concentration of innovation and firm-specific knowledge in the artificial intelligence industry. Journal of the Knowledge Economy, 1-31	MGT	RBV		1	1	1	1
2018	Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, Volume 61, Issue 4, 577-586	HUM	CDT		1	1	1	
2016	Jiang, P., Leng, J., Ding, K., Gu, P., & Koren, Y. (2016). Social manufacturing as a sustainable paradigm for mass individualization. Proceedings of the Institution of Mechanical Engineers, Part B: (pp. 1961–1968). Journal of Engineering Manufacture, 230(10).	HUM	SET		1	1	1	1
2018	Jin, X., Yu, S., Zheng, P., Liu, Q., & Xu, X. (2018). Cloud-based approach for smart product personalization. Procedia CIRP, Volume 72, 922-927.	HUM	TIM		1	1	1	
2019	Jo, K. (2019). Defensive Innovation and Firm Growth in the US: Impact of International Trade. Working Paper, 2019.	MGT	OIT		1			1
2019	Jobin, A. I. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389-399.	MGT	IPL				1	1
2024	Jonsson, A. (2024). Virtual Commissioning as a service: Standardizing modern co-simulation. Gothenburg, Sweeden: Chalmers University of Technology	ENG	MFG		1	1	1	
2017	Joshi, D.; Kumar, V.; 2017; The Big Analytics; AnalyticsWeek LLC	HUM	CDT			1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2019	Jung, Jisun. (2019). The fourth industrial revolution, knowledge production and higher education in South Korea. Journal of Higher Education Policy and Management. 42. 1-23. 10.1080/1360080X.2019.1660047.	MGT	OIT					1
2021	Jürjens, J. (2021, 10 27). THE INDUSTRIAL DATA SPACE: DIGITAL INDUSTRIAL PLATFORM ACROSS VALUE CHAINS IN ALL SECTORS OF THE ECONOMY . Retrieved from https://ec.europa.eu/futurium/: https://ec.europa.eu/futurium/en/system/files/ged/industrial_data_space.pdf	ENG	SMT		1	1		
1996	Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1996). Reinforcement Learning: A Survey . Journal of Artificial Intelligence Research. 4, 237-285.	ENG	AIT		1	1		1
2018	Kahneman, D. (2018). Discussion of Camerer. In A. Agrawal, J. Gans, & A. Goldfarb, The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press.	HUM	HUM		1	1	1	
2020	Kaloudi, N., & Li, J. (2020). The AI-Based Cyber Threat Landscape: A Survey. ACM Comput. Surv. 53, 1, Article 20, 1-34.	ENG	AIT		1	1		
2016	Kamal, S. Z., Al Mubarak, S. M., Scodova, B. D., Naik, P., Flichy, P., & & Coffin, G. (2016). IT and OT Convergence - Opportunities and Challenges. SPE Intelligent Energy International Conference and Exhibition. Aberdeen, Scotland, UK: Society of Petroleum Engineers.	ENG	CPS		1	1		1
1972	Kanter, R. M. (1972). Commitment and community: communes and utopias in sociological perspective. Harvard University Press.	MGT	OIT		1		1	1
2016	Kaplan, J. (2016). Artificial Intelligence. Oxford University Press.	ENG	AIT		1	1		
2000	Kasper, W., & Streit, M. E. (2000). Institutional economics: Social order and public policy. Cheltenham: Edward Elgar Publishing.	HUM	HUM		1		1	
2012	Katzy, B. R., Pawar, K. S., & Thoben, K. D. (2012). A living lab research agenda. Int. J. Product Development, 17(1/2), 1.	MGT	OIT				1	1
2023	Kaur, D. P., Singh, N. P., & Banerjee, B. (2023). A review of platforms for simulating embodied agents in 3D virtual environments. . Artificial Intelligence Review, 56(4), , 3711-3753.	ENG	AIT			1		1
2022	Kavakoglu, A. A., Almaç, B., Eser, B., & Alaçam, S. AI Driven Creativity in Early Design Education.	HUM	HUM		1	1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2022	Kazantsev, N., Pishchulov, G., Mehandjiev, N., Sampaio, P., & Zolkiewski, J. (2022). Investigating barriers to demand-driven SME collaboration in low-volume high-variability manufacturing. Supply Chain Management: An International Journal, 27(2), 265-282.	MGT	OIT		1		1	1
2002	Keizer, J. A., Dijkstra, L., & Halman, J. I. (2002). Explaining innovative efforts of SMEs.: An exploratory survey among SMEs in the mechanical and electrical engineering sector in The Netherlands. Technovation, 22(1), 1-13.	MGT	OIT		1		1	1
2016	Kelly, K. (2016). The inevitable: Understanding the 12 Technological Forces that Will Shape Our Future. Viking.	MGT	IMT		1	1	1	1
2016	Khani, A. H. A., Tabatabaei, S. E., & Parvari, Y. (2016). Evaluation of the Effect of Information and Communication Technology on Creativity of Employees of Public Organizations (Case Study: Office of Telecommunications of the County of Semnan). Mediterranean Journal of Social Sciences, 7(3 S2), 32-32.	MGT	IMT			1		1
2016	Khani, A. T. (2016). Evaluation of the Effect of Information and Communication Technology on Creativity of Employees of Public Organizations (Case Study: Office of Telecommunications of the County of Semnan). Mediterranean journal of social sciences, 7-32.	HUM	CDT		1			
2022	Kharub, M., Mor, R. S., & Rana, S. (2022). Mediating role of manufacturing strategy in the competitive strategy and firm performance: evidence from SMEs. . Benchmarking: An International Journal, 29(10), 3275-3301	HUM	TIM		1		1	
2021	Keshavarz, H., Mahdzir, A. M., Talebian, H., Jalaliyoon, N., & Ohshima, N. (2021). The value of big data analytics pillars in telecommunication industry. Sustainability, 13(13), 7160.	MGT	IMT	1	1	1	1	
2022	Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing–Evidence from a worldwide sample of manufacturing companies. Technovation, 110, 102375.	HUM	CDT		1	1	1	1
2015	Kline, R. B. (2015). Principles and practice of structural equation modeling. . Guilford publications.	HUM	HUM	1				
2018	Koch, J., & Oulasvirta, A. (2018). Group Cognition and Collaborative AI. Dans Zhou J., Chen F. (eds) Human and Machine Learning. Springer, Cham.	HUM	CDT		1			1
2009	Koller, D., & Friedman, N. (2009). Probabilistic Graphical Models: Principles and Techniques. MIT Press	ENG	AIT	1				

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2018	Korinek, A. a. (2018). Artificial Intelligence and Its Implications for Income Distribution and Unemployment. In A. Agrawal, J. Gans, & A. Goldfarb, The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press.	MGT	IPL			1		1
2017	Korvesis, P. (2017). Machine learning for predictive maintenance in aviation. Artificial Intelligence.	ENG	MFG		1	1		
2019	Kovaitė, K., & Stankevičienė, J. (2019, May). Risks of digitalisation of business models. In Proceedings of 6th International Scientific Conference Contemporary Issues in Business, Management and Economics Engineering '2019.	MGT	MGT		1	1	1	
2015	Kozlenkova, I. V., Tomas, G., Hult, M., Lund, D. J., Mena, J. A., & Kekec, P. (2015). The Role of Marketing Channels in Supply Chain Management. Journal of Retailing, Volume 91, Issue 4,, 586-609.	MGT	MGT				1	
2020	Krajčík, S. Z. D. Č. D. COMPETITIVENESS IN INTERNATIONAL BUSINESS. CHALLENGES FOR THE EU ECONOMIES - Wolters Kluwer	MGT	IPL		1			1
2019	Krkač, K. (2019). Corporate social irresponsibility: humans vs artificial intelligence. Social Responsibility Journal, Vol. 15 No. 6, 786-802.	MGT	IPL		1	1		1
2018	Kusiak, A. (2018). Smart manufacturing. International Journal of Production Research, 56(1-2), 508-517.	ENG	CPS		1	1		
2022	Labucay, I. (2022). Is There a Smart Sustainability Transition in Manufacturing? Tracking Externalities in Machine Tools over Three Decades. Sustainability, 14(2), 838.	MGT	IPL		1	1	1	1
2017	Lambrecht, A., & Tucker, C. (2017). Algorithmic Discrimination? Apparent Algorithmic Bias in the Serving of Stem Ads. Massachusetts Institute of Technology.	MGT	IPL			1	1	1
2021	Laskurain-Iturbe, I., Arana-Landín, G., Landeta-Manzano, B., & Uriarte-Gallastegi, N. (2021). Exploring the influence of industry 4.0 technologies on the circular economy. Journal of Cleaner Production, 128944.	HUM	HUM		1	1	1	
1995	Lee, J. (1995). Small firms' innovation in two technological settings. Research Policy, 24(3), 391-401.	MGT	IMT		1			1
2008	Lee, C. K., Tan, B., & Chiu, J. Z. (2008). The impact of organisational culture and learning on innovation performance. International Journal of Innovation and Learning, 5(4), 413-428.	MGT	IMT		1			1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2018	Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for Industry 4.0-based Manufacturing Systems. Manufacturing Letters 18. , 20-23.	ENG	CPS		1	1		
2015	Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. 33rd Annual ACM Conference on Human Factors in Computing Systems (pp. 1603–1612). New York, NY, USA: Association for Computing Machinery.	HUM	CDT		1	1	1	
2016	Leng, J., & Jiang, P. (2016). A deep learning approach for relationship extraction from interaction context in social manufacturing paradigm. Knowledge-Based Systems, Volume 100, 188-199.	HUM	SET		1	1	1	
2024	Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards Industry 5.0: Insights, pathways, and challenges. Journal of Manufacturing Systems, 73, 349-363	HUM	SET		1	1	1	1
2021	Lepri, B., Oliver, N., & Pentland, A. (2021). Ethical machines: the human-centric use of artificial intelligence. Iscience, 102249.	MGT	IPL			1	1	
2017	Li, B.-h., Hou, B.-c., Yu, W.-t., Lu, X.-b., & Yang, C.-w. (2017). Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers of Information Technology & Electronic Engineering 18, 86–96.	ENG	CPS		1	1		
2022	Li, B., & Song, P. (2022). Driving Force Mechanism of the Core Green Technology Innovation of Equipment Manufacturing Enterprises towards Industry 5.0 in China. Mathematical Problems in Engineering, 2022.	MGT	IPL	1	1		1	1
2018	Lichtenthaler, U. (2018). Substitute or synthesis: the interplay between human and artificial intelligence. Research-technology management, 61(5), 12-14.	MGT	RBV			1	1	1
2019	Lichtenthaler, U. (2019). An Intelligence-Based View of Firm Performance: Profiting from Artificial Intelligence. Journal of Innovation Management. 7. 7.	MGT	RBV		1	1	1	1
2017	Lihu, i. W., & Wei, J. (2017). Big data analytics based fault prediction for shop floor scheduling. Journal of Manufacturing Systems, 187-194.	ENG	SMT		1	1		
2020	Liu, J., Chang, H., Forrest, J. Y. L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. Technological Forecasting and Social Change, 158, 120142.	MGT	OIT		1	1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2023	Lo, H. W. (2023). A data-driven decision support system for sustainable supplier evaluation in the Industry 5.0 era: A case study for medical equipment manufacturing. Advanced Engineering Informatics, 56, 101998.	MGT	MGT		1	1	1	
2007	Lopez-Ortega, O., & Ramirez-Hernandez, M. (2007). A formal framework to integrate express data models in an extended enterprise context. J. Intell. Manuf. 18 (3), 371–381.	ENG	SMT		1		1	
2024	Lu, Y., Phillips, G. M., & Yang, J. (2024). The impact of cloud computing and ai on industry dynamics and concentration (No. w32811). National Bureau of Economic Research.	HUM	TCE		1	1	1	
2010	Lu, Y., Zhao, L., & Wangb, B. (2010). From virtual community members to C2C e-commerce buyers: Trust in virtual communities and its effect on consumers' purchase intention. Electronic Commerce Research and Applications 9.	HUM	SET		1		1	
1980	Macneil, I. (1980). The New Social Contract, An Inquiry into Modern Contractual Relations. New Haven, CT.: Yale University Press.	HUM	SET		1		1	
1974	Macneil, I. R. (1974). The many futures of contracts. Los Angeles: Gould School of Law, the Law Center Univ. of Southern California.	HUM	SET		1		1	
2021	Maddikunta, P. K. R., Pham, Q. V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., ... & Liyanage, M. (2021). Industry 5.0: A survey on enabling technologies and potential applications. Journal of Industrial Information Integration, 100257.	ENG	ENG		1			1
2020	Makkar, S., Devi, G. N. R., & Solanki, V. K. (2019, January). Applications of machine learning techniques in supply chain optimization. In International Conference on Intelligent Computing and Communication Technologies (pp. 861-869). Springer, Singapore. Control, Safety, Maintenance and Management.	ENG	SMT		1		1	
2017	Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 46-60.	HUM	CDT		1	1		1
2019	Malik, A. (2019). Creating competitive advantage through source basic capital strategic humanity in the industrial age 4.0. International Research Journal of Advanced Engineering and Science, 4(1), 209-215.	HUM	TIM		1	1	1	1
1987	Malone, T., Yates, J., & Benjamin, R. (1987). Electronic Markets and Electronic Hierarchies. . Communications of the ACM.	HUM	TCE				1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2019	Marcot, B. G., & Penman, T. D. (2019). Advances in Bayesian network modelling: Integration of modelling technologies. Environmental modelling & software, 111, 386-393.	ENG	AIT	1				
2022	Margherita, A., Banchi, E., Biffi, A., di Castri, G., & Morelli, R. (2022). Beyond Total Cost Management (TCM) to Systemic Value Management (SVM): Transformational Trends and a Research Manifesto for an Evolving Discipline. Sustainability, 14(19), 12890.	HUM	HUM		1		1	1
2016	Markoff, J. (2016). Machines of loving grace: The quest for common ground between humans and robots. HarperCollins Publishers.	HUM	CDT		1	1	1	1
2017	Markow, W., Braganza, S., Taska, B., Miller, S., & Hughes, D. (2017). The Quant Crunch: How the demand for data science skills is disrupting the job market. . Récupéré sur Burning Glass Technologies: https://public.dhe.ibm.com/common/ssi/ecm/im/en/iml14576usen	ENG	AIT				1	1
1867	Marx, K. (1867). Das Kapital: Kritik der politischen Oekonomie, Volume 1: Der Produktionsprozess des Kapitals (1 ed.). Hamburg, Germany: Verlag von Otto Meissne.	HUM	HUM		1			
2018	Mateos-Garcia, J. (2018). The Complex Economics of Artificial Intelligence. National Endowment for Science, Technology and the Arts (NESTA).	HUM	TCE		1	1	1	1
2021	Mazzucato, M. (2021). Mission economy: A moonshot guide to changing capitalism. Penguin UK.	MGT	IPL		1			1
1984	McArdle, J. J., & McDonald, R. P. (1984). Some algebraic properties of the Reticular Action Model for moment structures. British Journal of Mathematical and Statistical Psychology, 37, 234–251.	HUM	HUM	1				
1955	McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (1955). A Proposal for the Dartmouth Summer. AI Magazine, 27(4), 12.	ENG	AIT			1		
2020	MCDC; 2020; Future Leadership, A Multinational Capability Development Campaign project	MGT	MGT			1	1	
2019	Medioli, A., Marchini, P., Luigi Ferrari, G., Belli, L., & Davoli, L. (2019). Toiwards industry 4.0 with iot: Optimizing business processes in an evolving manufacturing. Frontiers in ICT.	ENG	CPS		1	1		
2024	Meng, B., Cheng, W., Ye, M., Keola, S., & YE, J. (2024). Visualizing Global Value Chains: Smile Curve, Network and Revealed Comparative Advantage. . IDE Discussion Paper, 924	HUM	TIM		1		1	
2024	Meng, X., & Gong, X. (2024). Digital transformation and innovation output of manufacturing companies—An analysis of the mediating role of internal and external transaction costs. . Plos one, 19(1), e0296876	HUM	TCE		1	1	1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2013	Mention, A.-L., & Al-Sharieh, S. (2013). Open Innovation and Intellectual Property: The Relationship and Its Challenges. . Information Age Publishing.	MGT	OIT					1
2014	Merkel, A. (2014). Speech by Federal Chancellor Angela Merkel to the OECD Conference. Retrieved from https://www.bundesregierung.de/Content/EN/Reden/2014/2014-02-19-oecd-merkel-paris_en.html	MGT	IPL		1			1
2021	MERTALA-LINDSAY, T. O. M. A. S., & STRÅLMAN, J. (2021). Construction Digital Twin: From Early Design to Project Delivery.	ENG	CPS		1	1		
2021	Mezzanotti, F. (2021). Roadblock to innovation: The role of patent litigation in corporate R&D. Management Science, 67(12), 7362-7390.	MGT	IPL				1	1
2019	Mikalef, P., Fjørtoft, S., & Torvatn, H. (2019). Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value. 4th Workshop on Big Data and Business Analytics Ecosystems (iDEATE 2019). Seville, Spain.	MGT	RBV					1
2020	Milazzo, M., Chiurazzi, M., Roccella Calogero, S., Oddo, M., Czimmermann, T., Ciuti, G., & Dario, P. (2020). isual-based defect detection and classification approaches for industrial applications-a survey. Sensors.	ENG	CPS		1	1		
2024	Miraz, M. H., Ya'u, A., Adeyinka-Ojo, S., Sarkar, J. B., Hasan, M. T., Hoque, K., & Jin, H. H. (2024). Intention to use determinants of AI chatbots to improve customer relationship management efficiency. Cogent Business & Management, 11(1), 241144	HUM	CDT		1	1	1	
2017	Mokyr, J. (2017). The Past and Future of Innovation: Some Lessons from Economic History. Northwestern University.	MGT	IPL		1	1		1
1970	Mori, M. (1970). The uncanny valley. Energy 7(4), 33–35.	ENG	AIT		1	1		
2009	Moriarty, J. P., & Smallman, C. (2009). En route to a theory of benchmarking. . Benchmarking: An International Journal.	MGT	MGT	1			1	1
2005	Moser, P. (2005). How do patent laws influence innovation? Evidence from nineteenth-century world's fairs. American economic review, 95(4), , 1214-1236.	MGT	IPL		1			1
2021	Mubarak, M. F., Tiwari, S., Petraite, M., Mubarik, M., & Raja Mohd Rasi, R. Z. (2021). How Industry 4.0 technologies and open innovation can improve green innovation performance? Management of Environmental Quality: An International Journal, 32(5), 1007-1022	MGT	OIT		1		1	1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2021	My, C. A. (2021). The role of big data analytics and AI in smart manufacturing: An overview. Research in Intelligent and Computing in Engineering: Select Proceedings of RICE 2020, 911-921	ENG	ENG		1	1		
2018	Nagy, J., Oláh, J., Erdei, E., Máté, D., & Popp, J. (2018). The role and impact of Industry 4.0 and the internet of things on the business strategy of the value chain—the case of Hungary. Sustainability, 10(10), 3491.	MGT	MGT		1	1	1	
2019	Nahavandi, S. (2019). Industry 5.0—A human-centric solution. Sustainability, 11(16), 4371.	HUM	CDT		1	1	1	
2022	Nair, M., Vaithilingam, S., Ahmed, P., Hwang, L. A., & Ng, J. W. J. Future-Proofing the Talent of Malaysia's Indian B40 Community for the New Economy: A Multi-Stakeholder Partnership Framework. In Malaysian Indians and Education (pp. 120-150). Routledge.	HUM	HUM		1	1		
2018	Namatēvs, I. (2018). Deep Reinforcement Learning on HVAC Control. Information Technology and Management Science 21, 29-36.	ENG	CPS		1	1		
2022	Naz, N., Gulab, F., & Aslam, M. (2022). Development of qualitative semi-structured interview guide for case study research. Competitive Social Science Research Journal, 3(2), 42-52.	HUM	HUM	1				
2006	Nichols, J., & Goul, M. (2006). Synergizing the Artificial Intelligence and Decision Support Research Streams: Over a Decade of Progress with New Challenges on the Horizon. Decision Engineering, 45–55. https://doi.org/10.1007/1-84628-231-4_3	HUM	CDT			1		
2023	Nicoletti, B., & Appolloni, A. (2023). Artificial Intelligence for the Management of Servitization 5.0. Sustainability, 15(14), 11113.	HUM	TIM		1	1	1	
2015	Noordin, M. F., & Karim, Z. A. (2015). Modeling the relationship between human intelligence, knowledge management practices, and innovation performance. Journal of Information & Knowledge Management, 14(01), 1550012.	HUM	HUM				1	1
2022	Nitlarp, T., & Kiattisin, S. (2022). The Impact Factors of Industry 4.0 on ESG in the Energy Sector. Sustainability, 14(15), 9198.	HUM	TIM		1		1	
2019	Noponen, N. (2019). Impact of Artificial Intelligence on Management. Electronic Journal of Business Ethics and Organization Studies, 24 (2),, 43-50.	MGT	IPL		1	1	1	1
2001	Norrie, D., Xue, D., & Sun, J. (2001). An intelligent optimal production scheduling approach using constraint-based search and agent-based collaboration. Computers in Industry, 209-231	ENG	MFG		1	1		
2013	O'Leary, D. E. (2013). Artificial intelligence and big data. . IEEE intelligent systems, 28(2), 96-99.	ENG	AIT		1	1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2017	Osoba, O. A., & Welser, W. (2017). The risks of artificial intelligence to security and the future of work. Santa Monica, CA: RAND.	HUM	CDT			1	1	1
2010	Osterwalder, A; Pigneur, Y (2013). Business Model Generation: A Handbook For Visionaries, Game Changers, And Challengers. New York, Wiley.	MGT	MGT			1	1	
2021	Ota, S., & Knudsen, M. S. M. (2021). EXPLORING JAPAN'S SOCIETY 5.0.	MGT	IPL		1	1		1
2020	Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. Journal of Intelligent Manufacturing, 31(1), 127-182.	ENG	CPS		1	1	1	1
2016	Pan, Y. (2016). Heading toward Artificial Intelligence 2.0. Engineering, 409–413.	ENG	AIT			1		1
2018	Panda, S. (2018). Impact of AI in Manufacturing Industries. International Research Journal of Engineering and Technology(IRJET), Volume 05, Issue 11, 1765-1767.	ENG	CPS		1	1		
2022	Parent-Rocheleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. Human resource management review, 32(3), 100838	HUM	CDT		1	1	1	
2019	Park, H. S., Phuong, D. X., & Kumar, S. (2019). AI Based Injection Molding Process for Consistent Product Quality. Procedia Manufacturing 28, 102-106.	ENG	CPS		1	1		
2017	Park, S. (2017). The Fourth Industrial Revolution and implications for innovative cluster policies. AI & Society 33(3), 433-445.	MGT	OIT		1	1		1
2024	Patil, K., Garg, V., Gabaldon, J., Patil, H., Niranjan, S., & Hawkins, T. (2024). Firm performance in digitally integrated supply chains: a combined perspective of transaction cost economics and relational exchange theory. Journal of Enterprise Information Management, 37(2), 381-413	HUM	TCE		1	1	1	
2018	Paul, P. (2018). The Skills Companies Need Most in 2018 – And The Courses to Get Them. . Retrieved from https://www.linkedin.com/pulse/	MGT	RBV		1	1		1
2022	Pech, M., & Vrchota, J. (2022). The product customization process in relation to industry 4.0 and digitalization. Processes, 10(3), 539.	HUM	SET		1	1		
2020	Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE Access, 8, 220121-220139.	ENG	CPS		1	1	1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2024	Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. International Journal of Information Management, 77, 102781.	MGT	RBV		1	1	1	1
2024	Piardi, L., Leitão, P., Queiroz, J., & Pontes, J. (2024). Role of digital technologies to enhance the human integration in industrial cyber–physical systems. Annual Reviews in Control, 57, 100934.	ENG	CPS		1	1		
1993	Pine, J. B. (1993). Mass Customization: The New Frontier in Business Competition, Cambridge, Mass: Harvard Business School Press.	HUM	TIM		1		1	
2018	Plastino, E., & Purdy, M. (2018). Game changing value from Artificial Intelligence: eight strategies. Strategy & Leadership, 46, 16-22.	HUM	CDT		1	1		1
2023	Plichta, J., & Plichta, G. (2023). Artificial intelligence as a factor in reducing transaction costs in the virtual space. In Artificial Intelligence, Management and Trust (pp. 161-185). Routledge	HUM	TCE		1	1	1	
2024	Pokrovskaya, A. V. (2024). Intellectual property rights infringement on e-commerce marketplaces: Application of AI technologies, new challenges. E3S Web of Conferences (Vol. 522, p. 01057). EDP Sciences	MGT	RBV		1	1		1
2017	Popa, S., Soto-Acosta, P., & Martinez-Conesa, I. (2017). Antecedents, moderators, and outcomes of innovation climate and open innovation: An empirical study in SMEs. *Technological Forecasting and Social Change*, *118*, 134-142.	MGT	OIT				1	1
1980	Porter, M. (1980). Competitive strategy: Techniques for analyzing industries and competitors. . Washington: Free Press.	MGT	MGT				1	1
1985	Porter, M. (1985). Competitive advantage. New York: Free Press.	MGT	MGT				1	
1985	Porter, M. E. (1985). Technology and competitive advantage. Journal of business strategy.	MGT	IMT		1		1	1
1990	Porter, M. (1990). E.(1990). The competitive advantage of nations. Harvard Business Review, 68(2), 73-93. 86: 79–93.	MGT	MGT			1	1	
1985	Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage.	MGT	MGT		1	1	1	1
2006	Prajogo, D. I., & Ahmed, P. K. (2006). Relationships between innovation stimulus, innovation capacity, and innovation performance. R&D Management, 36(5), 499-515.	MGT	IMT	1	1			1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2011	Quintane, E., Casselman, R. M., Reiche, B. S., & Nylund, P. A. (2011). Innovation as a knowledge-based outcome. Journal of knowledge management.	MGT	RBV				1	1
2011	Rabionet, S. E. (2011). How I learned to design and conduct semi-structured interviews: an ongoing and continuous journey. Qualitative Report, 16(2), 563-566.	HUM	HUM	1				
2021	Radanliev, P., De Roure, D., Van Kleek, M., Santos, O., & Ani, U. (2021). Artificial intelligence in cyber physical systems. AI & society, 36(3), 783-796.	ENG	SMT		1	1		
2000	Rayport, J. F., & Sviokla, J. J. (1995). Exploiting the virtual value chain. Harvard business review, 73(6), 75-85	HUM	TCE				1	1
2020	Redelinghuys, Anro & Basson, Anton & Kruger, Karel. (2020). A six-layer architecture for the digital twin: a manufacturing case study implementation. Journal of Intelligent Manufacturing. 31. 10.1007/s10845-019-01516-6.	ENG	CPS		1	1		
2022	Regenwetter, L., Nobari, A. H., & Ahmed, F. (2022). Deep generative models in engineering design: A review. Journal of Mechanical Design 144(7): 071704.	ENG	AIT		1	1	1	
2016	Regmi, P. R., Waithaka, E., Paudyal, A., Simkhada, P., & Van Teijlingen, E. (2016). Guide to the design and application of online questionnaire surveys. Nepal journal of epidemiology, 6(4), 640.	HUM	HUM	1				
2014	Reid, Alasdair & Giarracca, Flora. (2014). Evaluation of Cluster initiatives managed by DG Enterprise and Industry. 10.2769/89710.	MGT	OIT		1			1
2009	Rihoux, B., & Ragin, C. C. (2009). Qualitative comparative analysis using fuzzy sets (fsqca). . Applied Social Research Methods.	HUM	HUM	1				
2006	Rihoux, Benoît. (2006). Qualitative Comparative Analysis (QCA) and Related Systematic Comparative Methods. International Sociology - INT SOCIOL. 21. 679-706. 10.1177/0268580906067836.	HUM	HUM	1				
2017	Rodič, B. (2017). Industry 4.0 and the New Simulation Modelling Paradigm. Organizacija, 50(3), 193–207. https://doi.org/10.1515/ORGA-2017-0017	ENG	CPS		1	1		
2003	Rolf, P., & Fumiya, I. (2003). Embodied Artificial Intelligence: Trends and Challenges. Ad-Hoc, Mobile, and Wireless Networks, Second International Conference, ADHOC-NOW 2003 October 8-10, (pp. 1-26). Montreal, Canada.	ENG	AIT		1	1		
2015	Rosenblat, A. a. (2015). Uber's Drivers: Information Asymmetries and Control in Dynamic Work. SSRN Electronic Journal.	HUM	CDT		1	1	1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2020	Rotem-Gal-Oz, A. (2020). Methodology for developing Use Cases for large systems.	ENG	CPS	1	1			
2007	Rowley, J. (2007). The wisdom hierarchy: representations of the DIKW hierarchy. Journal of Information and Communication Science, 33(2), 163–180.	HUM	HUM					1
2000	Roy, R. (2000). Sustainable product-service systems. Futures 32, 289–299.	HUM	TIM		1		1	
2023	Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Tavakoli Ghinani, H., Suh, S., ... & Soldatos, J. (2023). Human-centric artificial intelligence architecture for industry 5.0 applications. International journal of production research, 61(20), 6847-6872.	ENG	AIT		1	1		
2009	Russell, S., & Norvig, P. (2009). Artificial Intelligence: A Modern Approach. Upper Saddle River, NJ, USA: Prentice Hall Press.	ENG	AIT			1		
2018	Sachs, J. (2018). R&D, Structural Transformation, and the Distribution of Income. In A. Agrawal, J. Gans, & A. Goldfarb, The Economics of Artificial Intelligence: An Agenda,. Chicago: University of Chicago .	MGT	IPL		1			1
2016	Sachsenmeier, P. (2016). Industry 5.0—the relevance and implications of bionics and synthetic biology. Engineering, 2(2), 225-229.	ENG	CPS		1	1		
2020	Sætra, H. S. (2020). The parasitic nature of social AI: sharing minds with the mindless. Integrative psychological & behavioral science, 54(2), 308.	HUM	HUM			1		1
2009	Salvador, F., De Holan, P. M., & Piller, F. (2009). Cracking the code of mass customization. MIT Sloan management review, 50(3), 71-78.	MGT	RBV		1		1	
1959	Samuel, A. L. (1959). Some Studies in Machine Learning Using the Game of Checkers. *IBM J. Res. Dev.*, 210--229.	ENG	AIT		1	1		
2004	Sandini, G., Metta, G., & Vernon, D. (2004). RobotCub: An open framework for research in embodied cognition. 4th IEEE-RAS International Conference on Humanoid Robots. 1. 13 - 32 Vol. 1.	ENG	CPS		1	1		
2011	Santofimia-Romeo, M.-J., Toro-Garcia, X. d., & Lopez, J.-C. (2011). Artificial intelligence techniques for smart grid applications. Green ICT: Trends and Challenges, 41-44	ENG	CPS		1	1		
2021	Saw, H. S., bin Azmi, A. A., Chew, K. W., & Show, P. L. (2021). Sustainability and Development of Industry 5.0. . In The Prospect of Industry 5.0 in Biomanufacturing (pp. 287-304). CRC Press.	ENG	CPS		1	1		

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2022	Shevchenko, A. I., Bilokobylsky, O. V., Vakulenko, M. O., Dovbysh, A. S., Kazimir, V. V., Klymenko, M. S., ... & Sosnytskyi, O. V. REGARDING THE DRAFT STRATEGY DEVELOPMENT OF ARTIFICIAL INTELLIGENCE IN UKRAINE.	MGT	IPL		1	1		
2018	Schneider, N. (2018). An internet of ownership: Democratic design for the oline economy. Sociological Review, 320–340.	HUM	CDT			1	1	
1986	Schroeder, R. G., Anderson, J. C., & Cleveland, G. (1986). The content of manufacturing strategy: an empirical study. Journal of operations management, 6(3-4), 405-415.	HUM	TIM		1		1	
1942	Schumpeter, J. A. (1942). Capitalism, Socialism and Democracy,. London, Unite Kingdom: Routledge.	HUM	CDT		1	1		1
2020	Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., . . . Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. Information & Management, Volume 57, Issue 2,	HUM	CDT		1	1		
2018	Shabbir, J., & Anwer, T. (2018). Artificial intelligence and its role in near future. arXiv preprint arXiv:1804.01396.	ENG	AIT		1	1		1
2022	Sharma, M., Sehrawat, R., Luthra, S., Daim, T., & Bakry, D. (2022). Moving Towards Industry 5.0 in the Pharmaceutical Manufacturing Sector: Challenges and Solutions for Germany. IEEE Transactions on Engineering Management.	MGT	MGT		1	1	1	1
2023	Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. Technological Forecasting and Social Change, 197, 122903.	HUM	TIM		1	1	1	
2012	Shin, N., Kraemer, K. L., & Dedrick, J. (2012). Value Capture in the Global Electronics Industry: Empirical Evidence for the “Smiling Curve” Concept. Industry and Innovation, 89-107.	HUM	TIM		1		1	
2010	Shin, S., & Park, C. (2010). A machine learning approach to yield management in semiconductor manufacturing. International Journal of Production Research, 4261-4271	ENG	MFG		1	1		
2018	Siau, K. &. (2018). Building Trust in Artificial Intelligence, Machine Learning, and Robotics. Cutter Business Technology Journal. 31., 47-53. .	ENG	AIT		1	1		1
2021	Siltanen, S., Heinonen, H., Burova, A., & Turunen, M. (2021). Reimagining innovation for remote, distributed teams with collaborative virtual reality. In ISPIM Conference Proceedings (pp. 1-14). The International Society for Professional Innovation Management (ISPIM).	ENG	ENG		1	1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2021	Silva, J., Ferreira, A. C., Peters, B., Carlos, J., & Teixeira, S. T. POTENTIAL OF FOREST BIOMASS RESIDUES: THERMAL AND ECONOMIC PERSPECTIVES. Belgrade School of Engineering Management Belgrade, 2021, 29.	ENG	ENG		1	1		1
2021	Sindhu, V., Anitha, G., & Geetha, R. (2021, June). Industry 4.0-A Breakthrough in artificial Intelligence the Internet of Things and Big Data towards the next digital revolution for high business outcome and delivery. In Journal of Physics: Conference Series (Vol. 1937, No. 1, p. 012030). IOP Publishing.	ENG	CPS		1	1	1	
2018	Singh, S., Shehab, E., Higgins, N., Fowler, K., Tomiyama, T., & Fowler, C. (2018). Challenges of digital twin in high value manufacturing (No. 2018-01-1928). SAE Technical Paper.	ENG	CPS		1	1		
2018	Skobelev, P. (2018). Towards Autonomous AI Systems for Resource Management: Applications in Industry and Lessons Learned. Advances in Practical Applications of Agents, Multi-Agent Systems, and Complexity: The PAAMS Collection. PAAMS 2018. Demazeau Y., An B., Bajo J., Fernández-Caballero A. (eds).	ENG	AIT		1	1		
2007	Skulmoski, G. J., Hartman, F. T., & Krahn, J. (2007). The Delphi Method for Graduate Research. JITE-Research Volume 6, Number 1	MGT	MGT	1				
2020	Solanki, G., Makkar, V., & Devi, S. (2020). Applications of machine learning techniques in supply chain optimization. In ICICCT 2019 – System Reliability, Quality Control, Safety, Maintenance and Management.	ENG	MFG		1	1		
2019	Soni, N., Khular Sharma, E., Singh, N., & Kapoor, A. (2019). Impact of Artificial Intelligence on Businesses: from Research, Innovation, Market Deployment to Future Shifts in Business Models. Journal of Business Research.	HUM	CDT			1	1	1
2014	Squalli, J., & Wilson, K. (2014). Intelligence, creativity, and innovation. Intelligence, 46, 250-257.	HUM	HUM				1	1
2021	Stroh, A. M., Erera, A. L., & Toriello, A. (2021). Tactical design of same-day delivery systems. Management Science.	ENG	MFG		1	1		
2023	Sundaram, S., & Zeid, A. (2023). Artificial intelligence-based smart quality inspection for manufacturing. Micromachines, 14(3), 570.	ENG	MFG		1	1		
1911	Taylor, F. W. (1911). The principles of scientific management. New York: Harper & Brothers	MGT	MGT		1		1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
1997	Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. . Strateg. Manag. J. 1997, 18, , 509–533	MGT	RBV				1	1
2007	Terada, K., Shamoto, T., Ito, A., & Mei, H. (2007). Reactive movements of non-humanoid robots cause intention attribution in humans. IEEE/RSJ International Conference on Intelligent Robots and Systems , (pp. 3715-3720).	ENG	AIT		1	1		
2017	The European Commission. (2017). Industry 4.0. (D. T. Germany, Éd.) Récupéré sur https://ec.europa.eu/growth/tools-databases/dem/monitor/sites/	HUM	CDT		1	1		
2021	Theben, A., Gunderson, L., López-Forés, L., Misuraca, G., & Lupiáñez-Villanueva, F. (2021). Challenges and Limits of an Open Source Approach to Artificial Intelligence. European Parliament.	MGT	IPL			1		1
2022	Thellman, S., De Graaf, M., & Ziemke, T. (2022). Mental state attribution to robots: A systematic review of conceptions, methods, and findings. . ACM Transactions on Human-Robot Interaction (THRI), 11(4), (pp. 1-51)	ENG	AIT		1	1		1
2003	Thoenig, M., & Verdier, T. (2003). A theory of defensive skill-biased innovation and globalization. American Economic Review, 93(3), 709-728.	MGT	RBV		1			1
2021	Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. Journal of Business Research, 122, 502-517.	ENG	SMT		1	1	1	
2019	Toshev, Asen. (2019). Particle Swarm Optimization and Tabu Search Hybrid Algorithm for Flexible Job Shop Scheduling Problem – Analysis of Test Results. Cybernetics and Information Technologies. 19. 26-44. 10.2478/cait-2019-0034.	ENG	AIT		1	1		
2014	Tuğçe Şimşit, Z., Vayvay, Ö., & Özgen, Ö. (2014). An Outline of Innovation Management Process: Building a Framework for Managers to Implement Innovation. Procedia - Social and Behavioral Sciences, 690-699.	MGT	IMT				1	1
2018	Trajtenberg, M. (2018). AI as the next GPT: a Political-Economy Perspective (No. w24245). National Bureau of Economic Research.	MGT	IPL		1	1		1
2018	Tricco, A. L. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. . Ann Intern Med., 467-473.	MGT	MGT	1				
2021	Troshani, I., Rao Hill, S., Sherman, C., & Arthur, D. (2021). Do we trust in AI? Role of anthropomorphism and intelligence. Journal of Computer Information Systems, 61(5), 481-491	ENG	AIT		1	1	1	

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2018	Tucker, C. (2018). Privacy, Algorithms, and Artificial Intelligence. (J. Lerner, & S. Stern, Eds.) Innovation Policy and the Economy, vol. 16, ed. , pp. 53–88.	MGT	IPL			1		1
2015	Tukker, A. (2015.). Product services for a resource-efficient and circular economy—a review. Journal of Cleaner Production 97, 76–91.	HUM	TIM		1		1	
2024	Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends. Applied Sciences, 14(2), 898.	ENG	MFG		1	1		
1988	Vandermerwe, S., & Rada, J. (1988). Servitization of business: Adding value by adding services. European Management Journal, 6, issue 4, 314-324.	HUM	HUM		1		1	
1994	Venkatraman, N. (1994). IT-enabled business transformation: from automation to business scope redefinition. Sloan Management Review	HUM	TCE				1	1
2018	Vicente-Saez, R., & Martinez-Fuentes, C. (2018). Open Science now: A systematic literature review for an integrated definition. Journal of business research, 88, 428-436.	MGT	OIT		1			1
2018	Vlachos, D., Singh Srai, J., Bechtsis, D., & Tsolakis, N. (2018). Inteligent autonomous vehicles in digital supply chains: A framework for integrating innovations towards sustainable value networks. Journal of Cleaner Production, Volume 181, 60-70.	ENG	CPS		1	1		
2019	Vlačić, E., Dabić, M., Daim, T., & Vlajčić, D. (2019). Exploring the impact of the level of absorptive capacity in technology development firms. . Technological forecasting and social change, 138, , 166-177	MGT	OIT				1	1
2019	Vocke, C., Constantinescu, C., & Popescu, D. (2019). Application potentials of artificial intelligence for the design of innovation processes. Procedia CIRP, 84, 810-813	MGT	IMT			1	1	1
2017	Vrontis, D., Thrassou, A., Santoro, G., & Papa, A. (2017). Ambidexterity, external knowledge and performance in knowledge-intensive firms. The Journal of Technology Transfer, 42(2), 374-388. JOURNAL OF TECHNOLOGY TRANSFER, 42(2), ; 374-388.;	MGT	OIT				1	1
2012	W. Cao, P. J. (2012). Cloud machining community for social manufacturing. Appl. Mech. Mater. 220–223 , 61–64.	HUM	SET		1		1	
2019	Wagner, R., Schleich, B., Haefner, B., Kuhnle, A., Wartzack, S., & Lanza, G. (2019). Challenges and Potentials of Digital Twins and Industry 4.0 in Product Design and Production for High Performance Products. *Procedia CIRP, Volume 84*, 83-93.	ENG	CPS		1	1		

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2022	Waheed, A., Alharthi, M., Khan, S. Z., & Usman, M. (2022). Role of Industry 5.0 in leveraging the Business Performance: Investigating Impact of Shared-Economy on Firms' Performance with Intervening Role of i5. 0 Technologies. SAGE Open, 12(2), 21582440221094608.	HUM	HUM	1	1		1	
2010	Wan, K., Man, K. L., & Hughes, D. (2010). Specification, Analyzing Challenges and Approaches for Cyber-Physical Systems (CPS). Engineering Letters, 18(3).	ENG	CPS			1		
2019	Wang, L. (2019). From Intelligence Science to Intelligent Manufacturing. Engineering,Volume 5, Issue 4, 615-618.	ENG	SMT		1	1		
2023	Wang, X., Yang, J., Wang, Y., Miao, Q., Wang, F. Y., Zhao, A., ... & Vlacic, L. (2023). Steps toward industry 5.0: Building "6S" parallel industries with cyber-physical-social intelligence. IEEE/CAA Journal of Automatica Sinica, 10(8), 1692-1703.	ENG	CPS		1	1		
2014	Wang, X., & Zhang, B. (2014). Research on the effects of university-industry collaborative innovation and the relationships with academic research on scientific performance. International Conference on Management Science & Engineering 21th Annual Conference. Helsinki: 1658-1663.	MGT	OIT		1			1
2018	Wason, R. (2018). Deep learning: Evolution and expansion. Cognitive Systems Research, Volume 52, 701-708.	ENG	AIT			1		
1998	Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. Nature. 393 (6684), 440–442.	MGT	OIT	1				1
2016	Williams, H. L. (2016). Intellectual property rights and innovation: Evidence from health care markets. Innovation Policy and the Economy, 16(1), 53-87	MGT	IPL				1	1
1981	Williamson, O. (1981). The economics of organization: the transaction cost approach, . American Journal of Sociology.	HUM	TCE				1	
2004	Willingham, D. T. ; 2004; Reframing the mind. ; Education Next, 4(3), ; 19-24.;	HUM	HUM			1		1
2017	Wisskirchen, Gerlind; Thibault Biacabe, Blandine; Bormann, Ulrich; Muntz, Annemarie; Niehaus, Gunda; Jiménez Soler, Guillermo; von Brauchitsch, Beatrice; 2017; Artificial Intelligence and Robotics and Their Impact on the Workplace;IBA Global Employment Institute	HUM	CDT		1	1	1	
2016	Wolf, C., Joye, D., Smith, T. W., & Fu, Y. C. (Eds.). (2016). The SAGE handbook of survey methodology. Sage.	HUM	HUM	1				

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
2016	World Economic Forum. (2016). The future of jobs: Employment, skills and workforce strategy for the fourth industrial revolution. Global Challenge Insight Report.	HUM	CDT			1	1	
2013	Wu, D., Schaefer, D., & Rosen, D. (2013). Cloud-based design and manufacturing systems: a social network analysis,. Nineteenth International Conference on Engineering Design. 1–10.	HUM	SET		1		1	
2006	Wu, F., Yeniyurt, S., Kim, D., & Tamer Cavusgil, S. (2006). The impact of information technology on supply chain capabilities and firm performance: A resource-based view. Industrial Marketing Management, Volume 35, Issue 4, 493-504.	MGT	RBV		1		1	1
2018	Xinhua. (2018). AI education booming as China cultivates talent. Récupéré sur ChinaDaily: http://www.chinadaily.com.cn/a/201807/02/WS5b39bd06a3103349141e0269.html	MGT	CDT		1	1		1
2022	Xiong, G., Tamir, T. S., Shen, Z., Shang, X., Wu, H., & Wang, F. Y. (2022). A survey on social manufacturing: A paradigm shift for smart prosumers. IEEE Transactions on Computational Social Systems, 10(5), 2504-2522.	HUM	SET		1	1	1	
2019	Xu, X., & Lu, Y. (2019). Cloud-based manufacturing equipment and big data analytics to enable on-demand manufacturing services. Robotics and Computer-Integrated Manufacturing,Volume 57, 92-102.	ENG	AIT		1	1		
2021	Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. Journal of Manufacturing Systems, 61, 530-535.	ENG	SMT		1			1
2001	Xue, D., Sun, J., Norrie, D., (2001). n intelligent optimal production scheduling approach using constraint-based search and agent-based collaboration. Computers in Industry, 209-231.	ENG	CPS		1	1		
2024	Yang, J., Wang, Y., Wang, X., Wang, X., Wang, X., & Wang, F. Y. (2024). Generative AI Empowering Parallel Manufacturing: Building a “6S” Collaborative Production Ecology for Manufacturing 5.0. IEEE Transactions on Systems, Man, and Cybernetics: Systems.	ENG	SMT		1	1	1	
2020	Yilma, B. A., Naudet, Y., & Panetto, H. (2020, July). A new paradigm and meta-model for cyber-physical-social systems. In 21st IFAC World Congress, IFAC 2020. Elsevier.	ENG	CPS	1	1	1		
2022	Yin, S., & Yu, Y. (2022). An adoption-implementation framework of digital green knowledge to improve the performance of digital green innovation practices for industry 5.0. Journal of Cleaner Production, 132608.	MGT	IMT		1	1	1	1
2016	Yun, J. J., Lee, D., Ahn, H., Park, K., & Yigitcanlar, T. (2016). Not deep learning but autonomous learning of open innovation for sustainable artificial intelligence. Sustainability, 8(8), 797.	MGT	OIT			1		1

Year	Reference	Science	Theory	MY	OA	AM	MS	IC
1965	Zadeh, L. (1965). Fuzzy sets. Information and Control, Volume 8, Issue 3, 338-353.	ENG	AIT			1	1	1
2010	Zeng, S. X., Xie, X. M., & Tam, C. M. (2010). Relationship between cooperation networks and innovation performance of SMEs. Technovation, 30(3), 181-194. of SMEs S.X. Zeng a,, X.M. Xie b , C.M. Tam c	MGT	OIT	1	1		1	1
2020	Zhang, J., Li, S., Zhang, J. Y., Du, F., Qi, Y., & Liu, X. (2020). A literature review of the research on the uncanny valley. In Cross-Cultural Design. User Experience of Products, Services, and Intelligent Environments: . 12th International Conference, CCD (pp. 255-268). Copenhagen, Denmark: Springer International Publishing	ENG	AIT		1	1		
2022	Zhao, C. (2022). Perspectives on nonstationary process monitoring in the era of industrial artificial intelligence. Journal of Process Control, 116, 255-272	ENG	SMT		1	1		
2018	Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., ... & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. Frontiers of Mechanical Engineering, 13(2), 137-150.	ENG	CPS		1	1		
2012	Zhou, J. (2012). Digitization and intelligentization of manufacturing. China Mech. Eng. 23.	MGT	IPL		1			1
2003	Ziemke, T. (2003). Embodied AI as Science: Models of Embodied Cognition, Embodied Models of Cognition, or Both? Embodied Artificial Intelligence: International Seminar, . Dagstuhl Castle, Germany.	ENG	AIT		1	1		
2014	Złotowski, J. &. (2014). Anthropomorphism: Opportunities and Challenges in Human–Robot Interaction. . International Journal of Social Robotics. 7. , 347-360	ENG	AIT			1		1

ANNEX 3: INTERVIEW GUIDE

Respondent's Consent:

Do you agree for this interview to be tape-recorded and the phonogram stored securely for a duration of a maximum of 3 years from the interview date?

Do you agree that your anonymized data will be kept for future research purposes such as publications related to this study?

About respondent's Profile

Open Question: What is your role in your Organisation?

- Related topics of discussion: assignments about manufacturing, artificial intelligence, digital transformation, innovation

Directed Question: Does your Organisational role include decision-making about manufacturing operations (eg. Head Of Manufacturing)

Directed Question: Does your Organisational role include decision-making about digital transformation (eg. Digital Transformation Officer)

Directed Question: Does your Organisational role include decision-making about innovation management (eg. Head Of Innovation)

Directed Question: Do you think your job could potentially be threatened by artificial intelligence?

Directed Question: Do you think the job of your collaborators could potentially be threatened by artificial intelligence?

About respondent's Industry

Open Question: Could you provide a brief description of your Organisation?

- Related topics of discussion: value proposal, company history, main locations, sector of activity, competitive position on the market

Directed Question: Would you qualify your industry mainly as a "Transformation" (processing raw material), "Production" (manufacturing simple goods) or "Integration" (assembling complex products) industry?

Directed Question: Would you say that your Organisation is "Small (independent <=30 employees), Medium (independent 30 < X <=300) or Large (> 300 or owned by > 300)?

Directed Question: Would you say that your industry was born with "Industry 1.0" (mechanical production), "Industry 2.0" (electrified mass production), "Industry 3.0" (automated & programmable), "Industry 4.0" (connected & autonomous), or "Industry 5.0" (sustainable, human-centric and resilient)?

About AI Maturity (AM)

Definition: in this study, we call "Industrial Artificial Intelligence (IAI) any application of Artificial Intelligence (AI) relating to the physical operations of an enterprise (Lee, Davari, Singh, & Pandhare, 2018)

Open Question: Are you aware of one or several use-cases for Industrial Artificial Intelligence with application to manufacturing activities in your Organisation?

- Related topics of discussion: nature of the use-case, level of automation, related employment considerations, related business model innovation

Directed Question: Concerning the previously described use-case(s), would you say that the role of IAI is rather passive (informing human decision) or active (making own decision and action)?

Directed Question: If active, would you say IAI is here autonomous (making decisions regardless of implicit/explicit human instruction) or collaborative (making consideration of human implicit/explicit instruction)?

About Manufacturing Strategy (MS)

Definition: in this study, we call "Enterprise Management Strategy" (EMS) the art of specifying the Organisation's objectives, developing policies and plans to achieve them, and allocating resources to implement the plans (Ayitey, 2010).

Open Question: In your opinion, does Industrial Artificial Intelligence affect Enterprise Management Strategy?

- Related topics of discussion: what factors explain this influence? In which direction? Who is involved?

Directed Question: With consideration for the above-discussed use-case(s), would you say that IAI would likely drive a preference for an EMS oriented towards "Hierarchy" (make strategy) or towards "Markets" (buy strategy)?

Directed Question: If oriented towards “Markets”, would you expect it to drive a Vertical (from raw material to finished product) or Horizontal (from market A to market Z) segmentation of the value chain?

About Innovation Capacity (IC)

Definition: in this study, we call “Innovation Capacity” the Organisational potential to innovate, determined by the skills and strengths in basic R&D and technology (Prajogo & Ahmed, 2006)..

Open Question: In your opinion, does Industrial Artificial Intelligence affect Innovation Capacity?

- Related topics of discussion: what factors explain this influence? In which direction? Who is involved?

Directed Question: Would you say that the above-described IAI use-case would likely drive a preference for an IMP oriented towards “Internal” (fully owned) or towards “open” (or collaborative) innovation?

Directed Question: If oriented towards “Open” innovation, would you expect your innovation management strategy to foster “Proprietary” (owned by each individual network member) or “Open Source” (owned by a community) innovations?

ANNEX 4: LIST OF EXPERTS

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
1	EXP.1	Maintenance Director	ORG.1	Manufacture of other textiles	Yes	Engineering
2	EXP.2	Vice President	ORG.2	Manufacture of machinery and equipment	Yes	Management
3	EXP.3	Development Manager	ORG.2	Manufacture of machinery and equipment	Yes	Engineering
4	EXP.4	Director of Engineering and R&D	ORG.3	Manufacture of other special-purpose machinery	Yes	Engineering
5	EXP.5	Production Engineer	ORG.4	Manufacture of consumer electronics	Yes	Engineering
6	EXP.6	Production Engineer	ORG.5	Manufacture of air and spacecraft and related machinery	Yes	Engineering
7	EXP.7	Innovation Manager	ORG.5	Manufacture of air and spacecraft and related machinery	Yes	Engineering
8	EXP.8	Chief Executive Officer	ORG.6	Manufacture of other special-purpose machinery	Yes	Management
9	EXP.9	Associate	ORG.7	Other telecommunications activities	Yes	Management
10	EXP.10	Associate	ORG.7	Other telecommunications activities	Yes	Management
11	EXP.11	Service Provider	ORG.8	Activities of extraterritorial organisations and bodies	Yes	Research
12	EXP.12	Director	ORG.9	Other research and experimental development on natural sciences and engineering	Yes	Research

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
13	EXP.13	Director	ORG.9	Other research and experimental development on natural sciences and engineering	Yes	Research
14	EXP.14	Head of Robotics, Automation & Virtual Reality	ORG.10	Other research and experimental development on natural sciences and engineering	Yes	Research
15	EXP.15	Head of Mechanical Design Office	ORG.11	Manufacture of weapons and ammunitions	Yes	Management
16	EXP.16	Head of Mechanical Design Laboratory	ORG.11	Manufacture of weapons and ammunitions	Yes	Engineering
17	EXP.17	Research Engineer in Robotics and Computer Vision	ORG.11	Manufacture of weapons and ammunitions	Yes	Engineering
18	EXP.18	Project Manager in Security Hardware Products	ORG.11	Manufacture of weapons and ammunitions	Yes	Management
19	EXP.19	Project Manager	ORG.12	Computer programming activities	No	Management
20	EXP.20	Innovation Manager	ORG.18	Other research and experimental development on natural sciences and engineering	No	Management
21	EXP.21	Software Engineer	ORG.19	Higher education	No	Engineering
22	EXP.22	Project Manager	ORG.25	Activities of extraterritorial organisations and bodies	No	Management
23	EXP.23	Investigador	ORG.45	Manufacture of other special-purpose machinery	No	Engineering
24	EXP.24	Professor of Manufacturing Engineering	ORG.26	Higher education	No	Research
25	EXP.25	Research Coordinator	ORG.46	Higher education	No	Engineering

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
26	EXP.26	Senior expert in manufacturing digitalisation technologies	ORG.47	Other research and experimental development on natural sciences and engineering	No	Engineering
27	EXP.27	EU Programme Manager	ORG.31	Other research and experimental development on natural sciences and engineering	No	Management
28	EXP.28	Additive Manufacturing & Project Manager	ORG.21	Manufacture of electric motors, generators and transformers	No	Engineering
29	EXP.29	Head of Manufacturing Market	ORG.22	Computer programming activities	No	Engineering
30	EXP.30	Innovation, Tech Transfer and Funding expert	ORG.34	Management consultancy activities	No	Management
31	EXP.31	Chief Technologist, Digital Manufacturing	ORG.35	Other research and experimental development on natural sciences and engineering	No	Engineering
32	EXP.32	Director of Innovation	ORG.36	Manufacture of other special-purpose machinery	No	Management
33	EXP.33	Corporate Technology and Innovation Director	ORG.37	Manufacture of other special-purpose machinery	No	Engineering
34	EXP.34	Manager Industry 4.0 / Innovation	ORG.38	Manufacture of other parts and accessories for motor vehicles	No	Engineering
35	EXP.35	Project Manager	ORG.39	Manufacture of motor vehicles	No	Management
36	EXP.36	Project Manager	ORG.40	Support activities for animal production	No	Management
37	EXP.37	Co-founder & CEO	ORG.41	Computer programming activities	No	Engineering
38	EXP.38	Data Scientist	ORG.42	Manufacture of other special-purpose machinery	No	Engineering

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
39	EXP.39	Director of Customer Success	ORG.43	Data processing, hosting and related activities	No	Engineering
40	EXP.40	Bioscience Engineering Researcher	ORG.44	Other research and experimental development on natural sciences and engineering	No	Research
41	EXP.41	Researcher	ORG.45	Manufacture of other special-purpose machinery	No	Research
42	EXP.42	R&D Manager - Innovation	ORG.48	Technical testing and analysis	No	Engineering
43	EXP.43	Innovation 4 Manufacturing Program Manager	ORG.15	Manufacture of irradiation, electromedical and electrotherapeutic equipment	No	Engineering
44	EXP.44	Senior Account Manager	ORG.49	Support activities to agriculture and post-harvest crop activities	No	Management
45	EXP.45	Data Scientist	ORG.50	Non-specialised wholesale trade	No	Engineering
46	EXP.46	Data Science Team Lead	ORG.51	Other retail sale of food in specialised stores	No	Engineering
47	EXP.47	Research Scientist	ORG.52	Data processing, hosting and related activities	No	Research
48	EXP.48	Senior Strategic Partner Development Manager at Google	ORG.53	Data processing, hosting and related activities	No	Management
49	EXP.49	Global Portfolio Manager - Cybersecurity	ORG.27	Manufacture of other special-purpose machinery	No	Engineering
50	EXP.50	Security Researcher	ORG.54	Manufacture of electronic components	No	Engineering
51	EXP.51	Chief Technology Officer	ORG.55	Other information service activities	No	Engineering

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
52	EXP.52	Professor - Entrepreneurship Strategy	ORG.56	Other information service activities	No	Management
53	EXP.53	President	ORG.57	Higher education	No	Research
54	EXP.54	Digital Lead	ORG.30	Manufacture of other special-purpose machinery	No	Engineering
55	EXP.55	Trustworthy Artificial Intelligence Engineer for Health	ORG.58	Other software publishing	No	Engineering
56	EXP.56	Researcher R&D	ORG.59	Motion picture, video and television programme post-production activities	No	Research
57	EXP.57	Computer Vision Data Scientist	ORG.60	Manufacture of wine from grape	No	Engineering
58	EXP.58	Associate Professor ll	ORG.61	Higher education	No	Research
59	EXP.59	Transverse R&T Manager	ORG.11	Manufacture of weapons and ammunitions	No	Engineering
60	EXP.60	Head of R&D Fundings EU	ORG.63	Other research and experimental development on natural sciences and engineering	No	Management
61	EXP.61	Research Scientist	ORG.65	Higher education	No	Research
62	EXP.62	Program Manager Al Engineering	ORG.66	Higher education	No	Management
63	EXP.63	Doctorant Chercheur	ORG.72	Higher education	No	Research
64	EXP.64	Graduate Student Member	ORG.73	Other research and experimental development on natural sciences and engineering	No	Research

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
65	EXP.65	Invited Assistant Professor	ORG.74	Other research and experimental development on natural sciences and engineering	No	Research
66	EXP.66	PHD Student	ORG.73	Other research and experimental development on natural sciences and engineering	No	Research
67	EXP.67	CEO & Co-Founder	ORG.75	Manufacture of machinery for mining, quarrying and construction	No	Management
68	EXP.68	Professor in Supply Chain Management	ORG.76	Higher education	No	Research
69	EXP.69	Professor	ORG.82	Higher education	No	Research
70	EXP.70	Researcher PhD Candidate	ORG.83	Higher education	No	Research
71	EXP.71	Researcher	ORG.84	Higher education	No	Research
72	EXP.72	Associate Professor	ORG.85	Higher education	No	Research
73	EXP.73	Associate Professor Dr.	ORG.86	Higher education	No	Research
74	EXP.74	Technology Translator	ORG.87	Other research and experimental development on natural sciences and engineering	No	Management
75	EXP.75	Director	ORG.88	Higher education	No	Management
76	EXP.76	Professor	ORG.89	Higher education	No	Research
77	EXP.77	Professor	ORG.90	Higher education	No	Research

IV-Nr	Exp. Pseudo.	Role	Org. Pseudo	Org.Class	Interview	Background
78	EXP.78	Researcher	ORG.91	Higher education	No	Research
79	EXP.79	Postdoc	ORG.92	Other research and experimental development on natural sciences and engineering	No	Research

ANNEX 5: ORGANISATIONS LIST

Org. N°	Org. Pseudo.	Type	NACE2	Class
1	ORG.1	SME	13.90	Manufacture of other textiles
2	ORG.2	SME	28.93	Manufacture of machinery and equipment
3	ORG.3	SME	28.99	Manufacture of other special-purpose machinery
4	ORG.4	IND	26.40	Manufacture of consumer electronics
5	ORG.5	IND	30.30	Manufacture of air and spacecraft and related machinery
6	ORG.6	SME	28.99	Manufacture of other special-purpose machinery
7	ORG.7	SME	61.90	Other telecommunications activities
8	ORG.8	NPO	99.00	Activities of extraterritorial organisations and bodies
9	ORG.9	RTO	72.19	Other research and experimental development on natural sciences and engineering
10	ORG.10	RTO	72.19	Other research and experimental development on natural sciences and engineering
11	ORG.11	IND	25.40	Manufacture of weapons and ammunitions
12	ORG.12	IND	62.01	Computer programming activities
13	ORG.13	SME	28.99	Manufacture of other special-purpose machinery
14	ORG.14	IND	41.20	Construction of residential and non-residential buildings
15	ORG.15	IND	26.60	Manufacture of irradiation, electromedical and electrotherapeutic equipment
16	ORG.16	IND	29.32	Manufacture of other parts and accessories for motor vehicles
17	ORG.17	RTO	72.19	Other research and experimental development on natural sciences and engineering
18	ORG.18	RTO	72.19	Other research and experimental development on natural sciences and engineering
19	ORG.19	ACA	85.40	Higher education
20	ORG.20	SME	28.96	Manufacture of plastics and rubber machinery
21	ORG.21	IND	27.11	Manufacture of electric motors, generators and transformers
22	ORG.22	IND	62.01	Computer programming activities
23	ORG.23	IND	29.32	Manufacture of other parts and accessories for motor vehicles
24	ORG.24	SME	30.30	Manufacture of air and spacecraft and related machinery

Org. N°	Org. Pseudo.	Type	NACE2	Class
25	ORG.25	NPO	99.00	Activities of extraterritorial organisations and bodies
26	ORG.26	ACA	85.40	Higher education
27	ORG.27	IND	28.99	Manufacture of other special-purpose machinery
28	ORG.28	IND	29.10	Manufacture of motor vehicles
29	ORG.29	IND	26.40	Manufacture of consumer electronics
30	ORG.30	IND	28.99	Manufacture of other special-purpose machinery
31	ORG.31	RTO	72.19	Other research and experimental development on natural sciences and engineering
32	ORG.32	IND	28.99	Manufacture of other special-purpose machinery
33	ORG.33	SME	31.09	Manufacture of other furniture
34	ORG.34	SME	70.20	Management consultancy activities
35	ORG.35	RTO	72.19	Other research and experimental development on natural sciences and engineering
36	ORG.36	IND	28.99	Manufacture of other special-purpose machinery
37	ORG.37	IND	28.99	Manufacture of other special-purpose machinery
38	ORG.38	IND	29.32	Manufacture of other parts and accessories for motor vehicles
39	ORG.39	IND	29.10	Manufacture of motor vehicles
40	ORG.40	SME	01.62	Support activities for animal production
41	ORG.41	SME	62.01	Computer programming activities
42	ORG.42	IND	28.99	Manufacture of other special-purpose machinery
43	ORG.43	SME	63.11	Data processing, hosting and related activities
44	ORG.44	RTO	72.19	Other research and experimental development on natural sciences and engineering
45	ORG.45	SME	28.99	Manufacture of other special-purpose machinery
46	ORG.46	ACA	85.40	Higher education
47	ORG.47	RTO	72.19	Other research and experimental development on natural sciences and engineering
48	ORG.48	IND	71.20	Technical testing and analysis
49	ORG.49	SME	01.60	Support activities to agriculture and post-harvest crop activities
50	ORG.50	IND	46.90	Non-specialised wholesale trade
51	ORG.51	IND	47.29	Other retail sale of food in specialised stores

Org. N°	Org. Pseudo.	Type	NACE2	Class
52	ORG.52	IND	63.11	Data processing, hosting and related activities
53	ORG.53	IND	63.11	Data processing, hosting and related activities
54	ORG.54	IND	26.11	Manufacture of electronic components
55	ORG.55	SME	63.99	Other information service activities
56	ORG.56	IND	63.99	Other information service activities
57	ORG.57	ACA	85.40	Higher education
58	ORG.58	SME	58.29	Other software publishing
59	ORG.59	IND	59.12	Motion picture, video and television programme post-production activities
60	ORG.60	SME	11.02	Manufacture of wine from grape
61	ORG.61	ACA	85.40	Higher education
62	ORG.62	SME	26.60	Manufacture of irradiation, electromedical and electrotherapeutic equipment
63	ORG.63	SME	72.19	Other research and experimental development on natural sciences and engineering
64	ORG.64	IND	30.20	Manufacture of railway locomotives and rolling stock
65	ORG.65	ACA	85.40	Higher education
66	ORG.66	ACA	85.40	Higher education
67	ORG.67	SME	82.92	Packaging activities
68	ORG.68	SME	82.92	Packaging activities
69	ORG.69	SME	82.92	Packaging activities
70	ORG.70	SME	82.92	Packaging activities
71	ORG.71	SME	82.92	Packaging activities
72	ORG.72	ACA	85.40	Higher education
73	ORG.73	RTO	72.19	Other research and experimental development on natural sciences and engineering
74	ORG.74	RTO	72.19	Other research and experimental development on natural sciences and engineering
75	ORG.75	SME	28.92	Manufacture of machinery for mining, quarrying and construction
76	ORG.76	ACA	85.40	Higher education
77	ORG.77	IND	62.01	Computer programming activities
78	ORG.78	SME	71.20	Technical testing and analysis

Org. N°	Org. Pseudo.	Type	NACE2	Class
79	ORG.79	IND	62.01	Computer programming activities
80	ORG.80	NPO	99.00	Activities of extraterritorial organisations and bodies
81	ORG.81	SME	62.01	Computer programming activities
82	ORG.82	ACA	85.40	Higher education
83	ORG.83	ACA	85.40	Higher education
84	ORG.84	ACA	85.40	Higher education
85	ORG.85	ACA	85.40	Higher education
86	ORG.86	ACA	85.40	Higher education
87	ORG.87	RTO	72.19	Other research and experimental development on natural sciences and engineering
88	ORG.88	ACA	85.40	Higher education
89	ORG.89	ACA	85.40	Higher education
90	ORG.90	ACA	85.40	Higher education
91	ORG.91	ACA	85.40	Higher education
92	ORG.92	RTO	72.19	Other research and experimental development on natural sciences and engineering

ANNEX 6: PROJECTS LIST

N°	Project Name	Proj. Pseudo.	Framework	Number	Website
1	CYBERFACTORY#1	PROJ.1	ITEA4	17032	https://www.cyberfactory-1.org/home/
2	SECOIIA	PROJ.2	H2020	871967	https://secoiia.eu/
3	MADE IN EUROPE	PROJ.3	HE	2027	https://www.effra.eu/made-in-europe-state-play
4	MANUFUTURE	PROJ.4	H2020	2020	https://www.manufuture.org/
5	SHERLOCK	PROJ.5	H2020	820689	https://cordis.europa.eu/project/id/820689
6	STAR	PROJ.6	HE	956573	https://cordis.europa.eu/project/id/956573
7	5GTIMBER	PROJ.7	HE	1011058505	https://cordis.europa.eu/project/id/101058505
8	PREVIEW	PROJ.8	H2020	636892	https://cordis.europa.eu/project/id/636892
9	QUALITY	PROJ.9	H2020	825030	https://cordis.europa.eu/project/id/825030
10	ZDMP	PROJ.10	H2020	825631	https://cordis.europa.eu/project/id/825631
11	EFPF	PROJ.11	H2020	825075	https://cordis.europa.eu/project/id/825075
12	FA3D2	PROJ.12	UKRI	113163	https://gtr.ukri.org/projects?ref=113163
13	TWIN-CONTROL	PROJ.13	H2020	680725	https://cordis.europa.eu/project/id/680725
14	BEINCPPS	PROJ.14	H2020	680633	https://cordis.europa.eu/project/id/680633
15	REBOOT IOT FACTORY	PROJ.15	PRIVATE	NA	https://portal.effra.eu/project/1917
16	SUSTAINABLE MANUFACTURING	PROJ.16	IMR	NA	https://imr.ie/pages/cleanroom-optimisation/
17	COLLABORATE	PROJ.17	H2020	820767	https://cordis.europa.eu/project/id/820767
18	QU4LITY	PROJ.18	H2020	825030	https://cordis.europa.eu/project/id/825030
19	SHOP4CF	PROJ.19	H2020	873087	https://cordis.europa.eu/project/id/873087
20	MTC	PROJ.20	EFFRA	4551	https://portal.effra.eu/result/show/4551
21	BOOST 4.0	PROJ.21	H2020	780732	https://cordis.europa.eu/project/id/780732

N°	Project Name	Proj. Pseudo.	Framework	Number	Website
22	PROPHESY	PROJ.22	H2020	766994	https://cordis.europa.eu/project/id/766994
23	IOF2020	PROJ.23	H2020	731884	https://cordis.europa.eu/project/id/731884
24	VICINITY	PROJ.24	H2020	688467	https://vicinity2020.eu/index.html
25	MONICA	PROJ.25	H2020	732350	https://cordis.europa.eu/project/id/732350
26	WAZIUP	PROJ.26	H2020	687607	https://cordis.europa.eu/project/id/687607
27	IPOL	PROJ.27	STU	652713	https://www.europarl.europa.eu/RegData/etudes/STUD/2020/652713/IPOL_STU(2020)652713_EN.pdf
28	AI4EU	PROJ.28	H2020	825619	https://cordis.europa.eu/project/id/825619
29	N2022J014	PROJ.29	NNSC	51975386	https://www.nsfc.gov.cn/english/site_1/index.html
30	EMERGING TECH	PROJ.30	VIS	NA	https://www.sciencedirect.com/science/article/pii/S026840122400029X?pes=vor
31	LINEACT	PROJ.31	CESI	NA	https://lineact.cesi.fr/
32	DEFACT	PROJ.32	CAS	NA	https://ieeexplore.ieee.org/abstract/document/10416760
33	PIDDAC	PROJ.33	FCT	UIDB/05757/2020	https://www.sciencedirect.com/science/article/pii/S1367578824000038
34	SAR	PROJ.34	STDFM	0050/2020/A1	https://www.ieee-jas.net/en/article/doi/10.1109/JAS.2023.123753
35	IV5.0	PROJ.35	IEEE TIV	NA	https://ieeexplore.ieee.org/abstract/document/10149821
36	AGILEHAND	PROJ.36	HE	101092043,	https://cordis.europa.eu/project/id/101092043
37	AHPA	PROJ.37	ITU	NA	https://papers.cumincad.org/data/works/att/ecaade2022_270.pdf
38	IFIP2023	PROJ.38	IFIP	2023	https://link.springer.com/book/10.1007/978-3-031-42622-3
39	FACTLOG	PROJ.39	H2020	869951	https://cordis.europa.eu/project/id/869951

ANNEX 7: USE-CASES LIST

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.1	Interview	EXP.1	ORG.1	Connected Looms	Textile	Portugal
UC.2	Interview	EXP.2	ORG.2	Intelligent Cheese Machine	Metallurgy	Finland
UC.3	Interview	EXP.4	ORG.3	Autonomous robot fleet	Robotics	Germany
UC.4	Interview	EXP.5	ORG.4	Automation of PCB production line	Electronics	Turkey
UC.5	Interview	EXP.5	ORG.4	Intelligent plastic injection molding	Electronics	Turkey
UC.6	Interview	EXP.5	ORG.4	Intelligent media recommendation	Electronics	Turkey
UC.7	Interview	EXP.7	ORG.5	Computer vision for shopfloor logistics	Aerospace	Spain
UC.8	Interview	EXP.6	ORG.5	Machine Learning for Industrial process control	Aerospace	Spain
UC.9	Interview	EXP.7	ORG.5	Natural Language Processing for aircraft test reporting	Aerospace	Spain
UC.10	Interview	EXP.8	ORG.6	Collaborative Robots	Robotics	Spain
UC.11	Interview	EXP.9	ORG.7	Industrial Data Services	Data services	Germany
UC.12	Interview	EXP.10	ORG.7	Drone Data Services	Data services	Norway
UC.13	Interview	EXP.11	ORG.8	Bonding Process Optimization	Semiconductor	Belgium
UC.14	Interview	EXP.11	ORG.8	Smart Weaving Process	Textile	Belgium
UC.15	Interview	EXP.11	ORG.8	Safe Human-Robot Interaction	Robotics	Belgium
UC.16	Interview	EXP.12	ORG.9	Industrial process optimization	Automation	Portugal
UC.17	Interview	EXP.13	ORG.9	Business process modelling	Informatics	Portugal
UC.18	Interview	EXP.14	ORG.10	Seamless and safe human-centred robotic applications for novel collaborative workplaces	Robotics	Greece
UC.19	Interview	EXP.15	ORG.11	Generative Design of Mechanical Parts	Defence	France

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.20	Interview	EXP.17	ORG.11	Safe area detection for Automated Mobile Robots	Robotics	France
UC.21	Interview	EXP.18	ORG.11	Trusted key manager anomaly detection	Computing	France
UC.22	Survey	EXP.18	ORG.13	Data and AI-driven industrial machines fault prediction and design support	Automation	Estonia
UC.23	Survey	EXP.18	ORG.14	Data-driven design to production cycle optimisation	Construction	Estonia
UC.24	Survey	EXP.18	ORG.14	Long-term structural health monitoring of wooden construction using IoT and embedded AI	Construction	Estonia
UC.25	Survey	EXP.19	ORG.15	Easy reconfiguration for automated part handling by cobots	Electronics	Netherlands
UC.26	Survey	EXP.19	ORG.15	Human supervised learning for visual quality inspection by cobots	Electronics	Netherlands
UC.27	Survey	EXP.19	ORG.15	Safe Collaboration between human and cobot	Electronics	Netherlands
UC.28	Survey	EXP.19	ORG.16	Production Processes Simulations for Accelerated Decisions and Safe Processes	Automotive	Portugal
UC.29	Survey	EXP.19	ORG.16	Production Planning Optimization	Automotive	Portugal
UC.30	Survey	EXP.19	ORG.16	Employee Training for Reduction of Human Errors	Automotive	Portugal
UC.31	Survey	EXP.19	ORG.16	Agile Production Management System Data Integrity and Reliability	Automotive	Portugal
UC.32	Survey	EXP.19	ORG.17	Human Intention Recognition by Automated Mobile Robots	Robotics	Germany
UC.33	Survey	EXP.19	ORG.17	Automated Mobile Robot reconfiguration based on dynamic layout	Robotics	Germany

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.34	Survey	EXP.19	ORG.17	Dynamic path planning for Automated Mobile Robots	Robotics	Germany
UC.35	Survey	EXP.19	ORG.20	Advanced Predictive System for Plastic Injection Moulding Industry	Automation	Spain
UC.36	Survey	EXP.28	ORG.21	Real-time injection moulding process monitoring-control	Electrical	Slovenia
UC.37	Survey	EXP.21	ORG.23	AI-supported optical defects detection	Automotive	Romania
UC.38	Survey	EXP.22	ORG.24	Visual Detection of Personal Protection Equipment	Aerospace	Germany
UC.39	Survey	EXP.24	ORG.26	Integrated Artificial Intelligence	Aerospace	United Kingdom
UC.40	Survey	EXP.23	ORG.27	Local Monitoring and Control System	Automation	Germany
UC.41	Survey	EXP.23	ORG.28	Fleet Management Platform for Machine Tools	Automotive	France
UC.42	Survey	EXP.25	ORG.29	Lombardy Champion - Zero-Hours Quality	Electronics	Italy
UC.43	Survey	EXP.26	ORG.30	Exploring the Challenges of Manufacturing with Learning Machine Vision	Automation	Switzerland
UC.44	Survey	EXP.27	ORG.31	Cleanroom Optimisation Through Machine Learning	Automation	Irland
UC.45	Survey	EXP.28	ORG.21	Challenge 1: Performing Car Starter Assembly	Automotive	Slovenia
UC.46	Survey	EXP.29	ORG.27	SIEMENS SIMATIC Products Quality Improvements	Automation	Germany
UC.47	Survey	EXP.22	ORG.33	Predictive Maintenance demonstrator in lot-size-1 manufacturing furniture domain	Furniture	Spain
UC.48	Survey	EXP.30	ORG.27	Manufacturing of a healthcare component for diagnostic imaging	Automation	Germany

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.49	Survey	EXP.30	ORG.27	Robot training for part sorting	Automation	Germany
UC.50	Survey	EXP.30	ORG.27	Frame manufacturing AR assistance	Automation	Germany
UC.51	Survey	EXP.31	ORG.35	Decision Making Robot Could Revolutionise Manufacturing	Electronics	United Kingdom
UC.52	Survey	EXP.32	ORG.36	Multi-stage zero-defect manufacturing railway axes production line	Automation	Spain
UC.53	Survey	EXP.33	ORG.37	Zero-Defects Manufacturing digital Hot Stamping process	Automation	Spain
UC.54	Survey	EXP.34	ORG.38	Predictive Maintenance and Service of a Hot Forming Line	Automotive	Germany
UC.55	Survey	EXP.35	ORG.39	Critical Cutting Tools	Automotive	United Kingdom
UC.56	Survey	EXP.36	ORG.40	Early Lameness Detection through Machine Learning	Food	Israel
UC.57	Survey	EXP.37	ORG.41	Fault detection and isolation in smart building	Construction	France
UC.58	Survey	EXP.38	ORG.42	FILL Smart Machine Tool Digital Engineering	Automation	Austria
UC.59	Survey	EXP.39	ORG.43	Happy cow	Food	Netherlands
UC.60	Survey	EXP.40	ORG.44	Pig Farm Management	Food	Belgium
UC.61	Survey	EXP.41	ORG.45	Poultry Chain Management	Food	Spain
UC.62	Survey	EXP.42	ORG.48	Sound Level Monitoring	Sensing	Denmark
UC.63	Survey	EXP.43	ORG.15	Remaining Useful Life prediction for cold forming production tooling	Automation	Netherlands
UC.64	Survey	EXP.43	ORG.15	Remaining Useful Life prediction for blank cutting production tooling	Automation	Netherlands
UC.65	Survey	EXP.44	ORG.49	Agriculture minimum viable product	Food	Ghana

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.66	Survey	EXP.44	ORG.49	Fish Farming minimum viable product	Food	Ghana
UC.67	Survey	EXP.45	ORG.50	Otto Retail scenario	Retail	Germany
UC.68	Survey	EXP.45	ORG.51	Ocado Retail Scenario	Retail	United Kingdom
UC.69	Survey	EXP.47	ORG.52	DeepMind Electric Utilities Scenario	Energy	United Kingdom
UC.70	Survey	EXP.48	ORG.53	Nest Electric Utilities Scenario	Energy	United States of America
UC.71	Survey	EXP.49	ORG.27	Siemens Electronic Manufacturing Scenario	Automation	Germany
UC.72	Survey	EXP.50	ORG.54	Intel Manufacturing Scenario	Informatics	United States of America
UC.73	Survey	EXP.51	ORG.55	Civitas Education Scenario	Education	United States of America
UC.74	Survey	EXP.52	ORG.56	Coursera Education Scenario	Education	United States of America
UC.75	Survey	EXP.53	ORG.57	AI4CITIZEN	Education	Italy
UC.76	Survey	EXP.54	ORG.30	AI4EU-AI4ROBOTICS	Automation	Norway
UC.77	Survey	EXP.49	ORG.27	AI4EU-AI4INDUSTRY	Automation	Germany
UC.78	Survey	EXP.55	ORG.58	AI4EU-AI4HEALTHCARE	Informatics	France
UC.79	Survey	EXP.56	ORG.59	AI4MEDIA	Data services	France
UC.80	Survey	EXP.57	ORG.60	AI4EU-AI4AGRICULTURE	Food	Spain
UC.81	Survey	EXP.58	ORG.61	AI4EU-AI4IOT	Sensing	Norway
UC.82	Survey	EXP.59	ORG.11	AI4EU-AI4CYBERSECURITY	Rail	France
UC.83	Survey	EXP.12	ORG.9	NA	Education	Portugal
UC.84	Survey	EXP.14	ORG.10	AI in Manufacturing	Robotics	Greece
UC.85	Survey	EXP.15	ORG.11	Generative Mechanics Design	Defence	France

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.86	Survey	EXP.9	ORG.62	Use of AI for Security and Safety	Space	United States of America
UC.87	Survey	EXP.2	ORG.2	Cheese Platform	Food	Finland
UC.88	Survey	EXP.16	ORG.11	Use an Ai to design mechanical parts meeting all requirements without compromise	Defence	France
UC.89	Survey	EXP.7	ORG.5	Digital Eye	Aerospace	Spain
UC.90	Survey	EXP.60	ORG.63	High Speed Packaging Machine	Manufacturing	Italy
UC.91	Literature	EXP.61	ORG.64	Edge computing-based proactive control method for industrial product manufacturing quality prediction	Rail	China
UC.92	Literature	EXP.62	ORG.67	ML-based efficiency improvement in manufacturing of packaging solutions	Packaging	Sweeden
UC.93	Literature	EXP.62	ORG.68	ML-based demand forecasting in jars and buckets production	Packaging	Sweeden
UC.94	Literature	EXP.62	ORG.69	AI-based capsules production quality control	Packaging	Sweeden
UC.95	Literature	EXP.62	ORG.70	AI-based bottles and cans manufacturing machines fault prediction	Packaging	Sweeden
UC.96	Literature	EXP.62	ORG.70	AI-based plastic and metal tubes production planning	Packaging	Sweeden
UC.97	Literature	EXP.63	ORG.72	Online human motion analysis	Manufacturing	France
UC.98	Literature	EXP.64	ORG.73	Decentralized Autonomous Operations (DAO)-based automated optical inspection (AOI) ecology	Electronics	China
UC.99	Literature	EXP.64	ORG.73	Language Foundation Model (LFM)-Based User-Friendly Human–Machine Interaction	Robotics	China

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.100	Literature	EXP.64	ORG.73	Decentralized Multirobot Task Allocation	Robotics	China
UC.101	Literature	EXP.65	ORG.74	Human-Robot Collaborative Work	Robotics	Portugal
UC.102	Literature	EXP.65	ORG.74	Augmented Environmentin Collaborative Work	Metallurgy	Portugal
UC.103	Literature	EXP.65	ORG.74	KPIs Visualization and Monitoring	Manufacturing	Portugal
UC.104	Literature	EXP.66	ORG.73	Transportation 5.0: Parallel driving, sensing and vision for	Transporation	China
UC.105	Literature	EXP.66	ORG.73	Manufacturing 5.0: Parallel machines, energy and unmanned systems for	Manufacturing	China
UC.106	Literature	EXP.66	ORG.73	Healthcare 5.0: Parallel skin, gout, eyes and gastro-intestine for	Healthcare	China
UC.107	Literature	EXP.67	ORG.75	Mining 5.0: Yugong parallel mining system	Mining	China
UC.108	Literature	EXP.68	ORG.53	AI-based energy consumption reduction in data centers	Informatics	United States of America
UC.109	Literature	EXP.68	ORG.77	AI-based weather forecasting for optimized asset management	Informatics	United States of America
UC.110	Literature	EXP.68	ORG.78	AI-based carbon capture from industrial processes	Manufacturing	United Kingdom
UC.111	Literature	EXP.68	ORG.79	AI-based crop yields improvement by water use reduction	Food	United States of America
UC.112	Literature	EXP.68	ORG.80	AI-based plastic waste detection and removal from the oceans	Ecology	The Netherlands
UC.113	Literature	EXP.68	ORG.81	AI-based carbon emission management	Ecology	Germany
UC.114	Literature	EXP.69	ORG.82	A data-driven decision support system for sustainable supplier evaluation in the Industry 5.0 era: A case study for medical equipment manufacturing	Electronics	Taiwan

UC.Pseudo.	Source	Exp. Pseudo.	Org. Pseudo	Use-case title	Industry	Country
UC.115	Literature	EXP.70	ORG.83	Intelligent Retrofitting for Oil and Gas Boosting Plant	Oil & gas	Italy
UC.116	Literature	EXP.71	ORG.84	Proactive and Predictive Maintenance for Smart Greasing System in Mining Facilities	Mining	Morocco
UC.117	Literature	EXP.72	ORG.85	Internet-of-Explainable-Digital-Twins: A Case Study of Versatile Corn Production Ecosystem	Food	India
UC.118	Literature	EXP.73	ORG.86	AI Driven Creativity in Early Design Education: A pedagogical approach in the age of Industry 5.0	Education	Turkey
UC.119	Literature	EXP.74	ORG.87	A Maturity Model for Collaborative Agents in Human-AI Ecosystems	Energy	The Netherlands
UC.120	Literature	EXP.75	ORG.88	Emerging Approaches for Enterprises and Human Integration Towards Industry 5.0	Manufacturing	Mexico
UC.121	Literature	EXP.76	ORG.89	AI-Supported Commissioning of Buildings	Construction	Germany
UC.122	Literature	EXP.77	ORG.90	Using Adversarial Reinforcement Learning to Improve the Resilience of Human-Robot Collaboration in Industrial Assembly	Robotics	Italy
UC.123	Literature	EXP.78	ORG.91	Event logic knowledge graph for collaborative railway freight scheduling decision	Rail	China
UC.124	Literature	EXP.79	ORG.23	Active-learning-based demand forecasting	Automotive	Romania
UC.125	Literature	EXP.79	ORG.15	Active learning-based label quality inspection	Electronics	Netherlands
UC.126	Literature	EXP.79	ORG.17	Adversarial Deep Learning based worker behaviour prediction	Robotics	Germany

Organisation Characteristics Data

UC-Pseudo.	Org. Age (OA)	Org. Product (OP)	Org. Type (OT)	Org. Skills (OS)
UC.1	Industry20	Goods	SME	Mechanics
UC.2	Industry10	Materials	SME	Mechanics
UC.3	Industry40	Software	SME	Electrical_Eng
UC.4	Industry30	Hardware	IND	Electrical_Eng
UC.5	Industry30	Hardware	IND	Electrical_Eng
UC.6	Industry30	Hardware	IND	Electrical_Eng
UC.7	Industry30	System	IND	Mechanics
UC.8	Industry30	System	IND	Mechanics
UC.9	Industry30	System	IND	Mechanics
UC.10	Industry50	System	SME	System_Eng
UC.11	Industry40	Service	NPO	System_Eng
UC.12	Industry40	Service	NPO	System_Eng
UC.13	Industry30	Hardware	NPO	Electrical_Eng
UC.14	Industry20	Goods	NPO	Mechanics
UC.15	Industry50	Software	NPO	Computing
UC.16	Industry30	System	IND	Electrical_Eng
UC.17	Industry30	System	IND	System_Eng
UC.18	Industry50	System	RTO	Mechanics
UC.19	Industry40	System	IND	System_Eng
UC.20	Industry40	Software	IND	System_Eng
UC.21	Industry40	System	IND	System_Eng
UC.22	Industry30	System	SME	Mechanics
UC.23	Industry30	Materials	IND	Construction
UC.24	Industry30	Materials	IND	Construction

UC-Pseudo.	Org. Age (OA)	Org. Product (OP)	Org. Type (OT)	Org. Skills (OS)
UC.25	Industry30	Goods	IND	Electrical_Eng
UC.26	Industry30	Goods	IND	Electrical_Eng
UC.27	Industry30	Goods	IND	Electrical_Eng
UC.28	Industry30	Hardware	IND	Mechanics
UC.29	Industry30	Hardware	IND	Mechanics
UC.30	Industry30	Hardware	IND	Mechanics
UC.31	Industry30	Hardware	IND	Mechanics
UC.32	Industry50	Software	RTO	Computing
UC.33	Industry50	Software	RTO	Computing
UC.34	Industry50	Software	RTO	Computing
UC.35	Industry50	Goods	IND	Computing
UC.36	Industry20	Hardware	IND	Electrical_Eng
UC.37	Industry30	Hardware	IND	Mechanics
UC.38	Industry30	Hardware	SME	Mechanics
UC.39	Industry50	Science	RTO	Computing
UC.40	Industry40	System	IND	Electrical_Eng
UC.41	Industry30	System	IND	Mechanics
UC.42	Industry30	Hardware	IND	Electrical_Eng
UC.43	Industry40	System	IND	Electrical_Eng
UC.44	Industry40	Science	RTO	Electrical_Eng
UC.45	Industry50	Hardware	IND	Mechanics
UC.46	Industry40	System	IND	Electrical_Eng
UC.47	Industry20	Goods	SME	Fabrication
UC.48	Industry40	System	IND	Electrical_Eng
UC.49	Industry40	System	IND	Electrical_Eng
UC.50	Industry40	System	IND	Electrical_Eng
UC.51	Industry50	Science	RTO	Computing

UC-Pseudo.	Org. Age (OA)	Org. Product (OP)	Org. Type (OT)	Org. Skills (OS)
UC.52	Industry30	Hardware	IND	Mechanics
UC.53	Industry30	Hardware	IND	Mechanics
UC.54	Industry30	Hardware	IND	Mechanics
UC.55	Industry30	System	IND	Mechanics
UC.56	Industry10	Goods	SME	Farming
UC.57	Industry20	Software	SME	System_Eng
UC.58	Industry30	System	IND	Electrical_Eng
UC.59	Industry10	Software	SME	System_Eng
UC.60	Industry10	Science	RTO	Farming
UC.61	Industry20	Hardware	SME	Mechanics
UC.62	Industry30	System	IND	Electrical_Eng
UC.63	Industry30	System	IND	Electrical_Eng
UC.64	Industry30	System	IND	Electrical_Eng
UC.65	Industry10	Service	SME	Farming
UC.66	Industry10	Service	SME	Farming
UC.67	Industry30	Goods	IND	Business
UC.68	Industry30	Goods	IND	Business
UC.69	Industry30	Software	IND	System_Eng
UC.70	Industry40	System	IND	System_Eng
UC.71	Industry40	System	IND	Electrical_Eng
UC.72	Industry30	Hardware	IND	System_Eng
UC.73	Industry50	Service	SME	Computing
UC.74	Industry50	Service	IND	Computing
UC.75	Industry50	Science	ACA	Computing
UC.76	Industry40	System	IND	Electrical_Eng
UC.77	Industry40	System	IND	Electrical_Eng
UC.78	Industry50	Service	SME	Life_Science

UC-Pseudo.	Org. Age (OA)	Org. Product (OP)	Org. Type (OT)	Org. Skills (OS)
UC.79	Industry50	Service	IND	Computing
UC.80	Industry40	Goods	SME	Farming
UC.81	Industry50	Science	ACA	Computing
UC.82	Industry30	System	IND	System_Eng
UC.83	Industry50	Science	RTO	Computing
UC.84	Industry50	System	RTO	
UC.85	Industry40	System	IND	Electrical_Eng
UC.86	Industry40	Software	SME	Computing
UC.87	Industry20	System	SME	Mechanics
UC.88	Industry40	System	IND	Computing
UC.89	Industry30	System	IND	System_Eng
UC.90	Industry40	System	IND	Mechanics
UC.91	Industry50	Hardware	IND	Mechanics
UC.92	Industry30	Materials	SME	Mechanics
UC.93	Industry30	Materials	SME	Mechanics
UC.94	Industry30	Materials	SME	Mechanics
UC.95	Industry30	Materials	SME	Mechanics
UC.96	Industry30	Materials	SME	Mechanics
UC.97	Industry50	System	ACA	Computing
UC.98	Industry50	Hardware	RTO	Computing
UC.99	Industry50	System	RTO	Computing
UC.100	Industry50	System	RTO	Computing
UC.101	Industry40	System	RTO	System_Eng
UC.102	Industry40	System	RTO	Mechanics
UC.103	Industry40	System	RTO	System_Eng
UC.104	Industry50	Service	RTO	System_Eng
UC.105	Industry50	Goods	RTO	Fabrication

UC-Pseudo.	Org. Age (OA)	Org. Product (OP)	Org. Type (OT)	Org. Skills (OS)
UC.106	Industry50	Service	RTO	Life_Science
UC.107	Industry50	Materials	SME	Mining
UC.108	Industry50	Service	IND	Computing
UC.109	Industry50	System	IND	Computing
UC.110	Industry50	Service	SME	Mechanics
UC.111	Industry30	Software	IND	Computing
UC.112	Industry50	Service	NPO	Life_Science
UC.113	Industry50	Software	SME	Computing
UC.114	Industry50	Science	ACA	Electrical_Eng
UC.115	Industry40	Science	ACA	System_Eng
UC.116	Industry50	Science	ACA	Computing
UC.117	Industry50	Science	ACA	Computing
UC.118	Industry50	Science	ACA	Construction
UC.119	Industry50	Service	RTO	Electrical_Eng
UC.120	Industry50	Science	ACA	Computing
UC.121	Industry50	Service	ACA	Construction
UC.122	Industry50	Science	ACA	Computing
UC.123	Industry20	Service	IND	Mechanics
UC.124	Industry30	Hardware	IND	Mechanics
UC.125	Industry30	Goods	IND	Electrical_Eng
UC.126	Industry50	Software	RTO	Computing

Artificial Intelligence Data

UC-Pseudo.	AI Maturity (AM)	AI Type (AT)	AI Place (AP)	AI Role (AR)
UC.1	Physical	Symbolic_Virtual_Object	Manufacturing	Monitoring
UC.2	Social	Symbolic_Embodied_Object	Operation	Optimization
UC.3	Cyber_Physical	Symbolic_Embodied_Humanoid	Operation	Optimization
UC.4	Cyber_Physical	Symbolic_Embodied_Object	Manufacturing	Automation
UC.5	Cyber	Machine_Learning_Virtual_Object	Maintenance	Prediction
UC.6	Cyber_Social	Machine_Learning_Virtual_Object	Commissionning	Collaboration
UC.7	Cyber	Machine_Learning_Virtual_Object	Operation	Monitoring
UC.8	Cyber_Physical	Machine_Learning_Virtual_Object	Manufacturing	Automation
UC.9	Cyber_Social	Machine_Learning_Virtual_Humanoid	Testing	Collaboration
UC.10	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Operation	Collaboration
UC.11	Cyber	Machine_Learning_Virtual_Object	Operation	Optimization
UC.12	Cyber_Physical	Machine_Learning_Embodied_Object	Operation	Prediction
UC.13	Cyber_Physical	Machine_Learning_Embodied_Object	Manufacturing	Optimization
UC.14	Cyber_Physical	Machine_Learning_Embodied_Object	Manufacturing	Automation
UC.15	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Operation	Collaboration
UC.16	Cyber_Physical	Symbolic_Embodied_Object	Manufacturing	Optimization
UC.17	Cyber	Symbolic_Virtual_Object	Commissionning	Collaboration
UC.18	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Collaboration
UC.19	Cyber	Generative_Unimodal	Design	Optimization
UC.20	Cyber_Physical	Machine_Learning_Embodied_Object	Operation	Automation
UC.21	Cyber	Machine_Learning_Virtual_Object	Commissionning	Detection
UC.22	Physical	Symbolic_Embodied_Object	Maintenance	Prediction
UC.23	Cyber_Physical	Symbolic_Embodied_Object	Operation	Monitoring

UC-Pseudo.	AI Maturity (AM)	AI Type (AT)	AI Place (AP)	AI Role (AR)
UC.24	Cyber_Physical	Machine_Learning_Virtual_Object	Commissionning	Monitoring
UC.25	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Manufacturing	Collaboration
UC.26	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Testing	Collaboration
UC.27	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Manufacturing	Collaboration
UC.28	Physical_Social	Symbolic_Virtual_Object	Manufacturing	Decision
UC.29	Physical_Social	Symbolic_Virtual_Object	Manufacturing	Optimization
UC.30	Physical_Social	Symbolic_Virtual_Object	Manufacturing	Education
UC.31	Physical_Social	Symbolic_Virtual_Object	Manufacturing	Optimization
UC.32	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Prediction
UC.33	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Optimization
UC.34	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Decision
UC.35	Cyber_Physical	Machine_Learning_Embodied_Object	Manufacturing	Optimization
UC.36	Physical_Social	Symbolic_Embodied_Object	Manufacturing	Monitoring
UC.37	Cyber	Machine_Learning_Virtual_Object	Manufacturing	Monitoring
UC.38	Cyber_Social	Machine_Learning_Virtual_Object	Manufacturing	Monitoring
UC.39	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Commissionning	Decision
UC.40	Cyber_Physical	Symbolic_Embodied_Object	Operation	Monitoring
UC.41	Cyber_Physical	Symbolic_Virtual_Object	Manufacturing	Prediction
UC.42	Cyber_Physical	Machine_Learning_Virtual_Object	Testing	Detection
UC.43	Cyber_Physical	Machine_Learning_Virtual_Object	Testing	Detection
UC.44	Cyber_Physical	Machine_Learning_Virtual_Object	Operation	Optimization
UC.45	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Manufacturing	Collaboration
UC.46	Cyber_Physical	Machine_Learning_Virtual_Object	Testing	Analysis
UC.47	Cyber_Physical	Machine_Learning_Virtual_Object	Manufacturing	Detection
UC.48	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Manufacturing	Collaboration
UC.49	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Manufacturing	Collaboration

UC-Pseudo.	AI Maturity (AM)	AI Type (AT)	AI Place (AP)	AI Role (AR)
UC.50	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Manufacturing	Collaboration
UC.51	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Decision
UC.52	Cyber_Physical	Symbolic_Embodied_Object	Testing	Detection
UC.53	Cyber_Physical	Symbolic_Embodied_Object	Testing	Detection
UC.54	Cyber_Physical	Machine_Learning_Virtual_Object	Maintenance	Prediction
UC.55	Cyber_Physical	Machine_Learning_Virtual_Object	Maintenance	Prediction
UC.56	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Detection
UC.57	Cyber_Physical	Symbolic_Virtual_Object	Maintenance	Monitoring
UC.58	Cyber_Physical	Symbolic_Embodied_Object	Commissionning	Automation
UC.59	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Operation	Monitoring
UC.60	Cyber_Physical	Symbolic_Virtual_Object	Commissionning	Optimization
UC.61	Cyber_Physical	Symbolic_Embodied_Object	Operation	Monitoring
UC.62	Cyber_Physical	Symbolic_Virtual_Object	Testing	Detection
UC.63	Cyber_Physical	Symbolic_Virtual_Object	Maintenance	Prediction
UC.64	Cyber_Physical	Symbolic_Virtual_Object	Maintenance	Prediction
UC.65	Cyber_Physical_Social	Symbolic_Embodied_Object	Operation	Monitoring
UC.66	Cyber_Physical_Social	Symbolic_Embodied_Object	Operation	Monitoring
UC.67	Cyber_Social	Machine_Learning_Virtual_Object	Commissionning	Prediction
UC.68	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Commissionning	Automation
UC.69	Cyber_Physical	Machine_Learning_Virtual_Object	Operation	Prediction
UC.70	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Optimization
UC.71	Cyber_Physical	Symbolic_Embodied_Object	Operation	Automation
UC.72	Cyber_Physical	Machine_Learning_Virtual_Object	Operation	Optimization
UC.73	Cyber_Social	Machine_Learning_Virtual_Humanoid	Commissionning	Collaboration
UC.74	Cyber_Social	Machine_Learning_Virtual_Humanoid	Commissionning	Detection
UC.75	Cyber_Social	Machine_Learning_Virtual_Object	Commissionning	Education

UC-Pseudo.	AI Maturity (AM)	AI Type (AT)	AI Place (AP)	AI Role (AR)
UC.76	Cyber_Physical	Symbolic_Embodied_Object	Maintenance	Prediction
UC.77	Cyber_Physical	Symbolic_Virtual_Object	Operation	Automation
UC.78	Cyber_Social	Symbolic_Virtual_Object	Operation	Detection
UC.79	Cyber_Social	Symbolic_Virtual_Humanoid	Design	Automation
UC.80	Cyber_Physical	Machine_Learning_Virtual_Object	Manufacturing	Optimization
UC.81	Cyber_Physical	Machine_Learning_Virtual_Object	Operation	Prediction
UC.82	Cyber_Physical	Symbolic_Embodied_Object	Operation	Monitoring
UC.83	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Manufacturing	Automation
UC.84	Cyber_Physical		Commissionning	Collaboration
UC.85			Design	Optimization
UC.86	Cyber_Social	Symbolic_Virtual_Object	Operation	Monitoring
UC.87	Physical	Symbolic_Embodied_Object	Manufacturing	Optimization
UC.88			Operation	Resilience
UC.89	Physical_Social	Machine_Learning_Virtual_Object	Manufacturing	Automation
UC.90	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Operation	Monitoring
UC.91	Cyber_Physical	Machine_Learning_Virtual_Object	Testing	Prediction
UC.92	Physical	Machine_Learning_Virtual_Object	Manufacturing	Optimization
UC.93	Physical	Machine_Learning_Virtual_Object	Commissionning	Prediction
UC.94	Physical	Symbolic_Embodied_Object	Testing	Detection
UC.95	Physical	Symbolic_Embodied_Object	Maintenance	Prediction
UC.96	Physical	Symbolic_Virtual_Object	Operation	Decision
UC.97	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Manufacturing	Analysis
UC.98	Cyber_Physical_Social	Machine_Learning_Virtual_Object	Testing	Detection
UC.99	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Operation	Collaboration
UC.100	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Operation	Resilience
UC.101	Cyber_Physical	Symbolic_Embodied_Object	Manufacturing	Collaboration

UC-Pseudo.	AI Maturity (AM)	AI Type (AT)	AI Place (AP)	AI Role (AR)
UC.102	Cyber_Physical	Symbolic_Embodied_Object	Testing	Collaboration
UC.103	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Monitoring
UC.104	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Optimization
UC.105	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Manufacturing	Automation
UC.106	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Commissionning	Decision
UC.107	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Collaboration
UC.108	Cyber_Physical	Machine_Learning_Virtual_Object	Commissionning	Optimization
UC.109	Cyber_Social	Machine_Learning_Virtual_Object	Commissionning	Optimization
UC.110	Cyber_Physical	Symbolic_Virtual_Object	Operation	Monitoring
UC.111	Cyber_Physical	Machine_Learning_Virtual_Object	Operation	Optimization
UC.112	Cyber_Physical	Machine_Learning_Virtual_Object	Recycling	Resilience
UC.113	Cyber	Symbolic_Virtual_Object	Operation	Monitoring
UC.114	Cyber_Social	Symbolic_Virtual_Object	Commissionning	Analysis
UC.115	Cyber_Physical	Machine_Learning_Embodied_Object	Operation	Monitoring
UC.116	Cyber_Physical	Machine_Learning_Virtual_Object	Maintenance	Optimization
UC.117	Cyber_Physical	Symbolic_Virtual_Object	Operation	Monitoring
UC.118	Cyber_Social	Generative_Unimodal	Design	Education
UC.119	Cyber_Physical_Social	Generative_Multimodal	Operation	Optimization
UC.120	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Operation	Collaboration
UC.121	Cyber_Social	Symbolic_Virtual_Object	Commissionning	Analysis
UC.122	Cyber_Physical_Social	Machine_Learning_Embodied_Humanoid	Manufacturing	Collaboration
UC.123	Cyber	Symbolic_Virtual_Object	Operation	Analysis
UC.124	Cyber_Social	Machine_Learning_Virtual_Object	Manufacturing	Prediction
UC.125	Cyber_Physical	Machine_Learning_Virtual_Object	Testing	Detection
UC.126	Cyber_Physical_Social	Machine_Learning_Embodied_Object	Operation	Prediction

Business Strategy Data

UC.Pseudo.	Manuf. Strat. (MS)	Resources Strat. (RS)	Network Strat. (NS)	Product Strat (PS)
UC.1	Product_Specialization	Replace_Operators	Purchase	Custom_Product
UC.2	Product_Specialization	Augment_Operators	Crowdsource	Custom_PSS
UC.3	Product_Servitization	Augment_Operators	Specify	Custom_PSS
UC.4	Product_Specialization	Replace_Operators	Develop	Standard_Product
UC.5	Process_Specialization	Replace_Operators	Specify	Custom_Service
UC.6	Product_Servitization	Replace_Customers	Customize	Standard_PSS
UC.7	Process_Specialization	Augment_Operators	Specify	Custom_Product
UC.8	Process_Servitization	Augment_Operators	Customize	Custom_Product
UC.9	Product_Specialization	Augment_Managers	Customize	Custom_PSS
UC.10	Product_Servitization	Replace_Operators	Develop	Custom_PSS
UC.11	Process_Servitization	Augment_Managers	Crowdsource	Custom_Service
UC.12	Process_Servitization	Replace_Operators	Crowdsource	Custom_Service
UC.13	Product_Specialization	Augment_Managers	Develop	Standard_Product
UC.14	Product_Specialization	Replace_Operators	Develop	Standard_Product
UC.15	Product_Customization	Augment_Operators	Specify	Custom_PSS
UC.16	Product_Specialization	Replace_Operators	Specify	Standard_Product
UC.17	Process_Specialization	Augment_Managers	Specify	Custom_Product
UC.18	Process_Specialization	Augment_Operators	Specify	Standard_Product
UC.19	Product_Specialization	Augment_Engineers	Purchase	Custom_PSS
UC.20	Process_Specialization	Replace_Operators	Develop	Custom_PSS
UC.21	Process_Servitization	Augment_Managers	Customize	Custom_Product
UC.22	Product_Specialization	Augment_Managers	Purchase	Custom_Product
UC.23	Process_Servitization	Augment_Operators	Crowdsource	Custom_Product
UC.24	Product_Servitization	Augment_Customers	Crowdsource	Custom_Product

UC.Pseudo.	Manuf. Strat. (MS)	Resources Strat. (RS)	Network Strat. (NS)	Product Strat (PS)
UC.25	Product_Customization	Augment_Operators	Customize	Custom_Product
UC.26	Product_Customization	Augment_Operators	Customize	Custom_Product
UC.27	Product_Customization	Augment_Operators	Customize	Custom_Product
UC.28	Product_Specialization	Augment_Managers	Purchase	Standard_Product
UC.29	Product_Specialization	Augment_Managers	Purchase	Standard_Product
UC.30	Product_Specialization	Augment_Operators	Purchase	Standard_Product
UC.31	Product_Specialization	Augment_Managers	Purchase	Standard_Product
UC.32	Process_Servitization	Augment_Operators	Develop	Custom_PSS
UC.33	Process_Servitization	Augment_Operators	Develop	Custom_PSS
UC.34	Process_Servitization	Augment_Operators	Develop	Custom_PSS
UC.35	Product_Specialization	Augment_Operators	Develop	Standard_Product
UC.36	Product_Specialization	Augment_Operators	Specify	Standard_Product
UC.37	Product_Specialization	Augment_Operators	Specify	Standard_Product
UC.38	Product_Specialization	Replace_Managers	Specify	Custom_Product
UC.39	Process_Servitization	Augment_Engineers	Develop	Custom_PSS
UC.40	Process_Servitization	Replace_Operators	Develop	Standard_Product
UC.41	Process_Servitization	Augment_Engineers	Specify	Custom_Product
UC.42	Product_Specialization	Augment_Engineers	Customize	Standard_Product
UC.43	Product_Customization	Augment_Engineers	Specify	Custom_Product
UC.44	Process_Servitization	Augment_Operators	Develop	Custom_Service
UC.45	Process_Customization	Augment_Operators	Develop	Custom_Product
UC.46	Process_Servitization	Augment_Engineers	Acquire	Standard_Product
UC.47	Process_Servitization	Augment_Operators	Specify	Custom_Product
UC.48	Process_Servitization	Augment_Operators	Develop	Standard_Product
UC.49	Process_Servitization	Augment_Operators	Develop	Custom_Product
UC.50	Process_Servitization	Augment_Operators	Develop	Custom_Product
UC.51	Process_Customization	Augment_Operators	Develop	Custom_PSS

UC.Pseudo.	Manuf. Strat. (MS)	Resources Strat. (RS)	Network Strat. (NS)	Product Strat (PS)
UC.52	Process_Specialization	Augment_Operators	Purchase	Standard_PSS
UC.53	Process_Specialization	Augment_Operators	Purchase	Standard_PSS
UC.54	Product_Specialization	Augment_Engineers	Specify	Standard_Product
UC.55	Product_Specialization	Augment_Engineers	Specify	Custom_Product
UC.56	Process_Servitization	Augment_Operators	Specify	Standard_PSS
UC.57	Product_Customization	Augment_Managers	Develop	Custom_PSS
UC.58	Process_Specialization	Replace_Engineers	Develop	Standard_PSS
UC.59	Product_Servitization	Augment_Operators	Develop	Custom_PSS
UC.60	Process_Specialization	Augment_Customers	Specify	Standard_PSS
UC.61	Process_Servitization	Augment_Managers	Develop	Custom_PSS
UC.62	Product_Specialization	Augment_Managers	Develop	Custom_PSS
UC.63	Product_Customization	Augment_Engineers	Customize	Custom_Product
UC.64	Product_Customization	Augment_Engineers	Customize	Custom_Product
UC.65	Process_Servitization	Augment_Operators	Crowdsource	Custom_PSS
UC.66	Process_Servitization	Augment_Operators	Crowdsource	Custom_PSS
UC.67	Process_Servitization	Augment_Customers	Crowdsource	Custom_Service
UC.68	Process_Customization	Replace_Operators	Crowdsource	Custom_Service
UC.69	Process_Servitization	Augment_Customers	Crowdsource	Custom_PSS
UC.70	Process_Customization	Augment_Customers	Crowdsource	Custom_PSS
UC.71	Process_Customization	Augment_Operators	Specify	Custom_PSS
UC.72	Process_Servitization	Augment_Operators	Specify	Standard_Product
UC.73	Product_Servitization	Augment_Customers	Specify	Custom_Service
UC.74	Product_Servitization	Augment_Customers	Crowdsource	Custom_Service
UC.75	Process_Customization	Augment_Customers	Specify	Custom_Service
UC.76	Process_Servitization	Augment_Engineers	Develop	Custom_Product
UC.77	Process_Servitization	Augment_Operators	Develop	Standard_Product
UC.78	Process_Servitization	Augment_Operators	Specify	Custom_Service

UC.Pseudo.	Manuf. Strat. (MS)	Resources Strat. (RS)	Network Strat. (NS)	Product Strat (PS)
UC.79	Process_Customization	Replace_Operators	Develop	Custom_Service
UC.80	Product_Customization	Augment_Operators	Develop	Custom_PSS
UC.81	Process_Customization	Augment_Managers	Crowdsource	Custom_PSS
UC.82	Process_Customization	Augment_Operators	Develop	Custom_Product
UC.83	Product_Servitization	Augment_All	Customize	Custom_PSS
UC.84	Process_Specialization	Augment_Operators	Customize	Custom_PSS
UC.85				
UC.86	Social_Manufacturing	Augment_Engineers	Develop	Custom_Product
UC.87	Process_Specialization	Replace_Operators	Customize	Custom_Product
UC.88				Custom_Product
UC.89	Product_Servitization	Augment_Operators	Develop	Custom_PSS
UC.90	Product_Specialization	Augment_Operators	Specify	Standard_Service
UC.91	Product_Specialization	Augment_Operators	Specify	Standard_Product
UC.92	Product_Specialization	Augment_Operators	Purchase	Standard_Product
UC.93	Product_Specialization	Augment_Managers	Purchase	Standard_Product
UC.94	Product_Specialization	Augment_Engineers	Purchase	Standard_Product
UC.95	Process_Specialization	Augment_Engineers	Purchase	Standard_Product
UC.96	Product_Customization	Replace_Managers	Purchase	Custom_Product
UC.97	Process_Customization	Augment_Operators	Specify	Standard_Product
UC.98	Social_Manufacturing	Replace_Engineers	Crowdsource	Custom_PSS
UC.99	Social_Manufacturing	Augment_Operators	Customize	Custom_PSS
UC.100	Social_Manufacturing	Replace_Operators	Crowdsource	Custom_Service
UC.101	Process_Customization	Augment_Operators	Specify	Custom_PSS
UC.102	Product_Specialization	Replace_Engineers	Develop	Standard_Product
UC.103	Process_Servitization	Augment_Managers	Crowdsource	Custom_PSS
UC.104	Process_Servitization	Replace_Operators	Crowdsource	Custom_Service
UC.105	Mass_Customization	Replace_Operators	Crowdsource	Custom_Product

UC.Pseudo.	Manuf. Strat. (MS)	Resources Strat. (RS)	Network Strat. (NS)	Product Strat (PS)
UC.106	Product_Customization	Augment_Customers	Crowdsource	Custom_PSS
UC.107	Social_Manufacturing	Replace_Operators	Develop	Custom_PSS
UC.108	Process_Servitization	Augment_Engineers	Develop	Custom_Service
UC.109	Process_Servitization	Augment_Engineers	Develop	Custom_Service
UC.110	Process_Servitization	Augment_Engineers	Customize	Custom_PSS
UC.111	Process_Customization	Augment_Operators	Crowdsource	Custom_Service
UC.112	Process_Specialization	Replace_Operators	Develop	Custom_Service
UC.113	Process_Servitization	Augment_Managers	Develop	Custom_PSS
UC.114	Process_Customization	Augment_Managers	Specify	Custom_Service
UC.115	Process_Servitization	Augment_Operators	Specify	Custom_PSS
UC.116	Process_Servitization	Augment_Operators	Specify	Custom_PSS
UC.117	Process_Customization	Augment_Operators	Specify	Custom_PSS
UC.118	Process_Servitization	Augment_Engineers	Customize	Custom_PSS
UC.119	Social_Manufacturing	Augment_All	Crowdsource	Custom_PSS
UC.120	Mass_Customization	Augment_Operators	Specify	Custom_PSS
UC.121	Social_Manufacturing	Augment_Engineers	Customize	Custom_Service
UC.122	Social_Manufacturing	Augment_Operators	Develop	Custom_PSS
UC.123	Process_Servitization	Replace_Managers	Specify	Standard_Service
UC.124	Product_Specialization	Augment_Managers	Specify	Standard_Product
UC.125	Product_Specialization	Replace_Operators	Specify	Standard_Product
UC.126	Social_Manufacturing	Augment_Operators	Specify	Custom_PSS
0				

Innovation Capacity Data

UC.Pseudo.	Innov. Capacity (IC)	Internal Innov. (II)	Open Innov. (OI)	Innov. Policy (IP)
UC.1	Analytic_Singleton	Operation_Driven	Systematic_Inbound	Private_Incremental
UC.2	Analytic_Singleton	Business_Driven	Regular_Outbound	Private_Disruptive
UC.3	Analytic_Swarm	Engineering_Driven	Casual_Outbound	Private_Incremental
UC.4	Analytic_Swarm	Operation_Driven	Systematic_Inbound	Private_Incremental
UC.5	Analytic_Swarm	Engineering_Driven	Casual_Outbound	Private_Incremental
UC.6	Parasitic_Singleton	Strategy_Driven	Systematic_Outbound	Private_Disruptive
UC.7	Analytic_Swarm	Engineering_Driven	Casual_Inbound	Private_Incremental
UC.8	Cognitive_Swarm	Engineering_Driven	Casual_Inbound	Private_Incremental
UC.9	Cognitive_Singleton	Expertise_Driven	Casual_Inbound	Private_Incremental
UC.10	Cognitive_Swarm	Engineering_Driven	Systematic_Outbound	Private_Disruptive
UC.11	Analytic_Singleton	Strategy_Driven	Systematic_Outbound	Private_Disruptive
UC.12	Analytic_Swarm	Strategy_Driven	Systematic_Outbound	Private_Disruptive
UC.13	Analytic_Singleton	Engineering_Driven	Regular_Inbound	Public_Incremental
UC.14	Analytic_Singleton	Operation_Driven	Regular_Inbound	Public_Incremental
UC.15	Cognitive_Swarm	Strategy_Driven	Regular_Outbound	Public_Disruptive
UC.16	Analytic_Singleton	Engineering_Driven	Systematic_Outbound	Public_Defensive
UC.17	Analytic_Singleton	Demand_Driven	Systematic_Outbound	Public_Defensive
UC.18	Cognitive_Swarm	Engineering_Driven	Systematic_Outbound	Public_Disruptive
UC.19	Generative_Singleton	Engineering_Driven	Regular_Outbound	Private_Disruptive
UC.20	Cognitive_Swarm	Expertise_Driven	Regular_Outbound	Private_Disruptive
UC.21	Analytic_Singleton	Demand_Driven	Regular_Outbound	Public_Defensive
UC.22	Analytic_Swarm	Engineering_Driven	Casual_Outbound	Private_Incremental
UC.23	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.24	Cognitive_Swarm	Engineering_Driven	Casual_Inbound	Private_Disruptive

UC.Pseudo.	Innov. Capacity (IC)	Internal Innov. (II)	Open Innov. (OI)	Innov. Policy (IP)
UC.25	Cognitive_Swarm	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.26	Cognitive_Swarm	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.27	Parasitic_Swarm	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.28	Cognitive_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.29	Analytic_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.30	Cognitive_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.31	Analytic_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.32	Cognitive_Swarm	Expertise_Driven	Systematic_Outbound	Public_Disruptive
UC.33	Cognitive_Swarm	Expertise_Driven	Systematic_Outbound	Public_Disruptive
UC.34	Cognitive_Swarm	Expertise_Driven	Systematic_Outbound	Public_Disruptive
UC.35	Analytic_Singleton	Engineering_Driven	Systematic_Outbound	Private_Incremental
UC.36	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.37	Analytic_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.38	Parasitic_Singleton	Demand_Driven	Casual_Inbound	Public_Defensive
UC.39	Cognitive_Swarm	Expertise_Driven	Weak_Outbound	Public_Disruptive
UC.40	Analytic_Singleton	Engineering_Driven	Systematic_Inbound	Private_Defensive
UC.41	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.42	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.43	Analytic_Singleton	Engineering_Driven	Regular_Inbound	Private_Disruptive
UC.44	Analytic_Swarm	Expertise_Driven	Casual_Outbound	Public_Disruptive
UC.45	Cognitive_Swarm	Business_Driven	Regular_Outbound	Private_Disruptive
UC.46	Analytic_Singleton	Engineering_Driven	Systematic_Inbound	Private_Defensive
UC.47	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Disruptive
UC.48	Cognitive_Swarm	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.49	Cognitive_Swarm	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.50	Analytic_Singleton	Engineering_Driven	Systematic_Inbound	Private_Disruptive
UC.51	Parasitic_Swarm	Expertise_Driven	Casual_Outbound	Public_Disruptive

UC.Pseudo.	Innov. Capacity (IC)	Internal Innov. (II)	Open Innov. (OI)	Innov. Policy (IP)
UC.52	Analytic_Swarm	Business_Driven	Casual_Outbound	Private_Incremental
UC.53	Analytic_Swarm	Business_Driven	Casual_Outbound	Private_Incremental
UC.54	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.55	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.56	Cognitive_Singleton	Demand_Driven	Weak_Inbound	Private_Disruptive
UC.57	Analytic_Singleton	Demand_Driven	Systematic_Outbound	Private_Incremental
UC.58	Parasitic_Singleton	Engineering_Driven	Regular_Outbound	Private_Incremental
UC.59	Cognitive_Singleton	Business_Driven	Casual_Outbound	Private_Disruptive
UC.60	Analytic_Swarm	Expertise_Driven	Regular_Outbound	Public_Incremental
UC.61	Analytic_Singleton	Engineering_Driven	Casual_Outbound	Private_Incremental
UC.62	Parasitic_Singleton	Engineering_Driven	Casual_Outbound	Private_Incremental
UC.63	Analytic_Swarm	Strategy_Driven	Systematic_Inbound	Private_Disruptive
UC.64	Analytic_Swarm	Strategy_Driven	Systematic_Inbound	Private_Disruptive
UC.65	Cognitive_Swarm	Strategy_Driven	Systematic_Outbound	Public_Disruptive
UC.66	Cognitive_Swarm	Strategy_Driven	Systematic_Outbound	Public_Disruptive
UC.67	Cognitive_Singleton	Demand_Driven	Weak_Inbound	Private_Disruptive
UC.68	Cognitive_Swarm	Demand_Driven	Weak_Inbound	Private_Disruptive
UC.69	Parasitic_Swarm	Demand_Driven	Casual_Outbound	Public_Disruptive
UC.70	Cognitive_Swarm	Business_Driven	Casual_Inbound	Private_Disruptive
UC.71	Parasitic_Singleton	Engineering_Driven	Systematic_Inbound	Private_Incremental
UC.72	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Incremental
UC.73	Cognitive_Singleton	Demand_Driven	Casual_Inbound	Private_Disruptive
UC.74	Cognitive_Singleton	Business_Driven	Casual_Inbound	Private_Disruptive
UC.75	Cognitive_Singleton	Strategy_Driven	Systematic_Outbound	Public_Disruptive
UC.76	Analytic_Singleton	Operation_Driven	Regular_Inbound	Private_Incremental
UC.77	Analytic_Singleton	Engineering_Driven	Systematic_Inbound	Private_Incremental
UC.78	Analytic_Singleton	Engineering_Driven	Casual_Inbound	Public_Incremental

UC.Pseudo.	Innov. Capacity (IC)	Internal Innov. (II)	Open Innov. (OI)	Innov. Policy (IP)
UC.79	Parasitic_Singleton	Demand_Driven	Regular_Inbound	Private_Disruptive
UC.80	Analytic_Swarm	Expertise_Driven	Casual_Outbound	Private_Disruptive
UC.81	Analytic_Swarm	Expertise_Driven	Casual_Outbound	Public_Defensive
UC.82	Analytic_Swarm	Engineering_Driven	Regular_Outbound	Public_Defensive
UC.83	Cognitive_Swarm	Strategy_Driven	Systematic_Outbound	Private_Disruptive
UC.84	Cognitive_Swarm	Engineering_Driven	Systematic_Outbound	Public_Incremental
UC.85				
UC.86	Generative_Singleton	Strategy_Driven	Casual_Inbound	Private_Defensive
UC.87	Cognitive_Singleton	Engineering_Driven	Casual_Outbound	Private_Disruptive
UC.88		Strategy_Driven		
UC.89		Operation_Driven	Systematic_Inbound	Public_Liberal
UC.90	Generative_Swarm	Demand_Driven	Systematic_Outbound	Private_Incremental
UC.91	Analytic_Singleton	Operation_Driven	Casual_Inbound	Public_Defensive
UC.92	Analytic_Singleton	Operation_Driven	Weak_Inbound	Private_Incremental
UC.93	Cognitive_Singleton	Demand_Driven	Weak_Inbound	Private_Incremental
UC.94	Analytic_Swarm	Engineering_Driven	Weak_Inbound	Private_Defensive
UC.95	Analytic_Swarm	Engineering_Driven	Weak_Inbound	Private_Liberal
UC.96	Analytic_Swarm	Demand_Driven	Weak_Inbound	Public_Incremental
UC.97	Analytic_Singleton	Expertise_Driven	Weak_Outbound	Public_Incremental
UC.98	Generative_Swarm	Engineering_Driven	Weak_Outbound	Public_Disruptive
UC.99	Generative_Swarm	Engineering_Driven	Weak_Outbound	Public_Disruptive
UC.100	Parasitic_Swarm	Operation_Driven	Weak_Outbound	Public_Disruptive
UC.101	Analytic_Swarm	Engineering_Driven	Casual_Outbound	Public_Incremental
UC.102	Analytic_Singleton	Expertise_Driven	Casual_Outbound	Public_Incremental
UC.103	Cognitive_Swarm	Business_Driven	Casual_Outbound	Public_Incremental
UC.104	Cognitive_Swarm	Operation_Driven	Weak_Inbound	Public_Disruptive
UC.105	Cognitive_Swarm	Demand_Driven	Weak_Inbound	Public_Disruptive

UC.Pseudo.	Innov. Capacity (IC)	Internal Innov. (II)	Open Innov. (OI)	Innov. Policy (IP)
UC.106	Cognitive_Swarm	Expertise_Driven	Weak_Inbound	Public_Disruptive
UC.107	Generative_Swarm	Engineering_Driven	Casual_Outbound	Private_Disruptive
UC.108	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Liberal
UC.109	Analytic_Singleton	Operation_Driven	Casual_Inbound	Private_Liberal
UC.110	Analytic_Swarm	Strategy_Driven	Regular_Outbound	Public_Disruptive
UC.111	Analytic_Swarm	Demand_Driven	Casual_Inbound	Private_Liberal
UC.112	Analytic_Singleton	Mission_Driven	Regular_Outbound	Private_Disruptive
UC.113	Analytic_Singleton	Business_Driven	Casual_Outbound	Private_Incremental
UC.114	Analytic_Singleton	Strategy_Driven	Regular_Outbound	Private_Liberal
UC.115	Analytic_Swarm	Expertise_Driven	Systematic_Outbound	Public_Incremental
UC.116	Analytic_Singleton	Expertise_Driven	Casual_Outbound	Public_Incremental
UC.117	Analytic_Singleton	Expertise_Driven	Casual_Outbound	Public_Incremental
UC.118	Generative_Singleton	Engineering_Driven	Casual_Outbound	Public_Disruptive
UC.119	Generative_Swarm	Expertise_Driven	Systematic_Outbound	Public_Liberal
UC.120	Cognitive_Swarm	Expertise_Driven	Regular_Outbound	Public_Liberal
UC.121	Analytic_Singleton	Demand_Driven	Casual_Outbound	Public_Incremental
UC.122	Cognitive_Swarm	Engineering_Driven	Systematic_Outbound	Public_Disruptive
UC.123	Analytic_Singleton	Strategy_Driven	Weak_Outbound	Public_Defensive
UC.124	Analytic_Singleton	Demand_Driven	Regular_Inbound	Public_Incremental
UC.125	Analytic_Singleton	Operation_Driven	Systematic_Inbound	Public_Incremental
UC.126	Cognitive_Swarm	Expertise_Driven	Systematic_Outbound	Public_Disruptive

ANNEX 8: SUMMARY OF INTERVIEWS

Respondent's Consent:

In this annex, we produce an analysis of interviews grouped by organisation. The interviewees are introduced as (**EXP.n**) according to the pseudonyms defined in ANNEX 3: List of Experts. The organisations are introduced as (**ORG.n**) according to the pseudonyms defined in ANNEX 6: Organisations List. Use cases are identified as (**UC.n**) according to the Pseudonyms defined in ANNEX 8: Use-cases List. Observable variables of interest are marked as (Variable = Observed Value). When the interview informs about one of the hypotheses extracted from the exploratory study, the related sentence is marketed with (***Hn***).

ORG.1 Manufacture of other textiles

ORG.1 is a small family business (OT = SME) located in Portugal, involved since 1965 in label printing (OA = I2.0). EXP.1 is the Maintenance Director and is in charge of the industrial shop floor, comprising looms involved in the production of textile labels, woven labels, and printed labels (OP = Goods). He introduces a use case for AI to improve the label printing process through connected looms **(UC.1)**.

Looms are legacy equipment, requiring regular maintenance and manual operations for production orders, process control, and product quality control (AP = Manufacturing). ORG.1 aims to deploy connected sensors that will collect machine data and feed a heuristic-based decision system for production monitoring (AR= Monitoring) (AT = Symbolic Virtual Object) (AM = Physical Systems) ***(H1)***.

According to EXP.1, the employees of this rather traditional industry consider with interest the potential for AI to automate some of their manual tasks (RS = Replace Operators). AI would also support improved management of product variants (PS = Custom Product), improved quality control, and reduced production cost (MS = Product Specialization) ***(H2)***.

The company relies on a local information technology vendor to deploy AI-based loom monitoring into the plant (NS = Purchase). The R&D is led by an academic research centre (OI = Systematic Inbound). Employees have rejected another innovation proposal involving AI in monitoring worker behaviour (IC = Analytic Singleton). Although this second use case was meant to improve worker safety, it has been perceived as violating workers' privacy ***(H3)***.

ORG.2 Manufacture of machinery and equipment

ORG.2 is a small Finnish company (OT = SME) that produces a wide variety of small series stainless steel products, including a growing branch of cheese-making machines (Product = Materials) (CA = I1.0). EXP.2 is the Vice President of the company and EXP.3 is the Development Manager. They introduce ORG.2 as a small-scale service-driven mechanical manufacturing company specialising in metal working. They consider AI adoption to improve the cheese production process **(UC.2)**.

The first implementations of Artificial Intelligence (AI) in this business have been for cheese quality control on ORG.2 customers' premises (AP = in Operations). Further potential lies in process optimisation and predictive maintenance applications (AR = Optimization). Yet, at this stage, ORG.2's activity relies essentially on the workforce of 30 metal workers (OS = Mechanics) (AM = Social System) ***(H1)*.**

Deploying UC.2 requires secure handling of customer data and the use of explainable AI embedded in the physical machines (AT = Symbolic Embodied Object). According to EXP.2, ORG.2's customers have been collecting process and product data for many years without using it

(NS = Crowdsource). AI-based image analysis supports cheese quality inspection, a task that historically relied solely on human observation (RS = Augment Operator). Having access to customer data will enable service integration in their offering and enhanced product differentiation (PS = Custom PSS) ***(H2)***.

ORG.2 uses public funds to engage in collaborative innovation projects with partners they consider for business development perspectives (OI = Regular Outbound). EXP.2 and EXP.3 believe AI integration in cheese machines eventually gives ORG.2 a greater influence on their customer's products in terms of quality, eventually displacing cheese production knowledge from the milkers to the ORG.2'industrial cloud (IC = Analytic Singleton) ***(H3)***.

ORG.3 Manufacture of other special-purpose machinery

ORG.3 is a medium size robotics programming company (OT = SME) (OP = Software) delivering decision software for Automated Guided Vehicles (AGVs) (OA = I4.0). EXP.4, Director of Engineering, is the inventor of an interesting AI use-case for robot fleet programming (AT = Self-learning Embodied Humanoid), with application in industrial logistics (AP = in Operation) **(UC.3)**.

An important aspect of this development is the ability of distributed AI to make optimal decisions while individual objectives of the robots may conflict (AR = Optimization). AGVs indeed embed a local decision module that commands robot actions in the physical space (AM= Cyber-Physical System) ***(H1)***.

The robot fleet management software requires customer-specific engineering and model fine-tuning, handled in project mode (PS = Custom PSS). It is meant to operate in a factory environment in support of human workers (RS = Augment Operators). Eventually, robot fleets might become intelligent enough to be deployed in any customer environment and be sold as a service (MS = Product Servitisation) ***(H2)***.

ORG.3 has an intellectual property policy, that is somewhat cautious and proprietary (IP = Private Incremental). In particular, product source code is homemade and not shared (II = Engineering Driven). However, ORG.3 occasionally uses open-source software and participates in collaborative innovation projects to create customer references (OI = Casual Outbound). Using simulation-based training involving multi-agent systems makes ORG.3's robot fleet remarkably adaptive and reduces dependence on customer data that is often lacking (IC = Analytic Swarm)***(H3)***.

ORG.4 Manufacture of consumer electronics

ORG.4 is a multi-industry group of 24 companies that manufacture electronics, household appliances, mobile technologies, lighting, and defence products (OT = IND) (OS= Electronics) (CA = Industry 3.0). EXP.5 is a Senior Software Architect at ORG.4. In this interview, he depicts three AI use cases.

UC.4 aims to automate Printed Circuit Board (PCB) assembly (AR = Automation) (AP = Manufacturing). It relies on the deployment of AGVs (AM = Cyber-Physical System) **(*H1*)**. UC.4 will automate shop-floor logistic activities currently handled by workers (RS = Replace Operators). EXP.5 reports that the COVID pandemic has positively affected the acceptance and adoption of AI by manufacturing professionals. The PCM assembly line must scale to meet the market demand for this mass-consumption product (MS = Product Specialization) **(*H2*)**. UC.4 is demanded by plant management and will ultimately give AGVs total control of PCB production line logistics (II = Operation-Driven) (IC = Analytic Swarm) **(*H3*)**.

UC.5 aims to improve equipment maintenance by the use of predictive analytics processing real-time machine data (AP = Maintenance) (AR = Prediction) (AM = Cyber System) **(*H1*)**. UC.5 will provide real-time maintenance recommendations to the machine supplier (NS = Specify). This helps ORG.4 improve their control of the plastic injection moulding process (MS = Process Specialisation) **(H2)**. UC.5 involves a

collaboration with the plastic injection machine supplier who will benefit from AI-generated maintenance instructions (OI = Systematic Outbound) (IC = Analytic Swarm) **(*H3*)**.

UC.6 aims to personalise media broadcast recommendations based on user behaviour data (AP = Commissioning) (AR = Collaboration) (AM = Cyber-Social System) ***(H1)***. UC.6 will integrate media recommendation service in the consumer electronics offering (PS = Custom PSS) (MS = Product Servitisation) ***(H2)***. UC.6 will exploit customer preference data, currently obfuscated by resellers, through the deployment of device-embedded recommendation agents (IP = Private Disruptive) (IC = Systematic Outbound) ***(H3)***.

ORG.5 Manufacture of spacecraft and related machinery

ORG.5 is a division of a large aerospace manufacturing group (OT = IND). Specifically, the ORG.5 military aircraft business unit manufactures troop transportation aircraft (OP = System). EXP.6 and EXP.7 manage automation projects for manufacturing activities performed in Spain, where military aircraft fuselage, rudder, and other mechanical parts are produced (OS = Mechanics). This activity dates back to the beginning of aeronautics in Spain (OA = I3.0). The interview gives insights into three industrial AI use cases.

UC.7 deals with applying Computer Vision (CV) technology for improved control of logistics activities (AR = Monitoring). The CV analytics process data at the edge of logistic automation and extract metrics that they passively report for human decision (AM = Cyber System) **(*H1*)**. UC.7 agent interprets camera pictures to extract valuable information about aircraft parts, namely to identify, position, or recognise (missing) parts (MS = Process Specialization) (***H2***). UC.7 replaces human visual inspection with CV analytics which eventually develops super-human performance (IC = Analytic Swarm) (***H3***).

UC.8 involves ML techniques for real-time monitoring and control of industrial automation (AR = Automation). This use case involves active control of the rivet-shaving process on aeronautical parts by a robotic arm (AM = Cyber-Physical System) (***H1***). UC.8 relies on a third-party IoT platform that processes real-time production data (MS = Process Servitisation) (***H2***). **UC.8** provides novel process improvement paths that humans would potentially not have considered (IC = Cognitive Swarm) (***H3***).

UC.9 deals with AI applications for aircraft testing in support of aeronautical engineers (AR = collaboration). It involves a Natural Language Processing (NLP) algorithm capable of natural interactions with test personnel (AM = Cyber-Social System) **(*H1*)**. **UC.9** greatly improves quality control on aircraft products to meet very high safety requirements demanded by this industry (MS = Analytic Swarm) **(*H2*)**. **UC.9** provides human-readable metrics for augmented human quality control (IC = Cognitive Singleton) ***(H3)***.

ORG.6 Manufacture of other special-purpose machinery

ORG.6 is a highly innovative startup involved in smart collaborative robotics established in Spain (OT = SME) (OA = I5.0). EXP.8 is the founder and CEO. He has a Master in Engineering of Telecommunications and an executive MBA (OS = Computing). He developed an offering for collaborative robots addressing the needs of the manufacturing sector (AR = Collaboration) **(UC.10)**.

Unlike programmable fixed automation, industrial cobots can handle small scale highly specific production activities (AP = Operation). The humanlike shape and learning ability of ORG.6 products make them usable in environments that have, up to now, resisted automation (AT = Machine-Learning Embodied Humanoid) (AM = Cyber-Physical-Social System) ***(H1)***.

EXP.8 considers their robots do not take the jobs of humans; rather, humans too often work like robots (RS = Replace Operators). ORG.6 develops both hardware and software layers of industrial cobots (NS = Develop). They have specific customer agreements enabling them to

complete robot learning in operations (PS = Custom PSS). Beyond native abilities, the underlying AI algorithms can be finetuned to address customer-specific demand (MS = Product Servitisation) ***(H2)***.

ORG.6 systematically uses collaborative innovation projects to expand its customer base (OI = Systematic Outbound). The company has no distinct R&D department as essentially the whole engineering workforce is doing R&D (II = Engineering Driven). The existence of a research business unit attests to the deliberate integration of research in the core business (IP = Private Disruptive). EXP.8 expects a growing share of the innovation to result from human-robot learning integration in distributed operational environments (IC = Cognitive Swarm) ***(H3)***.

ORG.7 Other telecommunications activities

ORG.7 is a Non-Profit Organisation established in Germany that aims to provide analytics as a service for applications such as electricity production monitoring or aviation security and safety (OT = NPO) (OA = I4.0). EXP.9 and EXP.10 are young entrepreneurs and cofounders of ORG.7. EXP.8 has a Master's degree in Aeronautics and a Doctoral degree in Philosophy in the field of Cognitive Systems and Artificial Intelligence (OS = System Engineering). EXP.9 owns a Doctoral degree in the fields of Behavioural Science and Epistemology and a Master's in Architecture (OS = Human Sciences). They introduce two service-driven AI use cases.

UC.11 leverages AI analytics for predictive maintenance and anomaly detection services operated on a cloud platform (AM = Cyber System) (***H1***). Customers are the primary sources of training data, and the algorithms only perform if many customers subscribe (NS = Crowdsource). In UC.11, cloud analytics support maintenance managers' decisions (RS = Augment Managers). The company is funded by private equity and the owners seek primarily private investors motivated by innovation promise (IP = Private Disruptive). UC.11 agent is centralised and hosted in a cloud platform that generates maintenance and security recommendations based on streaming data (IC = Analytic Singleton).

UC.12 leverages AI in drone-based water level monitoring for hydroelectricity supply prediction purposes (AM = Cyber-Physical System) **(*H1*)**. Here again, customers are the primary sources of training data, and the algorithms only perform if many customers subscribe (NS = Crowdsource). In UC.12 private drones replace water dam personnel (RS = Replace Operators). In both use cases, ORG.7 takes over support services within customer Organisations (MS = Process Servitisation) **(*H2*)**. The company is funded by private equity and the owners seek primarily private investors motivated by innovation promise (IP = Private Disruptive). UC.12 agents are distributed over a large fleet of private UAVs that collaboratively supply the relevant hydroelectric generation data (IC = Analytic Swarm) **(*H3*)**.

ORG.8 Activities of extra-territorial organisations and bodies

ORG.8 is a not-for-profit, industry-driven association promoting the development of new and innovative production technologies for the manufacturing sector. EXP.11 is a Service Provider at ORG.8. In his role, he has a 360° view of European Industry and a foresight on manufacturing trends and disruptions. This interview provides a useful outlook on the European innovation ecosystem for the manufacturing industry and a set of 3 AI use cases.

UC.13 deals with bonding process optimisation by the use of AI-enhanced machines (AI role = Optimization) (AM = Cyber-Physical System) (**H1**). **UC.13** helps the production manager set optimal bonding parameters for mass production of standard electronics (RS = Augment Manager) (BS = Product Specialization) (***H2***). **UC13** is driven by a central product quality control policy (II = Engineering Driven) (IC = Analytic Singleton) (***H3***).

UC.14 deals with smart weaving process automation by the use of AI-controlled looms (OS = Mechanics) (AM = Cyber-Physical System) (**H1**). **UC.14** takes over manual weaving activity for mass production of standard textile goods (RS = Replace Operator) (MS = Product

Specialization) (***H2***). The plant commands UC.14 and would eventually give AI complete control of the weaving process (Operation-Driven) (IC = Analytic Singleton) (***H3***).

UC.15 deals with Safe Human-Robot Interaction through the use of collaborative robotics (OS = Computing) (AM = Cyber-Physical Social Object) (***H1***). **UC.15** enables safe robotic support to workers for the flexible production of personalised goods (RS = Augment Operator) (MS = Product Customization) **(H2)**. **UC15** is directed by firm management in an attempt to leverage synergies of human-machine teaming (II = Strategy Driven) (IC = Cognitive Swarm) **(*H3*)**.

ORG.9 Other research and experimental development on natural sciences and engineering

ORG.9 is a Portuguese research and technology institute competent in systems and computer engineering with a long experience in R&D and technology transfer (OT = RTO). EXP.12 is a member of the Board at ORG.9 and an active member of several European manufacturing digitisation initiatives. EXP.13 is Chairman of the Board and Full Professor in a Portuguese engineering school. They introduce two AI use cases.

UC.16, proposed by EXP.12, deals with industrial process optimisation with AI embedded in Electrical Control Units (ECUs) (OS = Electrical Engineering). UC.16 involves deterministic AI embedded in automation systems to support process optimisation (AT = Symbolic Embodied Object) (AP = Manufacturing). **UC.16** aims to automatically adjust production parameters according to environmental conditions for the completion of very repetitive manufacturing tasks (RS = Replace Operator) (MS = Product Specialization) (***H2***). UC.16 is fostered by production engineers and supported by European funds to reduce production hazards inherent to human-led fabrication (II = Demand Driven) (IP = Public Defensive).

UC.17, proposed by EXP.13, deals with AI-based business process modelling (CS = Computing). UC.17 involves ontology-based reasoning for optimal enterprise resource management across supply chains (AT = Symbolic Virtual Object) (AP = Commissioning) **(*H1*)**. UC.17 aims to ensure optimal business process management by the use of AI-powered enterprise software (RS = Augment Manager) (AM = Process Specialization) ***(H2)***. UC.17 is led by supply chain management and supported by European standardisation initiatives, aiming to counter the lack of interoperability of proprietary technology (II = Demand-Driven) (IP = Public Incentive) ***(H3)***.

ORG.10 Other research and experimental development on natural sciences and engineering

ORG.10 is a laboratory that conducts research and development in cutting-edge scientific and technological fields relevant to manufacturing and industrial automation. EXP.14 is a Mechanical Engineer and Head of ORG.10 Laboratory (CS = Mechanics). He describes a use-case of AI for human-centred industrial robotic applications (**UC.18**).

It is a research and technology initiative driven by Industry 5.0 vision aiming to make robotics flexible and accessible, including to small companies (CA = Industry 5.0). The use-case involves collaborative robots using reinforcement learning, crafted with safe and intuitive human-machine collaboration abilities (AT = Machine-Learning Embodied Object) (AM = Cyber-Physical Social System) ***(H1)***.

The interviewee suggests that the rejection of AI by human experts is most often due to irrational fears that they would lose control. Unlike heavy automation, cobots support workers by completing on-demand manufacturing tasks, enabling flexible human-controlled production (RS = Augment Operators) (BS = Process Specialization) ***(H2)***.

EXP.14 supports the European regulatory approach to privacy-compliant, ethical, and trustworthy AI, which he believes can trigger product innovation (IP = Public Disruptive). He shows some concern that over-relying on AI may lead to laziness and, consecutively, a reduction of human ability to analyse situations critically (IC = Cognitive Swarm) ***(H3)***.

ORG.11 Manufacture of weapons and ammunition

ORG.11 is a large company involved in manufacturing aeronautics, defence and security systems (OT=IND). EXP.15 is the Head of the Mechanical Design Office. EXP.16 is the Head of the Mechanical Design Laboratory. EXP.17 is a Research Engineer in Robotics and Computer Vision. EXP.18 is a Project Manager in Security Hardware Products.

EXP.15 and EXP.16 use generative AI in the design of mechanical parts (**UC.19**). With adequate specifications from a system engineer (OS = System Engineering), the generative design software will provide optimal mechanical designs, reducing parts' weight and cost while improving resistance and aerodynamics compared to human-made designs (AR = Optimisation). The software manipulates structured design data, not yet natural language (AT = Generative Unimodal). It does not yet handle the complexity of mechanical production processes (AM = Cyber System) (***H1***). UC19 enables one-shot mechanical design to meet very specific customer requirements for unique systems or small-scale productions with integrated services (PS = Custom PSS). The software tool is a procurement item that comes either as a service (SaaS) or as a license for on-premise operations. The latter is preferred by ORG.11 because product design data can be very sensitive (NS = Purchase) (MS = Product Specialisation) (***H2***). UC19 results from a corporate initiative aiming to modernise mechanical design activities while reducing the environmental footprint of ORG.11's products (IP = Private Disruptive). While EXP.15 highlights the synergetic effect of confronting human-made and generative design, EXP.16 fears that the competence to challenge the generative AI vanishes with the generalisation of its use (IC = Generative Singleton) (***H3***).

EXP.17 develops computer vision techniques for Automated Mobile Robots to move safely around human workers (**UC.20**). He uses Convolutional Neural Networks (CNNs) to detect, classify and identify objects or humans in a shop-floor environment and adapt the robot navigation controls accordingly (AT = Machine Learning Embodies Object) (AM = Cyber-Physical) (***H1***). UC20 on the other hand relies on analytics developed by ORG.11 (NS = develop). These analytics can be deployed in the customer environment to support safe shopfloor logistics automation (MS = Process Specialisation) (***H2***). The AI agents would safely operate among human workers but also collaboratively optimise their routes in a distributed manner (IC = Cognitive Swarm) (***H3***).

EXP.18 manages a research and technology project addressing the connectivity of the wood supply chain. The contribution of ORG.11 in this project is to develop a trusted key manager to secure real-time data exchange between sawmills, wood factories and wooden houses (**UC.21**). The machine learning algorithm must detect cyber-attacks against the telecommunication infrastructure (AR = Detection) (AM = Cyber System) (***H1***). UC.21 provides information security assurance to the management level of wood industry organisations in adopting more connected supply chain approaches (RS = Augment Managers) (***H2***). AI, in this case, enables secure centralised identity and access management, relieving network administrators from routine surveillance tasks (IC = Analytic Singleton) (***H3***).

ANNEX 9: VARIABLE CATEGORIES

Organisation Characteristics

The following table displays the possible categories for each Organisation Characteristics variable.

Organisation Characteristics			
Organisation Age	Organisation Product	Organisation Type	Organisation Skills
-Industry 1.0	-Materials	-SME	-Farming
-Industry 2.0	-Goods	-IND	-Mining
-Industry 3.0	-Hardware	-RTO	-Construction
-Industry 4.0	-Software	-ACA	-Fabrication
-Industry 5.0	-System	-NPO	-Mechanics
	-Service		-Electrical Eng.
	-Science		-System Eng.
			-Computing
			-Life Science
			-Business

The Organisation variable classes have been matched with Industry 5.0 communication from the European Commission (2022), European Commission Recommendation 2003/361 and NACE Rev. 2 Statistical classification of economic activities in the European Community from EUROSTAT.

Artificial Intelligence

The following table displays the possible categories for each Artificial Intelligence variable.

Artificial Intelligence Variables			
AI Maturity -Human System -Physical System -Cyber System -Physical Social System -Cyber-Social System -Cyber-Physical-System -Cyber-Physical-Social System	AI Type -Symbolic Virtual / Embodied Object / Humanoid -Machine-Learning Virtual / Embodied Object / Humanoid -Generative Unimodal / Multimodal	AI Place -Design -Manufacturing -Testing -Commissioning -Operation -Maintenance -Recycling	AI Role -Education -Prediction -Detection -Monitoring -Automation -Analysis -Decision -Optimization -Collaboration -Resilience

The Artificial Intelligence variable classes have been matched with the system engineering taxonomy from Yilma et al (2020), a modern approach to AI from Russel & Norvig (2021) and contemporary work from manufacturing automation literature.

Business Strategy

The following table displays the possible categories for Business Strategy variable.

Business Strategy Variables (BS)			
Mfg. Strategy -Product / Process Specialization -Product / Process Servitisation -Product / Process Customization	Resources Strategy -Replace-Operators / Engineers / Managers / Customers / All -Augment- Operators / Engineers /	Network Strategy -Purchase -Customize -Specify -Develop -Acquire -Crowdsource	Product Strategy -Standard Product -Standard Service -Standard PSS -Custom Product -Custom Service -Custom PSS

-Mass-Customization -Social-Manufacturing	Managers / Customers / All		

The Business Strategy variables have been matched with the Porter value chain (1980), social manufacturing approaches from Jiang et al (2016), theories of replacement and augmentation (Noponen, 2019) and circular economics (Tukker, 2015.).

Innovation Management

The following table displays the possible categories for each Innovation Management variable.

Innovation Management Variables			
Innovation Capacity -Analytic / Cognitive / Generative / Parasitic Singleton -Analytic / Cognitive / Generative / Parasitic Swarm	<u>Internal Innovation</u> -Operation-Driven -Engineering-Driven -Business-Driven -Demand-Driven -Strategy-Driven -Expertise-Driven	<u>Open Innovation</u> -Weak Inbound / Outbound -Casual Inbound / Outbound -Regular Inbound / Outbound -Systematic Inbound / Outbound	<u>Innovation Policy</u> -Private-Defensive / Incremental / Liberal / Disruptive -Public Defensive / Incremental / Liberal / Disruptive

Innovation Management classes have been matched with research work on technology forecasting (Aghion, Jones, & Jones, 2017), open innovation management (Chesbrough, 2014) and innovation policy (Agrawal, Gans, & Goldfarb, 2019).

ANNEX 10: ONLINE QUESTIONNAIRE

AI effect on Innovation Capacity in the context of Industry 5.0

Survey Questionnaire

Survey Preamble: Hello, my name is Adrien Bécue, I [AM] AI & Cybersecurity expert at THALES, and PHD student at the University of Porto where I conduct this research about AI effect on Innovation Capacity in the context of Industry 5.0. This survey aims to answer the question:

"What factors influence the effect of Artificial Intelligence (AI) on Innovation Capacity in the context of Industry 5.0?"

If you are involved in industrial AI use-cases, please take a few minutes to answer this questionnaire. Your effort will be rewarded by free access to the study results, including strategic recommendations for a successful transition to Industry 5.0.

Any information collected during this study that identifies you or your Organisation will be kept confidential. Input data will be stored in environments secured by state-of-the-art cryptographic means. The data will be anonymised and aggregated in ways that prevent any reidentification.

If you feel like you are not competent to answer a specific question, or if you believe the right answer is not included in the choice list, please check the “I don’t know / others” item. You can provide personalised answers in the text box.

Consent form

I voluntarily agree to participate in the survey. I have read the survey preamble which includes information about the nature and purpose of the survey, as well as a description of the survey information. I understand that I [AM] free not to participate in the survey or to withdraw from it at any time.

- Yes
- No

General Information

This section aims to register your answer and identify your industrial AI use-case.

Q01- Please provide the following contact information

- Free text field for “First name”: []
- Free text field for “Family name”: []
- Free text field for “Organisation name”: []
- Free text field for “Organisation country”: []
- Free text field for “email”: []

Q02- Please provide a short title for your industrial AI use-case

- Free text field for “use-case title”: []

Section 1 – Organisation profile

This section aims to characterize the Organisation carrying the AI use-case

Q03- Which item describes the Organisation’s main product?

Choice list	Value
Materials (raw materials such as minerals, wood, metals,…)	Materials
Goods (consumable goods such as food, basic manufactured goods, …)	Goods
Hardware (physical components such as chips, processors, …)	Hardware
Software (logical components such as programs, applications, …)	Software
System (integrated systems such as computers, vehicles, robots, …)	System
Service (monitoring, maintenance, cloud services, data services, …)	Service
Science (research and technology work such as studies, prototypes…)	Science

I don’t know / Others (please specify)

Q04- Which type of Organisation is carrying the AI-use-case?

Choice list	Value
SME (small enterprise, up to 250 employees)	SME
LE (large enterprise, more than 250 employees)	LE

RTO (Research and technology Organisation)	RTO
NPO (non-profit Organisation)	NPO

I don’t know / Others (please specify)

Q05- What is the Organisation’s main skills area?

Choice list	Value
Farming (growing crops and raising livestock)	Farming
Extraction (collecting raw materials such as minerals, metals or wood)	Extraction
Construction (building large permanent or temporary infrastructures)	Construction
Mechanics (applied physics of motion and forces producing motion)	Mechanics
Energy (applied physics of power and energy systems)	Energy
Electronics (applied physics of electrons in conductors, vacuum or gas)	Electronics
Computing (study/use of computers to complete goal-oriented tasks)	Computing
Data Science (the extraction of actionable information from raw data)	Data Science

I don’t know / Others (please specify)

Q06- Which industrial age best characterizes the Organisation?

Choice list	Value
Industry 1.0 (mechanized production, coal and steam-power…)	Industry10
Industry 2.0 (electrified production, integrated production line…)	Industry20
Industry 3.0 (preprogrammed or computerized production…)	Industry30
Industry 4.0 (smart manufacturing, intelligent production…)	Industry40
Industry 5.0 (collaborative robotics, bionics, cybernetics …)	Industry50

I don’t know / Others (please specify)

Section 2 – Industrial AI use-case

This section aims to understand and qualify your industrial AI use-case.

Q07- Which item best describes the type of AI technique you aim to use?

Choice list	Value
Symbolic AI (knowledge-based)	Symbolic
Machine learning (learning from data)	Learning

I don’t know / Others (please specify)

Q08- Which item best describes the type of AI agent you aim to use?

Choice list	Value
Virtual agent (without sensorimotor capacities)	Virtual
Embodied agent (with sensorimotor capacities)	Embodied

I don’t know / Others (please specify)

Q09- Which item best describes the type of AI interface you aim to use?

Choice list	Value
Object (a machine-like interface)	Object
Humanoid (a human-like interface)	Humanoid

I don’t know / Others (please specify)

Q10- Which item best describes the place where you aim to use AI within the product lifecycle?

Choice list	Value
Design (at the design or development stage)	Design
Manufacturing (at the product manufacturing stage)	Manufacturing
Commissioning (at the delivery stage)	Commissioning
Operation (at product exploitation stage)	Operation
Maintenance (at product maintenance stage)	Maintenance
Recycling (at end of product life)	Recycling

I don’t know / Others (please specify)

Q11- Among the following, which item best describes the primary role of AI in this use-case?

Choice list	Value
Education (better educate/train students, employees or managers)	Education
Prediction (better anticipate events, incidents or trends)	Prediction
Decision (inform, support or make decision with industrial effects)	Decision
Monitoring (watch industrial processes or products usage)	Monitoring
Optimization (maximize asset productivity and/or product fit)	Optimization
Automation (carry activities previously performed by humans)	Automation
Collaboration (interact naturally with machines and/or humans)	Collaboration
Resilience (improve industrial safety, security, and/or reliability)	Resilience
Sustainability (reduce negative impacts on the environment)	Sustainability

I don’t know / Others (please specify)

Q12- Which item best describes the primary asset in your AI use-case?

Choice list	Value
Social System (it relies primarily on human power)	Social-
Physical System (it relies primarily on mechanical power)	Physical-
Cyber System (it relies primarily on computing power)	Cyber-

I don’t know / Others (please specify)

Q13- Which item best describes the secondary asset in your AI use-case?

Choice list	Value
None (my AI-use case does not involve a secondary asset)	System
Social System (it relies secondarily on human power)	Social
Physical System (it relies secondarily on mechanical power)	Physical
Cyber System (it relies secondarily on computing power)	Cyber

I don’t know / Others (please specify)

Q14- Which item best describes the third asset in your AI use-case?

Choice list	Value
None (my AI-use case does not involve a third asset)	System
Social System (it relies thirdly on human power)	Social
Physical System (it relies thirdly on mechanical power)	Physical
Cyber System (it relies thirdly on computing power)	Cyber

I don’t know / Others (please specify)

Section 3 – Manufacturing Strategy

This section aims to assess the manufacturing strategy of the Organisation carrying the AI use-case.

Q15- Which is the most likely outcome of the AI use-case implementation?

Choice list	Value
Replace employees (AI will likely replace employees by automating some or all of their activities)	Replace-
Augment employees (AI will likely augment employees by enhancing their physical, social or cognitive abilities)	Augment-

I don’t know / Others (please specify)

Q16- Which population will be most affected by AI use-case implementation?

Choice list	Value
Operators (AI will mostly affect activities handled by manual workers)	Operators
Engineers (AI will mostly affect activities handled by designers)	Engineers
Managers (AI will mostly affect activities handled by managers)	Managers
Customers(AI will mostly affect activities handled by customers)	Customers

I don’t know / Others (please specify)

Q17- Which item best describes the network strategy of the Organisation carrying the AI use-case?

Choice list	Value

Purchase (my Organisation buys technology off the shelf with no or little customization to our specific business)	Purchase
Customize (my Organisation integrates and customizes off-the-shelf technology to fulfil our specific business needs)	Customize
Specify (my Organisation provides technical specifications for technology to be developed and integrated by subcontractors)	Specify
Develop (my Organisation develops proprietary technology fulfilling our specific business requirements)	Develop
Acquire (my Organisation acquires technology from startups and tech firms through merger & acquisition campaigns)	Acquire
Crowdsource (my Organisation leverages technology from open source or collaborative source to fulfil our business requirements)	Crowdsource

I don’t know / Others (please specify)

Q18- Which item best describes the Organisation’s customization strategy?

Choice list	Value
Standard (my Organisation aims to deliver large quantities of standard products and/or services)	Standard-
Custom (my Organisation aims to deliver personalized products and/or services)	Custom-

I don’t know / Others (please specify)

Q19- Which item best describes the Organisation’s portfolio strategy?

Choice list	Value
Product (my Organisation primarily aims to manufacture products)	Product
Service (my Organisation primarily aims to deliver services)	Service

Product Service System (my Organisation aims to deliver a synergic mix of products and services)	PSS

I don’t know / Others (please specify)

Q20- Which item best describes your Organisation’s main competitive strategy?

Choice list	Value
Product/Service excellence (my Organisation aims to compete primarily by the quality of its products or services)	Product-
Process excellence (my Organisation aims to compete primarily by the efficiency of its processes)	Process-

I don’t know / Others (please specify)

Q21- Which item best describes your Organisation’s manufacturing strategy?

Choice list	Value
Specialization (my Organisation aims to focus on a single activity where it outperforms the competition)	Specialization
Servitization (my Organisation aims to differentiate by buying and/or selling more services)	Servitization
Customization (my Organisation aims to differentiate by further customizing its processes and/or products)	Customization

I don’t know / Others (please specify)

Section 4 – Innovation Capacity

This section aims to assess the manufacturing strategy of your Organisation

Q22- Which item best describes your internal innovation approach?

Choice list	Value
Operation-Driven (my Organisation defines innovation priorities based primarily on operators' requirements)	Operation-Driven
Engineering-Driven (my Organisation defines innovation priorities based primarily on upcoming engineers' ideas)	Engineering-Driven
Business-Driven (my Organisation defines innovation priorities based primarily on business objectives)	Business-Driven
Demand-Driven (my Organisation defines innovation priorities based primarily on demand trends)	Demand-Driven
Strategy-Driven (my Organisation defines innovation priorities based on a formalized innovation strategy)	Strategy-Driven
Expertise-Driven (my Organisation defines innovation priorities based on a formalized technology roadmap)	Expertise-Driven

I don't know / Others (please specify)

Q23- Which item best describes your approach to open innovation?

Choice list	Value
Weak (my Organisation never or rarely collaborates with academics, research centres and/or enterprises in matters of innovation)	Weak-
Casual (my Organisation sometimes collaborates with research Organisations and/or enterprises in matters of innovation)	Casual-
Regular (my Organisation regularly collaborates with research Organisations and/or enterprises in matters of innovation)	Regular-
Systematic (my Organisation always seeks for collaboration with research Organisations and/or enterprises in matters of innovation)	Systematic-

I don’t know / Others (please specify)

Q24- Which item best describes your Organisation’s motivation to engage in open innovation?

Choice list	Value
Inbound (my Organisation collaborates with other entities primarily to capture innovation)	Inbound
Outbound (my Organisation collaborates with other entities primarily to share innovation)	Outbound

I don’t know / Others (please specify)

Q25- Among the following, which item best describes your Organisation’s innovation policy?

Choice list	Value
Private-driven (my Organisation fosters innovations which creates value for investors, employees and/or customers)	Private-
Public-driven (my Organisation fosters innovations which improve compliance to regulation, security of citizens and public welfare)	Public-

I don’t know / Others (please specify)

Q26- Among the following, which item best describes your Organisation’s innovation ambition?

Choice list	Value
Defensive (my organisation fosters intellectual property protection and certification frameworks to protect established standards)	Defensive

Incremental (my Organisation fosters improvements of existing processes, products and/or services to develop established standards)	Incremental
Disruptive (my Organisation fosters new processes, products and/or services with the potential to disrupt existing standards)	Disruptive

I don’t know / Others (please specify)

Q27- Among the following, which item best describes the future role of AI in your Organisation’s innovation capacity?

Choice list	Value
Analytic (AI will gradually relieve humans from analytical tasks leaving creative tasks to humans)	Analytic
Cognitive (AI will help humans better interact with machines, freeing their minds for enhanced creative thinking)	Cognitive
Generative (AI will relieve humans from analytical and creative tasks, taking its share of innovation activities)	Generative
Parasitic (AI will become overwhelming and gradually take over human innovation capacity)	Parasitic

I don’t know / Others (please specify)

Q28- Among the following, which item best describes the future place of AI in your Organisation’s innovation capacity?

Choice list	Value
Singleton (A centralized/hegemonic AI capacity emerges which can make unilateral decisions and actions)	Singleton

Swarm (A decentralised/federated AI capacity emerges which negotiates decisions and distributes actions)	Swarm

I don’t know / Others (please specify)

Thanks!

Thanks a lot for your answers! They will contribute to a better understanding of the the effect of Artificial Intelligence (AI) on Innovation Capacity in the context of Industry 5.0.

Q29- Would you like to receive updates of this research by email?

- Yes, please send me survey results and major updates about the study progress
- No, please do not send me any update about this study

ANNEX 11: CONDITIONAL PROBABILITIES

Organisation Characteristics

Organisation Age [OA]

Industry10	0.03968254
Industry20	0.055555556
Industry30	0.3968254
Industry40	0.17460317
Industry50	0.33333333

Organisation Product [OP]

L_Organization...	Industry10	Industry20	Industry30	Industry40	Industry50
Materials	0.023809524	0.017857143	0.17927171	0.0062111...	0.023809524
Goods	0.19047619	0.14285714	0.17927171	0.049689441	0.047619048
Hardware	0.023809524	0.39285714	0.3557423	0.0062111...	0.071428571
Software	0.19047619	0.14285714	0.042016807	0.093167702	0.19047619
System	0.023809524	0.14285714	0.23809524	0.74534161	0.14285714
Service	0.35714286	0.14285714	0.0028011...	0.0062111...	0.26190476
Science	0.19047619	0.017857143	0.0028011...	0.093167702	0.26190476

Organisation Type [OT]

L_Organization...	Industry10	Industry20	Industry30	Industry40	Industry50
SME	0.7	0.525	0.18039216	0.095652174	0.11904762
IND	0.033333333	0.4	0.80784314	0.66086957	0.16666667
RTO	0.2	0.025	0.0039215...	0.1826087	0.45238095
ACA	0.033333333	0.025	0.0039215...	0.052173913	0.23809524
NPO	0.033333333	0.025	0.0039215...	0.0086956...	0.023809524

Organisation Skill [OS]

L_Organization_...	Industry10	Industry20	Industry30	Industry40	Industry50
Farming	0.68333333	0.0125	0.0019607...	0.047826087	0.0023255...
Mining	0.016666667	0.0125	0.0019607...	0.0043478...	0.025581395
Construction	0.016666667	0.0125	0.080392157	0.0043478...	0.048837209
Fabrication	0.016666667	0.1375	0.0019607...	0.0043478...	0.025581395
Mechanics	0.016666667	0.3875	0.49215686	0.091304348	0.095348837
Electrical_Eng	0.016666667	0.2625	0.2372549	0.4826087	0.048837209
System_Eng	0.18333333	0.1375	0.11960784	0.30869565	0.025581395
Computing	0.016666667	0.0125	0.021568627	0.0043478...	0.65348837
Life_Science	0.016666667	0.0125	0.0019607...	0.047826087	0.072093023
Business	0.016666667	0.0125	0.041176471	0.0043478...	0.0023255...

Artificial Intelligence

AI Maturity [AM]

L_Organization_Age_OA	Industry10	Industry20	Industry30	Industry40	Industry50
Social	0.023809524	0.017857143	0.0028011...	0.0062111...	0.0033222...
Physical	0.023809524	0.14285714	0.14005602	0.0062111...	0.0033222...
Cyber	0.023809524	0.14285714	0.081232493	0.049689441	0.026578073
Physical_Social	0.023809524	0.26785714	0.17927171	0.093167702	0.0033222...
Cyber_Social	0.023809524	0.017857143	0.081232493	0.049689441	0.21262458
Cyber_Physical	0.19047619	0.39285714	0.37535014	0.52795031	0.21262458
Cyber_Physical_Social	0.69047619	0.017857143	0.14005602	0.26708075	0.53820598

AI Type [AT]

L_AI_Maturity_AM	Social	Physical	Cyber	Physical_So...	Cyber_Social	Cyber_Physi...	Cyber_Physi...
Symbolic_Virtual_Object	0.1	0.12222222	0.3875	0.57857143	0.27333333	0.20222222	0.0024390...
Symbolic_Virtual_Humanoid	0.1	0.011111111	0.0125	0.0071428...	0.073333333	0.0022222...	0.0024390...
Symbolic_Embodied_Object	0.1	0.56666667	0.0125	0.15	0.0066666...	0.26888889	0.051219512
Symbolic_Embodied_Humanoid	0.1	0.011111111	0.0125	0.0071428...	0.0066666...	0.0022222...	0.0024390...
Machine_Learning_Virtual_Object	0.1	0.23333333	0.3875	0.078571429	0.40666667	0.42444444	0.17317073
Machine_Learning_Virtual_Humanoid	0.1	0.011111111	0.0125	0.0071428...	0.14	0.0022222...	0.0024390...
Machine_Learning_Embodied_Object	0.1	0.011111111	0.0125	0.0071428...	0.0066666...	0.091111111	0.4902439
Machine_Learning_Embodied_Humanoid	0.1	0.011111111	0.0125	0.0071428...	0.0066666...	0.0022222...	0.24634146
Generative_Unimodal	0.1	0.011111111	0.1375	0.15	0.073333333	0.0022222...	0.0024390...
Generative_Multimodal	0.1	0.011111111	0.0125	0.0071428...	0.0066666...	0.0022222...	0.026829268

AI Place [AP]

L_AI_Maturity_AM	Social	Physical	Cyber	Physical_So...	Cyber_Social	Cyber_Physi...	Cyber_Physi...
Design	0.14285714	0.015873016	0.14285714	0.081632653	0.14285714	0.0031746...	0.0034843...
Manufacturing	0.14285714	0.23809524	0.26785714	0.79591837	0.20952381	0.11428571	0.29616725
Testing	0.14285714	0.12698413	0.017857143	0.010204082	0.0095238...	0.2031746	0.076655052
Commissionning	0.14285714	0.12698413	0.26785714	0.010204082	0.47619048	0.13650794	0.076655052
Operation	0.14285714	0.12698413	0.26785714	0.081632653	0.14285714	0.35873016	0.54006969
Maintenance	0.14285714	0.34920635	0.017857143	0.010204082	0.0095238...	0.15873016	0.0034843...
Recycling	0.14285714	0.015873016	0.017857143	0.010204082	0.0095238...	0.025396825	0.0034843...

AI Role [AR]

L_AI_Maturity_AM	Social	Physical	Cyber	Physical_So...	Cyber_Social	Cyber_Physi...	Cyber_Physi...
Education	0.1	0.011111111	0.0125	0.15	0.14	0.0022222...	0.0024390...
Prediction	0.1	0.45555556	0.0125	0.0071428...	0.14	0.20222222	0.075609756
Detection	0.1	0.12222222	0.1375	0.0071428...	0.14	0.15777778	0.051219512
Monitoring	0.1	0.011111111	0.3875	0.15	0.20666667	0.24666667	0.12439024
Automation	0.1	0.011111111	0.0125	0.078571429	0.073333333	0.091111111	0.075609756
Analysis	0.1	0.011111111	0.1375	0.0071428...	0.14	0.024444444	0.026829268
Decision	0.1	0.12222222	0.0125	0.15	0.0066666...	0.0022222...	0.12439024
Optimization	0.1	0.23333333	0.1375	0.36428571	0.073333333	0.18	0.12439024
Collaboration	0.1	0.011111111	0.1375	0.0071428...	0.073333333	0.068888889	0.36829268
Resilience	0.1	0.011111111	0.0125	0.078571429	0.0066666...	0.024444444	0.026829268

Business Strategy

Manufacturing Strategy [MS]

L_AI_Maturity_AM	Social	Physical	Cyber	Physical_So...	Cyber_Social	Cyber_Physi...	Cyber_Physi...
Product_Specialization	0.125	0.56944444	0.390625	0.86607143	0.20833333	0.18055556	0.025
Process_Specialization	0.125	0.23611111	0.140625	0.0089285...	0.0083333...	0.15833333	0.025
Product_Servitization	0.125	0.013888889	0.015625	0.080357143	0.14166667	0.047222222	0.05
Process_Servitization	0.125	0.013888889	0.390625	0.0089285...	0.275	0.35833333	0.375
Product_Customization	0.125	0.125	0.015625	0.0089285...	0.0083333...	0.11388889	0.175
Process_Customization	0.125	0.013888889	0.015625	0.0089285...	0.20833333	0.13611111	0.125
Mass_Customization	0.125	0.013888889	0.015625	0.0089285...	0.0083333...	0.0027777...	0.05
Social_Manufacturing	0.125	0.013888889	0.015625	0.0089285...	0.14166667	0.0027777...	0.175

Resources Strategy [RS]

L_BS_Manufacturing_...	Product_Sp...	Process_Sp...	Product_Se...	Process_Se...	Product_Cu...	Process_Cu...	Mass_Custo...	Social_Man...
Replace_Operators	0.033333333	0.25833333	0.0125	0.053846154	0.0071428...	0.14	0.36666667	0.21
Replace_Engineers	0.033333333	0.091666667	0.0125	0.0025641...	0.0071428...	0.0066666...	0.033333333	0.11
Replace_Managers	0.063636364	0.0083333...	0.0125	0.028205128	0.078571429	0.0066666...	0.033333333	0.01
Replace_Customers	0.003030303	0.0083333...	0.0125	0.0025641...	0.0071428...	0.0066666...	0.033333333	0.01
Replace_All	0.003030303	0.0083333...	0.0125	0.0025641...	0.0071428...	0.0066666...	0.033333333	0.01
Augment_Operators	0.30606061	0.34166667	0.2625	0.54102564	0.50714286	0.54	0.36666667	0.31
Augment_Engineers	0.21515152	0.091666667	0.0125	0.20769231	0.22142857	0.0066666...	0.033333333	0.21
Augment_Managers	0.33636364	0.091666667	0.0125	0.10512821	0.078571429	0.14	0.033333333	0.01
Augment_Customers	0.003030303	0.091666667	0.5125	0.053846154	0.078571429	0.14	0.033333333	0.01
Augment_All	0.003030303	0.0083333...	0.1375	0.0025641...	0.0071428...	0.0066666...	0.033333333	0.11

Network Strategy [NS]

L_BS_Manufac...	Product_Sp...	Process_Sp...	Product_Se...	Process_Se...	Product_Cu...	Process_Cu...	Mass_Custo...	Social_Man...
Purchase	0.48989899	0.26388889	0.020833333	0.0042735...	0.083333333	0.011111111	0.055555556	0.016666667
Customize	0.035353535	0.18055556	0.14583333	0.081196581	0.58333333	0.011111111	0.055555556	0.21666667
Specify	0.36868687	0.26388889	0.14583333	0.20940171	0.083333333	0.41111111	0.38888889	0.11666667
Develop	0.095959596	0.26388889	0.27083333	0.46581197	0.1547619	0.27777778	0.055555556	0.31666667
Acquire	0.0050505...	0.013888889	0.020833333	0.02991453	0.011904762	0.011111111	0.055555556	0.016666667
Crowdsource	0.0050505...	0.013888889	0.39583333	0.20940171	0.083333333	0.27777778	0.38888889	0.31666667

Product Strategy [PS]

L_BS_Manufacturin...	Product_Sp...	Process_Sp...	Product_Se...	Process_Se...	Product_Cu...	Process_Cu...	Mass_Custo...	Social_Man...
Standard_Product	0.67171717	0.18055556	0.020833333	0.13157895	0.011904762	0.077777778	0.055555556	0.016666667
Standard_Service	0.035353535	0.013888889	0.020833333	0.026315789	0.011904762	0.011111111	0.055555556	0.016666667
Standard_PSS	0.0050505...	0.34722222	0.020833333	0.026315789	0.011904762	0.011111111	0.055555556	0.016666667
Custom_Product	0.15656566	0.18055556	0.27083333	0.21052632	0.72619048	0.14444444	0.38888889	0.11666667
Custom_Service	0.0050505...	0.097222222	0.27083333	0.15789474	0.011904762	0.34444444	0.055555556	0.21666667
Custom_PSS	0.12626263	0.18055556	0.39583333	0.44736842	0.22619048	0.41111111	0.38888889	0.61666667

Innovation Management

Innovation Capacity [IC]

L_BS_Manufacturing_...	Product_Sp...	Process_Sp...	Product_Se...	Process_Se...	Product_Cu...	Process_Cu...	Mass_Custo...	Social_Man...
Analytic_Singleton	0.51893939	0.17708333	0.140625	0.46474359	0.15178571	0.20833333	0.041666667	0.1125
Cognitive_Singleton	0.15530303	0.09375	0.390625	0.054487179	0.0089285...	0.075	0.041666667	0.0125
Generative_Singleton	0.09469697	0.010416667	0.015625	0.028846154	0.0089285...	0.0083333...	0.041666667	0.1125
Parasitic_Singleton	0.09469697	0.09375	0.015625	0.0032051...	0.0089285...	0.14166667	0.041666667	0.0125
Analytic_Swarm	0.09469697	0.34375	0.015625	0.080128205	0.29464286	0.275	0.041666667	0.0125
Cognitive_Swarm	0.0037878...	0.26041667	0.390625	0.33653846	0.36607143	0.20833333	0.70833333	0.2125
Generative_Swarm	0.034090909	0.010416667	0.015625	0.0032051...	0.0089285...	0.0083333...	0.041666667	0.4125
Parasitic_Swarm	0.0037878...	0.010416667	0.015625	0.028846154	0.15178571	0.075	0.041666667	0.1125

Internal Innovation [II]

L_IM_Innovation_Ca...	Analytic_Sin...	Cognitive_S...	Generative_...	Parasitic_Si...	Analytic_Sw...	Cognitive_S...	Generative_...	Parasitic_S...
Operation_Driven	0.52272727	0.31868132	0.023809524	0.020408163	0.007518797	0.035714286	0.023809524	0.19047619
Engineering_Driven	0.18181818	0.087912088	0.52380952	0.44897959	0.32330827	0.34821429	0.52380952	0.35714286
Business_Driven	0.022727273	0.16483516	0.023809524	0.020408163	0.11278195	0.098214286	0.023809524	0.023809524
Demand_Driven	0.11363636	0.31868132	0.023809524	0.44897959	0.11278195	0.066964286	0.19047619	0.19047619
Strategy_Driven	0.045454545	0.087912088	0.35714286	0.020408163	0.16541353	0.098214286	0.023809524	0.023809524
Expertise_Driven	0.090909091	0.010989011	0.023809524	0.020408163	0.27067669	0.34821429	0.19047619	0.19047619
Mission_Driven	0.022727273	0.010989011	0.023809524	0.020408163	0.007518797	0.0044642...	0.023809524	0.023809524

Open Innovation [OI]

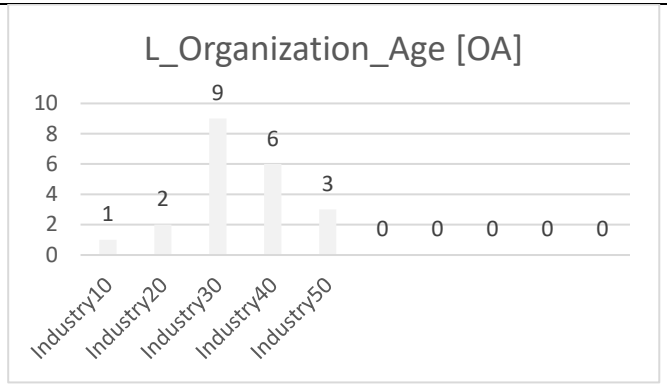
L_IM_Innovation_Capa...	Analytic_Sin...	Cognitive_S...	Generative_...	Parasitic_Si...	Analytic_Sw...	Cognitive_S...	Generative_...	Parasitic_S...
Weak_Inbound	0.022727273	0.24038462	0.020833333	0.017857143	0.16447368	0.12890625	0.020833333	0.020833333
Weak_Outbound	0.045454545	0.0096153...	0.020833333	0.017857143	0.0065789...	0.03515625	0.35416667	0.1875
Casual_Inbound	0.31818182	0.16346154	0.1875	0.30357143	0.059210526	0.09765625	0.020833333	0.020833333
Casual_Outbound	0.13636364	0.16346154	0.1875	0.16071429	0.42763158	0.03515625	0.1875	0.35416667
Regular_Inbound	0.20454545	0.31730769	0.35416667	0.16071429	0.0065789...	0.00390625	0.020833333	0.020833333
Regular_Outbound	0.068181818	0.0096153...	0.1875	0.16071429	0.16447368	0.09765625	0.020833333	0.020833333
Systematic_Inbound	0.13636364	0.0096153...	0.020833333	0.16071429	0.11184211	0.19140625	0.020833333	0.35416667
Systematic_Outbound	0.068181818	0.086538462	0.020833333	0.017857143	0.059210526	0.41015625	0.35416667	0.020833333

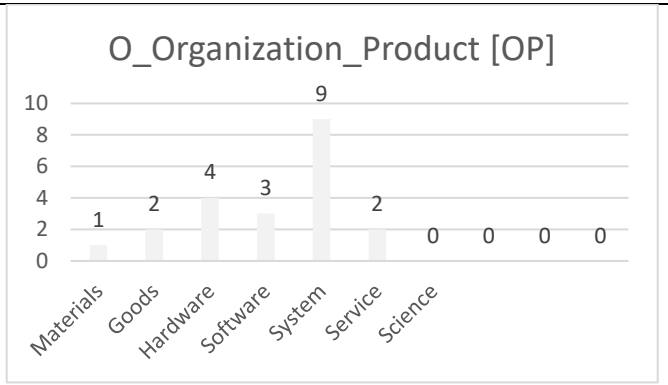
Innovation Policy [IP]

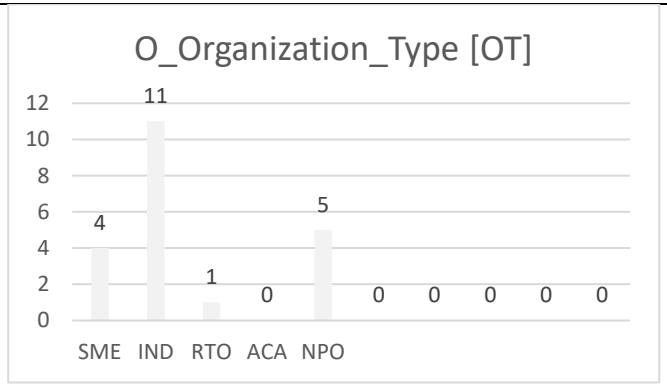
L_IM_Innovation_Ca...	Analytic_Sin...	Cognitive_S...	Generative_...	Parasitic_Si...	Analytic_Sw...	Cognitive_S...	Generative_...	Parasitic_S...
Private_Defensive	0.047222222	0.0096153...	0.52083333	0.017857143	0.059210526	0.00390625	0.020833333	0.020833333
Private_Incremental	0.49166667	0.39423077	0.020833333	0.44642857	0.21710526	0.00390625	0.1875	0.020833333
Private_Liberal	0.069444444	0.0096153...	0.020833333	0.017857143	0.11184211	0.00390625	0.020833333	0.020833333
Private_Disruptive	0.091666667	0.47115385	0.1875	0.16071429	0.16447368	0.41015625	0.1875	0.35416667
Public_Defensive	0.091666667	0.0096153...	0.020833333	0.30357143	0.11184211	0.00390625	0.020833333	0.020833333
Public_Incremental	0.18055556	0.0096153...	0.020833333	0.017857143	0.21710526	0.03515625	0.020833333	0.020833333
Public_Liberal	0.025	0.0096153...	0.020833333	0.017857143	0.0065789...	0.03515625	0.1875	0.020833333
Public_Disruptive	0.0027777...	0.086538462	0.1875	0.017857143	0.11184211	0.50390625	0.35416667	0.52083333

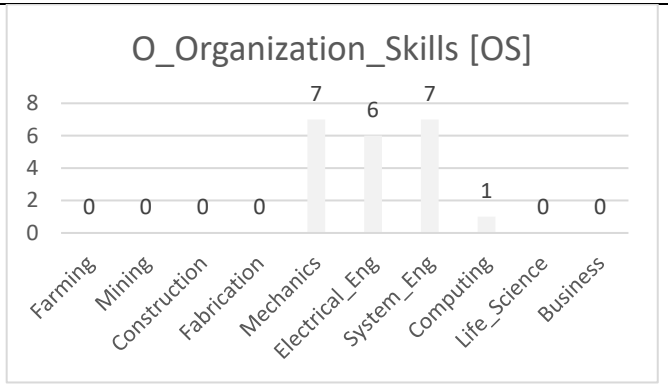
ANNEX 12: DESCRIPTIVE STATISTICS

[OC] Variables

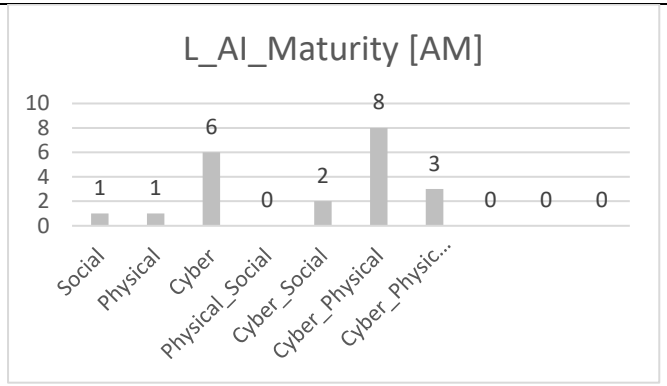


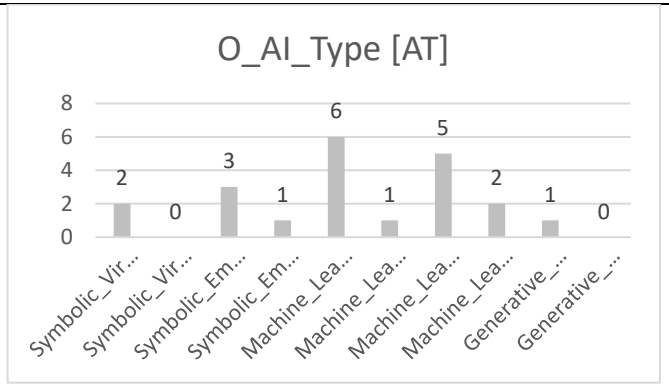


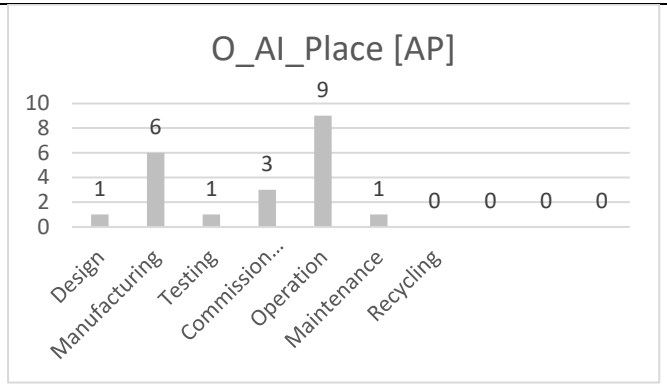


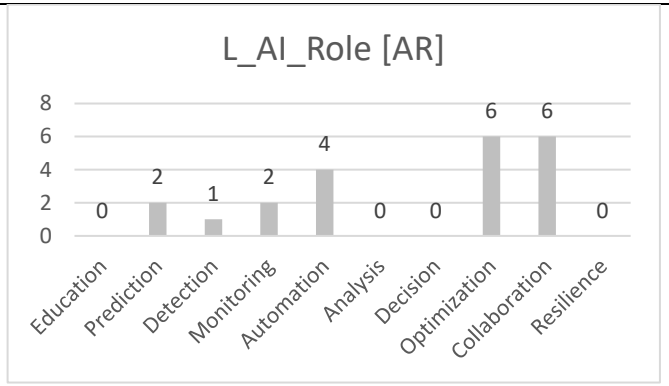


[AI] Variables

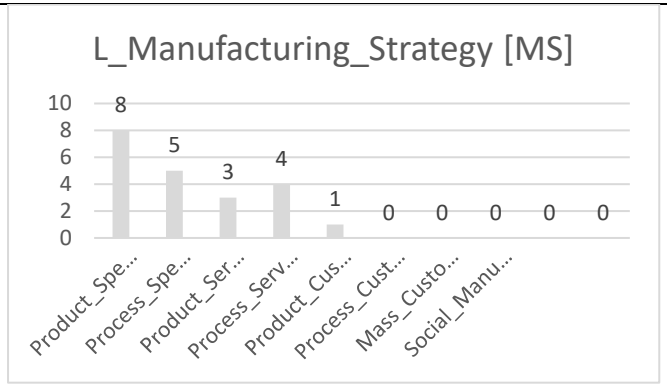


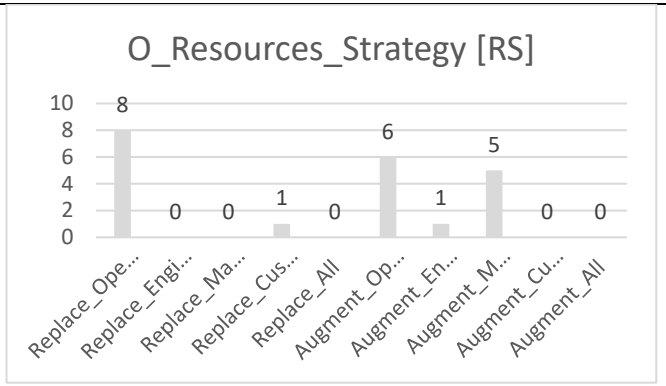


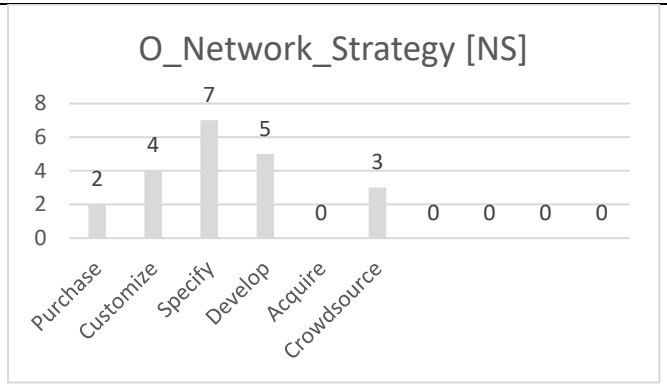


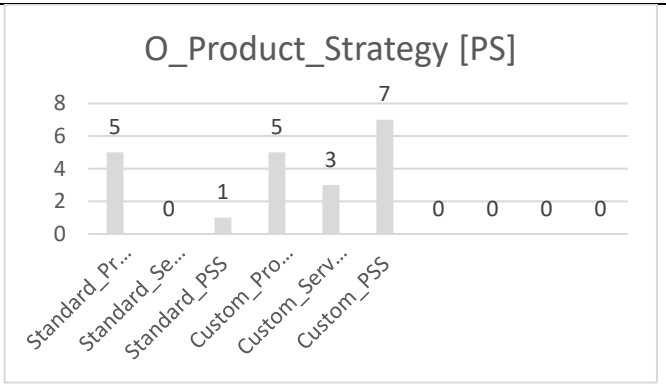


[MS] Variables









[IC] Variables

