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Technology adoption models for Operator 5.0 implementations: A harmonized framework

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ABSTRACT

This article examines the alignment and applicability of prominent technology adoption models in supporting the transition from Industry 4.0 to Industry 5.0, with a particular emphasis on the Operator 5.0 paradigm. Industry 5.0 extends beyond technological integration, emphasizing human-centricity, sustainability, and resilience. However, the practical implementation of Operator 5.0 initiatives faces significant barriers due to insufficient frameworks addressing these holistic dimensions. Through a systematic literature review of nine prominent technology adoption models (categorized into individual user-level, system-centered, and holistic theories), this research identifies their suitability for supporting human-centric, resilient, and sustainable Operator 5.0 initiatives. Findings reveal variability in model applicability across implementation phases (pre-implementation, implementation, post-implementation) and dimensions of Operator 5.0. A harmonized framework, termed the TAMOP 5.0 (Technology Adoption Models for Operator 5.0), was developed to map the strengths, limitations, and contextual applicability of these models using a three-round Delphi study concluded with consensus (a priori consensus rule). The TAMOP 5.0 is a strategic visual tool for practitioners and researchers, offering guidance to enhance employee acceptance, engagement, and successful adoption of Operator 5.0 initiatives. In an illustrative cobot-retrofit case, TAMOP 5.0 operationalizes phased adoption decisions by linking pre-change ergonomic/absence baselines, implementation support, and post-change KPI monitoring. The study concludes with recommendations for practical applications and highlights the need for further empirical validation of the proposed framework.

1. Introduction

Technological advancements of Industry 4.0 (I4.0) Human-Cyber-Physical Systems (H-CPSs) (Romero et al., 2016a) require increasing integration of humans with technologies, thereby enabling Operator 4.0 (O4.0) (Romero et al., 2020) to align with the vision of using different technologies for various purposes to support humans in industry (Romero et al., 2016b). However, workers are not expected to adapt their skills to the technologies; instead, technologies are used to adjust the production process to the workers' needs, considering their concerns such as privacy, autonomy, and dignity (Xu et al., 2021). For this reason, the concept of Industry 5.0 was born (Directorate-General for Research and Innovation (European Commission) et al., 2021) to further promote the vision of Industry 4.0 by going beyond productivity and profit and highlighting human-centricity, sustainability, and resilience as important issues when implementing I4.0 technology-driven initiatives. These initiatives were previously considered mainly from the perspective of techno-organizational and financial effectiveness, while the wave of

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Industry 5.0 aims to reverse this paradigm (Maddikunta et al., 2021). Indeed, previous research has examined various implementations of Industry 4.0 technologies. Several reports have cited reasons for the implementation's failure, including scarce participation and workforce involvement among the most relevant and broad topics, which lack a proper organizational perspective (Nayernia et al., 2022).

The vision of Industry 5.0 claims a re-thinking and an evolution of the O4.0 concept. Industry 5.0-aligned vision of Operator 5.0 is enabled by technologies that augment human capabilities while keeping operators empowered and in control. In particular, eXtended (Augmented/Virtual/Mixed) Reality (XR; AR/VR/MR) supports immersive training, contextual work instructions, and remote collaboration/assistance, which is especially relevant when production cannot be halted for learning and onboarding (de Giorgio et al., 2023; Gladysz et al., 2023). These technologies create closed feedback loops between guidance, execution, and performance monitoring, operationalizing human-centric Industry 5.0/Operator 5.0 adoption in practice, when integrated with connected-worker infrastructures (e.g., AR-linked Manufacturing Execution Systems) (Blaga et al., 2021; Rožanec et al., 2023). Drivers and restrainers for the so-called Operator 5.0 (O5.0), including support for workforce resilience, human-centric technology development, and technology support for sustainability, were generalized and categorized by Gladysz et al. (2023) which showed that a holistic top-level reference framework to support O5.0 initiatives is still missing from a technology adoption perspective. Therefore, challenges, problems, and barriers from the technology adoption domain could also be present in implementing the I5.0 paradigm (Salminen et al., 2023).

Consequently, there is still a gap in the successful implementation of O4.0 and O5.0 initiatives, as a structured focus and support for the long-term challenges and drivers of such deployments are lacking. As a result, both O4.0 and O5.0 are not yet widely adopted in industrial practice, despite policymakers and industries currently reorienting their paradigms from technology-driven to human-centricity. Nevertheless, a rich body of knowledge on technology adoption models exists that can be analyzed to identify and successfully decline the prominent ones in the context of O5.0, thereby enhancing the widespread adoption of O5.0 initiatives.

This study aims to examine the evidence of support for prominent technology adoption models in O5.0, with a particular focus on investigating which technology adoption model can best support Operator 4.0 and Operator 5.0 initiatives in terms of human-centricity, sustainability, and resilience. This research work aims to contribute to both theoretical and managerial perspectives by identifying the key aspects of O5.0 initiatives that require specific approaches to support and roadmap their introduction in the industry. It exploits well-established technology adoption models already discussed in the literature to minimize employees’ resistance and maximize benefits.

In doing this, the research is grounded in a systematic literature review and conceptual development, which leverages the multifaceted competencies of experts who participated in a three-round Delphi study to achieve a suitable consensus level and ultimately led to the development of a holistic framework.

The article is structured as follows. Section 2 will present the methodology used to achieve the research objective. Section 3 will provide a background related to the main technical aspects (Section 3.1) and the main socio-organizational aspects (Section 3.2) of technology adoption models, as well as the concepts of Operator 4.0 and 5.0, respectively. Section 4 presents evidence from the scientific literature on technology adoption models and operators 5.0. In contrast, Section 5 introduces and describes a framework for classifying theories on technology adoption for Operator 5.0. The paper will conclude with the discussion sections (Section 6) and the conclusion (Section 7).

2. Research Methodology

Building on the information presented in the Introduction section, a methodology has been established to achieve the research objectives. The main research workflow is illustrated in Fig. 1 and described in the following section.

Due to the research's socio-technical nature, the workflow's first step is to perform a background analysis on the two main topics: technical features and the socio-organizational perspective. The background analysis concerning technical aspects focuses on the main Operator 4.0 supporting technologies, merging the view of Industry 5.0 features (i.e., sustainability, resilience, and human centricity) and consequently depicting the Operator 5.0 dimensions. Analyzing the socio-organizational aspects, the focus of the investigation is on technology adoption models and their role in supporting the implementation of innovative technologies, as well as on the change management strategies that can be applied during the various phases of new technology implementation. Due to the practical dimensions and common recognition within practitioners' circles, it was decided to use the technology implementation stages as outlined by the World Economic Forum (WEF, 2024), which was informed by operators' insights. Therefore, it is workers-centric from its origins, which is in direct line with the human-centric orientation of this study. This first step of the research will be described in Section 3.

After the background analysis, an in-depth systematic literature review is conducted to understand the relationships between the technology adoption models and the implementation phases (i.e., before, during, and after implementing a new technology in a process) and the Operator 5.0 dimensions. As a first step, the Scopus database was chosen for queries because it provides a curated, multidisciplinary index of peer-reviewed literature that is widely used in quantitative and systematic evidence synthesis and is considered a trustworthy source for research purposes (Baas et al., 2020). Scopus typically offers broader journal and record coverage than other databases, including Web of Science, which is more selective. Scopus helps reduce the risk of missing relevant streams at the initial retrieval stage in interdisciplinary topics (Visser et al., 2021), such as Operator 5.0 and technology adoption, and was effectively used in other studies in the field (Gladysz et al., 2023). Importantly for fast-developing domains, bibliographic databases differ in how they represent early-access / in-press publication stages. Scopus exposes such records earlier, which supports capturing the most recent peer-reviewed contributions available at the time of the search (Zhu, 2025). Scopus provides suitable breadth for field delineation and comprehensive coverage at the retrieval stage for mapping and delineating a multidisciplinary field, such as technology adoption models for Operator 5.0 (Visser et al., 2021). Differences in indexation policies and database architectures can systematically affect metadata and citation-link characteristics across sources (Stahlschmidt & Stephen, 2022), so we used Scopus as a single, consistent data source and ensured relevance through subsequent title/abstract screening and full-text qualitative analysis.

Each prominent technology adoption model was reviewed by collecting documents that emerged from queries conducted on April 1, 2025 (Annex A. List of all queries). Only papers in English were included. No publication-year/timeframe restrictions were applied, and no other exclusion criteria were used at this stage. A qualitative exclusion criterion was applied at the stage of title and abstract screening to exclude papers not addressing the topic of our study from the set of 86 papers identified using the presented set of queries for 9 technology adoption models. Titles and abstracts screening resulted in a final set of 32 articles (after abstract screening and excluding irrelevant ones), which were analyzed qualitatively (Table 1). They were fully read to extract useful information. Results for each prominent technology adoption model were examined separately to find how they could be used in the implementation stages described in Section 3.2, outlining potential benefits and limitations in supporting O5.0 initiatives. The details of the systematic literature review process and the relationships extracted from the literature analysis will be described in Section 4 Results.

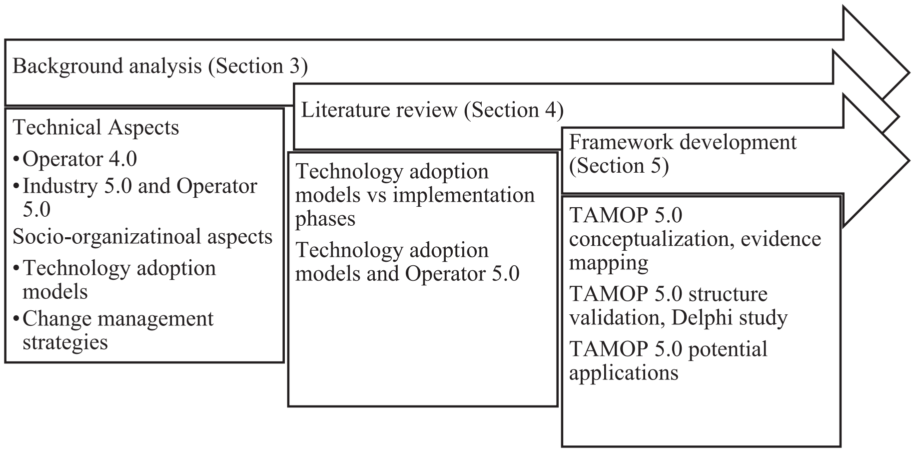

Fig. 1. Research workflow.

Table 1
PRISMA-like retrieval and screening counts.

Step / model	SCT	TRA/ TPB	DOI	PCI	MPCU	TRL	TAM	UTAUT	TOE	TOTAL (merged)
Scopus query hits	23	8	5	0	0	7	26	16	2	86
Excluded at screening	7	6	3	0	0	6	18	14	0	54
Retained after screening	16	2	2*	0	0	1	8	2	2*	32
Full-text assessed for eligibility										32
Full-text excluded										0
Full-text included in qualitative synthesis										32

*One paper was duplicated in the DOI and TOE.

In particular, we analyzed prominent theories from Salahshour Rad et al. (2018) in this study that overlapped with the taxonomy proposed by FakhrHosseini et al. (2022). We extended the study using TRL (Technology Readiness Levels), which is de facto a standard when discussing technology adoption from the perspective of research funders and policymakers. The societal level of technology adoption was delimited in this study.

The core step of our research method was the definition of a framework, more precisely, a Technology Adoption Models for OPerator 5.0 (TAMOP 5.0), in which the different technology adoption models are classified according to the implementation phase in which they could be successfully applied and the Operator 5.0 dimensions that they can help to support and develop. The sub-dimensions for the TAMOP 5.0 were defined by an analysis of the literature on specific technology adoption models and their possible support from O5.0′s main dimensions (human-centricity, resilience, sustainability). Then, the potential support of each model for each dimension was briefly summarized. Summaries were processed using a qualitative content analysis approach to discover joint patterns and, therefore, defined joint sub-dimensions for the main dimensions of O5.0. Recurrent themes were identified by systematically coding and categorizing the content, enabling the construction of a structured framework, the TAMOP 5.0, which can be considered a holistic and harmonized framework for the full life cycle of technology adoption for Operator 5.0.

The purpose of the empirical component at this stage was not to test implementation effects in a plant setting, but to establish the content validity, structural coherence, and expert-grounded usability of TAMOP 5.0. This objective was pursued through a three-round Delphi study, because Delphi is well suited when the aim is to obtain structured expert consensus on predefined framework elements rather than to conduct field testing. Its use in this staged role is consistent with published operations and manufacturing research, including work where Delphi provides the main empirical basis under high uncertainty and studies that develop and validate frameworks through expert consensus before subsequent practical testing (Ghobakhloo et al., 2024; McLean et al., 2023; Mukherjee et al., 2018; Ricárdez-Estrada et al., 2026; Spieske et al., 2023). Compared with interviews, focus groups, or Q-methodology, which are better suited to exploring divergent views or mapping perspectives, Delphi is specifically designed to support convergence toward agreement through anonymity, iteration, controlled feedback, and predefined consensus criteria, while also reducing biases such as dominance and groupthink in interactive settings. The panel therefore comprised 12 purposively selected international academic experts from the Operator4.com network, with backgrounds in production engineering (67%), ergonomics (25%), and change management (8%), mostly with more than six years of experience and with strong industry links across multiple sectors, including automotive, machinery, electronics, metal, textiles, and transport, and across regions, mainly Europe and the Americas (Table 2). The ratings themselves were based on the

Table 2
Delphi panel's composition.

Characteristic	Round 1 (n = 12)	Round 2 (n = 11)	Round 3 (n = 10)
Participants (response)	12 invited, 12 responded (100%)	12 invited, 11 responded (92%)	11 invited, 10 responded (91%)
Disciplinary background	Production/ Industrial Engineering: 8 (67%) Human Factors/ Ergonomics: 3 (25%) Change Management/ Organization: 1 (8%)	Production/ Industrial Engineering: 7 (64%) Human Factors/ Ergonomics: 4 (36%)	Production/ Industrial Engineering: 8 (80%) Human Factors/ Ergonomics: 2 (20%)
Years of experience	> 6 years: 7 (58%) 2–5 years: 5 (42%)	> 6 years: 8 (73%) 2–5 years: 3 (27%)	> 6 years: 7 (70%) 2–5 years: 3 (30%)

literature-derived matrix ratings presented in Section 4 rather than calculated from Delphi statistics. Empirical application-based validation is therefore positioned as a subsequent research stage rather than a prerequisite for reporting the present framework.

Response rates were 100%, 92%, and 91% ($n_1 = 12$, $n_2 = 11$, $n_3 = 10$) (Table 2). Structured remote questionnaires included both closed- and open-ended items, ensuring anonymity. Table 1 summarizes the composition and participation of the Delphi panel across the three rounds. Round 1 assessed the clarity and usefulness of the TAMOP 5.0 structure. Items meeting predefined consensus, i.e., median ≥ 4, IQR ≤ 1, or $\geq$ 70% agreement (Diamond et al., 2014; Jorm, 2025) were accepted. Others were revised. This dual criterion is standard, as an IQR of ≤ 1 indicates tight clustering. Given the high expertise and topic specificity, 8–20 participants are sufficient (Effah et al., 2016). Thus, 12 participants were adequate. Subsequent rounds refined items and presentation (definitions, context, visualization). Round 2 re-evaluated unresolved items. Round 3 resolved the final issue and compared two graphical formats. A consensus was reached on all framework elements and the preferred visualization, concluding the process.

One exemplary practical example of TAMOP 5.0 application is provided in Annex B.2 to demonstrate how the framework operationalises phase-specific adoption decisions in a cobot-retrofit scenario.

3. Background

The following sections describe the advancement of Operator 4.0 into Operator 5.0 (Section 3.1) and the role of technology adoption models (Section 3.2).

3.1. Advancement of Operator 4.0 into 5.0

3.1.1. Operator 4.0 concept and enabling technologies

The O4.0 concept aims to support human integration within any process or system. The O4.0 concept, with its eight fundamental pillars, significantly enhances the work of operators. O4.0 definition introduced by Romero et al. (Romero, Bernus, et al., 2016; Romero, Stahre, et al., 2016) has been crucial in developing human-centered systems. The continuous evolution of the technological environment surrounding operators and the industry contributes to a comprehensive understanding and enhancement of their roles and capabilities. When combined with the concept of Industry 4.0, the management tools and methodologies for technology adaptation take on a specific focus on human-centered solutions, meaning that they can be refined to address the awareness, desire, knowledge, ability, and reinforcement needs of human operators.

Within the O4.0 concept, technologies are crucial in augmenting human capabilities or assisting in task execution. After reviewing the literature, several technologies have been identified as related to the Industry 4.0 transition. An investigation is required concerning their relationship with humans. Since 2018, the first classifications of technologies have been published. Xu et al. (2018) only depict four main technologies: IoT, Cloud, Cyber-Physical Systems, and Industrial Integration. At the same time, Oztemel and Gursev (2020) presented a wider list of I4.0 components, including Cyber-Physical systems, Cloud and IoT, augmented reality and simulation, intelligent robotics, data mining, and others. Another technology classification directly related to the data value chain has been formalized by Klingenberg et al. (2019), which discusses data generation, transmission, processing, and application technologies. Specifically focusing on the role of technologies in relation to operators, Cimini et al. (2020) presented a summary of Industry 4.0 technologies classified according to whether they provide physical or cognitive support. This classification, aligning with the approach of Cimini et al. (2020), aims to highlight the role of technologies in augmenting or assisting human capabilities concerning the physical sphere (e.g., movements, sensing capabilities) or cognitive sphere (e.g., mental capabilities, decision-making, communication).

According to this scheme, fourteen technologies have been defined and grouped based on their capability to assist operators in executing manual tasks or augmenting and assisting in more mental, organizational, or cognitive activities. Always focused on human-centered systems, a specific taxonomy of technologies adopted in logistics has been presented by Lagorio et al. (2021), exploring a wide range of technologies related to material and information flows that are exploitable in the most relevant phases of logistics (e.g., picking, storage, kitting). Gazzaneo et al. (2020) proposed the Operator 4.0 Compass, providing an extensive set of technologies related to Operator 4.0. Since these last three models are more specifically devoted to classifying technologies based on human interaction, we decided to use them as a reference for identifying the main O4.0 technologies in Table 3.

3.1.2. Industry 5.0 features

Advancing the latest developments in the industrial landscape, the vision of Industry 5.0 proposes to orient the development of new advanced technological solutions from a human-centric approach, rather than starting from the potential of the technology to improve productivity. It promotes the focus on the sustainability of technological solutions to respect planetary boundaries. Ultimately, it examines the resilience of industrial solutions in withstanding various crises, unexpected occurrences, and challenging conditions. Although it completely refocuses the technology-driven policy of Industry 4.0, the toolset remains no different from a technological perspective. It includes the same modern and advanced technologies and solutions, including (but not limited to) AI, Digital Twins, and cobots. Industry 5.0 is commonly structured using the three widely adopted pillars, i.e., human-centricity, sustainability, and resilience, explicitly articulated in the European Commission's policy and widely reflected in academic discourse (Directorate-General for Research and Innovation (European Commission) et al., 2021; van Erp et al., 2024; Xu et al., 2021). We adopted this triad as the organizing scheme for Section 3.1.2 because it represents the most authoritative and policy-driven interpretation of Industry 5.0 values, ensuring conceptual alignment with strategic guidelines. Alternative lenses were considered. Some studies structure Industry 5.0 by enabling technology groups (Xu et al., 2021), technology-cluster synergies (e.g., cobots/ digital twins/ augmentation) (Zafar et al., 2024), technology-driven managerial measures linking tool categories and practices to human needs (Masiero et al., 2024), or operational/technological principles framing Industry 5.0 implementation (Ivanov, 2023). However, these approaches either overlap with enabling technologies discussed in Section 3.1.1 or introduce complexity without improving clarity for adoption modeling. The policy discourse also provides a stakeholder/value-oriented framing that motivates the three-pillar view (human-centricity, sustainability, resilience) (Directorate-General for Research and Innovation (European Commission) et al., 2021). We retained the three-pillar (human-centricity, sustainability,

Table 3
Operator 4.0 technologies based on (Cimini et al., 2020; Gazzaneo et al., 2020; Lagorio et al., 2021).

Physical support	Cognitive support
• Advanced robotics	• Cyber-Physical Systems (CPS)
• Additive manufacturing/ 3D printing	• Internet of Things (IoT)
• Autonomous vehicles	• Big Data Analytics (BDA)
• Drones	• Cloud technologies
• Collaborative robotics	• Smart sensors
• Exoskeletons	• Simulation
• Automated storage systems	• Additive manufacturing/ 3D printing
• Augmented Reality (AR)	• Energy saving systems
• Virtual Reality (VR)	• Horizontal and vertical integration
	• Multi-agent technologies
	• Wearable devices
	• Artificial Intelligence (AI)
	• Blockchain
	• Cybersecurity

and resilience) structure for parsimony. We interpreted it through our lens to operationalize these values in relation to technology adoption phases and subdimensions. This choice is grounded in policy discourse and literature synthesis, but its application in this study reflects the authors' interpretation aimed at linking Industry 5.0 principles to practical adoption strategies. Nevertheless, in considering the three pillars of Industry 5.0, it is worth mentioning that they present interconnections and, in the operationalization of the paradigm, some competing roles and trade-offs could be envisioned. This has been extensively discussed in the supply chain sector, in which promoting strategies for environmental efficiency without a holistic view can compromise the capability to absorb disruptions (Chichi & Mamad, 2025). When considering human-centricity, relations are evident within the social sustainability approach, which some authors summarize under the label of human-centred green transition (Afzal et al., 2024). For this reason, in the following, the three pillars of sustainability, resilience, and human-centricity will be reviewed by providing critical links among them.

Sustainability in the Industry 5.0 policy (Directorate-General for Research and Innovation (European Commission) et al., 2021) is primarily discussed using the United Nations Sustainable Development Goals (UN SDGs) categories. However, another widely adopted sustainability interpretation relies on a triple bottom line (TBL) approach (Elkington, 2013). Industry 5.0 policy discusses sustainability mainly from an environmental perspective, highlighting the "needs to develop circular processes that re-use, re-purpose and recycle natural resources, reduce waste and environmental impact, (…) energy consumption and greenhouse emissions, to avoid depletion and degradation of natural resources, (…) to ensure the needs of today's generations without jeopardizing the needs of future generations." It highlights the potential of AI and additive manufacturing to optimize resource efficiency and minimize waste. In this paper, we adopt the TBL typology of sustainability dimensions and consider it holistically through its economic, environmental, and social characteristics. Baig and Yadegaridehkordi (2024) categorized research themes in Industry 5.0 for sustainability, identifying four key categories: robotics advancement, ecosystem advancement, higher education sustainability, and human-centricity. Human-centricity and robot advancement were the most popular topics, specifically highlighting the need and interests for Operator 5.0 advancements, particularly when considering operators' collaboration with robots and cobots. These results prove that Industry 5.0 features are inseparable, and here, sustainability and human-centricity, conceived as a basis for social sustainability, overlap.

A resilient manufacturing system can adjust its operations to operational changes and disturbances. It should be able to operate under unexpected circumstances (Hollnagel et al., 2017; Mourtzis et al., 2021). There is no single resilience typology. However, resilience is worth considering holistically in the context of Industry 5.0. Resilience supports operators in introducing universal design, which involves considering the operator's health, environmental factors, personal factors, standards, cognitive processes, error-proofing, and productivity. This approach can lower the risk of accidents and improve ergonomics, ultimately leading to a safer work environment (Mattsson et al., 2023). It should include the technical/technological resilience of systems to deliver expected qualities and quantities of goods and services in unexpected conditions. This must always be combined with workforce resilience, which is the ability of workers to cope with unforeseen conditions and minimize negative impacts on their well-being. Those two features might be based on the reconfigurability of systems or task rotation between workers and equipment (e.g., cobots). Environmental resilience would require delivering expected environmental impacts in unexpected conditions, showing the linkage between resilience and sustainability dimensions of Industry 5.0.

Regarding the issue of human centricity, Industry 5.0 and Socio-Technical Systems (STS) theory share similarities. The latter advocates for a comprehensive understanding of the technical (i.e., tools, equipment, and processes) and social (i.e., people and their relationships) aspects when designing complex systems (Trist & Emery, 2015), which is in line with the view of Industry 5.0 in promoting a new design of human work with a proper distribution of responsibilities between the technological sub-system and human action able to exploit their respective best features. Since this socio-technical approach envisions direct links between human-technology interactions and the outcomes/performance of the entire system (Mumford, 2000), the I5.0 human-centricity highlights the necessity of integrating human-related issues into the shift to the smart manufacturing context, recalling the concept of usability and human-centered design (ISO, 2019). Human-centered design theory promotes the development of interactive systems that are more usable by focusing on the system's use and applying Human Factors/Ergonomics and usability knowledge and techniques, including concepts such as user involvement and evaluation-driven design. Human-centricity encompasses the development of safe and healthy workplaces (Gladysz et al., 2023), the respect for human values and ethical issues (Longo et al., 2020), and the implementation of shared decision-making between humans and machines (Pathak et al., 2019).

While the technologies listed in Table 3 are often labelled as "Industry 4.0", their role in Operator 5.0 should be interpreted through the Industry 5.0 lens, i.e., under an augmentation-with-responsibility logic as value-driven enablers of human-centricity, sustainability, and resilience rather than efficiency-only digitization. Six general categories of Industry 5.0 technologies are: 1/ individualized human–machine interaction technologies, 2/ bio-inspired technologies and smart materials (e.g. sneor-integrated recyclable), 3/ digital twins and simulation, 4/ data transmission, storage, and analysis technologies, 5/ AI, and 6/ technologies for energy efficiency, renewables, storage and autonomy (Xu et al., 2021). Augmentation technologies (e.g., XR, haptics) support immersive human–machine interaction, contextual guidance, education, and training (de Giorgio et al., 2023), e.g., in maintenance/repair operations (Mourtzis et al., 2023). Cobots, digital twins, augmentation technologies, haptics, wearables, manipulators, and sensors are enablers for Industry 5.0, assuring safe, collaborative human-robot teamwork and experimentation/validation in cyber-physical environments (Zafar et al., 2024). XAI and human-centric AI architectures with human-in-the-loop mechanisms strengthen transparency, trust, accountable decision support, and operators' protection (Catti et al., 2024; Rožanec et al., 2023). These emphases are consistent with Operator 4.0 to Operator 5.0 transition findings, including the need to mitigate restrainers (e.g., trust, skills, ergonomics integration gaps) before scaling human-centric technologies (Gladysz et al., 2023), and with technology-driven measures that translate human needs into actionable Industry 5.0 implementation levers (Masiero et al., 2024).

3.1.3. Operator 5.0

Since no significant differences are recognized in the enabling technology toolset for Operator 5.0, the main revolution concerns the perspective of using the technology that should be reoriented according to the Industry 5.0 policy. Mourtzis et al. (2022) listed enabling technologies from a survey-based study directly taken from I4.0 and discussed new applications for O5.0. In particular, our understanding of O5.0 complements the earlier O4.0 definition by specifically defining the resilience and sustainability orientation of operators across various aspects, adopting a human-centric approach to the applied solutions (Fig. 2).

Indeed, there are few works on the Operator 5.0 concept, and some of those works are limited to resilience orientation as they lack sustainability and human-centricity dimensions. Romero and Stahre (2021) proposed self-resilience (biological, physical, cognitive, and psychological occupational health and safety, as well as productivity) due to operator fragility and system-resilience for all human–machine systems (alternative ways to continue collaboration, e.g., alternating tasks between humans and cobots) categories as features of the Resilient Operator 5.0. Resilient Operator 5.0 is smart and skilled, leveraging human

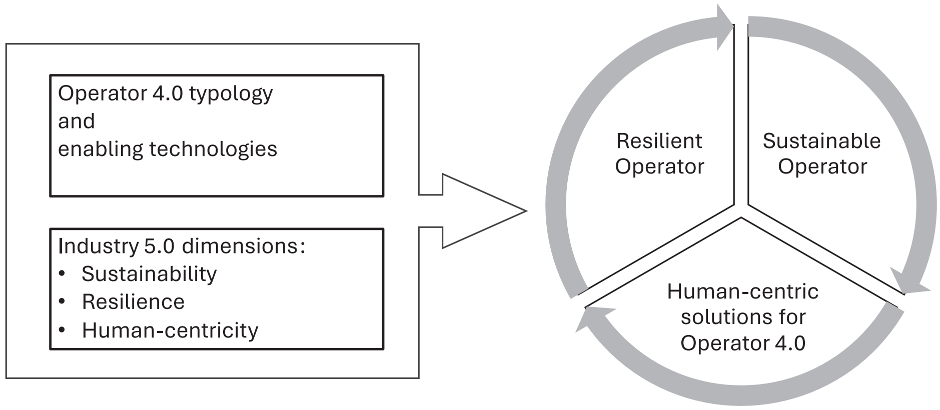

Fig. 2. Operator 5.0 holistic concept.

creativity, ingenuity, innovation, data, and technology to devise cost-effective, sustainable, and long-term solutions that prioritize workforce well-being in the face of disturbances (Romero & Stahre, 2021). Kaasinen et al. (2019) addressed a partially human-centric dimension by focusing on O4.0 solutions that support worker well-being. Resilience involves managing unexpected events effectively, supported by established standards, clear instructions, and comprehensive training materials (Mattsson & Kurdve, 2024).

The transition towards O5.0 has been studied in the work of Gladysz et al. (2023), which articulates resilience as the need to develop adaptable technologies for dynamic use by different users, design robust systems, promote targeted training, embrace dynamic task allocation, and anticipate safety measures against disruptions. This work lacks a clear definition of the full dimensions and features of O5.0. Another interpretation of the O5.0 is provided by Mourtzis et al. (2022), which emphasizes the need to create social factories as a working environment that supports humans in any working condition by engaging them in knowledge creation. The limited existing literature on O5.0 further demonstrates that the required evolution is not about the technologies recognized as the same as those of O4.0 (Table 3), but rather about how to design and integrate them to increase the involvement and well-being of operators. Therefore, a clear research gap exists in the understanding of sustainability and the human-centric dimensions of the Operator 5.0 concept, which are not fully discussed in the literature.

3.2. *Technology adoption and use (process and models)*

Technology adoption theories and models play a crucial role in understanding and predicting the acceptance and utilization of new technologies. Researchers and practitioners have relied on these frameworks for decades to analyze and explain the factors that influence individuals and organizations in adopting innovative technologies. Several prominent theories and models have been developed over the years, each offering unique perspectives on the adoption process. The broad literature review 'Information technology adoption: A review of the literature and classification' conducted by Salahshour Rad et al. (2018) revealed the most prominent ones. The Technology Acceptance Model (TAM) by Davis (1989) and its extensions (i.e., TAM2 and TAM3) featured prominently in almost half of the reviewed papers. This marked TAM as the most dominant theory among those reviewed. Rogers's Diffusion of Innovations (DOI) theory (2006) followed closely, appearing 44 times in the 330 reviewed papers, securing its position as the second most utilized theory. The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) and the Theory of Planned Behavior (TPB) by Ajzen (1991) ranked third and fourth, respectively. Finally, the Technology–Organization–Environment (TOE) framework proposed by Tornatzky and Fleischer (1990) was seen to have a relative lead among the theories used in organizational-level studies.

FakhrHosseini et al. (2022) reviewed technology adoption models focusing on user adoption of intelligent environments. Since digitalization often results in failed projects due to poor strategy, with staff losing trust and/or being fired, it is critical to investigate methods and frameworks such as UTAUT, TAM, and Task Technology Fit (TTF) (Dash et al., 2023). This study proposed a taxonomy of technology adoption models listing: i) individual user (Theory of Reasoned Action – TRA, Social Cognitive Theory – SCT), ii) system-centered (DOI, Perceived Characteristics of Innovation – PCI), iii) holistic approach (TAM, TOE, UTAUT, PC Utilization Model).

In recent years, some of these models have been used concerning Industry 4.0 technologies to study user acceptance of industrial exoskeletons (Elprama et al., 2022), to explore workers' perceptions and barriers when dealing with augmented reality (Schein & Rauschnabel, 2023), or to analyze employees' behaviors in using wearable devices in production (Schwambach et al., 2022). This demonstrates the validity of such approaches through the years and the capability to address technology introduction from a multifaceted perspective.

Numerous studies have examined technology adoption processes, highlighting the need for effective change management strategies to achieve successful results. There are different taxonomies and typologies to define technology adoption phases, considering various criteria. All of them could be discussed considering the classic Plan-Do-Check-Act approach, e.g., Thomas et al. (2008) proposed a looped model with consecutive top-level stages for advanced manufacturing technologies implementation: 1/ company analysis and planning stage, 2/ technology planning stage, 3/ technology selection stage, 4/ technology process engineering stage, 5/ technology development stage (looped back to stage 1/).

Simple but widely accepted in the manufacturing society division of technology adoption stages is the one adopted by the World Economic Forum report "Views from the Manufacturing Front Line: Workers' Insights on How to Introduce New Technology," which describes three main phases:

Before introducing the technology, how to prepare your employees;
While introducing the technology, how to ensure adoption;
Beyond the implementation, how to sustain success.

That approach is widely adopted in the literature. The terminology may differ slightly, e.g., stages could be referred to as pre-change, change, or post-change (Saghafian et al., 2021). Nevertheless, these approaches, are consistent with Lewin's foundational three-step model for change (Burnes, 2004), i.e.,

Unfreezing (Pre-change or Preparation);
Changing (Change or Transition);
Refreezing (Post-change or Consolidation).

The elements characterizing these three phases are well summarized in the framework Saghafian et al. (2021) addressing workstation and process (human-technology interaction, organizational interventions, accept-resist), system (organizational culture, structure, leadership, resources), and ecosystem (society, governing bodies, competition, external partners) levels.

Further, as already pointed out, the above-mentioned technology adoption models could be used in each phase, specifically addressing the individual level of technology acceptance, considering a single user (e.g., TPB) or adopting a more system-oriented (e.g., DOI) or holistic approach (e.g., UTAUT) to technology introduction (FakhrHosseini et al., 2022), embedding these contextual, social, and organizational key elements.

According to these features, which encompass the technology lifecycle from preparation to consolidation and provide a multi-level perspective on individuals and systems, technology adoption models can be successfully used to promote and sustain long-term O5.0 initiatives.

Nevertheless, based on the analysis of the context reported in this section, it is possible to state that a gap exists in the scientific literature regarding the relationships between the O5.0 concept and the related technologies, as well as the main technology adoption models and strategies. The analysis and framework developed in this paper, as explained in the following sections, aim to fill this gap.

4. Technology adoption models and Operator 5.0 – Evidence from literature

This section presents the results of the literature review, discussing the more relevant technology adoption models and their relationships with the O5.0. Multiple reviews indicate that the landscape of technology acceptance/adoption includes more models than the nine examined in this study (e.g., alongside TRA/TPB, TAM, UTAUT, DOI, and SCT, reviews also discuss models such as the Motivational Model and other variants/derivatives used across domains) (Nnaji et al., 2023; Taherdoost, 2018; Tarhini et al., 2015). For TAMOP, we therefore applied a deliberately bounded selection. We focused on nine prominent and repeatedly reviewed theories that are consistently treated as core (or “prominent”) in syntheses of technology adoption research, including both general IS-focused reviews and reviews of intelligent/embedded environments (FakhrHosseini et al., 2022; Kruger & Steyn, 2025; Salahshour Rad et al., 2018). This restriction ensures coverage of key individual-level acceptance/use mechanisms, organizational adoption perspective (TOE), and technology maturity/readiness perspective (TRL), while keeping the model set sufficiently manageable for the detailed, model-by-model evidence.

4.1. Individual user-level theories

4.1.1. Social cognitive theory (SCT)

Social Cognitive Theory (SCT), originally known as Social Learning Theory (SLT), was proposed in the 1960 s by Albert Bandura (1986). It developed into the SCT in 1986 and is a psychological framework that emphasizes the role of observational learning, imitation, and modeling in human behavior. This theory suggests that individuals learn not only through direct experiences but also by observing the actions and outcomes of others. This is something that can be said to have in common with Soviet developmental psychologist Lev Vygotsky’s socio-cultural perspective, which highlights the importance of both social and cultural perspectives, as well as the interaction with external tools and scaffolds (Lindblom & Ziemke, 2003). Mirror neurons, one of the most significant findings in neurology over the last 30 years, also attribute importance to SCT, as they exhibit similar activity both when an individual executes a motor action and when they observe the same or similar action performed by someone else (Kilner & Lemon, 2013). Social Cognitive Theory has been applied to various areas, including education, health promotion, and therapy. It provides a framework for understanding how individuals acquire new behaviors, develop and maintain certain behavior patterns, and how social factors contribute to these processes.

An initial literature search on Scopus returned only one article on the cognitive science of human–machine interactions. As the search was extended to include a wider scope of social cognition, 23 articles were identified, which were subsequently reduced to 16 through manual exclusion of irrelevant publications. However, SCT, as a theory and concept, can no longer be considered the primary topic of the literature search. Of these 16 articles, most (9) deal with artificial intelligence or intelligent cognitive agents, four focus on the design of complex systems, and another three address different aspects of simulation. While SCT is not a central concept in either of these articles, the importance of social cognition and the usage of social peer interaction is of some interest when training AI systems and designing cognitive agents for smooth interaction with human users.

4.1.2. Theory of Reasoned action (TRA) and theory of Planned behavior (TPB)

The Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) have been widely used to understand and predict technology acceptance and usage. In the context of technology adoption, these theories provide a framework for examining the factors that influence individuals' intentions to adopt and use technology (Ajzen, 2002). TRA can support technology acceptance by positing that individuals' attitudes toward a behavior significantly influence their intentions to perform that behavior. In the context of technology acceptance, this refers to the user's attitude toward adopting and using a specific technology. The subjective norms component of the TRA considers the influence of others' opinions and expectations on an individual's intention to embrace technology. Social factors, including peer influence and organizational expectations, significantly influence individuals' intentions to adopt technology. Perceived Behavioral Control (PBC) extends TRA by incorporating perceived behavioral control as a crucial factor. In the context of technology acceptance, PBC reflects an individual's perception of the ease or difficulty of adopting and using a specific technology. It includes factors such as perceived complexity, self-efficacy, and resource availability. Behavioral intention and actual technology use are like TRA; TPB emphasizes that behavioral intention strongly predicts actual behavior. In the context of technology adoption, this suggests that individuals with a strong intention to use a technology are more likely to use it. TRA and TPB laid the foundations for holistic models that will be discussed later, namely TAM and UTAUT.

As defined in the Methodology section, the query returned eight papers in Scopus related to TRA/TPB in the direct context of O4.0/O5.0 and related topics. After screening the abstracts, six papers were excluded because they were irrelevant to the topic. The remaining two papers focus on the technological adoption of biometric authentication and a national digital identity system. It is noteworthy that both studies primarily focus on the issue of trust in technology rather than the adoption process itself. Furthermore, these papers exclusively employ the TPB as their investigative framework. The study by Kathuria et al. (2020) focuses on user adoption of voice authentication technology, exploring trust from both psychological and technological perspectives, and integrating human-centered Artificial Intelligence (AI) to analyze the factors influencing consumer trust in voice authentication. Hilowle et al. (2023) employed and integrated the Technical Formal Informal (TFI) model with the TPB to investigate the factors that affect the adoption of National Digital Identity Systems (NDIDs) within the framework of Human-Centric Cybersecurity (HCCS). It draws on the TPB to propose and validate a research model depicting how HCCS factors impact the use of NDIDs. Notably, the study highlights the impact of human factors, including attitudes, beliefs, and behaviors, on the effectiveness of cybersecurity measures. The study identifies key predictors of adoption and usage, including perceived risk, utility, convenience of use, trust, security, privacy, and social influence, particularly in the context of mobile payment systems. The research underscores the significance of addressing human aspects in adopting technological systems such as NDIDs, highlighting a gap in attention to the human dimension in current studies. Drawing on social cognitive theory, the research highlights that users' behaviors and interactions play a crucial role in shaping their preferences for a system. Addressing cultural and social interference, the study underscores their potential to hinder the adoption and use of technology. The findings align with previous research by Thompson et al. (2020), which suggests that culture has a significant influence on technology adoption, shaping perceptions and the willingness to utilize technology. Social factors, including pressure to conform to norms, also impact the acceptance and utilization of Information Systems (IS).

4.2. System-centred theories

4.2.1. Innovation diffusion theory (IDT) or diffusion of innovation theory (DOI)

DOI is a well-established theory that has gained much interest from researchers and practitioners. Elements that impact the spread of innovation are the innovation itself, adopters, communication channels, time, and the social system. DOI is oriented towards human beings forming different innovation adopter categories, i.e., innovators, early adopters, early majority, late majority, and laggards, suggesting that individuals (acting within a social system like an organization) will adopt technology at differing paces. Analysis of adopters' categories enables us to define facilitators and inhibitors of innovation across all phases of the change process: 'before,' during, and'after.' It also proposes what factors potential adopters analyze when making decisions (characteristics of innovation: compatibility, trialability, relative advantage, observability, simplicity/complexity). Such analysis applies mainly to a change process's 'before'/'unfreezing' phase. Individual decisions could be better analyzed using additional frameworks, such as TAM or UTAUT. Organizational characteristics, such as the tension for change (motivation and ability), innovation-system fit (compatibility), and assessment of implications (observability), impact innovation diffusion, as well as the characteristics of individuals. DOI sketches the diffusion process using the S-curve concept and outlines several strategies for the diffusion process, highlighting that innovation can be rejected at any stage. DOI enables generic analyses during all the phases before'/'during'/after.' However, it is worth noting that the DOI has received serious criticism, which should be taken into account when applying the theory. DOI assumes that all innovations should be adopted as they are, assuming they are positive, which is not always true. It also assumes one-way communication, whereas information is received, sent, and feedback is provided from multiple sources in complex systems. It is essential to recognize that no diffusion theory can account for all variables. Therefore, none is full.

The literature analysis has not identified any papers focused on DOI in the direct context of O4.0/O5.0. The query defined in the Methodology section returned only five papers in Scopus. Only two deal with the diffusion of innovation theory, as developed by Rogers (2006). One of them proposed an integrated model for change management built on top of DOI, combined with other theories (Chasm theory, Kubler-Ross Grief Cycle). It claimed support for digital technologies but was not directly related to the context of O4.0 / O5.0 and related topics, nor was it validated/demonstrated (du Plessis & Smuts, 2021). The other deals with DOI and TOE and is presented in Section 4.3.5.

4.2.2. Perceived characteristics of innovation (PCI)

The Perceived Characteristics of Innovation (PCI) (Moore & Benbasat, 1991) was developed to measure individuals' perceptions of IT innovations. It encompasses 8 categories, expanding 5 categories from the Diffusion of Innovations theory, which was created by Rogers in 1962 (Rogers, 2006), focusing on the perceived attributes of innovation (see Section 4.2.1). It adds two additions, i.e., image (included in DOI's relative advantage) and voluntariness. PCI also uses visibility and results demonstrability instead of DOI's observability. DOI's complexity focus was reversed and renamed to ease of use. Other DOI attributes remained the same as for DOI. PCI is focused not only on innovation characteristics but also on developing methods to predict the potential users' perception of using an innovation.

Moore and Benbasat (1991) discussed the idea that image should be a new category, as it reflects the degree to which innovation is perceived to improve the image, social system, and individual. Voluntariness refers to the degree to which the use of an innovation is perceived as being voluntary or of one's own free will, and it forms an important aspect of social influence. This influence occurs through compliance, such as doing what is required.

There was no evidence from the literature of PCI applications in the direct context of O4.0 / O5.0. As defined in the Methodology section, the query returned no papers in Scopus that mentioned PCI in the direct context of O4.0/O5.0 and related topics. There is evidence of using PCI in various settings, such as adopting computer-based training (Yaacob & Yusoff, 2014). In this sense, PCI, as it was developed to measure potential adopters' perceptions, demonstrates applicability, especially in the "before" phase, in a general way with no specific focus on O4.0/O5.0 dimensions. However, it has been demonstrated for computer-based training that this is a very specific issue within the O4.0/O5.0 paradigm.

4.3. Holistic theories

4.3.1. PC utilization model or model of PC utilization (MPCU)

Model of PC Utilization (MPCU) defined behavior as "determined by what people would like to do (attitudes), what they think they should do (social norms), what they have usually done (habits), and by the expected consequences of their behavior." According to the MPCU, job fit, complexity, long-term consequences, perceived usefulness, social factors, and facilitating conditions are determinants of technology acceptance. MPCU is based on the theory that social factors, affect, and perceived consequences impact behavior through the impact on intentions (Triandis, 1980). It's a competing approach (the distinction between cognitive and affective factors) to those of TRA and TPB. MPCU is named after the application of this theory to PC utilization. However, MPCU's general construct can be easily discussed in relation to any technology and is much more generic than PC-oriented. Analysis of the behavior determinants, as defined in MPCU, is applicable in the phases 'before' and 'after' implementation to determine the factors influencing positive decisions to implement and, subsequently, the technology's utilization level. There was no evidence from the literature of MPCU applications in the direct context of Operator 4.0/ 5.0. As defined in the Methodology section, the query returned no papers in Scopus that directly referenced MPCU in the context of Operator 4.0/5.0 and related topics.

4.3.2. Technology readiness levels (TRLs)

Technology Readiness Levels (TRLs) constitute a systematic metric based on 9 levels designed to gauge the maturity of diverse technologies, enabling a standardized evaluation across different types. Originating from NASA's space mission programs in the 1970 s, TRLs have undergone evolution, transcending industry boundaries and serving as a valuable tool for technology assessments and communication about maturity. Despite widespread adoption, TRLs encounter challenges, including subjective interpretations, a lack of guidance on maturation likelihood, and a predominant focus on hardware applications (Tomaschek et al., 2016). To address these limitations, comprehensive technology readiness methods have been proposed, as the one advocated by Clausing and Holmes (2010), which incorporates a technology readiness development process, a technology readiness assessment, and a technology implementation plan. This systematic approach aims to ensure the stability and smooth transition of new technologies into the marketplace, accounting for sensitivities that could lead to production delays and customer dissatisfaction. TRLs have proven pivotal in understanding technological maturity in terms of performance, reliability, durability, and operational experience, but they fail to address human-centric aspects comprehensively. Human Readiness Levels (HRLs) emerged as a complementary concept, introduced to evaluate technology readiness for human support, performance, ease of use, and user satisfaction (Salazar & Russi-Vigoya, 2021). HRLs mirror the structure of TRLs to assess and emphasize the human element within the system, aiming to enhance human performance, safety, and overall user satisfaction (See et al., 2019). Although HRLs are discussed in the literature as complementary to TRLs, they are not operationalized as a separate construct, and readiness is represented in the TAMOP 5.0 through TRL only.

As defined in the Methodology section, the query returned 7 papers in Scopus. However, after scanning the papers' contents, none specifically address the TRL in the direct context of O4.0/O5.0. Only one paper effectively discusses the role of TRL and humans in technological innovation. In particular, Wang et al. (2022) demonstrate through a case study the role of TRL as a success factor for the deployment of AI applications, highlighting that the standard TRL protocol supports the technology introduction as a business-transformative process in which people are involved. During the proof of concept and technology testing phases, end-users and stakeholders are encouraged to provide feedback to refine the technology. This user-centric approach proves crucial to enhancing acceptance. Therefore, TRL could be suitable for evaluating technological advancements in O4.0/O5.0 solutions before and during the implementation, ensuring they align with human needs and expectations.

4.3.3. Technology acceptance model (TAM)

TAM (Davis, 1989) is a key theory. It aims to predict user acceptance and to highlight potential design issues before users interact with the technological system (Koul & Eydgahi, 2017). TAM assumes that an individual's technology usage is controlled by two major variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEU), which can further influence an Individual's Attitude (ATT), Behaviour Intention (BI), and Actual Behaviour (U) (Wu et al., 2011). TAM considers technical factors, such as usefulness, enjoyment, and safety in technology adoption (Arpaci et al., 2015; Venkatesh et al., 2004), as well as socio-cultural factors related to social influence, commitment, and involvement (Charalambous et al., 2015). Additionally, personal attitudes such as autonomy, experience, self-confidence, and age are examined as key factors influencing technology adoption (Hoff & Bashir, 2015). In 2003, the Unified Technology Acceptance and Use of Technology (UTAUT) model based on TAM was developed (see Section 4.3.4).

The query, as defined in the Methodology section, returned 26 papers in Scopus. After abstract screening, 8 were retained. Three papers discussed the context of Operator 4.0 / 5.0. This paper used TAM to investigate the acceptance of augmented reality in industry (Jetter et al., 2018). Recent studies confirm the relevance of TAM for assessing technology acceptance in industrial AR applications. Marino et al. (2024) developed an augmented reality assembly guidance tool (ARAGT) following a user-centered design (UCD) approach was tested with industrial operators in a real facility. The evaluation employed the SUS and TAM instruments and confirmed high levels of user acceptance, underscoring the suitability of TAM for capturing human-centric dimensions in Industry 5.0 contexts. Barbieri et al. (2025) proposed an AR-based inspection tool to support Operator 4.0 tasks. TAM was applied in a real case study to assess acceptance, confirming that user involvement throughout the design process and a TAM-based evaluation ensure better alignment with operators' needs and facilitate technology integration in smart manufacturing environments. Five other papers were indirectly related to the Operator 4.0/5.0 context. One of the papers used TAM to investigate the acceptance of mobile applications to understand users' preferences for AR (Do et al., 2020), and two papers used both TAM and UTAUT in their investigations (Correia et al., 2021; Dash et al., 2023). One paper stated that the experimental vignette methodology (EVM) was used to study the acceptance of collaborative robots in the Industry 5.0 context (Liao et al., 2023), which was more suitable than TAM. Vervier et al. (2023) showed the application of TAM and UTAUT2 to explain the acceptance of the use of personal data in a smart factory using two examples (cobots and chatbots). They said, "The more fun it is to use and the higher the expected performance, the higher the acceptance of technology using personal data." This indicates that TAM could be useful in studying acceptance, mostly before and during implementation.

4.3.4. Unified theory of acceptance and use of technology (UTAUT)

The UTAUT aims to assess the probability of success of new technology introductions (Venkatesh et al., 2003). The tool UTAUT has four categories of intention and usage, helping to understand proactive design work, such as training, marketing, and other interventions for a target group that is less likely to adopt and use the new technology. The UTAUT model consists of four categories: 1) performance expectance, 2) effort expectance, 3) social influence, and 4) facilitating conditions. It was based on eight previous models of user acceptance and technology use (Venkatesh et al., 2003). UTAUT has investigated the following aspects of technology use: acceptance (Heerink et al., 2010; Kaye et al., 2020; Madigan et al., 2016; Schuster et al., 2021), intention (Alqahtani & Kavakli, 2017; Correia et al., 2021; Kamsvåg et al., 2022; Li et al., 2023; Ren & Zhou, 2023), adoption (Calisto et al., 2022; Jain et al., 2022; Tam et al., 2023), and use (Kamsvåg et al., 2022; Kazoun et al., 2022; Ren & Zhou, 2023). Other factors have also been investigated, e.g., risk, exception, trust (Choudhury et al., 2022), perception (Horodyski, 2023), comfort level (Anua et al., 2023), and reliability (Correia et al., 2021).

The query identified 16 papers in Scopus. Two directly mention the I4.0/I5.0. One paper examined the acceptance of collaborative robots and the factors that can drive perceived work performance improvement at an organizational level (Prassida & Asfari, 2022). The other paper studied the willingness to adopt AI systems in the Brazilian industry (de Almeida Pedro et al., 2023). Here, UTAUT was used to understand potential adoption behavior for risk management. Due to that, UTAUT has been used to investigate intention, technology adoption, and use for AI systems or other technologies related to Industry 4.0. UTAUT could be a useful model for O4.0/O5.0. These concerns delve into detail, for example, the influencing factors of visual quality when implementing AR (Schuster et al., 2021).

4.3.5. Technology Organization environment (TOE)

The TOE framework is a theoretical approach used in organizational studies and management to understand how internal organizational factors and external environmental factors influence technology adoption and innovation within an organization. The framework comprises three primary dimensions, i.e., Technology, Organization, and Environment. The technology dimension focuses on the specific characteristics of the technology, including technological complexity, compatibility with existing systems, and the relative advantage it offers compared to current technologies. The organizational dimension examines internal factors that influence technology adoption, encompassing organizational structure, culture, resources, capabilities, and readiness for technological change. Finally, the environmental dimension considers external factors that impact technology adoption beyond the organization. This involves industry trends, market conditions, regulatory environment, and broader economic and societal contexts. The TOE framework finds application in various contexts with different purposes, such as innovation management and strategic decision-making, for assessing the alignment between a technology and companies' internal capabilities and evaluating how external factors may impact technology success; policy and planning, to design strategies for technology adoption; and change management to guide organizations in implementing technological changes addressing challenges associated with technology adoption.

Despite the potential offered by this approach, few scientific articles use it to examine the impacts of new technologies on the workforce and operators. The literature analysis has identified only one paper by Mahroof (2019) in the direct context of Operator 4.0/5.0, and one by Liu and Cao (2022) in the narrowed context of cobots. That paper applies the TOE framework to explore the readiness of a significant retail distribution warehouse to implement smart warehousing practices. The study investigates various human-centric factors, including the skills and capabilities of the workforce, their attitudes toward technology adoption, and the overall organizational culture regarding smart warehousing initiatives. Specifically, the TOE approach is used to highlight the impacts in terms of opportunities and barriers that the new technology could have on the three dimensions of the framework. Liu and Cao (2022) combined the TOE and DOI models to identify the most important determinants of SMEs' adoption of collaborative robot innovation. The survey among Chinese SMEs highlighted that technology advantage, compatibility, trialability, and observability positively affect SMEs' adoption of collaborative robots, while complexity has a negative effect. Additionally, top management support and organizational readiness, particularly in terms of financial and human resources, as well as vendor support, were the most significant organizational and environmental determinants, respectively. The Technology-Organization-Environment (TOE) framework, as well as usefulness, enjoyment, and safety in technology adoption, stand out in the portfolio model, which adopts a holistic approach that considers both internal organizational factors and external environmental influences.

5. TAMOP 5.0 development

In summary, the investigation of prominent models yielded results reported in Table 4, where the models were grouped according to system levels and the connection to Operator 5.0, along with the adoption phases, was presented. As a summary of the previously discussed literature analysis, it has been possible to map the phases in which the different technology adoption models are most suitable for use (Table 4), also grounded in the key elements of the three phases as already presented in Section 3.2.

As a further step, to identify the most suitable technology adoption models to rely on in developing O5.0 initiatives, a link has been created between the models and the operationalized features of O5.0. Based on the description provided in Section 3.1, five key subdimensions have been identified: Attitude/Mindset, Technologies, Tasks and procedures, Performance, and Policy/Strategy/Organization. These subdimensions serve as common analytical lenses observed across three core values of Industry 5.0: Sustainability, Resilience, and Human-Centricity. While the same five categories recur in each domain, they are declined in distinct ways, reflecting each dimension's unique priorities and interpretations.

In the context of Sustainability, the Operator 5.0 initiatives require an environmentally conscious *Attitude and mindset*, which shows proper awareness of the ecological impact of operations and a high commitment to responsible practices. The *Technologies* employed are geared toward energy efficiency, low emissions, and resource optimization. *Tasks and procedures* refer to structured operational approaches to minimize waste and support circular economy principles. *Performance* assessment is relevant to measure the operator's contribution to sustainable goals, such as reducing carbon footprint or energy consumption. At a higher level, *Policy, Strategy, and Organization* are engaged to integrate sustainability into long-term planning, training, and incentive systems to promote green practices.

Considering the Resilience dimension, O5.0 implementations require a flexible and proactive *Mindset*, capable of adapting to changing conditions and managing stress or uncertainty effectively. Supporting *Technologies* should be robust, redundant, and capable of maintaining functionality in the face of disruptions. *Tasks and procedures* are

Table 4
Theory connections to Operator 5.0.

Level	Theory	Connection to Operator 5.0	Pre-change	Implementation	Post-change
Individual users	SCT	The importance of social cognition and the usage of social peer interaction is of some interest when training AI systems and when designing cognitive agents for smooth interaction with human users.	X	X	X
	TRA & TPB	Individual attitude can affect the trust in new technology introduction: It has specifically adopted in technological solutions dealing with privacy issues and cybersecurity.	X		
System	DOI	No evidence from the literature of IDT or DOI applications in the direct context of Operator 4.0 / 5.0. Limitations of this theory includes lack of feedback, only “optimistic” view of innovation.	X	X	X
	PCI	No evidence from the literature of PCI applications in the direct context of Operator 4.0 / 5.0. Literature suggests that PCI could be adopted when dealing with computer-based training.	X		
Holistic	MPCU	There was no evidence from the literature of MPCU applications in the direct context of Operator 4.0 / 5.0.	X		X
	TRL	TRL could be suitable for evaluating technological advancements in Operator 4.0/5.0 solutions before and during the implementation, ensuring that they align with human needs and expectations.	X	X	
	TAM	TAM could be useful in studying acceptance, and it was already used directly in the context of O5.0.	X	X	
	UTAUT	UTAUT provided support for what	X		

(*continued on next page*)

Table 4 (*continued*)

Level	Theory	Connection to Operator 5.0	Pre-change	Implementation	Post-change
		influencing factors are relevant and provides support for its use in the context of I4.0.			
	TOE	TOE offers a structured method to assess technology adoption and innovation processes with a holistic consideration of human and organizational aspects.	X		

designed for adaptability, enabling rapid reconfiguration in response to unexpected challenges. *Performance* is assessed in terms of output and the operator's ability to maintain continuity and stability under pressure. Considering *Policy, Strategy, and Organization*, agility, risk management, and cultivating a learning-oriented culture are the most relevant aspects to respond to crises.

In the Human-centricity domain, O5.0 refers to a *Mindset* rooted in self-awareness, motivation, and psychological well-being. *Technologies* are developed to be human-friendly, supporting rather than replacing the operator, including collaborative robots, intuitive interfaces, and ergonomic tools. *Tasks and procedures* are tailored to human needs, aiming to reduce cognitive and physical stress while encouraging engagement and satisfaction. *Performance* holistically encompasses properly valuing worker empowerment and development, as well as work-life quality indicators. Finally, *Policy, Strategy, and Organization* should reflect inclusiveness and respect for diversity, promoting active participation, continuous learning, and a supportive organizational culture.

To validate the above-discussed dimensions in the TAMOP 5.0, we ran a three-round Delphi study. Round 1 evaluated 27 items on the structure and content, of which 18 (67%) reached consensus. All conceptual definitions, the three phases (pre-change, implementation, post-change), the three value dimensions (human-centricity, resilience, sustainability), the five sub-dimensions under each, and the overall goal received an acceptance rate of 92–100% (agree/yes or top-two answers in a 5-point scale). Pre-change and implementation were rated as important/critical (top two in a 5-point scale) by 92% and 83%, respectively. The post-change rate was 67% (<70%), prompting clarification. Of 15 sub-dimensions, nine were considerable/highly adequate (75–92% top-two in a 5-point scale), whereas six, i.e., HC (performance, technologies, policy/strategy), RES (performance, technologies), SUS (technologies), achieved only 50–67% top-two answers and moved forward for revision. Usefulness scored 67% and clarity 17% in the top two answers on a 5-point scale, which is below consensus.

In Round 2 (n = 11), we re-tested the nine unresolved items after adding or revising definitions for the six sub-dimensions, expanding the post-change explanation, and simplifying the visualization with a legend. Post-change was affirmed (median = 4, IQR = 1; over 80% answers ≥ 4), and usefulness reached consensus (median = 4, IQR = 0; 82% answers ≥ 4). Overall, Round 2 resolved 7 out of 9 items. Five of six sub-dimensions then met consensus (median ≥ 4, IQR ≤ 1, and over 70% of answers ≥ 70%). The exception was RES-Technologies (median = 4; IQR = 1.5; 55% answers ≥ 4). The other exception was clarity, which improved to a median of 4, with an IQR of 1 (satisfying the median/IQR rule consensus), but only 55% of answers were ≥ 4 (divergence remained). Those two moved on to a micro-Round 3, including a head-to-head test of two visualization formats.

In Round 3 (n = 10), the revised RES-Technologies reached consensus (median = 4, IQR = 1; 90% answers ≥ 4). Sixty percent of the experts preferred a circular representation of the framework, while forty percent preferred a refined table. We fused the features and finalized the figure. By Round 3, all phases, dimensions, and sub-dimensions had consensus. Full results and accompanying practical example are available in Annex B.

Table 5 summarizes how the reviewed technology adoption models can support the three O4.0 dimensions, while Table 6 delves into the specific match between the models and the above-explained subdimensions.

Table 6 shows that individual models provide uneven coverage across the Industry 5.0 dimensions and adoption phases. Blank cells indicate dimensions/phases for which no supporting evidence was identified in the reviewed literature. Fig. 3 depicts circular mapping of models to phases and dimensions. The diagram is partitioned into three dimensions (Human-Centricity, Resilience, Sustainability) and three concentric rings (outer = Pre-change, middle = Adoption, inner = Post-change). In each sector, the applicable adoption models are listed with dot strength (• weak, •• moderate, ••• strong). These ratings were assigned based on evidence from the literature and expert judgment as a three-level ordinal coding for readability (not a statistical Delphi score). The figure shows the strongest model availability in Pre-change, less in Adoption, and the least in Post-change, with Sustainability being the most sparsely populated in the later phases. Post-change is sparse, where only a few models recur (notably DOI ••, MPCU ••, SCT •••, excluding Sustainability). Dimension-wise, Human-Centricity and Resilience contain more entries with stronger support (more dots) than Sustainability overall, with Sustainability showing the fewest items in Post-change. Human-centricity demonstrated the strongest potential support from models (mostly ••• entries).

Model-wise analysis uncovers some potentially prominent models. SCT appears in all three rings, but two dimensions (no Sustainability in any phase), consistently strong (•••). DOI is widespread across sectors/rings, typically moderate (••). MPCU is present in all dimensions in pre-change and post-change, but absent in the adoption phase. It scores moderately (••), except for the human-centric dimension, where it scores strongly (•••). TAM and TRL are useful in the pre-change and adoption phases. TAM scored moderately (••), except for the human-centric dimension, where it got strong (•••). TRL scores varied across dimensions (• resilience, •• sustainability, ••• human-centric). Other models were demonstrated only in the pre-change phase with varying support strength.

Fig. 3 offers a visual and synthetic representation of the potential of the different technology adoption models to support O5.0 and is based on the final evaluation results, which are reported in Table 6 (sum). As discussed, in the map, SCT and DOI show high potential. Table 6 shows that SCT is not suitable to evaluate all the sub-dimensions (specifically "Technologies"). The same occurs for the DOI model, which is not applicable for Attitude/Mindset and Policy/Strategy sub-dimensions. This suggests that it is impossible to select only one or two models that are suitable for all the operational scenarios in which the Operator 5.0 initiatives are implemented. Different conditions in the industrial sector, jobs, and workforce characteristics can influence model applicability, and combinations of models could be recommended according to the contextual situation. For example, the classification among individual user-level, system-centred, and holistic theories signals that the former are more suitable when dealing with specific tasks and job roles. At the same time, the latter needs to be preferred when introducing technologies affecting larger work environments, such as workshops or factories. Further discussions are presented in the next section.

6. Discussion

The TAMOP 5.0 highlights the differential capacity of adoption models to support Operator 5.0 features (Table 6). The analysis of

Table 5
TAMOP 5.0: support for Operator 5.0 dimensions.

Model	Dimension	Support	Short reasoning
SCT	Sustainable (S)	No	Focus on social/observational learning; no explicit ecological emphasis
	Resilient (R)	Strong	Promotes adaptive, problem-solving behaviors through modeling and self-efficacy
	Human-Centric (H)	Strong	Centers on self-efficacy, peer collaboration, and social reinforcement
TRA & TPB	Sustainable (S)	Moderate	Attitudes/norms can encourage pro-environment intentions but no direct eco-scope
	Resilient (R)	Moderate	Strengthens perceived control for handling disruptions; lacks system-level resilience coverage
	Human-Centric (H)	Moderate	Focus on individual intention; user well-being not inherent, but can be shaped by social norms
DOI	Sustainable (S)	Moderate	Spread of innovations; no inherent sustainability focus
	Resilient (R)	Moderate	Considers trialability, complexity; not explicitly resilience-focused
	Human-Centric (H)	Moderate	Focus on compatibility, simplicity; lacks direct human feedback loop
PCI	Sustainable (S)	Moderate	Emphasizes image, voluntariness; no direct ecological metrics
	Resilient (R)	Moderate	Ease of use, results demonstrability; partial coverage of resilience
	Human-Centric (H)	Strong	Voluntariness, image, ease of use align with user-centric needs
MPCU	Sustainable (S)	Moderate	Addresses social factor, job fit; no explicit environmental framing, but impact on sustainability depends on technology fit to social tasks and values
	Resilient (R)	Moderate	Emphasis on long-term consequences, facilitating conditions
	Human-Centric (H)	Strong	Affect toward use, social context align with human-centric focus
TRL	Sustainable (S)	Moderate	Evaluates tech maturity; can include sustainability in testing, but not by default
	Resilient (R)	Weak	Tracks robustness of solutions; no built-in workforce resilience approach
	Human-Centric (H)	Strong	Technical milestones only; ignores user comfort, acceptance, or well-being; strong when combined with Human Readiness Levels
TAM	Sustainable (S)	Moderate	Perceived usefulness can drive eco-adoption; no direct green emphasis
	Resilient (R)	Moderate	Ease of use fosters resilience adoption; lacks organizational scope
	Human-Centric (H)	Strong	Focus on attitudes and behavioral intention directly supports HC goals
UTAUT	Sustainable (S)	Moderate	Performance expectancy, social influence can encourage eco-tools; no explicit "green" lens
	Resilient (R)	Moderate	Effort expectancy, social context aid resilience adoption; limited to individual acceptance
	Human-Centric (H)	Strong	Integrates social influence, facilitating conditions; well-aligned with user-centric design
TOE	Sustainable (S)	Weak	Primarily external/market environment; sustainability not assumed unless specified
	Resilient (R)	Strong	Holistic coverage of tech, organization, environment; supports resilience strategies
	Human-Centric (H)	Moderate	Covers organizational culture but not intrinsically people-centered unless tailored

Table 5 reveals that some models display broader support across dimensions, especially regarding human-centric and resilient aspects. A comparison with Table 3 does not confirm a consistent pattern. The individual-level model of SCT aligns with all phases, but only for human-

Table 6
TAMOP 5.0: consolidated summary of support for features and dimensions.

Operator 5.0 features	SCT			TRA/TPB			DOI			PCI			MPCU			TRL			TAM			UTAUT			TOE			SUM
Attitude/ mindset	S	R	H		R					S		H	S							R	H						H	10
Technologies							S	R					S	R	H	S	R	H					R	H		R		11
Tasks/ procedures	S		H		R	H		R				H			H			H	S	R	H							11
Performance		R					S		H		R					S			S		H	S						8
Policy/ strategy/org.		R	H		R					S		H	S	R			R								S	R	H	11
SUM	2	3	3	0	3	1	2	2	1	2	1	3	3	2	2	2	2	2	2	2	3	1	1	1	1	2	2	51
Summa Summarum	8			4			5			6			7			6			7			3			5			

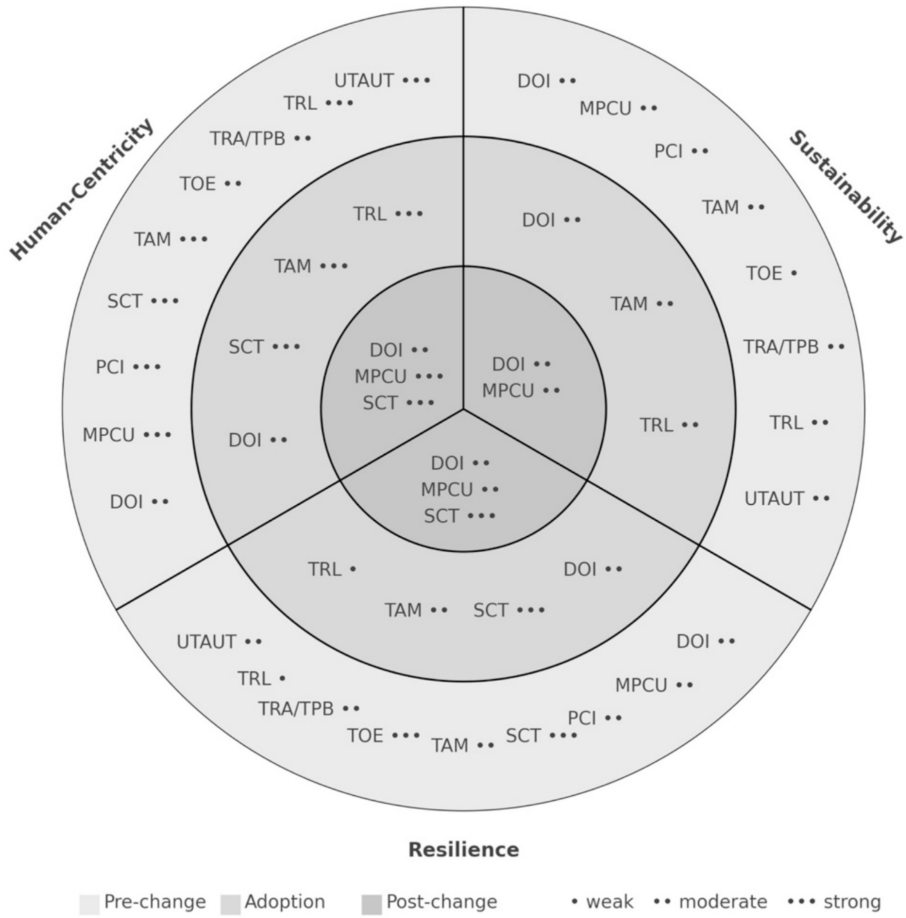

Fig. 3. Technology adoption models mapped on the change phase and Operator 5.0 dimensions.

centric and resilience dimensions. Other individual-level models, such as TRA/TPB, are more closely aligned with the pre-change phase, where user behavior, beliefs, and perceived control are critical. These models tend to be explanatory, focusing on social, psychological, and motivational dimensions, and are thus particularly useful for influencing operator engagement, acceptance, and initial readiness to adopt.

System-level models, such as DOI and PCI, offer more descriptive insights. These are suited to early-stage planning and classification purposes, such as identifying innovation characteristics or adopter categories. But DOI demonstrated moderate support across all phases. Interestingly, PCI has not, which might be a result of a lack of evidence, but not a lack of potential, considering PCI and DOI dependencies. While they can inform strategic scoping and segmentation, their applicability to post-change or human-centric challenges may be limited. Their assumptions of linear diffusion and one-way communication do not adequately capture the dynamic and interactive nature of Industry 5.0 environments.

In contrast, the holistic model of MPCU (but not TAM, UTAUT, and TOE, which may be too complex) exhibits versatility across all three implementation phases and the five dimensions of Operator 5.0. TAM and UTAUT, with their emphasis on behavioral intention and perceived usefulness, support technology design and deployment with a clear user-centered focus. UTAUT extends this by integrating social influence and facilitating conditions, adding explanatory power in more complex settings. TOE, while structurally comprehensive, considering technology, organization, and environment, lacks intrinsic human-centric elements and thus requires tailoring to better address the values of well-being, inclusivity, and empowerment central to the Operator 5.0 vision.

There is no pattern to apply individual, system, or holistic methods. The widest application scope is demonstrated for SCT (individual), DOI (system), and MPCU (holistic).

Regarding feature-level support, the most consistently covered aspects across models are technologies, tasks/procedures, and policy/strategy/organization. These are relatively tangible and actionable components of the Operator 5.0 framework. Performance, particularly in its psychological or ethical dimension, is less frequently addressed. This shows a conceptual gap in existing models regarding framing the evolution of operator identity, values, and long-term personal and organizational growth.

The framework also reflects significant variation in the conceptual nature of the models. Some, like TRL and DOI, are taxonomical or categorical. They serve well in “phasing” technologies or describing the state of readiness and innovation diffusion, but are less helpful in explaining causal relationships or designing behavioral interventions. Others, such as TAM, UTAUT, or MPCU, are relational and explanatory, making them well-suited to uncovering the mechanisms behind user acceptance, system interaction, and longer-term use. These models offer pathways to intervene, modify, or support specific adoption dynamics and are crucial for developing sustainable, resilient, and human-centric transitions.

A further layer of distinction lies in the temporal orientation of several models. TRL explicitly maps the trajectory of technology maturity, while DOI frames adoption through an S-curve lens. MPCU adds nuance by introducing long-term consequences and habitual behavior. These time-sensitive perspectives are especially relevant when managing long-cycle implementation processes and continuous adaptation, such as in environments characterized by rapid technological change or evolving workforce roles. The harmonized view provided by the TAMOP 5.0 allows for a modular, layered application of models. During early stages, projects may benefit from using PCI or DOI to map out perceived innovation characteristics and diffusion pathways. SCT and TRA/TPB could support targeted communication or training strategies. UTAUT and TAM can monitor engagement and refine interface design as projects evolve, whereas TOE and TRL become increasingly relevant for assessing organizational alignment and maturity. This layered approach proposes that rather than selecting a single adoption model, effective implementation of Operator 5.0 initiatives may rely on orchestrating complementary frameworks over time.

TAMOP 5.0 provides a harmonized view of technology adoption models across phases and Industry 5.0 dimensions, but it is not conceived as a formal multi-criteria decision-making (MCDM) method. The framework does not aim to compute optimal solutions, weights, or rankings across competing criteria. It supports structured comparison, and informed shortlisting of adoption models by aligning qualitative evidence from the literature with expert judgment. The use of a simplified, ordinal dot-based notation reflects this intention. It is designed to enhance transparency, interpretability, and usability for both researchers and practitioners, rather than to replace quantitative decision-analytic techniques. More formal MCDM approaches (e.g., AHP, ANP, TOPSIS, ELECTRE, PROMETHEE, or similar) would require additional assumptions, weighting schemes, and empirical data that fall outside the scope of the present conceptual study. Nevertheless, future research could explore the operationalization of TAMOP 5.0 through MCDM-based extensions, where the framework could act as a structuring layer or pre-processing step to define criteria, alternatives, and phases before applying quantitative evaluation methods in specific industrial contexts.

Theoretically, the TAMOP 5.0 contributes to the ongoing dialogue on integrating socio-technical, behavioral, and organizational dimensions within complex technology transitions. It demonstrates that while individual models may offer strength in certain phases or dimensions, no single theory fully encompasses the breadth of the Operator 5.0 challenge. This reinforces the need for a harmonized and situational application of models, as well as the potential value of hybrid frameworks that combine the explanatory power of individual-level theories with the structural insights of system-level or holistic approaches.

This study addresses three gaps in Operator 5.0 adoption research. First, prior work offers many adoption models but provides limited guidance on which model to use when across an Operator 5.0 adoption pathway. TAMOP 5.0 structures model selection by phase and scope. Second, the evidence linking adoption-model constructs to Operator 5.0-relevant technologies and decision needs is fragmented. TAMOP consolidates this evidence in comparative matrices to support consistent planning and communication. Third, existing approaches rarely integrate individual-, organizational-, and readiness-oriented perspectives in one actionable scheme. TAMOP combines these lenses without proposing a new acceptance theory. Future research should empirically validate TAMOP through multiple case studies and comparative applications, refine the matrix representation (e.g., higher-granularity coding beyond the three-level dot notation), and test optional extensions such as combined readiness overlays (e.g., TRL with HRL as a separate layer).

7. Conclusions

This research aimed at discussing the potential of technology adoption models to support the widespread and successful adoption of Operator 5.0 initiatives. The visual mapping provided by the TAMOP 5.0, conceptualized and validated in this study, highlights that a combination of models is necessary to support Operator 5.0 initiatives fully. Practitioners can use the framework to identify which theoretical models to apply at each stage of change and which areas might require additional attention or new frameworks. It demonstrates the “TAMOP 5.0” approach of orchestrating multiple adoption models over time to ensure that technology adoption in Industry 5.0 is human-centered, resilient, and sustainable from initiation (pre-change) through implementation to post-implementation (post-change).

At the current stage, TAMOP 5.0 is not yet a turnkey software tool. Still, it is a decision-aid concept that helps researchers and practitioners identify which adoption theory is most helpful at various stages (pre-change, implementation, post-change) and for which Operator 5.0 value (human-centricity, resilience, sustainability). The TAMOP 5.0 represents a novel and structured approach to interpreting how existing technology adoption models can support the transition toward the Operator 5.0 paradigm. By organizing models according to their alignment with implementation phases and ability to address sustainability, resilience, and human-centricity, the framework enables researchers and practitioners to make informed and context-sensitive choices.

Nonetheless, the TAMOP 5.0 framework also has limitations. It remains a conceptual synthesis and lacks empirical validation, which is necessary to prove its practical value. It also provides only shallow treatment of the individual models, assuming users have prior knowledge or access to expert interpretation. The current model's societal and policy-level context is not sufficiently captured, which may limit its use for public-sector or cross-sectoral transformation strategies. Finally, if not properly introduced, the TAMOP framework could risk cognitive overload, presenting too many variables without clear guidance, especially in SMEs or low-maturity settings. The nine adoption models should not be read as static, universally applicable tools in the Industry 5.0 context. In our results, the comparative matrix (Table 6) shows uneven coverage of Industry 5.0 dimensions across models. The blank cells are where no supporting evidence was identified for a given model–dimension–phase combination. This should be interpreted as a scope limitation of single-theory approaches and reinforces the need to combine models depending on the adoption phase and decision focus, which is consistent with the Operator 4.0 to Operator 5.0 transition evidence emphasizing issues such as trust, skills, and human-factors integration (Gladysz et al., 2023). Single adoption models have clear scope limits in the Industry 5.0 setting (human-centricity, sustainability, resilience). TRA/TPB are intention-based and mainly individual-level, with limited representation of organizational constraints and implementation conditions. TAM is intentionally parsimonious and typically requires extensions to cover organizational and human-factors aspects beyond perceived usefulness and ease of use. UTAUT integrates multiple predictors but still primarily models individual acceptance and is highly context- and moderator-dependent. DOI emphasizes perceived innovation attributes and diffusion patterns, but is less explicit on within-firm implementation mechanisms. SCT provides broad socio-cognitive determinants (e.g., learning/self-efficacy) but is not an adoption-process model in itself. MPCU is rooted in personal computing use and does not capture organizational governance or socio-technical integration. PCI focuses on perceived innovation characteristics and therefore covers only a subset of adoption determinants. TOE captures organizational and environmental drivers but does not model individual acceptance and work-level human-centric mechanisms. TRL reflects technology maturity but does not address workforce readiness or human-factors preparedness. These well-known boundaries are consistent with adoption-model review literature (Nnaji et al., 2023; Taherdoost, 2018; Tarhini et al., 2015) and with Operator 5.0 transition evidence stressing restrainers such as trust, skills, and human-factors integration (Gladysz et al., 2023). In our matrices (Table 6), blank cells should therefore be interpreted as model scope limits and/or missing evidence for a given model–dimension–phase combination, motivating phase-dependent model selection and orchestration rather than reliance on a single model. The model support strength notation (ordinal, three-level, dots) is a simplified representation, as the TAMOP 5.0 is intended to guide model shortlisting and combination across phases/dimensions rather than provide a quantitative ranking of models. Future research should focus on empirically validating the TAMOP framework through in-depth case studies, action research, or simulation-based evaluations. Future work may extend TAMOP by adding an HRL overlay to each phase, so that workforce readiness (skills, training, human factors preparedness) is assessed alongside technology maturity (TRL), enabling a combined

TRL/HRL readiness view without changing the current model set. It would also be valuable to explore combinations or interactions between models, for instance, integrating TAM's user-centered elements with TOE's organizational insights. A further extension could involve embedding ethical and humanistic principles, such as autonomy, fairness, and diversity, more explicitly into the evaluation framework. Additionally, digital tools could be developed to enable the real-time tailoring of adoption strategies based on model inputs and contextual variables. A further step will involve operationalizing the TAMOP5.0 through the identification of practical approaches to provide step-by-step guidance to industrial companies approaching O5.0 initiatives, as well as customizing the choice of the most effective technology adoption models based on specific company situations and requirements. The operationalization of the TAMOP also includes refinement in the visual representation and graphical tools that will be used to adopt it in business cases.

In conclusion, the TAMOP 5.0 offers a much-needed harmonization of existing technology adoption models within the emergent Operator 5.0 paradigm. It clarifies an otherwise fragmented theoretical landscape, guiding selection of the most suitable models for different dimensions and phases of technology implementation. While conceptual, it lays the groundwork for structured, multidisciplinary, and human-centric adoption strategies, making it a valuable stepping stone toward more inclusive and resilient industrial futures. TAMOP 5.0 does not introduce a new acceptance theory. It provides a structured, phase-based mechanism (pre-change, implementation, post-change) that operationalizes model selection against the core Industry 5.0 values (human-centricity, resilience, and sustainability). Unlike prior taxonomies that primarily classify adoption models by theoretical level or scope without actionable guidance (FakhrHosseini et al., 2022; Salahshour Rad et al., 2018; Taherdoost, 2018) and single-theory models, TAMOP 5.0 maps specific models to concrete implementation phases and aligns them with Industry 5.0 dimensions, turning descriptive classifications into a practical decision-support tool. Crucially, the framework's explicit Operator 5.0 orientation is novel. It consistently places the operator at the center of adoption decisions, integrating worker well-being and competence development with system resilience and sustainability objectives (Romero & Stahre, 2021). In doing so, TAMOP 5.0 enables coherent planning, assessment, and communication of model choices across the adoption lifecycle and provides useful guidance for practitioners, while establishing a clear foundation for future empirical validation and decision-support tooling (e.g., readiness overlays and human-centric AI integration) (Rožanec et al., 2023; Salazar & Russi-Vigoya, 2021).

Data statement

Data is summarized in the Annexes. Full data is available directly from the authors upon reasonable request.

CRediT authorship contribution statement

Bartlomiej Gladysz: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chiara Cimini:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Alexandra Lagorio:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Sandra Mattsson:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Marta Pinzone:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **David Romero:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Tamas Ruppert:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Peter Thorvald:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

Annex A. List of all queries

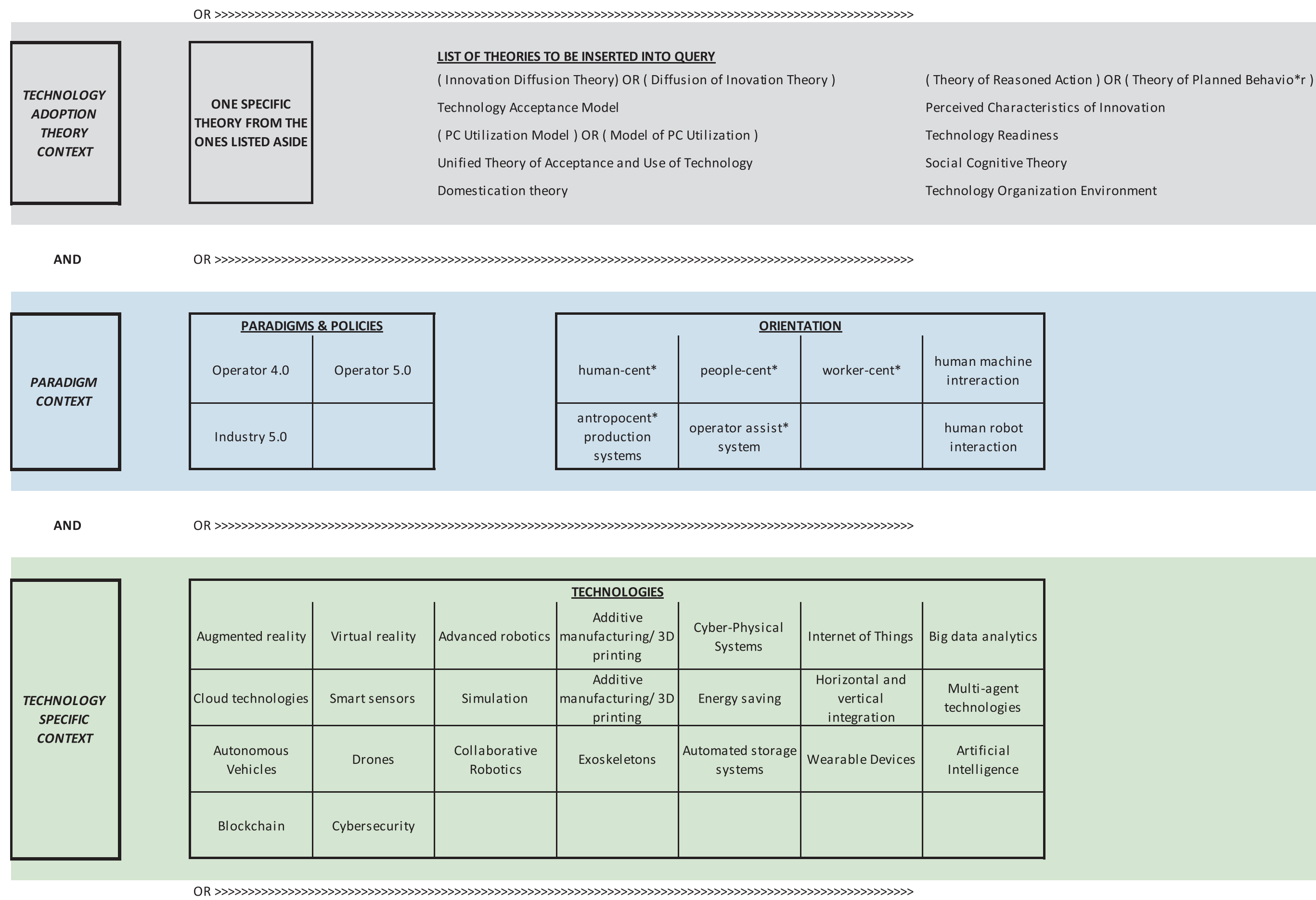

Fig. A1. Structure of queries

UTAUT

TITLE-ABS-KEY (

("Unified Theory of Acceptance and Use of Technology" OR utaut).

AND ("operator 4.0″ OR "operator 5.0″ OR "industry 5.0″ OR human-cent* OR people-cent* OR worker-cent* OR "antropocent* production systems" OR hmi OR "human-machine interaction" OR "operator assist* system" OR oas).

AND ("augmented reality" OR AR OR "virtual reality" OR VR OR "advanced robot*" OR "additive manufacturing" OR "3D printing" OR "cyber-physical system*" OR CPS* OR "Internet of Things" OR IoT OR "big data" OR "cloud technolog*" OR "smart sensor*" OR simulation* OR "energy saving" OR "horizontal integration" OR "vertical integration" OR "multi-agent technolog*" OR "autonomous vehicle*" OR "automated guided vehicle*" OR AGV* OR drone* OR "collaborative robot*" OR cobot* OR exoskeleton* OR "automated storage system*" OR wearable* OR "artificial intelligence" OR AI OR blockchain OR cybersecurity).

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Annex B. Full Delphi study results and accompanying materials

B.1. Delphi study results

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Table B1
Round 1 results.

Evaluation block	Consensus rule	Result *	Status for R2 / next action / note
Concept check (definitions)	$\geq$ 70% “Yes + Partly”	Phases 100% Values (dimensions) 100% Subdimensions 100% Goal 92%	OK – drop from R2
Validation of the three phase structure	$\geq$ 70% answers 45 Likert 1–5 scale	Prechange 92% Implementation 83% Postchange 67%	nOK – rerate Postchange only in R2 add definition of post-change
Validation of Operator 5.0 Value System (Dimensions)	$\geq$ 70% answers 45 Likert 1–5 scale	Human-Centricity (HC) 92% Resilience (RES) 92% Sustainability (SUS) 83%	OK – drop from R2
Subdimension adequacy as analytical lenses	$\geq$ 70% answers 4–5 Likert 1–5 scale	Belowthreshold: HCPerformance 50% HCTechnologies 67% HCPolicy/S&O 67% RESPerformance 58% RESTechnologies 67% SUSTechnologies 50% Abovethreshold: all others 75–92%	nOK – six descriptors to be rerated in R2 add definitions of all 6 pairs
Usefulness of matrix	$\geq$ 70% answers 45 Likert 1–5 scale	67%	nOK – addressed via improvement priority list attach short example of using the TAMOP (e.g. cobot)
Clarity of matrix presentation	$\geq$ 70% answers 45 Likert 1–5 scale	17%	nOK – graphic simplification & legend remain high priority add to R2 new matrices – less colors – blue instead of green, add legend about dots (strength)/no_models use colors for summarised no of dots (strength) instad no of models

Table B2
Round 2 results.

Items (problematic in R1)	Round 1 score % of answers 4–5 in Likert 1–5 scale	Median / IQR / % of answers 4–5 in Likert 1–5 scale)	R2 consensus		Status for R3 / next action / note
Post-change (Consolidation)	67% < 70%	4 / 1 / 91%	Median $\geq$ 4 & IQR $\leq$ 1 & % of answers 4–5 in Likert 1–5 scale > 70%	YES	OK – drop from R3 keep 3phase model
HC-Performance	50% < 70%	4 / 1 / 82%		YES	OK – drop from R2
HC-Technologies	67% < 70%	4 / 1 / 82%		YES	OK – drop from R2
HC-Policy/S&O	67% < 70%	4 / 0.5 / 82%		YES	OK – drop from R2
RES-Performance	58% < 70%	4 / 1 / 91%		YES	OK – drop from R2
RES-Technologies	67% < 70%	4 / 1.5 / 55%		NO	nOK – refine descriptor, move to round 3
SUS-Technologies	50% < 70%	4 / 0.5 / 82%		YES	OK – drop from R2
Usefulness for planning or researching O5.0 projects	62% answers 4–5 (<70%) Likert 1–5 scale	4 / 0 / 82%		YES	OK – drop from R2
Clarity of the matrix presentation	17% < 70%	4 / 1 / 55%		YES	nOK – further visual & wording simplification

Table B3
Round 3 results.

Item (problematic in R2)	Median / IQR / % of answers 4–5 in Likert 1–5 scale)		R3 consensus	Status / next action / note
	Round 2	Round 3		
RES-Technologies	4.0 / 1.5 / 55%	4.0 / 1.0 / 90%	Yes	No further actions
Preferred figure format	Not applicable	B (circular) 60% A (matrix) 40%	Not applicable	Preference item (no consensus rule applied); Circular format chosen

B.2. Practical example

B.2.1. Context

A mid-sized European domestic appliance manufacturer with ∼ 300 employees runs several semi-automated assembly lines. In recent years, the company has faced growing challenges related to workforce health and operational adaptability. A rise in musculoskeletal disorders (MSDs), absenteeism, and ergonomic audit feedback triggered a strategic review of workstation design, especially for repetitive, high-strain tasks.

The screw-fastening workstation was identified as a critical area, where operators performed hundreds of repetitive motions per shift in constrained postures. Earlier investments in adjustable benches and rotation schedules were not sufficient to improve long-term well-being or adapt to shifting production needs. As a response, the company launched a digital transformation project focused on human-centric and sustainable goals. A pilot initiative aimed to retrofit a collaborative robot (cobot) at the fastening station to reduce physical strain and improve flexibility for variable configurations and batch sizes.

The decision was based on internal risk analysis, operator input, and external benchmarks. Selection criteria included technical capabilities (e.g., force/torque control, programming ease) and alignment with Operator 5.0 goals: human empowerment, system resilience, and sustainability. This context provides the basis for applying the TAMOP 5.0 Matrix to assess how the cobot retrofit supports organizational goals across technology implementation phases.

B.2.2. TAMOP 5.0 matrix application

The use case has been analyzed through the TAMOP 5.0 Matrix to assess how the cobot retrofit supports the three foundational dimensions of Operator 5.0 (human-centricity, resilience, and sustainability) throughout the technology adoption lifecycle: pre-change, implementation, and post-change. The matrix provides a structured way to align technological integration with organizational values, while drawing on established technology adoption models (e.g., TAM, UTAUT, TOE, SCT, TPB).

Pre-change: The cobot introduction is based on a risk-driven workstation redesign, utilizing indicators such as ergonomic load index and absenteeism as baselines (Human-Centricity – Performance). Operators take part in co-design workshops and mapping sessions (Policy/S&O – SCT). The cobot is chosen for its intuitive interface and energy efficiency (Sustainability – Technologies), aligned with TAM and UTAUT principles of usefulness and ease of use. Organizational and process fit, based on the TOE framework, also supports the selection.

Implementation: The cobot is deployed with AR-based training to support onboarding and task co-execution (Human-Centricity – Technologies). Real-time feedback enhances perceived competence and motivation (SCT, TAM). Predictive maintenance is activated (Resilience – Technologies), and updated SOPs reflect reconfigurability and fault tolerance (Tasks/Procedures – TOE). Technology acceptance and trust are monitored using TAM and UTAUT metrics.

Post-change, indicators such as recovery time, uptime, and first-pass yield are tracked (Resilience – Performance) via dashboards. Policies evolve to include digital skills training and learning pathways (Human-Centricity – Policy/S&O), analyzed through TOE and SCT. Environmental metrics such as CO_2/unit, waste, and sustainability compliance are monitored (Sustainability – Performance), guiding operations and employee engagement (Attitude/Mindset – TPB, SCT).

B.2.3. Summary matrix

In summary, the TAMOP 5.0 Matrix facilitates a comprehensive and dynamic evaluation of the cobot retrofit, integrating insights from technology acceptance models (TAM, UTAUT), organizational and environmental readiness (TOE), and behavioral models (TPB, SCT) to ensure that technological change supports both worker well-being and long-term operational excellence. The case is visualised using the TAMOP matrix, which highlights strong contributions across Operator 5.0 dimensions.

O5.0 Dimension	Sub-dimension	Pre-change	Implementation	Post-change
Human-Centricity	Technologies	Selection of ergonomic cobot (TAM, UTAUT)	AR-guided training, intuitive UI (TRL)	Worker acceptance monitored (TAM, SCT)
	Tasks/ Procedures	Worker engagement in process mapping (TPB)	Task sharing with cobot (TOE – org. process fit)	Continued refinement via feedback (TOE, SCT)
	Performance	Ergonomic load index, absenteeism baseline (TAM)	Tracking perceived workload, comfort (DOI, TAM)	KPI review: absenteeism ↓, satisfaction ↑ (TOE)
	Policy /Strat. / Org.	Inclusive planning sessions, skill mapping (SCT, PCI)	Flexible scheduling and safety protocols (TOE)	Continuous-learning schemes introduced (SCT)
	Attitude /Mindset	Trust-building workshops, perceived usefulness (TPB, TAM)	Motivation supported by real-time task feedback (TAM, UTAUT)	Reinforcement of empowerment and autonomy (SCT)
Resilience	Technologies	Choice of adaptable cobot with predictive maintenance (TOE)	Fault-tolerant setup, reconfigurability (DOI, TRL)	Stable operation + quick repair metrics tracked (TAM, TOE)
	Tasks/ Procedures	Risk scenarios explored in design workshops (SCT)	Standard operating procedures revised for cobot integration (TOE)	Resilience KPIs (e.g., MTTR) monitored and refined
	Performance	MTTR targets defined (TOE)	First-pass yield and uptime measured (TAM, TRL)	Recovery-time objective achieved, resilience dashboard created (SCT)
	Policy /Strat. / Org.	Risk management protocols updated (TOE)	Real-time monitoring escalation paths (TOE)	Feedback loop for resilience scenarios embedded
	Attitude /Mindset	Psychological safety emphasized, adaptability trained (SCT)	Workers experience increased agency during disruptions (SCT)	Resilience culture reinforced in daily meetings (TPB, SCT)
Sustain-ability	Technologies	Low-energy cobot shortlisted (DOI, MPCU, TRL)	Circular-material compatible model installed (TOE)	Life-cycle impact assessed (TRL)

(continued on next page)

(*continued*)

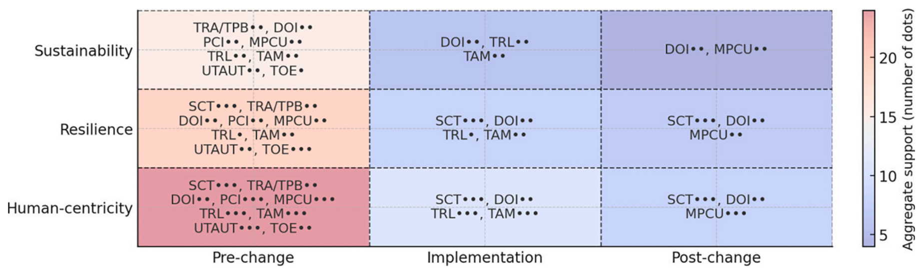
O5.0 Dimension	Sub-dimension	Pre-change	Implementation	Post-change
	Tasks/ Procedures	Waste minimization goals set in planning (TOE)	Eco-efficient procedures embedded (TOE)	SOPs updated for long-term eco compliance
	Performance	Baseline CO_2/unit estimated (TRL)	Emission tracking during operations (TOE)	KPI: CO_2/unit ↓ confirmed (TAM/TOE)
	Policy /Strat. / Org.	Inclusion of green policies in RFPs (TOE)	Environmental checklists used by the team (TOE)	Sustainability goals embedded in incentive schemes (TOE)
	Attitude /Mindset	Employee awareness on sustainability raised (TPB, SCT)	Shared ownership of green goals (TPB)	Engagement with continuous green innovation (TPB, SCT)

B.2.4. Generic TAMOP5.0 matrices

All matrices were provided (see Table 3, Table 4, Table 5).

B.2.5. Support for O5.0 dimensions and phases

The first version of the graphical representation was provided, while the final circular representation (see Fig. 3) was provided in round 3.



The 3 × 3 matrix maps the dimensions of Operator 5.0 (Sustainability, Resilience, Human-centricity) against the change phases (Pre-change, Implementation, Post-change). Each cell lists relevant technology adoption models for a given phase and dimension, with dot symbols indicating support strength: • = weak, •• = moderate, ••• = strong. Cell colors range from blue to red based on the total number of dots, reflecting aggregate support.

Dots represent how strongly each model addresses a specific dimension, as derived from the manuscript's matrix ratings. Weak support (•) indicates marginal relevance, moderate (••) means partial alignment, and strong (•••) reflects direct and substantial support. For example, SCT scores ••• under Resilience and Human-centricity in all phases due to its emphasis on learning and behavioral change. These ratings were assigned based on evidence from the literature and expert judgment as a three-level ordinal coding for readability (not a statistical Delphi score).

Model placement in the matrix reflects both its relevance to a change phase and the dimension it supports. For instance, TRA/TPB focus on user attitudes in Pre-change, while SCT and DOI span multiple phases and dimensions. The dot notation further qualifies the strength of each model's contribution. This layout helps identify which models are useful at specific moments and where gaps remain, e.g., lower support for Human-centricity during Implementation. The matrix illustrates how multiple models must be orchestrated to address all Operator 5.0 priorities across time.

Data availability

Data will be made available on request.

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