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Industry 4.0 in Portugal: validation of a readiness assessment model through an empirical approach

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Abstract

Purpose – Industry 4.0 requires businesses to adapt strategically and continuously assess their readiness. However, many manufacturing companies struggle to evaluate and implement Industry 4.0 due to the lack of clear assessment frameworks. This study addresses this gap by applying a structured maturity model to assess Industry 4.0 readiness in Portuguese companies.

Design/methodology/approach – The study uses the Shift2Future model, an adaptation of the IMPULS model designed for Portuguese companies. Data were collected through a structured questionnaire and empirical research validated the model. The internal consistency of responses, measured by Cronbach's alpha (0.9040), confirmed its reliability.

Findings – The results highlight the importance of structured assessments in guiding digital transformation. The Shift2Future model helps companies understand their current Industry 4.0 readiness and plan their transition. The study also shows that success requires more than just investing in technology; it demands a holistic approach, including strategy and workforce skills.

Practical implications – This research provides a practical tool for companies to assess their Industry 4.0 readiness and identify areas for improvement. It can also help policymakers and business leaders develop strategies to support digital transformation.

Originality/value – This study fills a gap in the literature by offering a structured, validated model tailored to the Portuguese industrial context. The Shift2Future model provides a reliable framework for evaluating Industry 4.0 readiness and can be adapted to other regions facing similar challenges.

Keywords Maturity model, Readiness, Industry 4.0, Empirical validation, Portugal

Paper type Research article

1. Introduction

In today's highly competitive global market, digital transformation has become a strategic priority for companies seeking to improve performance, enhance productivity, and remain competitive (Guimarães *et al.*, 2025a, b). The transition to Industry 4.0, characterized by the integration of cyber-physical systems, Internet of Things (IoT), cloud computing, and big data analytics, is reshaping how businesses operate, innovate, and create value (Mittal *et al.*, 2018a;

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Albannai *et al.*, 2024). This transformation enables greater automation, real-time monitoring, and data-driven decision-making, while fostering new business models and service offerings (Tortorella *et al.*, 2024; Hughes *et al.*, 2022).

Despite its potential, many small and medium-sized enterprises (SMEs) struggle to adopt Industry 4.0 technologies due to limited financial resources, insufficient digital skills, and a lack of tailored guidance (Stentoft *et al.*, 2021; Contieri *et al.*, 2024). These challenges are especially critical in Southern European economies, where traditional sectors dominate and digital transformation is unevenly distributed (Henriques *et al.*, 2019; Silva *et al.*, 2023; Guimarães *et al.*, 2024).

To support companies in this transition, several maturity models have been developed to assess Industry 4.0 readiness, helping organizations understand their current capabilities and identify areas for improvement (Schumacher *et al.*, 2016; Gökalp *et al.*, 2017). However, many of these models were created for large industrial firms in highly developed countries, limiting their applicability to SMEs and service companies operating in different contexts (Rajnai and Kocsis, 2018; Mittal *et al.*, 2018b). Moreover, some models rely heavily on expert judgment or theoretical synthesis, without undergoing empirical validation (Tripathi and Gupta, 2021).

Recent studies highlight the need for context-sensitive and validated tools that reflect the specific challenges of SMEs and less industrialized regions (Amaral and Peças, 2021; Hajoary *et al.*, 2024). A bibliometric analysis by Guimarães *et al.* (2025c) confirms the scarcity of empirical studies on maturity models tailored to SMEs, especially in countries like Portugal. Additionally, existing models often overlook service firms, which represent a significant portion of the economy and have distinct digitalization needs (Ganzarain and Errasti, 2016; Santos and Martinho, 2020).

Digital transformation is a national priority in Portugal, supported by policies to improve competitiveness and innovation (Yang and Gu, 2021). Many Portuguese companies lack structured methods to assess digital maturity and define strategic priorities. Traditional models, such as the IMPULS framework, are not fully aligned with the Portuguese context, particularly regarding language, sectoral applicability, and baseline digital capabilities.

This study addresses this gap by validating the Shift2Future model, an adaptation of the IMPULS model specifically designed for the Portuguese industrial and service landscape. The Shift2Future model introduces key improvements, including simplified language, flexible weighting, and broader applicability to SMEs and service firms. It aims to provide a practical and inclusive tool for assessing Industry 4.0 readiness.

The main objective of this research is to empirically validate the Shift2Future model using data from 615 Portuguese companies, applying Exploratory and Confirmatory Factor Analysis (EFA and CFA) to assess its structure, reliability, and practical relevance. This is the first study to validate such a model in Portugal using real-world data and statistical techniques. The findings aim to support managers and policymakers by offering a reliable tool for diagnosing digital maturity and guiding strategic investment and planning.

Accordingly, the study seeks to answer the following research question (RQ):

RQ. To what extent is the Shift2Future model a valid and reliable tool to assess Industry 4.0 readiness in Portuguese companies from both industrial and service sectors?

The article is structured as follows: Section 1 presents the context, research motivation, and opportunities. Section 2 reviews the literature on Industry 4.0 readiness and maturity models. Section 3 explains the data collection methods. Section 4 presents the results and discussion, and Section 5 outlines the main conclusions, implications, and directions for future research.

2. Literature review

2.1 Industry 4.0

Industry 4.0 emerged in Germany through the High-Tech Strategy 2020, a coordinated initiative involving industry, academia, and government (Mittal *et al.*, 2018a; Schumacher and

Sihn, 2020; Zangiacomi *et al.*, 2020; Stentoft *et al.*, 2021; Zheng *et al.*, 2021). Its goal was to modernize production using digital technologies (Reischauer, 2018). This fourth industrial revolution integrates intelligent machines, cyber-physical systems (CPS), cloud computing, IoT, and big data analytics, enabling wireless communication, autonomous decisions, and integrated process management (Contieri *et al.*, 2024).

Over the last decade, companies have had to modernize to remain competitive. Industry 4.0 supports this by improving efficiency, reducing costs, and enhancing product quality through digital system integration (Lele and Bose, 2019). Although still evolving, it is being adopted by firms of all sizes, fostering human–machine interaction via connected technologies (Öberg and Graham, 2016; Tortorella *et al.*, 2024).

Due to its complexity, transitioning to Industry 4.0 requires strategic planning and assessment of current systems and capabilities (Hughes *et al.*, 2022; Wankhede and Vinodh, 2023). Therefore, evaluating companies' maturity and readiness is essential.

In Portugal, the national Industry 4.0 strategy was launched in 2017, focusing on digitization, innovation, and education. It aims to identify industrial needs, accelerate technology adoption, and enhance the competitiveness of Portuguese industry (Henriques *et al.*, 2019; Yang and Gu, 2021).

2.2 Overview of Industry 4.0 readiness assessment

The literature shows that many studies focus on how companies implement Industry 4.0. For example, Zheng *et al.* (2021) identified various factors and indicators used to assess organizational readiness for this transition.

Most assessment models use qualitative methods, such as Likert scales and self-assessment tools, to evaluate the level of implementation (Schumacher and Sihn, 2020). These maturity and readiness models help companies understand their current situation and position in the market, serving as a reference point for planning future improvements (Hajoary *et al.*, 2024).

Maturity models are essential tools that provide a structured overview of how close an organization is to reaching its digital transformation goals (Pöppelbuß and Röglinger, 2011). They help companies follow industrial trends and make the most of their potential.

Specific tools can guide companies in assessing their Industry 4.0 readiness (Rajnai and Kocsis, 2018). These tools measure technological progress and highlight gaps in areas such as strategy and skills. Digital transformation is a gradual process that requires a clear understanding of the current stage of development and the areas needing attention.

2.3 Industry 4.0 maturity and readiness models

The assessment of Industry 4.0 readiness has become increasingly important, especially in Europe (Ávila Bohórquez and Gil Herrera, 2022). Maturity models help organizations understand their digitalization stage and define priorities for transformation. These models usually combine qualitative and quantitative indicators (Schumacher *et al.*, 2016), but many still lack empirical validation and remain descriptive.

Despite several frameworks, many companies, particularly SMEs, struggle to adopt Industry 4.0 technologies effectively (Sopadang *et al.*, 2020; Contieri *et al.*, 2024). Studies also show the absence of a universally accepted method for assessing readiness (Rajnai and Kocsis, 2018; Wankhede and Vinodh, 2023). For instance, Botha (2018) and Tripathi and Gupta (2021) proposed models that include technology, labor, and external factors without empirical validation.

Various maturity models have been proposed, such as IMPULS (Lichtblau *et al.*, 2015), Schumacher *et al.* (2016), SIMMI 4.0 (Leyh *et al.*, 2016), SMSRA (Jung *et al.*, 2016), and SM3E (Mittal *et al.*, 2018b). Although these models offer structured assessments, they have limitations: a strong focus on technology over organizational or human aspects, heterogeneous evaluation scales without standardization, and reliance on expert judgment or case studies, often without statistical validation. Most importantly, they were developed for highly industrialized economies and are not easily adapted to contexts like Portugal, where SMEs and service firms are prevalent.

The Shift2Future model was created to address these shortcomings. Recent bibliometric analyses confirm the lack of tailored and empirically validated models focused on SMEs, emphasizing the need for tools suited to national contexts (Guimarães *et al.*, 2025c).

In Portugal, the dominance of micro and small enterprises and the weight of the service sector make traditional models less applicable. The IMPULS model, for example, was developed for German manufacturing firms with advanced digitalization and presents challenges when applied in Portugal due to sectoral differences and more limited digital maturity.

To overcome these challenges, Shift2Future was developed with permission from the IMPULS creators. While keeping its core structure, it introduces several improvements: simplified language, revised indicators, broader applicability to services and industry, and a flexible weighting system that avoids penalizing companies for non-applicable dimensions like Smart Products or Smart Infrastructure. It also adjusts the minimum criteria per dimension to reflect Portugal's digital maturity and provides automatic feedback reports with suggestions for improvement.

Though inspired by IMPULS, Shift2Future adds innovations relevant to Portugal's reality. It includes technological and organizational elements and supports firms of all sizes and sectors. Its six dimensions are aligned with dynamic capabilities theory (Teece *et al.*, 1997; Yogeswaran *et al.*, 2025), emphasizing sensing opportunities, seizing them, and reconfiguring resources to enhance strategy, operations, and workforce capacity.

The model was empirically validated using data from 615 Portuguese companies through Exploratory and Confirmatory Factor Analysis (EFA and CFA), ensuring methodological robustness and practical relevance for national strategies and companies' transformation planning.

Compared to models such as Schumacher *et al.* (2016) or Gökalp *et al.* (2017) based on interviews or theoretical syntheses, Shift2Future offers a replicable and scalable tool supported by real-world data. It also incorporates key data from the literature on staged, but often non-linear, digital transformation, especially in the face of challenges like lack of skills, small size, and limited investment (Mittal *et al.*, 2018b).

Despite the growing number of maturity models for Industry 4.0, few studies have empirically validated these frameworks using large-scale data, particularly in countries like Portugal, where SMEs and service firms dominate the business landscape. Moreover, existing models such as IMPULS are often not fully adaptable to national or sectoral specificities, as they were initially designed for large industrial firms. This reinforces the need for a context-sensitive and statistically validated tool to assess digital maturity across diverse organizational types.

This gap leads to the central research question of this study. These adaptations make Shift2Future a statistically robust, inclusive, and practical framework for supporting more effective digital transformation planning in the Portuguese context.

3. Methodology and data

This study adopts an empirical validation approach to assess the Shift2Future model, a framework specifically designed to evaluate Industry 4.0 readiness in Portuguese companies. Developed with authorization from the IMPULS model creators, Shift2Future introduces key adaptations, such as simplified language, redefined minimum criteria, and flexible weighting, ensuring applicability to SMEs and service firms. Unlike traditional models limited to industrial contexts, Shift2Future combines technological and organizational dimensions and provides practical feedback. Its validation with a broad sample (615 companies), using EFA and CFA, confirms the model's structural robustness and contextual alignment.

3.1 Data collection

The data was collected through voluntary participation in the Shift2Future self-assessment platform, promoted nationally by the consortium, where 615 Portuguese companies responded via the online platform, covering various sectors, sizes, and regions, providing a comprehensive overview of the national industrial landscape. All companies received support during the process through on-site consultant visits or remote assistance (by phone, email, or virtual meetings). Each submission was reviewed and validated by a qualified external consultant, and only then considered complete. This structured and supported process ensured the collected data's consistency, clarity, and reliability. Although the sampling was not random, efforts were made to ensure sectoral and geographical diversity, with significant representation across the main (NACE) [1] sectors in Portugal.

All responses were monitored and validated by specialist consultants from IAPMEI – Portuguese Agency for Competitiveness and Innovation and ISQ – Portuguese Institute of Welding and Quality, with additional support from ANI – Portuguese National Innovation Agency and universities and business clusters. This collaboration ensured the technical reliability and contextual consistency of the collected data and guided participants throughout the process.

The analyzed sample is characterized by significant heterogeneity in terms of size, encompassing approximately micro (28%), small (35%), medium-sized (33%), and 4% large companies (according to the EU classification methodology) [2].

The most representative economic sectors in Portugal were utilized to validate the digital maturity assessment questionnaire. Metalworking and Tourism sectors are predominant, accounting for 23.61% and 8.59%, respectively. Subsequently, sectors such as Ceramics (8.05%), Agri-food (7.51%), Stone (6.62%), Automotive (5.90%), Footwear (4.12%) and Textile (4.11%) are also well represented. Finally, there are sectors like Molds (1.61%), Glass (1.61%), and Aeronautics (0.36%).

The geographical distribution was also considered, covering samples from all Territorial Statistical Units (NUTS II), 62 from the North region (10%), 428 from the Centre region (70%), 65 from the Lisbon Metropolitan Area (10%), 54 from the Alentejo region (9%), and 6 from the Algarve region (1%).

Before analysis, the dataset was reviewed for completeness and consistency. Records with missing values in any questionnaire items were excluded from the final dataset. Outlier detection was performed using standardized z-scores, and no extreme values were found that would compromise the validity of the results. The final sample included 615 valid and complete responses.

3.1.1 Questionnaire structure. As referred on the previews section, the questionnaire instrument was adopted from a study conducted by VDMA (Lichtblau *et al.*, 2015), with some questions altered and modified to suit the context of Portuguese companies. For this new context, the study utilized the mentioned questionnaire to validate the assessment model for the level of digital maturity in Industry 4.0. The complete version of the questionnaire is provided in the Appendix. This model consists of a set of questions organized into the following sections:

Section 1: General inquiries sought details about respondents' industry, organizational size, role, and comprehension of "Industry 4.0".

Section 2: Questions related to organizational strategy gauged strategy execution, alignment with Industry 4.0, and investment in initiatives. This section also identified the technologies in use during the research.

Section 3: Infrastructure issues collected data on equipment adaptability to Industry 4.0 requirements, linking the physical and virtual worlds.

Section 4: Operational questions assessed vertical and horizontal integration, establishing connections between the physical and virtual realms within and across enterprises.

Section 5: Product questions measured the ability to collect product data, understand production, and communicate with higher-level systems. Respondents shared information on complementary communication products.

Section 6: Questions focused on data-driven aspects gauged how organizations assessed and analyzed data for enterprise-wide integration and continuous improvement.

Section 7: Employee-related questions evaluated the availability of skills for digital transformation, assessing skills relevant to future Industry 4.0 requirements.

3.2 Data analysis

This study applies the Shift2Future model, a self-assessment framework adapted from the original "Industry 4.0 Readiness" model developed by the IMPULS Foundation (Lichtblau *et al.*, 2015), redesigned to reflect the Portuguese industrial and service landscape. At the time of its development, no model existed in Portugal capable of capturing the heterogeneity of national companies in terms of digital maturity. Therefore, with formal authorization from the original authors, the Shift2Future model was created to meet the specific needs of Portuguese organizations, particularly SMEs and service-oriented firms.

All six core dimensions of the IMPULS model, Strategy and Organization, Smart Infrastructure, Smart Operations, Smart Products, Data-Driven Services, and Human Resources, were retained for their theoretical consistency and alignment with Industry 4.0 principles (Lichtblau *et al.*, 2015; Schumacher *et al.*, 2016; Mittal *et al.*, 2018b). However, essential adaptations were introduced: (1) terminology was simplified to ensure better comprehension across sectors (e.g. "Smart Factory" became "Smart Infrastructure" to avoid misinterpretation); (2) minimum scoring criteria were adjusted to reflect the lower digitalization baseline in Portugal; (3) a flexible weighting system was implemented, allowing dimensions not applicable to specific sectors (such as Smart Products in tourism or hospitality) to be redistributed across relevant areas. This ensures inclusivity and contextual alignment with Portugal's diverse economic fabric (Guimarães *et al.*, 2023).

The model includes an online questionnaire with actionable indicators that automatically generate a feedback report with suggestions for improvements, helping companies define their strategic priorities. This feature, which was not available in the original IMPULS model, improves the practical use of the tool. The adaptations were based on data from pilot tests with hundreds of companies and the input of industry experts during the national implementation.

The theoretical foundation of Shift2Future is based on dynamic capabilities theory (Teece *et al.*, 1997; Yogeswaran *et al.*, 2025), which highlights the importance of sensing opportunities, acting on them, and adapting resources to manage technological change. The model also aligns with digital transformation maturity frameworks that describe the transformation as a gradual and often nonlinear process.

Finally, the empirical validation of the Shift2Future model using data from 615 companies, through Exploratory and Confirmatory Factor Analysis (EFA and CFA), reinforces its structural consistency, analytical robustness, and suitability for supporting national digitalization strategies.

3.2.1 Similarities and differences between the IMPULS and Shift2Future models. The Shift2Future model adapts the IMPULS model, tailored to the Portuguese business context. At the same time, both assess Industry 4.0 readiness across areas like strategy, operations, innovation, data, and human resources. Shift2Future emphasizes technological infrastructure and operational flexibility.

The two models share a similar structure but differ in question organization, weighting, and specific dimensions. Shift2Future was explicitly designed to reflect the needs of Portuguese companies, ensuring more accurate and relevant assessments.

In its original form, the IMPULS model could penalize service companies for not having a "Smart Factory" or producing "Smart Products". Shift2Future corrects this by adapting the model to include industrial and service firms, promoting fairer and more balanced evaluations. These differences are summarized in Table 1.

In the Shift2Future model, the "Smart Factory" dimension was renamed "Smart Infrastructures" to reflect the reality of both industrial and service companies in Portugal.

Table 1. Comparison of dimensions and questions in IMPULS and Shift2Future models of Industry 4.0

IMPULS model Dimension	Sub-dimension	Questions	Shift2Future model Dimension	Sub-dimension	Questions
Strategy and Organization (25.4%)	Strategy	Q1. How do you describe the level of implementation of Industry 4.0 strategy in your company? Q2. Are there indicators to monitor the state of implementation of the Industry 4.0 strategy? Q3. What technologies does your company use?	Strategy and Organization (25.0%)	Strategy	Q1. How would you describe the level of implementation of Industry 4.0 strategy in your company? Q2. Are there indicators to monitor the state of implementation of the Industry 4.0 strategy?
	Investments	Q4. In which areas of your company have you invested in implementing Industry 4.0 in the past two years and what are your plans for the future?		Investments	Q3. Has there been investment in Industry 4.0 in the last 2 years? Q4. Is there a plan to invest in Industry 4.0 in the next 5 years?
	Innovation management	Q5. In which areas does your company systematically manage technology and innovation?		Innovation	Q5. Is there systematic management of technology and innovation?
Smart Factory (14.3%)	Equipment infrastructure	Q6. How would you assess the infrastructure of your equipment regarding the following functionalities? Q7. How is the capacity to update existing functionalities evaluated in the company?	Smart Infrastructures (14.0%)	Infrastructure	Q6. How are the functionalities of the equipment infrastructure evaluated in the company? Q7. How is the capacity to update existing functionalities evaluated in the company?
	Digital modeling	Q8. Is there data collection on all equipment and processes during production?		Modeling	Q8. Is there data collection from all equipment and processes in the company?
	Data usage	Q9. Which of the following systems do you use? Does the system have an interface with the leading system?		Data	Q9. Are the collected data in digital format? Q10. What is the purpose of using the collected data?
	IT systems			IT systems	Q11. What are the Information Systems and Technologies used by the company? Q12. Of the Information Systems and Technologies used, which ones have interfaces with the central data storage and processing system?

(*continued*)

Table 1. Continued

IMPULS model Dimension	Sub-dimension	Questions	Shift2Future model Dimension	Sub-dimension	Questions
Smart Operations (10.2%)	Information sharing	Q10. What internal and external information is shared among operational areas in your company's system?	Smart Operations (10.0%)	Information	Q13. Is internal information shared and integrated into the central system? Q14. Is external information shared and integrated into the central system?
	Autonomous processes	Q11. Are there already cases of autonomous control observed in the company? Q12. Does your company have production processes that respond autonomously/automatically in real-time to changes in production conditions?		Autonomous	Q15. Are there already cases of autonomous control observed in the company? Q16. Are there processes in the company that are reactive and adjustable, in real-time, to changes in operational conditions?
	IT security	Q13. How is your company's Information Technology (IT) department organized? Q14. What is the status of your IT security solutions?		IT security	Q17. What is the state of IT security solutions in the company?
	Cloud usage	Q15. Do you already use cloud services?		Cloud	Q18. Are cloud services utilized in the company?
Smart Products (18.5%)	ICT add-on functionalities	Q16. Does your company offer products equipped with the following complementary functionalities based on information and communication technology (ICT)?	Smart Products (19.0%)	ICT functionalities	Q19. Does the company have products equipped with functionalities based on ICT?
	Data analytics in usage phase			Data analysis	Q20. Are the data collected during the usage phase analyzed?
Data-driven Services (13.8%)	Data-driven services	Q17. Do the process data collected in different development, production, and usage phases enable new services?	Data-driven Services (14.0%)	New services	Q21. Do process data collected in different stages of development, production, and usage enable new services?
	Share of revenues			Revenue sources	Q22. What is the importance of data-based services in the company's revenue?
	Share of data used	Q18. Are the data collected during the usage phase analyzed?		Usage level	Q23. What is the level of utilization of the collected data?
Employees (17.9%)	Employee skill sets	Q19. How do you assess the skills of your employees regarding future Industry 4.0 requirements?	Human Resources (18.0%)	Existent skills	Q24. How are the competencies of your human resources evaluated regarding Industry 4.0 requirements?
	Skill acquisition			Skills acquisition	Q25. Are efforts being made to acquire missing competencies through training sessions, seminars, etc.?

Source(s): Authors' own creation

The “Smart Infrastructures” and “Smart Products” dimensions, more relevant to manufacturing, are optional for service companies. When excluded, their weight is redistributed to the other dimensions.

Most questions were adapted to be more inclusive. For example, the IMPULS question Q8 focuses on data from production equipment, while in Shift2Future, it applies to all equipment and processes. Question Q9, which initially covered two subdimensions, was split into two for better detail.

Unlike IMPULS, which sometimes uses one question for several subdimensions, Shift2Future includes at least one question per subdimension for greater accuracy. The wording was also adjusted for service companies. This flexibility makes the tool more adaptable and ensures fairer assessments across different business types. These changes improve the model’s accuracy, inclusiveness, and relevance for Portuguese companies.

3.3 Model for Industry 4.0 maturity

According to this model adapted version for the Portuguese context, the assessment of a company’s Industry 4.0 maturity level is based on 6 dimensions: (1) Strategy and Organization (A), (2) Smart Infrastructure (B), (3) Smart Operations (C), (4) Smart Products (D), (5) Data-driven Services (E), and (6) Human Resources (F). Each dimension is divided into several subdimensions which, together, determine the state of digital maturity. This model encompasses a total of 18 subdimensions: Strategy (A1); Investments (A2); Innovation (A3); Infrastructure (B1); Modeling (B2); Data (B3); IT Systems (B4); Information (C1); Autonomous (C2); IT Security (C3); Cloud (C4); ICT (D1); Data Analytics (D2); New Services (E1); Revenue Sources (E2); Usage Level (E3); Existing Skills (F1); and Skills Acquisition (F2), as illustrated in Table 2. These subdimensions enable the evaluation of the maturity level of each dimension based on the lowest value obtained within the set of subdimensions that constitute each dimension.

Each of these 6 dimensions is assessed by various questions that follow established criteria to align with the Portuguese reality, being converted into a Likert scale of 0–5.

Upon survey completion, a comprehensive assessment is provided, where the overall maturity level of the company is calculated as described in the following Sections 4.5 and 4.6, and it can be visually represented, such as through an Aster-type chart. The chart offers a holistic view of the current maturity status of the companies, broken down by dimension and sub-dimension (theme).

3.4 Description of model dimensions

The questions posed (Q1–Q25) contribute to the individual assessment of the six dimensions and, subsequently, the 18 subdimensions of the digital maturity assessment model for Industry 4.0. These dimensions, regarded as constructs in this study, are subsequently described briefly.

3.4.1 Strategy and Organization (A). Implementing Industry 4.0 is strategically essential, covering strategy, performance indicators, investments, and innovation management. The Strategy and Organization dimension assesses whether the company has defined a business model and culture aligned with digital transformation, based on three subdimensions: strategy (A1), investment (A2), and innovation management (A3), as shown in Figure 1.

3.4.2 Smart Infrastructures (B). The Smart Infrastructure dimension evaluates whether the company uses automated systems to produce goods or deliver services. In manufacturing, it checks if IT systems control equipment, communicate with other machines, are interoperable, and support data collection and use. For service companies, the focus is on the infrastructure that supports operations. If this dimension is irrelevant, its weight is redistributed to the others in the final maturity score. It covers four areas: Infrastructure and Equipment (B1), Digital Models (B2), Data Usage (B3), and IT Systems (B4), as shown in Figure 1.

Table 2. Readiness assessment model for Industry 4.0 in Portugal

Dimension		Sub-dimension	Questions	Indicator
Strategy and Organization	A	Strategy (A1)	Q1 Q2	- Strategy Implementation Status - Strategy Alignment with Overall Organizational Strategy
		Investments (A2)	Q3 Q4	- Number of areas investing or planning to invest in Industry 4.0
		Innovation (A3)	Q5	- Number of areas with organized technology and innovation management
Smart Infrastructures	B	Infrastructure (B1)	Q6 Q7	- Use of IT to control machines - Machine-to-Machine communication - Machines' interoperability level
		Modeling (B2)	Q8	- Collecting and processing machine data
		Data (B3)	Q9 Q10	- Purpose of use for collected data
		IT systems (B4)	Q11 Q12	- Quantity of operational systems - Quantity of systems utilizing a leading interface
Smart Operations	C	Information (C1)	Q13 Q14	- Internal cross-departmental information sharing - External cross-departmental information sharing
		Autonomous (C2)	Q15 Q16	- Autonomous workpiece guide availability - Real time availability of autonomous production process response
		IT security (C3)	Q17	- IT organization - Security solutions implementation level
		Cloud (C4)	Q18	- Use of cloud services
Smart Products	D	ICT (D1)	Q19	- Quantity of add-on functionalities
		Data analysis (D2)	Q20	- Use of data analytics
Data-driven Services	E	New services (E1)	Q21	- Processing to create new services
		Revenue sources (E2)	Q22	- Utilization of data-driven services in the company's revenue
		Usage level (E3)	Q23	- Level of utilization of collected data
Human Resources	F	Existent skills (F1)	Q24	- Level of existing skills
		Skills acquisition (F2)	Q25	- Level of acquisition skills

Source(s): Authors' own creation

3.4.3 Smart Operations (C). This dimension assesses how the company shares information internally with suppliers, customers, and partners. It also considers IT system structure, security measures, and cloud service usage. A key focus is the company's ability to run operations autonomously.

The Smart Operations dimension shows the company's progress in automating and integrating physical and digital processes. It includes four themes: Information Sharing (C1), Autonomous Processes (C2), IT Security (C3), and Cloud (C4), as shown in Figure 1.

3.4.4 Smart Products (D). This dimension evaluates whether the company's products include Information and Communication Technology (ICT) features, such as sensors, RFID, or communication tools. These smart products, used or produced, can collect data to improve operations and support new services like customer interaction.

The assessment checks for ICT functions, data collection during use, and how this data is analyzed. If the company doesn't produce or use such products, this dimension can be excluded, and its weight is redistributed.

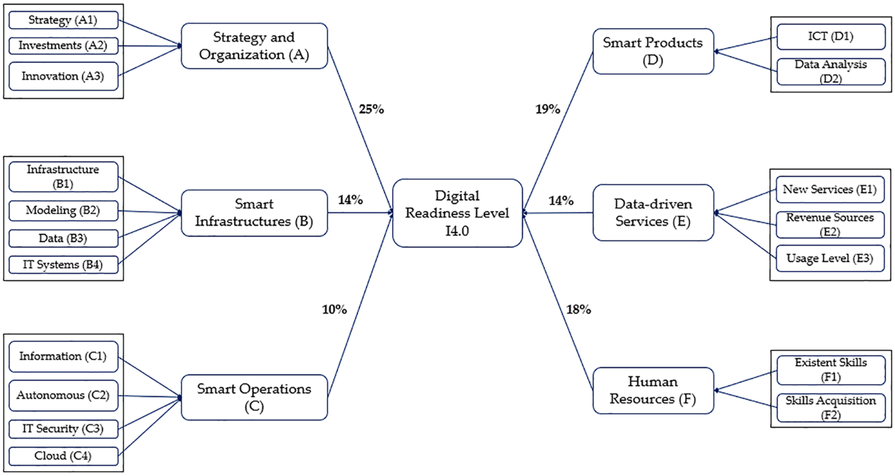

Figure 1. Description of multi-dimensional Industry 4.0 conceptual framework. Source: Authors' own creation

A high score shows strong ability to use product data to enhance quality and customer experience. It covers two themes: ICT Functionalities (D1) and Data Analysis during Usage (D2), as shown in Figure 1.

3.4.5 Data-Driven Services (E). The Data-Driven Services dimension assesses how the company uses data to support customer relationships and after-sales services, and whether this data is integrated into its business operations. It looks at data-based services' existence, usage, and revenue impact.

Maturity is evaluated across three themes: New Services (E1), Revenue Contribution (E2), and Data Usage Level (E3), as shown in Figure 1.

3.4.6 Human Resources (F). The Human Resources dimension evaluates whether employees have the necessary skills for Industry 4.0 and what actions are taken to develop them.

Digital transformation relies on a skilled and motivated workforce. Maturity is assessed through two themes: Existing Skills (F1) and Skills Acquisition (F2), as shown in Figure 1.

3.5 Classification criteria of model dimensions

The final maturity level is calculated using a weighted average of all dimensions. Each dimension has a specific weight: Strategy and Organization (25%), Smart Infrastructure (14%), Smart Operations (10%), Smart Products (19%), Data-Driven Services (14%), and Human Resources (18%), as shown in Figure 1.

To ensure the representativeness of the Shift2Future model across the diverse landscape of Portuguese companies, four calculation scenarios were defined for the Digital Maturity Level (DML), adjusting the weighting of the assessed dimensions according to each company's context. When specific dimensions, such as Smart Infrastructure or Smart Products, are not applicable, their respective weights are redistributed among the remaining ones, ensuring a consistent and meaningful result even for less industrialized or service-oriented firms.

The final score of the DML is calculated using a weighted average, applying the weights defined for each of the four possible scenarios to reflect only the dimensions applicable to each company's reality. For each dimension, the lowest score among its sub-dimensions is considered, ensuring a more rigorous and conservative assessment of digital maturity, as presented in Equation (1):

$$\mathrm{DML} = \sum_{i=1}^{6} \left[\min_{j} \left(SD_{ij} \right) \right] \mathrm{P}_i \quad (1)$$

Where:

(1) DML is the Digital Maturity Level,

(2) SD_{ij} represents the sub-dimensions of each main dimension i,

(3) $\min_j (SD_{ij})$ denotes the minimum score among sub-dimensions of dimension i,

(4) P_i is the weight assigned to dimension i.

3.6 Classification criteria for maturity level

Each dimension is evaluated based on responses to the questionnaire, using a 0 to 5 scale, as shown in Table 3: 0 – Outsider, 1 – Beginner, 2 – Intermediate, 3 – Experienced, 4 – Expert, and 5 – Top Performer.

In the Shift2Future model, each theme is rated individually on this scale, based on predefined criteria. The score for each dimension is determined by the lowest rating among its themes, following the approach proposed by Lichtblau *et al.* (2015).

To validate the six-level scoring system (0–5) in the Shift2Future model, a k-means cluster analysis was performed on the standardized maturity scores. The results confirmed that six clusters aligned well with the predefined categories. ANOVA tests also showed significant differences ($p < 0.001$) between levels across all dimensions. These findings confirm that the maturity levels reflect real and distinct company profiles, and are not arbitrarily defined.

Table 3. Levels of readiness for Industry 4.0 and their description (Lichtblau *et al.*, 2015)

Readiness level	Description
Level 0: Outsider	- No requirements are fulfilled, or Industry 4.0 is not recognized and deemed irrelevant
Level 1: Beginner	- Pilot initiatives in Industry 4.0 with investments concentrated in a specific area - The infrastructure partially aligns with future needs - Skills are concentrated in limited areas
Level 2: Intermediate	- Integration of Industry 4.0 into the company's strategic planning - Diversified investments across multiple areas - Partial automation implemented for data collection - Adequate skills available in specific areas to drive Industry 4.0 initiatives
Level 3: Experienced	- Defined Industry 4.0 strategy - Considerable investments made in various sectors - Infrastructure is potentially upgradeable - Security measures implemented for information technology systems
Level 4: Expert	- Actively using Industry 4.0 strategy - Investments spread throughout the entire organization - Automated collection of large amounts of data for optimization purposes - Additional information technology features are available in products
Level 5: Top performer	- Successfully implemented and monitored an Industry 4.0 strategy - Executed extensive investments across the entire company for Industry 4.0 - Infrastructure fully complies with all requirements of Industry 4.0

Source(s): Authors' own creation

4. Results and discussion

This study used exploratory and confirmatory statistical analyses to validate the structure of the Shift2Future questionnaire. The model assesses the digital maturity of companies in the context of Industry 4.0, adapted to the Portuguese reality. Data was collected from 615 companies across Portugal, and to our knowledge, this is the first empirical validation of the Shift2Future model based on the original IMPULS/VDMA framework.

4.1 Descriptive analysis

Table 4 presents descriptive statistics for the variables Q1 to Q25, grouped by categories A to F. The table includes the mean, standard deviation, minimum and maximum values, and the 50th and 95th percentiles. These data help to understand how each variable is distributed, showing trends, variability, and possible outliers. This analysis provides valuable insights into how the responses vary across the dataset.

4.2 Methods employed for questionnaire validation and confirmation

An empirical study used the collected responses to validate the questionnaire structure. These methods were applied in sequence to ensure the model's internal validity and statistical robustness. First, Reliability Analysis was used to check the consistency of the items, using Cronbach's alpha. Then, an Exploratory Factor Analysis (EFA) was conducted to identify how the questions grouped into underlying factors. After that, a Confirmatory Factor Analysis (CFA) was performed to confirm the structure found in the EFA. The model's fit was evaluated

Table 4. Descriptive statistics for questionnaire items (Q1–Q25), grouped by model dimension (A–F), showing mean, standard deviation, and percentiles

	Variable	Obs	Mean (%)	Std. Dev. (%)	Min (%)	Max (%)	N° obs 95%	Percentile 95%	N° obs 50%	Percentile 50%
A	Q1	615	1.465	1.448	0	5	584	4	308	1
	Q2	615	1.779	1.372	1	5	584	4	308	1
	Q3	615	2.34	1.244	0	5	584	4	308	3
	Q4	615	2.603	1.111	0	5	584	4	308	3
	Q5	615	3.509	1.086	2	5	584	5	308	3
B	Q6	615	0.850	1.234	0	5	584	3	308	0
	Q7	615	0.863	1.406	0	5	584	4	308	0
	Q8	615	2.062	1.941	0	5	584	4	308	1
	Q9	615	1.816	1.609	0	5	584	4	308	2
	Q10	615	1.915	1.684	0	5	584	4	308	2
	Q11	615	1.332	1.648	0	5	584	5	308	1
	Q12	615	1.115	1.472	0	5	584	5	308	1
C	Q13	615	2.857	1.674	0	5	584	5	308	4
	Q14	615	3.055	1.467	0	5	584	5	308	3
	Q15	615	3.476	0.805	3	5	584	5	308	3
	Q16	615	3.769	0.925	0	5	584	5	308	3
	Q17	615	3.037	1.494	0	5	584	5	308	3
	Q18	615	3.846	1.248	2	5	584	5	308	4
D	Q19	615	0.811	1.538	0	5	584	5	308	0
	Q20	615	1.309	1.960	0	5	584	5	308	0
E	Q21	615	1.200	1.813	0	5	584	5	308	0
	Q22	615	1.338	1.801	0	5	584	5	308	0
	Q23	615	2.629	1.575	1	5	584	5	308	2
F	Q24	615	2.137	1.187	0	5	584	5	308	2
	Q25	615	2.984	1.178	1	5	584	5	308	3

Source(s): Authors' own creation

using indicators such as the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA), to assess how well the model matched the data.

4.3 Reliability analysis

Scale reliability refers to how consistent the results are when the same tool is used repeatedly (Huang *et al.*, 2017). Non-parametric tests compared early and late responses to the Likert scale questions to check for response bias. The results showed no significant differences (Lindner *et al.*, 2001).

In this study, STATA 18.0 was used to calculate Cronbach's Alpha, which measures the internal consistency of the questionnaire. The overall value was 0.9040, indicating excellent reliability, as values above 0.7 are considered high (Cronbach, 1951; Pestana and Gageiro, 2008; Taber, 2018). Most indicators scored above 0.8, confirming very good to excellent consistency.

Due to this strong reliability, descriptive statistics and non-parametric tests were applied, confirming that the questionnaire is a highly reliable tool for assessing digital maturity in Portuguese. Table 5 presents the Cronbach's Alpha values for each question.

Table 5 shows the results of a psychometric test with 25 questions (Q1 to Q25). The correlation between each question and the overall score is strong (between 0.53 and 0.75), indicating good validity. The item-rest correlations (0.42–0.71) confirm that each question contributes meaningfully to the total result, even when considered separately. The average correlation between questions is 0.27, showing moderate consistency.

Table 5. Cronbach's alpha values in different fields

Variable	Obs	Sign	Item-test correlation	Item-rest correlation	Average interitem correlation	Cronbach's alpha
Q1	615	+	0.5978	0.5479	0.2712	0.8993
Q2	615	+	0.5417	0.4872	0.2740	0.9006
Q3	615	+	0.5467	0.4926	0.2737	0.9005
Q4	615	+	0.5321	0.4768	0.2745	0.9008
Q5	615	+	0.6109	0.5621	0.2705	0.8990
Q6	615	+	0.6000	0.5503	0.2711	0.8993
Q7	615	+	0.5854	0.5345	0.2718	0.8996
Q8	615	+	0.7202	0.6823	0.2651	0.8965
Q9	615	+	0.7489	0.7142	0.2637	0.8958
Q10	615	+	0.7398	0.7041	0.2641	0.8960
Q11	615	+	0.6923	0.6515	0.2665	0.8971
Q12	615	+	0.6821	0.6402	0.2670	0.8974
Q13	615	+	0.5735	0.5216	0.2724	0.8999
Q14	615	+	0.4381	0.3765	0.2792	0.9029
Q15	615	+	0.5436	0.4893	0.2739	0.9005
Q16	615	+	0.5201	0.4640	0.2751	0.9011
Q17	615	+	0.5125	0.4559	0.2754	0.9012
Q18	615	+	0.3435	0.2771	0.2839	0.9049
Q19	615	+	0.4847	0.4261	0.2768	0.9018
Q20	615	+	0.4731	0.4137	0.2774	0.9021
Q21	615	+	0.4776	0.4186	0.2772	0.9020
Q22	615	+	0.3530	0.2870	0.2834	0.9047
Q23	615	+	0.4969	0.4392	0.2762	0.9016
Q24	615	+	0.4599	0.3997	0.2781	0.9024
Q25	615	+	0.4785	0.4195	0.2771	0.9020
Test scale					0.2736	0.9040

Source(s): Authors' own creation

Cronbach's Alpha values range from 0.8958 to 0.9049 for individual questions, and 0.9040 overall, indicating excellent internal consistency. These results confirm that the questionnaire is reliable and valid, with the items working together to measure the intended concept (Cronbach, 1951).

4.3.1 Response bias analysis. The standard deviation of each respondent's answers to the 25 Likert-scale items was calculated to assess potential response bias. According to Baumgartner and Steenkamp (2001) and Baumgartner and Weijters (2015), standard deviations below 0.30 may indicate low response variability and suggest satisficing or uniform answering.

In this sample of 615 respondents, the average response variability was 1.56, with a minimum of 0.77, well above the critical threshold. The distribution of standard deviations was symmetrical (skewness = −0.075) and showed normal dispersion (kurtosis = 2.84), with no outliers or anomalies. These results confirm that participants meaningfully differentiated their answers across items, and no significant response bias was present. Therefore, the data is considered reliable for subsequent statistical analysis.

4.4 Construct validity

Construct validity shows how well a questionnaire measures the concepts it was designed to assess. Factor Analysis (FA) is commonly used to test this. FA groups related variables into factors, helping explain data patterns and reduce complexity.

Before applying FA, two tests are used to check if the data is suitable: Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) test. Bartlett's test checks whether the variables are correlated enough for FA. In our case, the result was highly significant ($p < 0.000$), confirming this. The KMO value was 0.878, which is considered very good (Li, 2022), indicating strong suitability of the data for factor analysis (see Table 6).

To confirm construct validity, each item must load strongly on a factor, and the total variance explained by all aspects should be at least 40%. These conditions were met, supporting the structural validity of the questionnaire.

4.5 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was applied to examine the underlying structure of the questionnaire and assess whether the items grouped into meaningful and coherent factors. This analysis aimed to empirically confirm the theoretical six-dimensional structure of the Shift2Future model. Factor extraction followed the latent root criterion (eigenvalues > 1), as recommended by Hair *et al.* (2005), and only factors meeting this threshold were retained. The analysis confirmed six distinct factors aligning with the model's theoretical dimensions, supporting its construct validity. Before applying EFA, two key tests were performed: the KMO test and Bartlett's test of sphericity. The data was considered suitable because the KMO value was 0.878 (well above the minimum threshold of 0.5) and Bartlett's test was significant ($p < 0.05$), confirming strong correlations between variables.

Table 6. Bartlett test of sphericity and Kaiser-Meyer-Olkin

	Factor 1	2	3	4	5	6
KMO	0.691	0.870	0.662	0.500	0.637	0.500
Chi-square	816.376	3882.790	652.258	442.755	266.923	93.797
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Source(s): Authors' own creation

Three main conditions were checked:

(1) Correlation matrix: More than half of the variables showed correlations above 0.5.

(2) Bartlett's test: Confirmed the presence of significant correlations for factor analysis.

(3) KMO test: Showed that the data had sufficient common variance, with all variables scoring above 0.5.

After these checks, EFA was conducted to extract the factors.

The correlation matrix (see Table 7) shows the relationships between the variables Q1 to Q25. Diagonal values are always 1, as each item perfectly correlates with itself. Off-diagonal values indicate the strength and direction of the relationships: values closer to 1 show a strong positive correlation, values closer to −1 indicate a strong negative correlation, and values near zero show weak relationships. Asterisks (*) mark statistically significant correlations.

The matrix shows several moderate positive correlations between related items, such as Q1 with Q2, Q3, and Q4, indicating consistent relationships within the same dimension.

Table 8 shows the correlation matrix between the questionnaire dimensions. Most correlations are low but statistically significant. For example, the correlation between dimensions A and B is 0.3826. Other low correlations are seen between C and B, C and A, D and C, E and A, and E and B. The weakest correlation is between F and D (0.0978).

It is important to remember that correlation does not mean causation. These values show associations between dimensions but do not imply that one causes the other. The meaning of each correlation also depends on the context and what each dimension (A to F) represents.

Table 9 shows the correlation between the 25 questions (Q1 to Q25) and the six main factors (A to F). Questions Q1 to Q5 are linked to Factor 1, Q6 to Q12 to Factor 2, and Q13 to Q18 to Factor 3, all showing clear connections based on shared themes. Similarly, Q19 and Q20 relate to Factor 4, Q21 to Q23 to Factor 5, and Q24 and Q25 to Factor 6.

These results reveal clusters of questions that measure similar concepts, helping to understand the underlying structure of the questionnaire and how the different variables relate to each other.

The Kaiser-Meyer-Olkin (KMO) test helps confirm that the data is suitable for factor analysis. Values above 0.5 are acceptable, and values above 0.8 are considered very good.

According to Table 10, most variables have KMO values above 0.5, showing that the data is suitable. Variables Q6 to Q10 stand out with values above 0.88, indicating strong suitability for factor analysis.

Overall, the KMO values for sets 1, 2, 3, and 5 are excellent. Although KMO4 and KMO6 have slightly lower values, expected due to fewer supporting questions, they are still within acceptable limits. These results confirm that the sample is appropriate for factor analysis.

Table 11 summarizes the main results of the Exploratory Factor Analysis (EFA), presenting each extracted factor's eigenvalues, variance explained, and cumulative contribution. The factor extraction followed the latent root criterion (eigenvalues > 1), as recommended by Hair *et al.* (2005), resulting in six distinct factors that together explain a substantial portion of the total variance.

Importantly, the items grouped naturally into clusters that align with the six theoretical dimensions of the Shift2Future model: Strategy and Organization (A), Smart Infrastructure (B), Smart Operations (C), Smart Products (D), Data-Driven Services (E), and Human Resources (F). This alignment supports the model's construct validity and confirms that the questionnaire reliably captures conceptually distinct aspects of Industry 4.0 readiness.

Among the six factors, Factor 2 (B), which includes Q6 to Q12, has the highest eigenvalue (4.5805), indicating it explains the most significant share of variance. Factors 1 (A), 3 (C), 4 (D), and 5 (E) also show strong contributions. Although Factor 6 (F) has a lower eigenvalue (0.5188), explaining the variation in Q24 and Q25 related to human resource capabilities is essential.

Table 7. Pearson's correlation matrix among the questionnaire items

		A Q1	Q2	Q3	Q4	Q5	B Q6	Q7	Q8	Q9	Q10	Q11	Q12
A	Q1	1											
	Q2	_0.5790*_	1										
	Q3	0.3706*	0.2979*	1									
	Q4	0.3773*	0.2662*	_0.6602*_	1								
	Q5	0.3103*	0.2954*	0.2528*	0.2785*	1							
B	Q6	0.3226*	0.3038*	0.2349*	0.2003*	0.3440*	1						
	Q7	0.3600*	0.2426*	0.2640*	0.2624*	0.2173*	0.4895*	1					
	Q8	0.3479*	0.3237*	0.2618*	0.2343*	0.3776*	_0.5528*_	_0.5185*_	1				
	Q9	0.4044*	0.3599*	0.2989*	0.2699*	0.3771*	_0.5842*_	_0.5415*_	_0.8675*_	1			
	Q10	0.3321*	0.2985*	0.2843*	0.2729*	0.3879*	_0.5944*_	_0.5149*_	_0.8455*_	_0.8643*_	1		
	Q11	0.3359*	0.3054*	0.2921*	0.2820*	0.4261*	_0.5371*_	0.4994*	_0.6787*_	_0.6818*_	_0.6947*_	1	
	Q12	0.3217*	0.3198*	0.2889*	0.2911*	0.4441*	_0.5333*_	0.4654*	_0.6210*_	_0.6414*_	_0.6661*_	_0.9056*_	1
C	Q13	0.2532*	0.1677*	0.3557*	0.3592*	0.4487*	0.2869*	0.2448*	0.3470*	0.3033*	0.3884*	0.3908*	0.3978*
	Q14	0.1749*	0.2043*	0.1548*	0.1884*	0.3207*	0.1440*	0.1410*	0.1823*	0.1981*	0.2022*	0.2213*	0.2496*
	Q15	0.3324*	0.3553*	0.2188*	0.2028*	0.3503*	0.2180*	0.3095*	0.2950*	0.3319*	0.3098*	0.3535*	0.3550*
	Q16	0.3309*	0.3088*	0.2778*	0.2215*	0.3054*	0.1838*	0.2487*	0.2275*	0.2297*	0.1987*	0.2009*	0.2277*
	Q17	0.1930*	0.1010*	0.3131*	0.3123*	0.4080*	0.2691*	0.1466*	0.2598*	0.2373*	0.3366*	0.3329*	0.3254*
	Q18	0.1876*	0.1455*	0.2059*	0.2554*	0.1819*	0.0844*	0.0937*	0.0927*	0.0564	0.1100*	0.0732	0.1028*
D	Q19	0.2779*	0.2249*	0.1740*	0.1745*	0.1337*	0.2015*	0.2923*	0.4082*	0.4644*	0.3762*	0.2650*	0.2168*
	Q20	0.2546*	0.2010*	0.1820*	0.1275*	0.1005*	0.2253*	0.3030*	0.4333*	_0.5064*_	0.3898*	0.2399*	0.2055*
E	Q21	0.3169*	0.3177*	0.2226*	0.1649*	0.2502*	0.1598*	0.2464*	0.2621*	0.2683*	0.2088*	0.1020*	0.1006*
	Q22	0.2525*	0.2939*	0.2445*	0.1584*	0.0709	0.0558	0.0678	0.0793*	0.0765	0.0277	−0.045	−0.0534
	Q23	0.1964*	0.1926*	0.2473*	0.2333*	0.3400*	0.2162*	0.1954*	0.2200*	0.2493*	0.2767*	0.2130*	0.2081*
F	Q24	0.1952*	0.1496*	0.1804*	0.2328*	0.3632*	0.2677*	0.1966*	0.2099*	0.2272*	0.2698*	0.2591*	0.2473*
	Q25	0.1935*	0.1953*	0.2350*	0.2914*	0.4166*	0.2427*	0.1894*	0.2583*	0.2596*	0.3244*	0.2762*	0.2998*

		C Q13	Q14	Q15	Q16	Q17	Q18	D Q19	Q20	E Q21	Q22	Q23	F Q24	Q25
A	Q1													
	Q2													
	Q3													
	Q4													
	Q5													

(*continued*)

Table 7. Continued

		C						D		E			F	
		Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25
B	Q6													
	Q7													
	Q8													
	Q9													
	Q10													
	Q11													
	Q12													
C	Q13	1												
	Q14	0.3625*	1											
	Q15	0.2466*	0.2122*	1										
	Q16	0.3373*	0.2494*	0.4742*	1									
	Q17	0.4137*	0.2115*	0.1762*	0.2856*	1								
	Q18	0.1383*	0.2039*	0.0896*	0.2513*	0.4617*	1							
D	Q19	0.2102*	0.1829*	0.1860*	0.1766*	0.1002*	0.1324*	1						
	Q20	0.1346*	0.1492*	0.1802*	0.2200*	0.0567	0.0988*	*0.7174**	1					
E	Q21	0.1843*	0.2297*	0.3242*	0.2995*	0.0766	0.1504*	0.2764*	0.3299*	1				
	Q22	0.0928*	0.1599*	0.2067*	0.2885*	0.0885*	0.2305*	0.2636*	0.2333*	0.4640*	1			
	Q23	0.2874*	0.1618*	0.2643*	0.2307*	0.3008*	0.1547*	0.1076*	0.1390*	0.3094*	0.3945*	1		
F	Q24	0.2468*	0.3371*	0.2354*	0.1579*	0.3012*	0.1188*	0.0481	0.0596	0.1485*	0.1186*	0.3774*	1	
	Q25	0.2895*	0.1833*	0.2488*	0.2208*	0.3410*	0.1047*	0.0558	0.0191	0.1556*	0.0855*	0.3180*	0.3768*	1

Note(s): Observation: Items in italic are provided for a significance level of 5%
Strategy and Organization (A), Smart Infrastructures (B), Smart Operations (C), Smart Products (D), Data-driven Services (E), Human Resources (F)

Source(s): Authors’ own creation

Table 8. Pearson's correlation matrix among the questionnaire dimensions

	A	B	C	D	E	F
A	1					
B	0.3826*	1				
C	0.2901*	0.2831*	1			
D	0.2355*	0.2235*	0.2089*	1		
E	0.3124*	0.1919*	0.2162*	0.3090*	1	
F	0.1964*	0.2137*	0.2966*	0.0978*	0.1766*	1

Note(s): Observation: Items in italic are provided for a significance level of 5%
Strategy and Organization (A), Smart Infrastructures (B), Smart Operations (C), Smart Products (D), Data-driven Services (E), Human Resources (F)

Source(s): Authors' own creation

Table 9. Factor loadings

	Variable	Factor 1	2	3	4	5	6
A	Q1	0.6601					
	Q2	0.5825					
	Q3	0.6830					
	Q4	0.6830					
	Q5	0.4245					
B	Q6		0.6581				
	Q7		0.6003				
	Q8		0.8730				
	Q9		0.8929				
	Q10		0.8900				
	Q11		0.8633				
	Q12		0.8310				
C	Q13			0.5749			
	Q14			0.4507			
	Q15			0.4666			
	Q16			0.5988			
	Q17			0.5984			
	Q18			0.4512			
D	Q19				0.7849		
	Q20				0.7849		
E	Q21					0.5831	
	Q22					0.6443	
	Q23					0.5148	
F	Q24						0.5093
	Q25						0.5093

Note(s): Strategy and Organization (A), Smart Infrastructures (B), Smart Operations (C), Smart Products (D), Data-driven Services (E), Human Resources (F)

Source(s): Authors' own creation

In short, the EFA confirms a well-structured and theoretically coherent questionnaire, with each factor representing a relevant latent construct in the digital maturity assessment. The factor loadings showed that the questionnaire items were grouped under the expected factors. Most items had loadings above 0.7, indicating strong links with their respective factors. Two items had slightly lower values, around 0.5, but within the minimum acceptable range. These results confirm the overall validity and consistency of the questionnaire structure.

Table 10. Kaiser-Meyer-Olkin

		KMO											
	Variable	1	2	3	4	5	6	1	2	3	4	5	6
A	Q1	0.7086						*0.6914*					
	Q2	0.6808											
	Q3	0.6626											
	Q4	0.6524											
	Q5	0.8710											
B	Q6		0.9582						*0.8698*				
	Q7		0.9577										
	Q8		0.8865										
	Q9		0.8791										
	Q10		0.9039										
	Q11		0.7998										
	Q12		0.7881										
C	Q13			0.6657						*0.6623*			
	Q14			0.7492									
	Q15			0.6614									
	Q16			0.6982									
	Q17			0.6380									
	Q18			0.5827									
D	Q19				0.5000						*0.5000*		
	Q20				0.5000								
E	Q21					0.6370						*0.6370*	
	Q22					0.6053							
	Q23					0.6902							
F	Q24						0.5000						*0.5000*
	Q25						0.5000						

Note(s): Strategy and Organization (A), Smart Infrastructures (B), Smart Operations (C), Smart Products (D), Data-driven Services (E), Human Resources (F)
Source(s): Authors’ own creation

Table 11. Results of exploratory factor analysis: eigenvalues, variance explained, and item groupings aligned with the six Shift2Future dimensions

Factor	Number of items	Items	Eigenvalue	Difference	Proportion	Cumulative
1 (A)	5	Q1, Q2, Q3, Q4, Q5	1.8884	1.4951	1.0335	1.0335
2 (B)	7	Q6, Q7, Q8, Q9, Q10, Q11, Q12	4.5805	4.1151	0.9401	0.9401
3 (C)	6	Q13, Q14, Q15, Q16, Q17, Q18	1.6716	1.3041	1.0292	1.0292
4 (D)	2	Q19, Q20	1.2320	1.4348	1.197	1.1970
5 (E)	3	Q21, Q22, Q23	1.0201	1.1238	1.4675	1.4675
6 (F)	2	Q24, Q25	0.5188	0.7536	1.8269	1.8269

Note(s): Strategy and Organization (A), Smart Infrastructures (B), Smart Operations (C), Smart Products (D), Data-driven Services (E), Human Resources (F)

Source(s): Authors' own creation

4.6 Confirmatory Factor Analysis (CFA)

Following the EFA, a Confirmatory Factor Analysis (CFA) was conducted to verify the factor structure identified and test how well the model fits the empirical data. This step aimed to confirm the six-factor organization of the Shift2Future model using standard fit indices widely adopted in structural equation modeling.

The impact of each factor is measured through its loadings (and corresponding *p*-values) in the regression equations. Two incremental fit indices are used to evaluate model fit: the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), which compare the model to a baseline model. Both range from 0 to 1, with values closer to 1 indicating a better fit. Additionally, the Root Mean Square Error of Approximation (RMSEA) is used as an absolute fit measure, with values closer to 0 indicating a better fit (Lin, 2021).

The model fit indices confirm the adequacy of the six-factor structure. The Comparative Fit Index (CFI = 0.977) and the Tucker-Lewis Index (TLI = 0.973) exceed the recommended threshold of 0.90, indicating excellent fit. The Root Mean Square Error of Approximation (RMSEA = 0.041) is below 0.05, confirming a perfect model fit. Together, these values provide strong empirical support for the validity of the proposed structure. It's essential to note that *p*-values are not displayed in the tables due to the use of the marker method, where the first loading of each factor is fixed at 1 to simplify parameter estimation (Lin, 2021).

Although there is no strict rule on the minimum number of variables required for Confirmatory Factor Analysis (CFA), several authors suggest guidelines based on practical experience. Rencher (2005) states that CFA is suitable with a "moderate number of variables", but doesn't define a minimum. Hair *et al.* (2010) highlight the need for a sufficient number of variables relative to the sample size to ensure validity.

Green (1991) also notes that the number of variables must be balanced with sample size for reliable results in regression and CFA. Most researchers recommend at least three variables per factor, with some suggesting 4 to 6 items per factor for greater stability (Anderson and Rubin, 1956; Rindskopf, 1984; Fabrigar *et al.*, 1999). Factors with fewer than three items are usually considered weak or unstable (Costello and Osborne, 2019).

5. Conclusions

The central research question addressed in this study concerns the validity and reliability of the Shift2Future model, adapted from the IMPULS framework, as a tool for assessing Industry 4.0 maturity in Portuguese companies. The statistical validation confirmed the internal structure of the model and demonstrated its practical applicability for both companies and policymakers.

5.1 Discussion of findings

Analyzing data from 615 Portuguese companies offers a clear picture of digital maturity in Portugal within the Industry 4.0 context. The Shift2Future model revealed varying maturity levels across dimensions, some showing progress, others exposing significant gaps.

As shown in Table 4, the Strategy and Organization dimension (A) achieved moderate results. Notably, Q5 (mean = 3.509) suggests that some companies already have structured innovation practices. However, Q1 to Q4, related to investment and strategic alignment, scored lower (between 1.4 and 2.6), indicating that many companies are still at an early stage of Industry 4.0 adoption.

Smart Operations (Dimension C) showed the highest maturity, especially in cloud use (Q18, mean = 3.846) and autonomous processes (Q15 and Q16, both above 3.4), suggesting progress in digitalizing operations, likely due to easier access to cloud and automation tools.

In contrast, Smart Infrastructures (Dimension B) and Smart Products (Dimension D) had the lowest results. Questions like Q6, Q7, and Q19 had means below 1, with many firms selecting zero. This reveals challenges in machine interoperability, innovative product development, and digital infrastructure.

Data-Driven Services (Dimension E) also showed low maturity (Q21 and Q22 around 1.2–1.3), indicating that most companies do not yet use data to develop services or generate revenue. Human Resources (Dimension F) had intermediate scores, with Q24 (skills) at 2.137 and Q25 (training) at 2.984, showing some awareness of upskilling, though not fully implemented.

While digital transformation is advancing in Portuguese firms, gaps remain, especially in areas requiring investment in equipment, innovation, and data capabilities. These challenges are more evident in SMEs, which form most of the sample and often lack resources.

These findings align with Guimarães *et al.* (2024), who reported that automotive and aeronautics have higher maturity levels, while traditional sectors such as ceramics and agri-food face more difficulties. The results highlight the need for tailored strategies, particularly in low-tech industries.

This evidence supports the theoretical foundations of the model and its relevance as a practical tool based on organizational and technological change dynamics. It also confirms that the Shift2Future model reliably captures different readiness levels across sectors and firm sizes. The model identifies priority areas for improvement in line with its structure and intended use.

Finally, the study reinforces that digital transformation is a socio-technical process requiring technological upgrades, strategic alignment, and workforce development. By aligning with staged maturity models, Shift2Future provides a structured and theory-based method to support companies' transformation journeys.

5.2 Implications of this study

5.2.1 Theoretical implications. This study makes several theoretical contributions to the literature on Industry 4.0 readiness and digital maturity assessment. First, it provides the first empirical validation of the Shift2Future model, which was specifically designed to address the limitations of previous Industry 4.0 maturity models when applied to SMEs and service companies. Compared to the original IMPULS model (Lichtblau *et al.*, 2015), our results show that adapting maturity models to national contexts enhances their relevance, diagnostic accuracy, and applicability to diverse organizational realities.

Our findings are partially consistent with studies such as Hajoary *et al.* (2024) and Mittal *et al.* (2018a), which validated models in industrial settings, but did not focus on service sectors or countries with lower digital maturity. While Albannai *et al.* (2024) highlighted the role of digital leadership, our study draws attention to broader organizational and structural readiness gaps, including digital infrastructure, workforce skills, and operational integration, particularly in SMEs.

Unlike previous models based on qualitative data or expert opinion (e.g. Schumacher *et al.*, 2016), we validated Shift2Future with a large sample of 615 companies, using exploratory and confirmatory factor analyses (EFA and CFA), ensuring empirical robustness. The model also features flexible weighting, simplified language, and applicability to services and industry, which respond directly to gaps identified in the literature, as Guimarães *et al.* (2025c) noted.

This study directly addresses the research question (RQ), demonstrating that Shift2Future is a valid and reliable tool for assessing Industry 4.0 readiness in Portuguese companies across different sectors. Furthermore, it contributes to the theoretical development of Industry 4.0 maturity models, offering a scalable and context-aware framework that can support future research in other national or regional contexts. Lastly, the study provides empirical support for dynamic capabilities theory (Teece *et al.*, 1997), showing how companies adapt and reconfigure internal resources to enable digital transformation for Industry 4.0.

This contribution is particularly relevant for advancing the theoretical development of maturity models beyond static assessments, incorporating dynamic, scalable, and context-aware features applicable to economies with diverse industrial structures.

5.2.2 Managerial implications. From a managerial perspective, this study offers practical guidance for different types of companies. The Shift2Future model helps managers identify digital infrastructure or data use weaknesses, supporting informed decision-making. For small and medium-sized enterprises (SMEs) in traditional sectors such as ceramics or agri-food, the findings suggest that priority should be given to basic investments in digital infrastructure and workforce training, as these companies demonstrated low maturity in these areas (questions Q6, Q7, Q24, and Q25). For service companies, the focus should be on improving the use of data to develop new services, since data-driven innovation scored particularly low (questions Q21 to Q23). More advanced firms, such as those in the automotive or metalworking sectors, should build on their strengths in Smart Operations (questions Q15 to Q18) to enhance supply chain integration and invest in developing innovative products (Q19 and Q20).

In all cases, the automated feedback provided by the Shift2Future model supports strategic planning, resource allocation, and benchmarking, enabling companies to define realistic goals and continuously improve their digital maturity. For policymakers, the results highlight priority areas for targeted support, such as training programs focused on digital skills, incentives for investment in technology and infrastructure, and sector-specific transformation plans developed in collaboration with industrial clusters and universities.

5.3 Limitations and scope for future research

Despite the robustness of the results, this study has some limitations that should be acknowledged. First, the model was validated solely within the Portuguese context, which may limit its direct applicability to other countries without appropriate adaptation. Additionally, the data is based on self-assessment, which may introduce bias, as it reflects respondents' perceptions rather than external evaluations or objective performance indicators.

Moreover, while the Shift2Future model is designed to be inclusive, specific dimensions, such as Smart Products and Data-Driven Services, may have limited applicability in specific service-oriented companies, potentially affecting comparability across sectors. Another limitation concerns potential selection bias, as participation was voluntary, and companies already engaged in digital transformation may be overrepresented in the sample.

These limitations open important avenues for future research. First, it would be valuable to replicate this study in other countries or regions to assess the adaptability and relevance of the Shift2Future model in different industrial contexts. Additionally, longitudinal studies could explore how companies evolve in digital maturity over time and which factors drive successful transitions.

Sector-specific adaptations of the model, for industries such as healthcare, tourism, or logistics, could enhance its practical relevance and diagnostic precision. Finally, triangulating self-assessment results with external audits or performance data would help to validate the objectivity and reliability of the maturity levels identified.

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Notes

1. NACE definition (Economic Activities European Community – European Commission (europa.eu)).
2. SMEs definition (SME definition – European Commission (europa.eu)).

Supplementary material
The supplementary material for this article can be found online.

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