An Exploration of Organisational Readiness for Industry 4.0: A Predictive Maintenance Perspective

DOI: 10.12776/qip.v28i1.1984

Damjan Maletič, Matjaž Maletič

Received: 2024-02-05 Accepted: 2024-03-22 Published: 2024-03-31

ABSTRACT

Purpose: The aim of this paper is to examine the extent to which selected Slovenian companies are prepared to integrate the complex requirements of Industry 4.0 (I4.0) into their asset management practices, using the specific example of predictive maintenance.

Methodology/Approach: A research study was conducted on a sample of Slovenian manufacturing companies. Data was collected using a structured questionnaire to investigate the extent to which companies are engaged with new technologies and their current and future focus on their use in predictive maintenance.

Findings: The analysis of the empirical data shows that companies are aware of the benefits that can be achieved with I4.0 solutions. The results also show that the companies surveyed lack a clear vision and implementation roadmap for I4.0. The results also show that the majority of companies in the sample are still at an early stage of predictive maintenance strategy maturity.

Research Limitation/implication: The sample of responding companies is limited to the Slovenian manufacturing industry, and the subjective information comes from only one representative person in each company.

Originality/Value of paper: The paper is one of the first studies to highlight digitalisation and predictive maintenance in the context of I4.0.

Category: Research paper

Keywords: predictive maintenance; digitalization; maturity assessment; Industry 4.0

1 INTRODUCTION

Nowadays, organisations are faced with the necessity to meet customer demands in a highly competitive environment (Sony and Naik, 2020), which can be achieved by digitising internal and external business processes to continuously reduce operational costs (Kern et al., 2020; Fatorachian and Kazemi, 2018). In addition to being highly competitive in the markets, the integration of modern decision support tools is an indispensable prerequisite that makes maintenance management an important factor in adding value to the company's assets (Candón et al., 2019). In this context, it can be argued that effective and high-quality maintenance is crucial to keep production facilities at a level that allows the desired product quality to be achieved and the company's objectives and results in terms of competitiveness and sustainability to be met (Psarommatis, May and Azamfirei, 2023).

While asset availability and reliability become critical issues in capital-intensive operations, the strategic importance of maintenance in such businesses should be recognised (Tsang, 2002). Faced with the challenges of changing business models and increased cost pressures, organisations need to focus on striking a balance between costs and risks and achieving the desired performance (Maletič et al., 2023, 2020). With the support of maintenance management, which is a very important part of asset management (AM), companies should realise their full potential and achieve their business goals effectively. An Asset Management System (AMS) based on the ISO 55000 family of standards helps an organisation to establish a coherent approach and coordinated deployment of appropriate resources and activities. The effective management of assets consequently plays an increasingly important role in optimising the profitability of the company (Maletič et al., 2018; Schuman and Brent, 2005).

Technological innovation is opening the door to a whole new world of AM. The Internet of Things (IoT) is a key enabler for Industry 4.0 (I4.0), as well as big data and analytics, cloud computing, mobile networks, virtual reality, digital twins, building information modelling (BIM) and real-time monitoring of physical assets are some of the trends currently entering the AM world. The digital age presents organisations with new challenges and is enabled by communication between people, machines and resources (Kagermann, 2015). In this context, there are also new emerging and systemic risks that should be considered (Brocal et al., 2019). AM is no exception. It is widely recognised in the literature (Hodkiewicz 2015; Maletič et al., 2019; Trindade et al. 2019; Komljenovic et al., 2019) that AM is about aligning planning, procurement, operations and maintenance to create value through effective asset utilisation. However, we are now facing a new challenge: how can we effectively use the huge amounts of data that are generated every day, every minute and every second? Therefore, digital transformation in AM should ensure that the right business information and operational technology data is available at the right time, across the system and throughout the asset lifecycle. In this context, Trindade and Almeida (2018) have highlighted the importance of digitalisation as a contributor to value creation from assets in asset-intensive companies.

With I4.0, the new maintenance paradigm, innovative methods, tools and systems must now be developed to meet the new requirements of I4.0 (Al-Najjar et al., 2018). Many studies show that maintenance plays an important role in increasing business performance (e.g. Al-Najjar, 2007; Maletič et al., 2014). Although life cycle cost (LCC) is mainly influenced at the design stage (Schuman and Brent, 2005), maintenance is considered an essential element to meet the current trend of automation and data sharing in industrial technology and to ensure that assets deliver value to the organisation. Therefore, maintenance should be recognised as a value driver by supporting AM in achieving business goals (Kans and Galar, 2017).

As I4.0 is a relatively new technology, research in this area is still under development, particularly in relation to maintenance and AM (Al-Najjar et al., 2018; Kans and Galar, 2017; Kumar and Galar, 2018). Although there are several publications on the topic of I4.0 and maintenance, the combination of these topics is worth further investigation. For example, a recent study addresses how I4.0 can improve the asset management of electric grids (Biard and Nour, 2021), highlighting the need to combine these two research areas. Furthermore, Tortorella et al. (2022) provide empirical evidence of the impact of I4.0 technologies on the relationship between total productive maintenance (TPM) practices and maintenance performance, which further substantiates the importance of this topic. In addition, I4.0 readiness is also a research topic with a strong interest in the literature (e.g., Stentoft et al., 2021) and is considered as a contemporary topic in management studies (Hizam-Hanafia et al., 2020). Notwithstanding the above, there is still a lack of empirically based research on the application of I4.0 in the field of maintenance and/or AM. As such, this study aims to examine and explore the companies' technology readiness for I4.0 with an emphasis on predictive maintenance.

The rest of the paper is structured as follows: the second section presents a review of the PdM and I4.0 literature, followed by the methodology and the research results. Finally, the paper discusses the findings and ends with the main concluding remarks.

2 LITERATURE REVIEW APPROACH

A comprehensive synthesis of the scientific literature on PdM in relation to I4.0 and digitalisation was carried out prior to empirical research. The aim of the systematic literature review is to collect and analyse the existing relevant studies on the topic of predictive maintenance in the context of I4.0 and digitalisation in order to identify and highlight possible potentials for empirical research. This approach allows other researchers to replicate and update the literature review by presenting the reviewer's procedures in a transparent way. This review went through the following phases of search, screening and extraction/synthesis.

2.1 Searching

In order to have a holistic coverage of all possible papers, a structured keyword search was conducted using the following databases: ISI Web of Science (WoS), Scopus, and Google Scholar. Accordingly, the scientific literature, represented by peer-reviewed journals, was searched for relevant studies. As can be seen in Table 1, the search strings were linked using the Boolean operator (AND). The searching process and the selecting process were performed between January 2010 and November 2023.

Table 1 – Search string and number of published papers in bibliometric databases during the years 2010-2023

Search string	**Web of Science Core Collection (topic)**	**Scopus (article title, abstract, keywords)**	**Google Scholar (all fields)**
“Industry 4.0”	17808	28957	138000
“Digitalisation”	16109	32358	255000
“Predictive maintenance”	4141	6609	27200
“Maintenance 4.0”	53	95	1540
“Industry 4.0” AND “Predictive maintenance”	575	844	16100
“Digitalisation” AND “Predictive maintenance”	77	182	9710

2.2 Screening

Table 2 lists the inclusion and exclusion criteria used to screen article titles and abstracts. This step resulted in the retention of 300 articles relevant to the topic of this paper. These articles were assessed independently according to the quality criteria (Pittaway et al., 2004) (see Appendix).

Table 2 – Inclusion and Exclusion Criteria

Criterion	**Inclusion**	**Exclusion**
Study type	Peer-reviewed empirical and theoretical/conceptual studies; conference articles included if high-quality	
Sector	Manufacturing	
Relevance	Addresses predictive maintenance within Industry 4.0 or digitalisation paradigms	Not directly relevant to the research question Level of analysis—not firm-level practices and processes

Criterion	Inclusion	Exclusion
	Level of analysis—firm-level practices and processes	

2.3 Extraction and Synthesis

This section summarises the main findings of the systematic literature review. Considering inclusion and exclusion criteria as well as qualitative criteria, 50 articles were extracted and compared based on descriptive, methodological and thematic characteristics and categories. The final selection of articles was relatively heterogeneous, coming from different contexts and containing a mix of empirical (qualitative and quantitative) and conceptual approaches. We followed previous review articles (Watson et al., 2018) that used the qualitative cross-case analysis approach (Mays, Pope, and Popay, 2005) to synthesise key findings from the systematic literature review. Table 3 summarises the most important findings and gives some examples of extracted articles.

Table 3 – Examples of articles pertaining to the systematic review of literature

Study	Research approach	Key findings	Pre	Int	Tec	Per
Zonta et al. (2020)	LR	This article discusses the current challenges and limitations of PdM and proposes a new taxonomy to classify this field of research, taking into account the requirements of I4.0.	✓			
Jasiulewicz-Kaczmarek et al. (2020)	C/LR	In this article, intelligent and sustainable maintenance was considered from three perspectives, namely from a historical perspective, from a development perspective and from a sustainable development perspective.	✓	✓		
Kumar and Galar (2018)	LR	The article highlights the concept of I4.0 and presents maintenance solutions that address the needs of the next generation of manufacturing technologies and processes with regard to the vision of I4.0.	✓	✓		
Mohapatra et al. (2023)	ER	In this article, a remote monitoring and data acquisition system is proposed to realise the concept of PdM.	✓	✓	✓	✓
Mohan et al. (2023)	ER	In this paper, an LSTM-based prediction model is proposed to achieve zero downtime in a real-time application based on condition monitoring to	✓	✓	✓	✓

Study	Research approach	Key findings	Pre	Int	Tec	Per
		improve the availability rate and performance rate.				
Paolanti et al. (2018)	ER	In this article, a machine learning architecture for PdM based on the random forest approach is proposed.	✓	✓	✓	✓
Yan et al. (2017)	ER	The results of this work show that heterogeneous data from multiple sources can provide new solutions for PdM, scheduling and optimisation of machining processes to save energy.	✓	✓	✓	✓
Schmidt et al. (2017)	CS	This article highlights the results of a case study in a real industrial environment by proposing a new visualisation method to support the decision-making process.	✓			✓
Cachada et al. (2018)	C	This article presents the architecture of an intelligent PdM system based on the principles of Industry 4.0.	✓	✓		

Notes: C: Conceptual. ES: Empirical survey. CS: Case study. ER: Experimental research. LR: Litereature review. Pre: Predictive. Int: Intelligent. Tec: Technological. Per: Performance

The systematic literature review in this study has shown that it makes sense to further empirically investigate predictive maintenance against the background of the I4.0 paradigm and digitalisation. The result of this systematic literature review is seen as further support for the interpretation of our empirical research, namely the coverage of relevant aspects of PdM in the context of I4.0.

3 METHODOLOGY

PdM, grounded in the maintenance, AM and I4.0 perspectives, provides the frame of reference of the present research, which focuses on identifying the I4.0 readiness of Slovenian organisations and determining the maturity level of predictive maintenance. This study responds to the need for theoretically anchored and empirically founded studies that bridge the I4.0 and maintenance management (García & García, 2019). Given the research objective, it was considered appropriate to draw on empirical research.

3.1 Sample and Data Collection

The data was collected through an online survey using the 1ka web survey platform (https://www.1ka.si/d/en). The sampling frame for this study was derived from the Slovenian Business Register. Since the unit of analysis is a company, each of these companies is represented by the responses of a single person within that company. The respondents were typically operations and production managers, usually working in corporate functions such as operations, maintenance, production and technology, quality or general management. Assuming that these positions provide a comprehensive overview of the relevant business processes and management systems, these managers can provide valid assessments of I4.0 readiness and the adoption of predictive maintenance concepts and technologies. Following a random sampling method, questionnaires were sent to a total of 350 organisations. Follow-up reminder e-mails were sent after the initial e-mailing to increase the response rate. In total, 71 responses were received, with a response rate of 20.3 %. The companies were classified based on Slovenian Standard Industrial Classification Codes (SIC). According to the results, the majority of responses to the survey were from the manufacturing industry (52 %). The remainder portion of companies corresponds to electricity, gas, steam, and air conditioning supply, wholesale and retail trade, repair of motor vehicles and motorcycles, transportation and storage and other type of industries. Regarding the number of employees (following the guidelines of the Statistical Office of the Republic of Slovenia), the greatest proportion of organisations that responded were medium-sized organisations (51–250 employees) (approximately 35 %), while the smallest portion corresponds to organisations employing 251–500 employees (approximately 7 %).

3.2 Measures

Several topics (related to AM and digitalisation) were conceptualised to formulate a questionnaire, each measured by using five-point Likert scales (1 = “strongly disagree”, 5 = “strongly agree”) or categorical-level type of questions. Questionnaire items are based on previous studies and literature to ensure content validity (Sekaran and Bougie, 2016). Accordingly, the measures for this study were derived and adapted from Haarman, Mulders and Vassiliadis (2017) and Breunig et al. (2016). Furthermore, face validity was ensured by validating the questionnaire by academic expert panels (n = 5) and industry experts (n = 2).

4 RESULTS

The following section provides results regarding the perceived level of I4.0, an estimation of the maturity level of predictive maintenance (PdM), as well as a review of supporting tools for predictive maintenance.

Results regarding the perceived features of I4.0 are presented in Figure 1. As indicated by the results, digitalisation prevails (48%) as a perceived building block of I4.0 concept. Other aspects of I4.0 were selected and outlined in smaller portions; i.e. new IT technology (19%), smart factory (16%), and cyber-physical systems (10%).

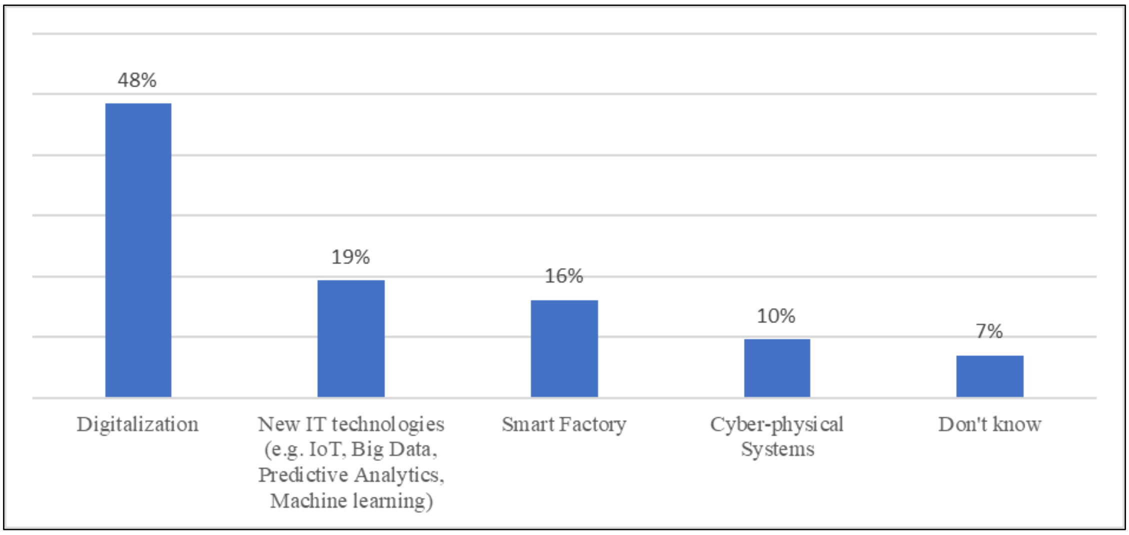

Figure1 – Key features of I4.0

Taking a closer look at our results (Table 1), it can be argued that sample companies face a lack of I4.0 technology readiness level (M = 2.9). Intriguingly, companies recognise the potential and opportunity (M = 3.8) of I4.0 and its impact on their business (M = 3.5).

Table 1 – Descriptive statistics for I4.0 readiness

	M	SD	SEM	t
Do you consider your company well-prepared for Industry 4.0?	2.92	0.76	0.122	0.167
Industry 4.0 is an opportunity rather than a risk	3.81	0.74	0.108	7.48**
Do you expect Industry 4.0 to impact your company's business model?	3.53	0.97	0.142	3.74**

Notes. M - Mean. SD – Standard Deviation. SEM - Std. Error Mean. **statistically significant at 0.01 level

It is undoubtedly that I4.0 needs to be led from the top, with a strong, clear vision (Amrita and Akhilesh, 2020). One can argue that companies need to put their effort on the development of the I4.0 roadmap, with a clear and truthful assessment of both the current situation and the I4.0 transformation objectives. As shown by the results (Table 2), on average, companies don't have a clear strategy for I4.0 adoption (M = 2.73), neither do they have a straightforward roadmap (M = 2.64).

Table 2 – Strategic orientation towards I4.0

	M	SD	SEM	t
We have an overall Industry 4.0 strategy in place	2.73	0.90	0.151	-0.846

	M	SD	SEM	t
We have assigned clear responsibilities for implementing Industry 4.0	2.58	0.92	0.144	-2.573*
We have a clear roadmap for implementing Industry 4.0	2.64	0.94	0.147	-1.733

Notes. M - Mean. SD – Standard Deviation. SEM - Std. Error Mean. *statistically significant at 0.05 level

In terms of PdM readiness, there are some causes for concern, mixed with some positive future perspectives. It is encouraging that 34% of companies are either working on PdM or have a clear strategic plan for implementation of PdM in the near future – although there is a significant and concerning 48% who disagree or have no future plans for implementing PdM (Figure 2).

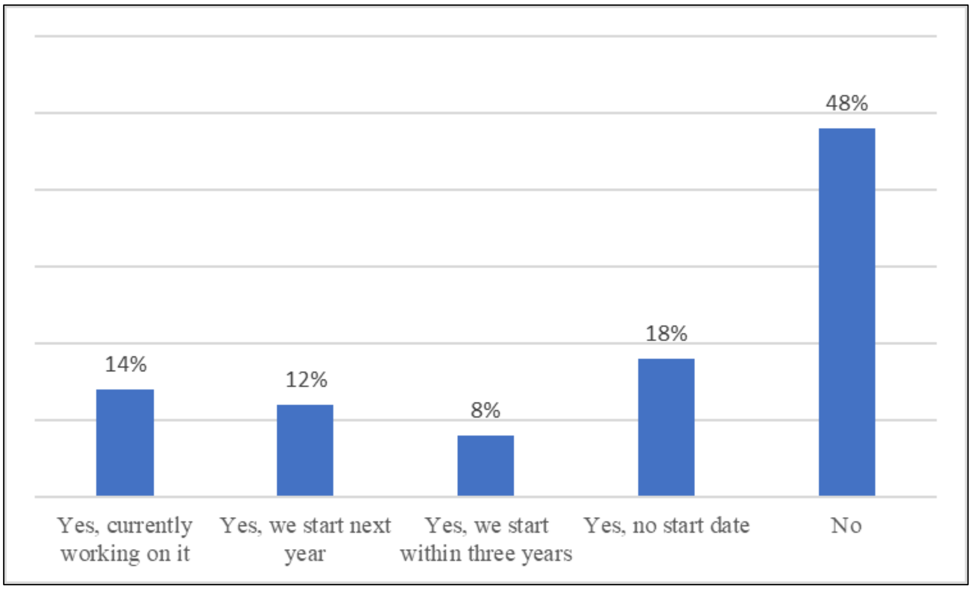

Figure 2 – Organization's plan to embed predictive maintenance

In order to compare the differences in I4.0 readiness and Strategic orientation to I4.0 among the two categories of company size, an independent t-test was applied to compare the mean values. The results of this statistical analysis are presented in Table 3, demonstrating that t values are not statistically significant. Therefore, our results suggest that there are no differences between small and medium-sized enterprises (SMEs) and large (no. of employees > 250) companies.

Table 3 – I4.0 in relation to company size

	Size	N	M	SD	SEM	t (p)
Industry4.0 readiness	SME	30	3.29	0.704	0.129	-1.368 (0.178)
	> 250	19	3.60	0.858	0.197	

	Size	N	M	SD	SEM	t (p)
Strategic orientation to Industry4.0	SME	28	2.64	0.839	0.159	-1.036 (0.306)
	> 250	19	2.93	1.098	0.252	

Notes. N - Sample size. M - Mean. SD – Standard Deviation. SEM - Std. Error Mean

Furthermore, we found that more than three-fourths of survey respondents are still at maturity levels one or two (Figure 3). As expected, there are not a lot of companies that consider themselves front-runners in the predictive maintenance maturity race. Only 4% have already achieved level four. We can divide sample companies into four distinct categories. Each category is characterised by a different organisational stage and activity level according to the maturity scale (Haarman, Mulders and Vassiliadis, 2017):

Level 1: Visual inspections: periodic physical inspections; conclusions are based solely on the inspector's expertise.

Level 2: Instrument inspections: periodic inspections; conclusions are based on a combination of the inspector's expertise and instrument read-outs.

Level 3: Real-time condition monitoring: continuous real-time asset monitoring, with alerts based on pre-established rules or critical levels.

Level 4: Predictive maintenance with Big Data Analytics: continuous real-time monitoring of assets, with alerts sent based on predictive techniques, such as regression analysis.

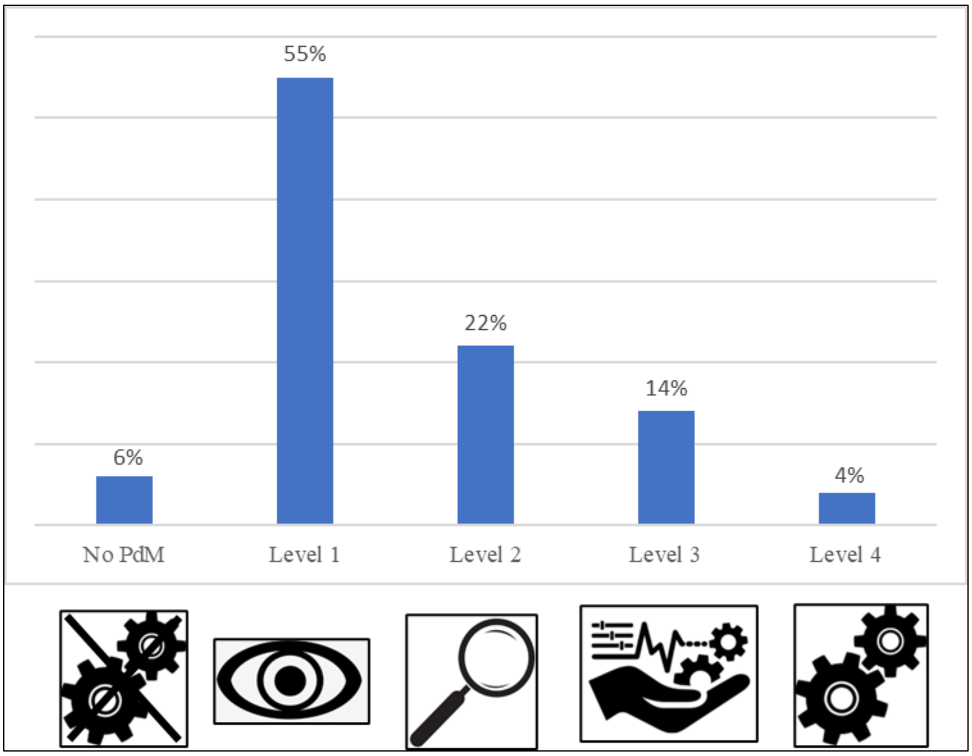

Figure 3 – Estimation of predictive maintenance level maturity

Most sample companies only have a limited number of supported tools available (Figure 4). The majority of companies have basic tools in place (e.g. office tools). Just a little below one-third of companies use condition monitoring software tools, followed by data warehouses (16%), statistical tools (14%), cloud software tools (14%), etc.

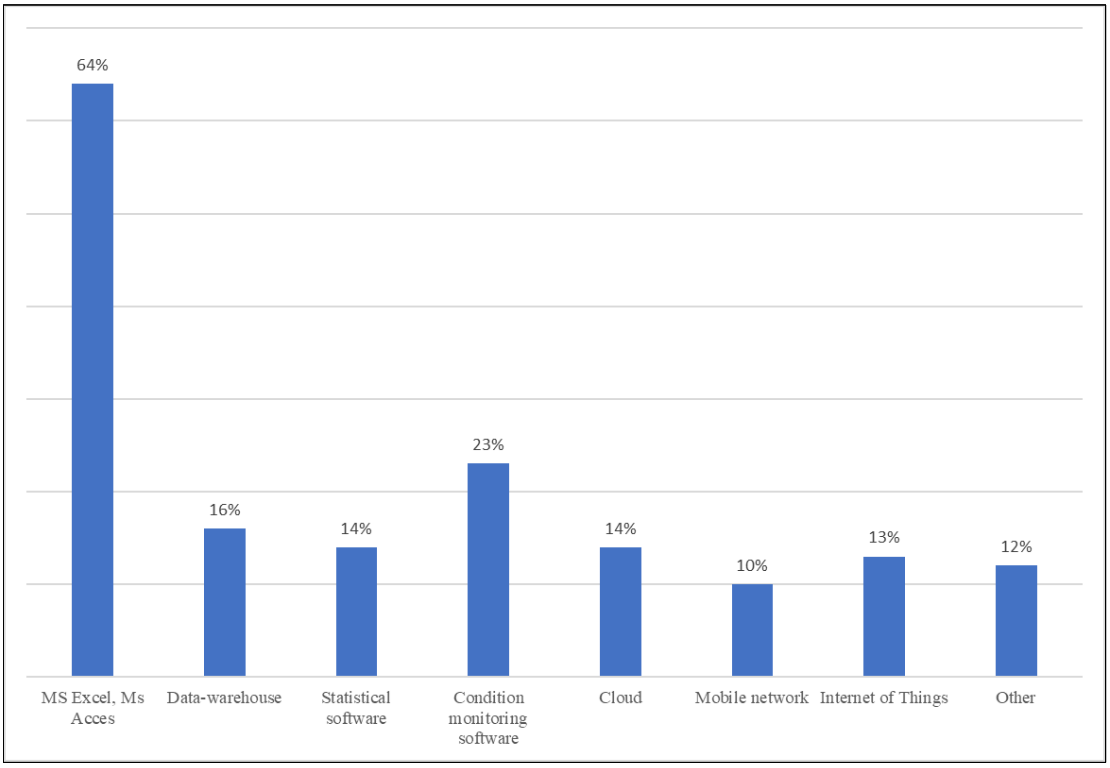

Figure 4 – Overview of predictive maintenance supporting tools (hardware and software)

Table 4 presents the results of descriptive statistics, t-tests, and the one-way analysis of variance (ANOVA) for perceived performance outcomes of PdM, as perceived by the respondents in different maturity level categories. Due to the sample size restrictions, category Level 4 was omitted from this analysis. As shown by the results (Table 4), respondents expect PdM to contribute to further improvements in all commonly perceived value drivers in maintenance and asset management. Improvement in operating time is clearly the most important in this respect since respondents in all maturity level categories emphasised these performance measures as most important (4.36, 4.45, 4.47; respectively). Similarly, improvement in OEE was also found to be an important outcome of PdM as far as respondents' perspectives are concerned (4.41, 4.38, 4.47, respectively). It should be pointed out that all performance measures are statistically significantly higher than the test value of 3. Furthermore, we were interested in whether there are differences regarding the perceived performance outcomes between particular categories (i.e. Level 1, Level 2 and Level 3). As evidenced by the results of ANOVA, we are not able to claim that there are certain differences between maturity level categories.

Table 4 – Overview of perceived performance outcome regarding the predictive maintenance level maturity

Performance measure	**Maturity level category**			**ANOVA**
	Level 1 M(SD); t	Level 2 M(SD); t	Level 3 M(SD); t	F
Cost reduction	3.97 (0.986); 6.00**	3.95 (0.921); 19.67**	3.94 (0.998); 16.76**	0.122
Increase in operating time (e.g. less unplanned stoppages)	4.36 (0.683); 11.97**	4.45 (0.605); 19.67**	4.47 (0.624); 29.53**	0.211
Improving health and safety performance	4.05 (0.848); 7.56**	3.90 (0.995); 17.98**	4.24 (0.831); 21.00**	0.654
Improving overall equipment effectiveness (OEE)	4.41 (0.599); 14.27**	4.38 (0.590); 34.05**	4.47 (0.514); 35.83**	0.016
Asset life extension	4.11 (0.843); 7.99**	4.00 (0.894); 20.50**	4.12 (0.857); 19.79**	0.581
Improving equipment reliability	4.27 (0.693); 11.15**	4.14 (0.854); 22.24**	4.18 (0.809); 21.29**	0.959
Enhancing profitability	4.08 (0.722); 9.11**	4.05 (0.805); 23.04**	4.29 (0.588); 30.12**	0.581
Improving customer satisfaction	4.00 (0.850); 7.16**	3.86 (0.910); 19.42**	4.24 (0.831); 21.00**	0.959

Notes: M – Mean. SD – Standard Deviation. **statistically significant at 0.01 level

5 CONCLUDING REMARKS

This paper addresses digitalisation and predictive maintenance challenges that companies need to cope with in a competitive business environment. The progress in digital transformation raises new challenges for the organisation since I4.0 significantly changed products and production systems concerning the design, processes, operations, services and quality (Ślusarczyk, 2018; Markulik et al., 2019; Brocal et al., 2019). The theoretical contribution to the AM and PdM literature refers to our evidence that there is a lack of a systematic approach to the use of predictive technologies to fully support the process of using asset data to gain value in asset decision-making. As such, the use of predictive technologies to support AMS by bringing and keeping asset performance and condition in line with asset management strategy and objectives is not well utilised. The latter is also reflected in the lack of appropriate strategy and a clear roadmap, as our results show.

Empirical evidence of the PdM implementation and the prevalence of the concept within the I4.0 manufacturing environment is rather scarce and incomplete (Bousdekis et al., 2019). In particular, this paper intends to outline the readiness of Slovenian companies to adopt predictive technologies to improve asset-related decision-making, especially by taking into account value creation and the shift that should be done towards digitalisation. It is widely recognised that predictive maintenance could be considered as an AM enabler merely through the acquisition and analysis of data (Candón et al., 2019). As such, digital technologies will facilitate the development of maintenance practices by shifting asset maintenance to a certain extent from traditional preventive to predictive, based on analysis of digital data. However, despite the fact that I4.0 brings numerous advantages, it must contend with emerging risks and challenges associated with organisational and human factors.

Furthermore, although our study revealed that the sample organisations have not yet achieved the desired level of I4.0 and the use of predictive technologies and analytics, they are aware of the potential benefits of using the PdM. As pointed out by the results of this study, the weaknesses are reflected in the lack of a clear strategy concerning both I4.0 and predictive maintenance. Consequently, the majority of sample companies are quite far from the highest predictive maintenance maturity level. In line with the findings of the present study, Ślusarczyk (2018) highlights that the majority of organisations recognise the concept of I4.0 as a great opportunity for development and improvement in competitiveness, although there is a need to broaden the understanding of new technologies, such those of predictive maintenance as well as to establish a strong business case. These findings, albeit not surprising, complement those of existing literature. Present research on asset management indicates that new technologies, such as predictive maintenance analytics combined with big data, are becoming an integral part of contemporary AMS (Crespo Marquez et al., 2020). The results of our study appear to be complementary to studies linking core and supportive technologies of I4.0 to production and maintenance management tasks (García and García, 2019).

The purpose of this study was also to determine the PdM level maturity of Slovenian organisations. Based on our results, the conclusion can be made that the majority of sample organisations (more than two-thirds) have yet to implement more advanced PdM technologies. As organisations adopt new PdM practices striving to attain higher levels of maturity it would enable them to further support their AMS. Since PdM practices lead to better organisational performance (Swanson, 2001), managers need to establish a clear strategy and roadmap to facilitate the transition towards higher levels of PdM maturity. In this respect, this study contributes to the literature on I4.0 maturity models (Sütőová, Šooš and Kóča, 2020).) and PdM maturity models (Mesarosova et al., 2022).

As observed in our study, organisations need to strengthen their strategic orientation towards I4.0 and, consequently, PdM adoption. As Turisová et al. (2021) show, companies face several challenges when implementing modern maintenance solutions in the context of I4.0. Furthermore, comparing the I4.0 readiness of Slovenian organisations and their strategic orientation in the two different organisational settings of SME and large companies, it is apparent that there are no statistically significant differences between these two categories. Contrary to our findings, Stentoft et al. (2021) found that large companies have a significantly higher I4.0 readiness than SMEs, which can be explained by the fact that larger companies have relatively more resources available to use the technologies. As suggested by the aforementioned study (Stentoft et al., 2021), there is a significant relationship between I4.0 readiness and actual I4.0 practice, suggesting that it is important to build I4.0 readiness first and then benefit from actual I4.0 practice. In the search for plausible reasons why companies are not taking advantage of all the benefits of I4.0 and why they have not yet reached the higher level of PdM maturity, factors such as resource constraints and lack of time could be cited (Poor et al., 2019). This finding has the potential to inform the stream of literature on PdM implementation, which has so far examined the factors that act as barriers to the adoption of PdM solutions (Bukhsh & Stipanovic, 2020), as well as studies that have focused on the challenges that lie ahead in implementing the I4.0 (Kumar et al., 2020). Among commonly identified barriers and challenges, the following could be highlighted (Bukhsh & Stipanovic, 2020; Kumar et al., 2020): data management, data security, economic feasibility and organisational factors (e.g. knowledge base, employee skills, resource allocation, etc.).

In response to this paper's research question, one can argue that the transition towards digitalisation is still emerging. Although the aim of this paper was not to examine the relationship between predictive maintenance and performance benefits, it can be emphasised that the current exploitation of new technologies is not sufficient enough to fully gain asset-related benefits. It can be argued that I4.0 aims to achieve economic goals through digital transformation, but attention must also be paid to social and environmental goals as emphasised by I5.0 (Psarommatis et al., 2023; Hein-Pensel et al., 2023; Borchardt et al., 2022).

6 LIMITATIONS AND FUTURE RESEARCH SUGGESTIONS

The findings and implications of the present work contribute to the field of management with a focus on predictive maintenance. However, the study presented in this paper has certain limitations that give rise to suggestions for future research. The sample of the responding companies is limited to the Slovenian business environment. In the future, it would be worth testing the validity of the suggested framework in companies operating in different European countries. Moreover, using multinational data, comparisons could be made to find any potential patterns, similarities, and differences.

Furthermore, concerning further research areas to be developed, it might be interesting to investigate the main drivers and enablers of predictive maintenance in depth. With this in mind, a case study approach could perhaps be useful, as it would provide qualitative data and insights that could help uphold the findings of our study. Last but not least, I4.0 maintenance perspectives can be further developed towards more human-centred and sustainable maintenance solutions, especially in relation to the Maintenance 5.0 paradigm (Psarommatis et al., 2023).

ACKNOWLEDGEMENTS

This research was supported by the Slovenian Research Agency; Program [No. P5-0018—Decision Support Systems in Digital Business].

APPENDIX

Table A1 – Quality assessment criteria

Element	Level				
	0 Absence	**1 Low**	**2 Medium**	**3 High**	**Not applicable**
1. Theory robustness	The article does not provide enough information to assess this criterion	Poor awareness of existing literature and debates. Under- or over-referenced. Low validity of the theory	Basic understanding of the issues around the topic being discussed. The theory weakly is related to data	Deep and broad knowledge of relevant literature and theory relevant to addressing the research. Good relation theory-data	This element is not applicable to the document or study
2. Implication for practice	As above	Very difficult to implement the concepts and ideas presented. Not relevant for practitioners or professionals	There is a potential for implementing the proposed ideas with minor revisions or adjustments	Significant benefit may be obtained if the ideas being discussed are put into practice	As above
3. Methodology, data supporting arguments	As above	Data inaccuracy and not related to theory. Flawed research design	Data are related to the arguments, though there are some gaps. Research design may be improved	Data strongly supports arguments. Besides, the research design is robust: sampling, data gathering, and data analysis are rigorous	As above
4. Generalizability	As above	Only the population studied	Generalisable to organisations of similar characteristics	High level of generalizability	As above
5. Contribution plus a short statement summarising the article’s contribution	As above	Does not make an important contribution. It is not clear the advances it makes	Although using others’ ideas builds upon the existing theory	Further develops existing knowledge, expanding the way the issue was explained so far	As above

Source: Pittaway et al. (2004)

REFERENCES

Al-Najjar, B., 2007. The lack of maintenance and not maintenance which costs: A model to describe and quantify the impact of vibration-based maintenance on company's business. International Journal of *Production Economics*, 107(1), p.p.260-273. https://doi.org/10.1016/j.ijpe.2006.09.005

Al-Najjar, B., Algabroun, H. and Jonsson, M., 2018. Maintenance 4.0 to fulfil the demands of Industry 4.0 and Factory of the Future. *International Journal of Engineering Research and Applications*, 8(11), p.p.20-31.

Amrita, M. A. and Akhilesh, K. B., 2020. *Digital Masters: Blueprinting Digital Transformation. In Smart Technologies*. Singapore: Springer.

Biard, G. and Nour, G. A., 2021. Industry 4.0 Contribution to Asset Management in the Electrical Industry. *Sustainability*, 13(18), 10369. https://doi.org/10.3390/su131810369

Borchardt, M., Pereira, G.M., Milan, G. S., Scavarda, A. R., Nogueira, E. O. and Poltosi, L.C., 2022. Industry 5.0 Beyond Technology: An Analysis Through the Lens of Business and Operations Management Literature. *Organizacija*, 55(4), p.p.305-321. https://doi.org/10.2478/orga-2022-0020

Bousdekis, A., Lepenioti, K., Apostolou, D. and Mentzas, G., 2019. Decision Making in Predictive Maintenance: Literature Review and Research Agenda for Industry 4.0. *IFAC-PapersOnLine*, 52(13), p.p.607-612. https://doi.org/10.1016/j.ifacol.2019.11.226

Breunig, M., Kelly, R., Mathis, R. and Wee, D., 2016. *Industry 4.0 after the initial hype. Where manufacturers are finding value and how they can best capture it*. [pdf] McKinsey Digital. [Online] Available at: https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/getting%20the%20most%20out%20of%20industry%204%200/mckinsey_industry_40_2016.pdf [Accessed 20 November 2023]

Brocal, F., González-Gaya, C., Komljenovic, D., Katina, P.D. and Sebastián, M.A., 2019. Emerging risk management in Industry 4.0: an approach to improve organisational and human performance in the complex systems, *Complexity*, 2019, p.p.1-13, https://doi.org/10.1155/2019/2089763

Bukhsh, Z. A. and Stipanovic, I., 2020. Predictive Maintenance for Infrastructure Asset Management. *IT Professional*, 22(5), p.p.40-45. https://doi.org/10.1109/MITP.2020.2975736

Cachada, A., Barbosa, J., Leitño, P., Gcraldcs, C. A., Deusdado, L., Costa, J., ... and Romero, L., 2018. Maintenance 4.0: Intelligent and predictive maintenance system architecture. *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA),* Turin, Italy, 2018, pp. 139-146. https://doi.org/10.1109/ETFA.2018.8502489

Candón, E., Martínez-Galán, P., De la Fuente, A., González-Prida, V., Márquez, A. C., Gómez, J., Sola, A. and Macchi, M., 2019. Implementing intelligent asset management systems (IAMS) within an industry 4.0 manufacturing environment. *IFAC-PapersOnLine*, 52(13), p.p.2488-2493. https://doi.org/10.1016/j.ifacol.2019.11.580

Crespo Marquez, A., Gomez Fernandez, J. F., Martínez-Galán Fernández, P. and Guillen Lopez, A., 2020. Maintenance Management through Intelligent Asset

Management Platforms (IAMP). Emerging Factors, Key Impact Areas and Data Models. *Energies*, 13(15), 3762. https://doi.org/10.3390/en13153762

Fatorachian, H. and Kazemi, H., 2018. A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework. *Production Planning & Control*, 29(8), pp.1-12. https://doi.org/10.1080/09537287.2018.1424960

García, S.G. and García, M.G., 2019. Industry 4.0 implications in production and maintenance management: An overview. *Procedia Manufacturing*, 41, p.p.415-422. https://doi.org/10.1016/j.promfg.2019.09.027

Haarman, M., Mulders, M. and Vassiliadis, C., 2017. Predictive Maintenance 4.0-Predict the unpredictable. [online] Available at: https://www.pwc.be/en/documents/20171016-predictive-maintenance-4-0.pdf [Accessed 19 July 2023].

Hein-Pensel, F., Winkler, H., Brückner, A., Wölke, M., Jabs, I., Mayan, I. J., Kirschenbaum, A., Friedrich, J. and Zinke-Wehlmann, C., 2023. Maturity assessment for Industry 5.0: A review of existing maturity models. *Journal of Manufacturing Systems*, 66, p.p.200-210. https://doi.org/10.1016/j.jmsy.2022.12.009

Hizam-Hanafiah, M., Soomro, M. A. and Abdullah, N. L., 2020. Industry 4.0 readiness models: a systematic literature review of model dimensions. *Information*, 11(7), 364. https://doi.org/10.3390/info11070364

Hodkiewicz, M., 2015. Asset management-quo vadis (where are you going)?. *International Journal of Strategic Engineering Asset Management*, 2(4), p.p.313-327. https://dx.doi.org/10.1504/IJSEAM.2015.075411

Jasiulewicz-Kaczmarek, M., Legutko, S. and Kluk, P., 2020. Maintenance 4.0 technologies–new opportunities for sustainability driven maintenance. *Management and production engineering review*, 11(2), p.p.74-87. 10.24425/mper.2020.133730

Kagermann, H., 2015. *Change through digitisation—Value creation in the age of Industry 4.0*. In Management of permanent change. Wiesbaden: Springer Gabler.

Kans, M. and Galar, D., 2017. The impact of maintenance 4.0 and big data analytics within strategic asset management. *Maintenance Performance and Measurement and Management 2016 (MPMM 2016)*. Luleå, Sweden, 28 November 2017. Luleå tekniska universitet.

Kern, T., Krhač Andrašec, E., Urh, B. and Senegačnik, M., 2020. Digital transformation reduces costs of the paints and coatings development process. *Coatings*, 10(7), 703. https://doi.org/10.3390/coatings10070703

Komljenovic, D., Abdul-Nour, G. and Boudreau, J.F., 2019. Decision-making in asset management under regulatory constraints. *Asset Intelligence through Integration and Interoperability and Contemporary Vibration Engineering Technologies*. Cham: Springer.

Kumar, U. and Galar, D., 2018. Maintenance in the era of industry 4.0: issues and challenges. In P.K. Kapur, Kumar, U. and A.K. Verma, 2018. *Quality, IT and Business Operations*. Singapore: Springer.

Kumar, S., Suhaib, M. and Asjad, M., 2020. Industry 4.0: complex, disruptive, but inevitable. *Management and Production Engineering Review*, 11(1), p.p.43-51. 10.24425/mper.2020.132942

Kumar, U. and Galar, D., 2018. *Maintenance in the era of industry 4.0: issues and challenges*. In: Kapur, P., Kumar, U., Verma, A. (eds) Quality, IT and Business Operations. Springer Proceedings in Business and Economics. Springer, Singapore. https://doi.org/10.1007/978-981-10-5577-5_19

Maletič, D., Marques de Almeida, N., Gomišček, B. and Maletič, M., 2023. Understanding motives for and barriers to implementing asset management system: an empirical study for engineered physical assets. *Production Planning & Control*, 34(15), p.p.1497-1512. https://doi.org/10.1080/09537287.2022.2026672

Maletič, D., Maletič, M., Al-Najjar, B. and Gomišček, B., 2020. An analysis of physical asset management core practices and their influence on operational performance. *Sustainability*, 12(21), 9097. https://doi.org/10.3390/su12219097

Maletič, D., Maletič, M., Al-Najjar, B. and Gomišček, B., 2018. Development of a model linking physical asset management to sustainability performance: An empirical research. *Sustainability,* 10(12), 4759. https://doi.org/10.3390/su10124759

Maletic, D., Maletic, M., Al-Najjar, B. and Gomišcek, B., 2014. The role of maintenance in improving company's competitiveness and profitability: a case study in a textile company. *Journal of Manufacturing Technology Management*, 25(4), p.p.441-456. https://doi.org/10.1108/JMTM-04-2013-0033

Markulik, Š., Sinay, J. and Pačaiová, H., 2019. Quality Assurance in the Automotive Industry and Industry 4.0. *In Smart Technology Trends in Industrial and Business Management* (pp. 217-225). Cham: Springer.

Mays, N., C. Pope, and J. Popay., 2005. Systematically reviewing qualitative and quantitative evidence to inform management and policymaking in the health field. *Journal of Health Services Research & Policy*, 10(1), p.p.6–20. https://doi.org/10.1258/1355819054308576

Mesarosova, J., Martinovicova, K., Fidlerova, H., Chovanova, H. H., Babcanova, D. and Samakova, J., 2022. Improving the level of predictive maintenance maturity matrix in industrial enterprise. *Acta Logistica*, 9(2), p.p.183-193. 10.22306/al.v9i2.292

Mohan, R., Roselyn, J.P. and Uthra, R.A., 2023. LSTM based artificial intelligence predictive maintenance technique for availability rate and OEE improvement in a TPM implementing plant through Industry 4.0 transformation. *Journal of Quality in Maintenance Engineering*, 29(4), p.p. 763-798. https://doi.org/10.1108/JQME-07-2022-0041

Mohapatra, A. G., Mohanty, A., Pradhan, N. R., Mohanty, S. N., Gupta, D., Alharbi, M., ... and Khanna, A., 2023. An Industry 4.0 implementation of a condition monitoring system and IoT-enabled predictive maintenance scheme for diesel generators. *Alexandria Engineering Journal*, 76, p.p.525-541. https://doi.org/10.1016/j.aej.2023.06.026

Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E. and Loncarski, J., 2018. Machine learning approach for predictive maintenance in industry 4.0. *2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*, Oulu, Finland, 2018, pp. 1-6, 10.1109/MESA.2018.8449150

Pittaway, L., M. Robertson, K. Munir, D. Denyer, and Neely, A., 2004. Networking and innovation: A systematic review of the evidence. *International Journal of Management Reviews*, 5–6(3–4), p.p.137–168. https://doi.org/10.1111/j.1460-8545.2004.00101.x

Poor, P., Basl, J. and Ženíšek, D., 2020. Assessing the predictive maintenance readiness of enterprises in West Bohemian region. *Procedia Manufacturing*, 42, p.p.422-428. https://doi.org/10.1016/j.promfg.2020.02.098

Psarommatis, F., May, G. and Azamfirei, V., 2023. Envisioning maintenance 5.0: Insights from a systematic literature review of Industry 4.0 and a proposed framework. *Journal of Manufacturing Systems*, 68, p.p.376-399. https://doi.org/10.1016/j.jmsy.2023.04.009

Schmidt, B., Gandhi, K., Wang, L. and Galar, D., 2017. Context preparation for predictive analytics–a case from manufacturing industry. *Journal of Quality in Maintenance Engineering*, 23(3), p.p.341-354. https://doi.org/10.1108/JQME-10-2016-0050

Schuman, C.A. and Brent, A.C., 2005. Asset life cycle management: towards improving physical asset performance in the process industry. International *Journal of Operations & Production Management*, 25(6), p.p.566-579, https://doi.org/10.1108/01443570510599728

Sekaran, U. and Bougie, R., 2016. *Research methods for business: A skill building approach*. John Wiley & Sons.

Ślusarczyk, B., 2018. Industry 4.0: Are we ready? *Polish Journal of Management Studies*, 17(1), p.p.232-248. https://doi.org/10.17512/pjms.2018.17.1.19

Sony, M. and Naik, S., 2020. Key ingredients for evaluating Industry 4.0 readiness for organisations: a literature review. *Benchmarking: An International Journal*, 27(7), p.p.2213-2232. https://doi.org/10.1108/BIJ-09-2018-0284

Stentoft J., Adsbřll Wickstrřm K., Philipsen K. and Haug A., 2021. Drivers and barriers for Industry 4.0 readiness and practice: Empirical evidence from small and medium-sized manufacturers, *Production Planning & Control*, 32(10), pp. 811–828. https://doi.org/10.1080/09537287.2020.1768318

Sütőová, A., Šooš, Ľ. and Kóča, F., 2020. Learning needs determination for industry 4.0 maturity development in automotive organisations in Slovakia. *Quality Innovation Prosperity*, 24(3), p.p.122-139. https://doi.org/10.12776/qip.v24i3.1521

Swanson, L., 2001. Linking maintenance strategies to performance. *International journal of production economics*, 70(3), p.p.237-244. https://doi.org/10.1016/S0925-5273(00)00067-0

Tortorella, G., Saurin, T.A., Fogliatto, F.S., Tlapa, D., Moyano-Fuentes, J., Gaiardelli, P., ... and Forstner, F.F., 2022. The impact of Industry 4.0 on the relationship between TPM and maintenance performance. *Journal of Manufacturing Technology Management*, 33(3), p.p.489-520. https://doi.org/10.1108/JMTM-10-2021-0399

Trindade, M. and Almeida, N., 2018. The impact of digitalisation in asset-intensive organisations. *Network Industries Quarterly*, 20(4), p.p.14-17. [online] Available at: https://www.network-industries.org/wp-content/uploads/2019/07/The-impact-of-digitalisation-in-asset-intensive-organisations.pdf [Accessed 20 November 2023]

Trindade, M., Almeida, N., Finger, M. and Ferreira, D., 2019. Design and Development of a Value-Based Decision Making Process for Asset Intensive Organisations. In *Asset Intelligence through Integration and Interoperability and Contemporary Vibration Engineering Technologies* (pp. 605-623). Cham: Springer.

Tsang, A. H., 2002. Strategic dimensions of maintenance management. *Journal of Quality in Maintenance Engineering*, 8(1), p.p.7-39. https://doi.org/10.1108/13552510210420577

Turisová, R., Pačaiová, H., Kotianová, Z., Nagyová, A., Hovanec, M. and Korba, P., 2021. Evaluation of eMaintenance application based on the new version of the EFQM Model. *Sustainability*, 13(7), 3682. https://doi.org/10.3390/su13073682

Yan, J., Meng, Y., Lu, L. and Li, L., 2017. Industrial big data in an industry 4.0 environment: Challenges, schemes, and applications for predictive maintenance. In *IEEE Access*, vol. 5, pp. 23484-23491, 2017. https://doi.org/10.1109/ACCESS.2017.2765544

Watson, R., Wilson, H.N., Smart, P. and Macdonald, E.K., 2018. Harnessing difference: A capability-based framework for stakeholder engagement in environmental innovation. *Journal of Product Innovation Management*, 35(2), p.p.254-279. https://doi.org/10.1111/jpim.12394

ABOUT AUTHORS

Damjan Maletič[0000-0002-6871-2720] (D.M.) – University of Maribor, Faculty of Organizational Sciences, Slovenia, Assist. Prof., e-mail: damjan.maletic@um.si.

Matjaž Maletič[0000-0002-3845-744X] (M.M.) – University of Maribor, Faculty of Organizational Sciences, Slovenia, Assist. Prof., e-mail: matjaz.maletic@um.si.

AUTHOR CONTRIBUTIONS

Conceptualisation, D.M. and M.M.; Methodology, D.M. and M.M.; Validation, M.M. and D.M.; Formal analysis, D.M. and M.M.; Investigation, D.M.; Resources, D.M. and M.M. Data curation, D.M.; Original draft preparation, D.M. and M.M.; Review and editing, M.M. and D.M.; Supervision, D.M. and M.M.

CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.