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The Impact of Single Minute Exchange of Die and Total Productive Maintenance on Overall Equipment Effectiveness

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Abstract

Due to intense global competition, manufacturing companies need to improve and optimize productivity, increase production and flexibility, and gain competitive advantages. Companies have begun to look for new approaches and strategies in the field of production management. This includes tools like Single Minute Exchange of Die (SMED) and Total Productive Maintenance (TPM), which aim to manage machines and equipment, reduce waste and lead time, and ensure and enhance competitiveness. The main objective of this study is to explore the connection and the context of the use of industrial engineering tools, namely SMED and TPM, and to monitor and evaluate Overall Equipment Effectiveness (OEE) in industrial companies in the Czech Republic. A comprehensive questionnaire survey of 200 companies and a detailed evaluation of the operational performance of 92 companies were carried out from the third quarter of 2019 to the third quarter of 2020. It was found out that 20.5% of companies implemented SMED, 26.5% of companies implemented TPM, and 54.0% of companies did not monitor and evaluate OEE. The research confirms the theoretical link between SMED and OEE and between OEE and TPM. The statistical significance of the use of SMED and TPM separately was not demonstrated. However, the mutual interaction of using TPM and SMED on the OEE level was proved.

Keywords: Single Minute Exchange of Die, Total Productive Maintenance, Overall Equipment Effectiveness, competitiveness, lean company, industrial companies, Czech Republic
JEL Classification: M11, L23

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1. INTRODUCTION

In the current global and dynamic marketplace and technological development, there is a lot of competition that drives profits and profitable survival with pressure on process efficiency, especially among small and medium-sized enterprises (Saravanan et al., 2018). Companies are under pressure to introduce and provide the right quality products, delivered at the right time, at a lower price, with high performance and commitment to satisfy customer requirements (Singh &

Singh, 2015). It is essential that every company achieves and improves performance, success and competitiveness (Pribeanu & Toader, 2016). Due to intense global competition, manufacturing companies need to improve and optimize manufacturing productivity, increase production and flexibility, and gain competitive advantages (Saravanan et al., 2018). The critical factor of competitiveness is differentiation through innovation of products, processes and organization (Salam & Khan, 2018).

To survive and meet the demand and customer requirements, companies need to improve their production systems. Companies must work efficiently by updating and implementing new working methods and techniques (Saravanan et al., 2018). Companies should also gather efforts and reduce production costs, produce quality products, and increase productivity. The best way to reduce costs is through waste elimination and implementing production process improvements (Godina et al., 2018). Therefore, companies have begun looking for new approaches and strategies in production management, eliminating waste, improving efficiency and effectiveness of operations and business performance (Sangwan et al., 2014). In this way, companies intend to introduce improvements and changes through the Lean paradigm to help them achieve these goals (Tyagi et al., 2015). Many companies across different industries, sizes and regions apply Lean Management and Lean Manufacturing because they can shorten lead time and improve product quality, which leads to better customer satisfaction and competitiveness (Antosz & Pacana, 2018; Udokporo et al., 2020). The practical implementation of this concept focuses on implementing and using different principles, tools, and methods. In this article, we focus on tools such as Single Minute Exchange of Die (SMED) and Total Productive Maintenance (TPM), which are aimed at managing machines and equipment, reducing waste and lead time. Short lead times mean higher flexibility and improved competitive position (Malindzakova et al., 2021; Ribeiro et al., 2022). These tools were chosen concerning their impact on competitiveness and at the same time with regard to the focus of the author's collective. Compared to other previously published studies by other authors, this is not just a case study. The article presents the results of our research carried out in a wide range of companies. Of course, the article works with previously established information but observes it from a different perspective due to the influence of other factors and expands them.

2. LITERATURE REVIEW

2.1 Single Minute Exchange of Die

Single Minute Exchange of Die (SMED) is a methodology used to analyze, reduce, and standardize the changeover time; the changeover is considered a loss, non-productive activity (Naboureh & Safari, 2016). Reducing changeover time leads to a reduction of lead time and ensuring and enhancing competitiveness, as manufacturing loss is related to loss of competitiveness (Malindzakova et al., 2021). Benefits of implementing SMED include cost and waste reduction, increased production capacity and flexibility of the equipment, increased machine efficiency and customer satisfaction (Ribeiro et al., 2022). Thanks to increasing the availability and the efficiency of the production line, SMED allows for increasing the Overall Equipment Effectiveness (Otero & Lopes, 2018; Suryaprakash et al., 2021; Pattaro Jr. et al., 2022). Many kinds of research confirm the implementation of SMED in different countries and industries, e.g., in hygiene production (Malindzakova et al., 2021), automotive (Rosa et al., 2017), plastics industry (Saravanan et al., 2018), or manufacturing (Otero & Lopes, 2018). Antosz & Pacana (2018) studied the effects of SMED on conventional, semi-automatic and automatic production work stands. Gálová et al. (2018) revealed that approximately 18% of industrial companies in the Czech Republic use SMED in their practice. The authors add that SMED is primarily used in the automotive (40%), followed by the wood processing (30%), mechanical (12%) and electro-technics (7%) industries (Gálová et al., 2018). Filla (2016) focused his case study on applying SMED to a high-mix processing line in a flat glass processing company in the Czech Republic.

2.2 Total Productive Maintenance

Total Productive Maintenance (TPM) is a methodology of strategic equipment management to reduce losses and waste and maintain equipment to its optimum level of operational effectiveness (Singh & Gurtu, 2021). TPM approach leads to a reduction of equipment downtimes, breakdowns, accidents, inventory, lead time, maintenance costs, an increase in equipment productivity and operational efficiency, and product quality improvement (Ahuja & Khamba, 2008; Bashar et al., 2022). Brah & Chong (2004) found out that the business performance of companies with implemented TPM is significantly superior to non-TPM companies. Improved maintenance process using TPM enhances manufacturing performance and customer satisfaction (Kalpande & Toke, 2022). Implementing TPM leads to an increase in Overall Equipment Effectiveness (Gherghea et al., 2021). Adoption of TPM can help to ensure the competitiveness of a company because maintenance is the area with great potential to be used as a competitive advantage (Mwanza & Mbohwa, 2015; Kalpande & Toke, 2022); it is one approach used to make business more competitive (Pinto et al., 2020). Gálová et al. (2018) and Rajnoha et al. (2018) found that approximately 21% of industrial companies in the Czech Republic use the TPM methodology in their practice. Gálová et al. (2018) add that TPM is primarily used in the automotive (45%), followed by the electro-technics (22%), wood processing (20%), and mechanical (14%) industries. Tomaskova & Strakova (2015) studied alternative ways to provide maintenance in the Czech coal power plants. Branska et al. (2016) focused on the current form of maintenance management systems used in the chemical and food industries in the Czech Republic.

2.3 Overall Equipment Effectiveness

Overall Equipment Effectiveness (OEE) is a commonly used performance evaluation metric focused on monitoring and controlling the productivity of production companies (Slaichova & Marsikova, 2013; Tsarouhas, 2019). OEE allows an evaluation of the effect of several types of losses on equipment performance and shows what work the equipment performs concerning a theoretically ideal value (Zammori et al., 2011). OEE can also be used to measure the efficiency of SMED and TPM implementation (Logesh et al., 2017). The indicator is made up of three sub-indicators: (i) the availability rate, (ii) the performance rate, and (iii) the quality rate (Zammori et al., 2011; Jasial et al., 2014). According to Kechaou et al. (2022), the standard availability rate should be at least 90%, the standard performance rate should be at least 95%, and the standard quality rate should be at least 99%. According to Ylipää et al. (2017), around 50% has been identified as the average OEE because such a level (and less than 50%) is generally more realistic in companies. Companies achieving OEE of at least 85% are considered World Class Manufacturing (Ahuja & Khamba, 2008), as superior performance standards (De La Vega, 2020), with high competitiveness and a tremendous competitive advantage (Petrillo et al., 2018). All organizations using their manufacturing capabilities to achieve a greater competitive advantage can be considered World Class Manufacturing (de Andrade et al., 2021); it depends, among other things such as continuous improvement and manufacturing excellence, on its TPM performance (De Felice et al., 2019), measured by OEE (D'Orazio et al., 2020). Increasing OEE has become a goal in achieving a competitive advantage, as evidenced by numerous pieces of research and case studies (Nallusamy & Majumdar, 2017; Chikwendu et al., 2020). From the essence of the matter, the OEE level can be increased by increasing sub-indicators (availability, performance and quality); e.g., the quality of products is one of the most critical factors that affect competitiveness (Khafizov & Nurullin, 2017), and also the availability in connection with the flexibility of processes is a crucial factor of competitiveness (Singh et al., 2015). Ahmad et al. (2018) used Kaizen and TPM to improve OEE of a spinning mill. Krachangchan & Thawesaengskulthai (2018) focused on enhancing OEE by implementing TPM, Reliability Centered Maintenance and Failure Modes and Effects Analysis. Many pieces of research confirm the implementation of TPM and SMED to increase OEE and improve processes in different countries and industries, e.g., in the chemical industry (Mwanza & Mbohwa, 2015), food industry (Tsarouhas, 2019), oil and gas industry (Pattaro Jr. et al., 2022), manufacturing industry (Suryaprakash et al., 2021), pharmaceutical industry (Chikwendu et al., 2020), and service sector (Manjunatha et al., 2018).

Based on the literature review, the following research questions (RQs) have been defined:

RQ1: What proportion of industrial companies in the Czech Republic use SMED, TPM and monitor and evaluate OEE?

RQ2: Does the extent of the monitoring and evaluation of OEE differ between companies with SMED implemented and companies without SMED implemented?

RQ3: Does the extent of the monitoring and evaluation of OEE differ between companies with TPM implemented and companies without TPM implemented?

RQ4: Do companies with SMED achieve higher OEE than companies without SMED?

RQ5: Do companies with TPM achieve higher OEE than companies without TPM?

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

Based on the literature review, it is clear that companies use SMED and TPM to increase OEE because these tools can increase OEE. Therefore, it can be assumed that using SMED and TPM should lead to higher OEE than companies that do not use these tools. However, this assumption has two shortcomings. First, companies may use SMED and TPM but may not monitor and evaluate OEE, which means that we cannot demonstrate the impact of SMED and TPM despite a possible change in OEE. And second, the level of OEE itself does not have to be determined solely by whether the company uses SMED and TPM. Still, other factors and influences may also act, such as company size or production type. Knowledge in this area is still lagging, which we perceive as a research gap that needs to be explored.

The main objective of this study is to explore the connection and the context of the use of industrial engineering tools, namely TPM and SMED, and to monitor and evaluate OEE in industrial companies in the Czech Republic. This study collected data from industrial companies in the Czech Republic because the Czech Republic as one of the leading industrial countries in central and eastern Europe based on STI.Scoreboard (OECD, 2010-2022), Manufacturing Value Added (United Nations, 2020), Share of industry in total Gross Value Added (Eurostat, 2019), and Global Manufacturing Risk Index (Cushman & Wakefield, 2021) provides context for exploring such associations related to SMED and TPM. Based on the stated primary objective, the following associated hypotheses have been defined:

Hypothesis 1: Monitoring and evaluation of OEE are statistically significantly associated with the use of SMED.

Hypothesis 2: Monitoring and evaluation of OEE are statistically significantly associated with the use of TPM.

The research was done in industrial companies in the Czech Republic. Within the study, a comprehensive questionnaire survey was carried out. Questions from the areas of production and business processes were the primary focus of the survey. The questionnaire was created using Google Forms, then sent by e-mail to the production managers and industrial engineers in industrial companies in the Czech Republic. The questionnaires were directed to companies of various sizes and ages from different industrial areas. A sample of 200 industrial companies was obtained, representing approximately 10 percent of the contacted companies to which the questionnaires were disseminated (approximately 2,000 industrial companies). The participants of the survey were selected using the Albertina database randomly across individual specializations within all regions of the Czech Republic while adhering to the rule that their shares will be the same concerning size and age. In our research, the non-response bias has not been examined, but we have tried our best to avoid it. Questionnaires were distributed at once at one relatively short point in time, and non-responding (potential) respondents were not contacted again. We focused primarily on OEE, and the results presented in this article show approximate equality of companies in this direction. This is also why we subsequently decided to examine only companies that measure and evaluate OEE so that the detailed examined sample is not influenced by those companies that do not measure and evaluate OEE. In case of the social desirability bias, we do not consider this to be significant in our research since it was completely anonymous, the names of the companies will not be mentioned anywhere, and we know from our experience that companies do not have the need to improve their position in this way. But, of course, this cannot be said about every company, and therefore there is a possibility of this bias occurring.

The obtained sample was composed of industrial companies with various specializations: mining and processing of materials (33.0%), production of machinery (32.5%), production of chemical products (13.0%), production of electrical components (12.0%) and agricultural and food production (9.5%). Within these specializations, the companies were divided based on the production type (Říha et al., 2002; Thuis & Stuive, 2019; Poor et al., 2020) into companies with piece (project-based) production (40.0%), serial (batch) production (39.5%) and mass production (20.5%). Based on the categorization of companies by the number of employees and annual turnover, the sample was composed of medium companies (33.5%), large companies (27.5%), small companies (27.0%) and micro-companies (12.0%).

Subsequently, companies from the survey were involved in the evaluation of their operational performance. The primary criterion for selection was monitoring and evaluating OEE; companies that do not monitor and evaluate OEE were excluded. It was crucial that the sample was not influenced by those companies that do not measure and evaluate OEE. In this step, information related to SMED, TPM and OEE was obtained by analyzing internal documents and reports from enterprise information systems in collaboration with industrial engineers. These phases were carried out from the third quarter of 2019 to the third quarter of 2020. The examined sample included 92 companies from the original sample (200). The selected sample (92) showed a different representation of companies from different perspectives. Also, in this sample were represented companies of individual specializations: production of machinery (41.3%), mining and processing of materials (20.6%), production of chemical products (17.4%), production of electrical components (12.0%) and agricultural and food production (8.7%). The sample included companies with serial production (47.8%), piece production (31.5%) and mass production (20.7%). Based on the categorization of companies by the number of employees and annual turnover, the sample was composed of medium companies (38.0%), large companies (37.0%), small companies (16.3%) and micro-companies (8.7%).

The original sample (200) was expanded to include additional data from companies that monitor and evaluate OEE. Statistical techniques and tools were used to process and evaluate data from the original (200) and selected (92) samples. Basic descriptive statistics were processed in Microsoft Excel. Statistical data analysis was performed in Software R 3.6.3. Pearson's Chi-square Test of Independence was conducted to explore the relationships between categorical variables with no intrinsic ordering, such as monitoring and evaluation of OEE and the use of SMED and TPM. For answering RQ4 and RQ5, ordinal logistic regression was conducted. This method was used to determine the effect of selected factors on the OEE level, following the theoretical concept of ordinal logistic regression (Harrell, 2015). Based on explanatory variables, different models were compiled, and the individual factors were examined separately and in various combinations with other factors for the actual verification of the effects (Liu & Koirala, 2012; Singh et al., 2022). Most of the research (often case studies) in this area to date focuses primarily on the change of OEE depending on the use of SMED and TPM, or partial principles and tools and methods of the Lean concept (Nallusamy & Majumdar, 2017; Manjunatha et al., 2018; Otero & Lopes, 2018; Krachangchan & Thawesaengskulthai, 2018; Tsarouhas, 2019; Chikwendu et al., 2020; Suryaprakash et al., 2021; Pattaro Jr. et al., 2022). In our research, we were interested in whether basic factors such as company size or production type affect the OEE level, which has not been investigated in previous research.

4. RESULTS

4.1 The use of SMED and TPM, and monitoring and evaluation of OEE

First, we examined the proportion of industrial companies in the Czech Republic using SMED and TPM and measured and evaluated OEE to answer the RQ1. The original sample (200) was used for this purpose. Based on data processing, it was found that only 20.5% of companies (41 companies) implemented and used SMED. Research suggests that SMED is most commonly used in the production of machinery (32.3% of this specialization), in Mass production (35.0% of Mass production) and especially in Large companies (27.3% of Large companies). Although it is possible to achieve various benefits thanks to SMED, only 9.4% of the remaining companies that do not use this tool (159 companies) plan to start using SMED in the future. Medium-sized companies (10.4% of Medium-sized companies), Mass production companies (9.8% of Mass production) and companies with production of electrical components (12.5% of this specialization) show the most significant interest.

In the case of TPM, it was revealed that only 26.5% of companies (53 companies) implemented and used this tool. According to the research, TPM is most commonly used in the production of machinery (40.0% of this specialization), in Serial production (38.0% of Serial production) and especially in Large companies (32.7% of Large companies). Of the remaining companies that do not use this tool (147 companies), approximately 17.7% plan to start using TPM in the future. Large companies (16.4% of Large companies), Mass production companies (17.1% of Mass production) and companies with agricultural and food production (26.3% of this specialization) show the most significant interest.

In connection with the use of SMED and TPM, it was essential to find out how many companies monitor and evaluate OEE in their production processes and what average values they achieve for the whole production. It was found out that 54.0% of companies (108 companies) do not monitor and evaluate OEE. Research suggests that OEE is most commonly monitored and evaluated in the production of chemical products (61.5% of this specialization), in Serial production (55.7% of Serial production) and especially in Large companies (61.2% of Large companies). Companies with the production of electrical components (12.5% of this specialization), Serial production (6.3% of Serial production) and Large companies (10.9% of Large companies) could achieve the most significant OEE values (80-100%) and be considered World Class Manufacturing. Based on this study, we can comply with the following the OEE levels: Below-average companies (OEE <40%; approx. 13.5% of companies), Average companies (OEE 40-60%; approx. 9.5% of companies), Above-average companies (OEE 60-80%; approx. 18.0% of companies) and World Class companies (OEE 80-100%; approx. 5.0% of companies). Companies that use SMED, TPM, and monitor and evaluate OEE simultaneously were identified, but also those companies that do not monitor and evaluate OEE in these cases.

4.2 The association between monitoring and evaluation of OEE and use of SMED and TPM

Given the initial findings concerning the imbalances in the structure of companies and their approach to monitoring and evaluating OEE, the associations between monitoring and evaluation of OEE and the use of SMED and TPM were further examined. To answer RQ2 and RQ3 and test Hypothesis 1 and Hypothesis 2, it was necessary to conduct statistical testing of the independence of two variables, namely the monitoring and evaluation of OEE and use of SMED and use of TPM. Concerning the nature of the processed data and the required outputs, Pearson's Chi-square Test of Independence was used. For the purpose of failing to reject or reject the null hypothesis, the significance level was set to $\alpha = 0.05$. The results are shown in Table 1 and Table 2.

Based on the Pearson's Chi-Square Test value = 10.318, p = 0.001, we can reject the null hypothesis and conclude that there is a statistically significant association between monitoring and evaluation of OEE and the use of SMED. Based on the correlation coefficient Phi = 0.227 (for 2x2 contingency tables), it can be stated that there is a small to a medium association; the effect is not a particularly large one. If the monitoring and evaluation of OEE had no association with the use of SMED, almost nineteen companies using SMED that monitor and evaluate OEE could be expected. Still, there are twenty-eight such companies. This means that companies using SMED monitor and evaluate OEE more than expected. On the other hand, companies not using SMED are more likely not to monitor and evaluate OEE.

Tab. 1 – SMED and OEE. Source: own research

		Companies do not monitor and evaluate OEE	Companies monitor and evaluate OEE
Companies do not use SMED	Count	95	64
	Expected Count	85.86	73.14
	Residual	9.14	-9.14
Companies use SMED	Count	13	28
	Expected Count	22.14	18.86
	Residual	-9.14	9.14
	Total	108	92

Based on the Pearson's Chi-Square Test value = 19.171, $p < 0.05$, we can reject the null hypothesis and conclude that there is a statistically significant association between monitoring and evaluation of OEE and the use of TPM. Based on the correlation coefficient Phi = 0.309 (for 2x2 contingency tables), it can be stated that there is a medium to large association between these variables. If the monitoring and evaluation of OEE had no association with TPM, we would expect twenty-four companies using TPM that monitor and evaluate OEE. Still, there are thirty-eight such companies. This means that companies use TPM to monitor and evaluate OEE more than expected. On the other hand, companies not using TPM are more likely not to monitor and evaluate OEE.

Tab. 2 – TPM and OEE. Source: own research

		Companies do not monitor and evaluate OEE	Companies monitor and evaluate OEE
Companies do not use TPM	Count	93	54
	Expected Count	79.38	67.62
	Residual	13.62	-13.62
Companies use TPM	Count	15	38
	Expected Count	28.62	24.38
	Residual	-13.62	13.62
	Total	108	92

4.3 The effect of SMED, TPM and other factors on the OEE level

According to the literature, the implementation of TPM and SMED is reflected in an increase in OEE level (Ahmad et al., 2018; Krachangchan & Thawesaengskulthai, 2018; Tsarouhas, 2019). Regarding this finding, we defined RQ4 and RQ5. The answers to these questions are based on examining the effect of selected factors on the OEE level. A detailed research sample (92 companies) was used. Considering the findings from the literature review, the OEE values obtained, and the emphasis on World Class, the OEE levels were chosen as follows: below average (<40%), above average (40-80%), and World Class (>80%). Due to the nature of the response variable OEE level, ordinal logistic regression was used to determine the effects of the explanatory variables: (1) Use of SMED ("Y" for "yes" and "N" for "no"); (2) Use of TPM ("Y" for "yes" and "N" for "no"); (3) Company size (Micro, Small, Medium-sized and Large); and (4) Production type (Piece, Serial and Mass). Based on these explanatory variables, different models were compiled. The individual factors were examined separately and in various combinations with other factors for the actual verification of the effects (Liu & Koirala, 2012; Singh et al., 2022). Each model examines the effect of various factors and their categories on the OEE level by testing the hypothesis that the regression coefficient estimate is zero (Estimate or $\beta k = 0$). Estimates of regression coefficients represent the effect of each factor category compared to the reference category.

Table 3 summarizes the first four models. Model M01 represents the examination of the effect of the Use of SMED, and model M02 represents the examination of the effect of the Use of TPM. In model M03, the results of both of these factors are examined together. The latest model, M04, examines these factors' effect and mutual interaction on the OEE level. The non-use of SMED and non-use of TPM are chosen as the reference categories. Models M01 (Chi-square (1) = 1.612, p = 0.204), M02 (Chi-square (1) = 0.154, p = 0.694), M03 (Chi-square (2) = 1.612, p = 0.447), and M04 (Chi-square (3) = 4.686, p = 0.196) were not found to be statistically significant. Based on the Nagelkerke Pseudo R-values, M01 explains 2.1% of the variance of OEE level; M02 explains 0.2% of the variance of OEE level; M03 explains 2.1% of the variance of OEE level, and M04 explains 5.9% of the variance of OEE level. It is unclear whether these factors are decisive; their ability to determine the size of the response variable cannot be discussed. Therefore, other factors need to be taken into account.

Tab. 3 – Ordinal Logistic Regression Models M01-M04. Source: own research

Model	Factor	Est.	Std. Error	Odds ratio	Odds ratio CI		Wald	Sig.	Goodness of Fit	Pseudo R	Parallel Lines
					5%	95%					
M01	SMED_Y	0.572	0.461	1.772	-0.331	1.476	1.540	**0.215**	**0.265**	**0.021**	**0.261**
M02	TPM_Y	0.165	0.422	1.179	-0.662	0.992	0.153	**0.695**	**0.671**	**0.002**	**0.671**
M03	SMED_Y	0.569	0.484	1.766	-0.379	1.517	1.384	**0.239**	**0.294**	**0.021**	**0.525**
	TPM_Y	0.010	0.443	1.010	-0.859	0.879	0.001	**0.982**			
M04	SMED_Y	-0.296	0.695	0.744	-1.658	1.066	0.181	**0.670**	**0.440**	**0.059**	**0.334**
	TPM_Y	-0.526	0.535	0.591	-1.574	0.522	0.968	**0.325**			
	Interaction	1.662	0.973	5.270	-0.246	3.570	2.913	**0.088**			

Model M05 (Table 4) represents the examination of the effect of the explanatory variables Production type, Company size, Use of SMED, and Use of TPM. Mass production, Large companies, non-use of SMED and non-use of TPM are chosen as the reference categories. Model M05 was found to be statistically significant (Chi-square (8) = 44.516, $p < 0.05$). The Goodness of Fit test was non-significant, which suggests a good model fit. Based on the Nagelkerke Pseudo R-value, M05 explains 45.8% of the variance of the OEE level. Serial production (Chi-square (1) = 13.345, $p < 0.05$), Micro (Chi-square (1) = 10.756, $p < 0.05$), Small (Chi-square (1) = 14.002, $p < 0.05$), and Medium-sized companies (Chi-square (1) = 14.393, $p < 0.05$) were found to be statistically significant in predicting the odds of higher OEE level. This means that these factors affect the OEE level and competitiveness. Specifically, the odds of a company achieving a higher OEE level is, on average, increased by 1249.1% for companies with Serial production (OR = 12.491). The odds of a company achieving a higher OEE level is, on average, increased by 3.7% in case of Micro companies, by 4.6% in case of Small companies, and by 8.5% in case of Medium-sized companies (OR = 0.037, 0.046, 0.085).

However, the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not met. To solve this, separate binomial logistic regressions on cumulative dichotomous dependent variables in the model M05 were conducted. In order to include a categorical predictor (OEE level), it was converted to three dichotomous variables (<40%, 40-80%, and 80-100%; each of values "Yes" and "No"). The first binomial logistic regression of model M05 (OEE <40%) was found statistically significant (Chi-square (7) = 68.888, $p < 0.05$). The model explains 75.1% of the variance of OEE level (Nagelkerke Pseudo R-value = 0.751) and correctly classifies 90.2% of cases, with a sensitivity of 90.8% and specificity of 88.9%. However, based on parameter estimates, there is no significant predictor between independent variables. The second binomial logistic regression of model M05 (OEE 40-80%) was found statistically significant (Chi-square (7) = 36.036, $p < 0.05$). The model explains 43.8% of the variance of the OEE level (Nagelkerke Pseudo R-value = 0.438) and correctly classifies 83.7% of cases, with a sensitivity of 70.3% and specificity of 92.7%. Based on estimates, Serial production (Chi-square (1) = 14.280, $p < 0.05$), Micro (Chi-square (1) = 4.753, $p = 0.029$), Small (Chi-square (1) = 5.666, $p = 0.017$), and Medium-sized companies (Chi-square (1) = 11.645, $p = 0.001$) were found to be statistically significant predictor of the OEE level of 40-80%. The odds of a company achieving an OEE level of 40-80% is, on average, increased by 2056.7% for companies with Serial production (OR = 20.567), by 10.9% in the case of Micro companies (OR = 0.109), by 13.9% in case of Small companies (OR = 0.139), and by 8.4% in case of Medium-sized companies (OR = 0.084). The third binomial logistic regression of model M05 (OEE 80-100%) was not found statistically significant (Chi-square (7) = 6.851, $p = 0.445$), and based on the Nagelkerke Pseudo R value (0.144), it explains only 14.4% of the variance of OEE level. On the other hand, the model correctly classifies 89.1% of cases with 100% sensitivity but 0% specificity.

Tab. 4 – Ordinal Logistic Regression Model M05. Source: own research

Model	Factor	Est.	Std. Error	Odds ratio	Odds ratio CI		Wald	Sig.	Goodness of Fit	Pseudo R	Parallel Lines
					5%	95%					
M05	P_Piece	0.824	0.726	2.280	-0.599	2.247	1.288	**0.256**	**0.266**	**0.458**	**0.035**
	P_Serial	2.525	0.691	12.491	1.170	3.879	13.345	**0.000**			
	C_Medium	-2.466	0.650	0.085	-3.740	-1.192	14.393	**0.000**			
	C_Small	-3.078	0.823	0.046	-4.691	-1.466	14.002	**0.000**			
	C_Micro	-3.293	1.004	0.037	-5.261	-1.325	10.756	**0.001**			
	SMED_Y	0.133	0.559	1.142	-0.963	1.228	0.056	**0.812**			
	TPM_Y	-0.359	0.524	0.698	-1.386	0.668	0.470	**0.493**			

In addition, the individual factors were examined separately from other factors for verification of the effects (Liu & Koirala, 2012; Singh et al., 2022). Table 5 below summarizes three models with explanatory variables Production type (M06) and Company size (M07); in model M08, the results of both of these factors are examined together. Mass production and Large companies are chosen as reference categories. Model M06 was found to be statistically significant (Chi-square (3) = 15.498, $p < 0.05$), but the Goodness of Fit test was significant, which suggests poor model fit. In addition, based on the Nagelkerke Pseudo R-value, M06 explains only 18.5% of the variance of the OEE level, and the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not satisfied.

Tab. 5 – Ordinal Logistic Regression Models M06-M08. Source: own research

Model	Factor	Est.	Std. Error	Odds ratio	Odds ratio CI		Wald	Sig.	Goodness of Fit	Pseudo R	Parallel Lines
					5%	95%					
M06	P_Piece	0.524	0.585	1.689	-0.623	1.671	0.802	**0.371**	**0.022**	**0.185**	**0.022**
	P_Serial	2.044	0.605	7.723	0.859	3.230	11.423	**0.001**			
M07	C_Medium	-2.133	0.628	0.118	-3.365	-0.901	11.521	**0.001**	**0.009**	**0.278**	**0.007**
	C_Small	-2.551	0.746	0.078	-4.013	-1.089	11.693	**0.001**			
	C_Micro	-3.166	0.916	0.042	-4.962	-1.370	11.941	**0.001**			
M08	P_Piece	0.918	0.702	2.505	-0.458	2.295	1.710	**0.191**	**0.011**	**0.454**	**0.013**
	P_Serial	2.511	0.686	12.323	1.166	3.857	13.387	**0.000**			
	C_Medium	-2.483	0.647	0.083	-3.750	-1.215	14.738	**0.000**			
	C_Small	-3.032	0.817	0.048	-4.634	-1.430	13.757	**0.000**			
	C_Micro	-3.302	0.986	0.037	-5.234	-1.370	11.218	**0.001**			

Model M07 was found to be statistically significant (Chi-square (3) = 24.349, $p < 0.05$). Even though it explains 27.8% of the variance of the OEE level (based on the Nagelkerke Pseudo R-value), it shows a poor model fit because the Goodness of Fit test was significant. In addition, the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not satisfied. Model M08 was found to be statistically significant (Chi-square (6) = 44.052, $p < 0.05$), and based on the Nagelkerke Pseudo R-value, it explains 45.4% of the variance of the OEE level, which is almost the same as in the model M05. However, the Goodness of Fit test was significant, which suggests poor model fit. In addition, the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not satisfied.

Table 6 summarizes the models with explanatory variables Company size, Use of SMED and Use of TPM. Model M09 represents the examination of the effects of Company size and the Use of SMED examined together. In M10, the Use of SMED is replaced by the Use of TPM. Large companies, non-use of SMED and non-use of TPM are chosen as the reference categories. Model M09 was found to be statistically significant (Chi-square (4) = 25.375, $p < 0.05$), but based on the Nagelkerke Pseudo R-value, M09 explains only 28.8% of the variance of the OEE level. In addition, the Goodness of Fit test was significant, which suggests poor model fit, and the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not satisfied. Almost the same applies to M10, which was found statistically significant (Chi-square (4) = 24.454, $p < 0.05$). However, it explains only 27.9% of the variance of the OEE level. It shows a poor model fit and the assumption of proportional odds is not satisfied.

Tab. 6 – Ordinal Logistic Regression Models M09-M10. Source: own research

Model	Factor	Est.	Std. Error	Odds ratio	Odds ratio CI		Wald	Sig.	Goodness of Fit	Pseudo R	Parallel Lines
					5%	95%					
M09	C_Medium	-2.135	0.630	0.118	-3.370	-0.899	11.467	**0.001**	**0.027**	**0.288**	**0.008**
	C_Small	-2.596	0.750	0.075	-4.066	-1.125	11.971	**0.001**			
	C_Micro	-3.017	0.928	0.049	-4.837	-1.198	10.565	**0.001**			
	SMED_Y	0.482	0.484	1.619	-0.467	1.431	0.911	**0.319**			
M10	C_Medium	-2.151	0.630	0.116	-3.386	-0.916	11.625	**0.001**	**0.044**	**0.279**	**0.013**
	C_Small	-2.542	0.747	0.079	-4.006	-1.079	11.588	**0.001**			
	C_Micro	-3.145	0.919	0.043	-4.946	-1.345	11.726	**0.001**			
	TPM_Y	0.144	0.441	1.155	-0.721	1.008	0.106	**0.721**			

Table 7 summarizes the other two models with explanatory variables Production type, Use of SMED and Use of TPM. Model M11 represents examining the effects of Production type and the Use of SMED examined together. In model M12, the Use of SMED is replaced by the Use of TPM. Mass production, non-use of SMED and non-use of TPM are chosen as the reference categories. The model M11 was found to be statistically significant (Chi-square (4) = 15.765, $p < 0.05$), but based on the Nagelkerke Pseudo R-value, M11 explains only 18.8% of the variance of the OEE level. In addition, the Goodness of Fit test was significant, which suggests poor model fit, and the test of Parallel Lines indicates significance. Therefore, the assumption of proportional odds is not satisfied. Model M12 is no exception. Even though it is statistically significant (Chi-square (4) = 15.730, $p < 0.05$), it explains only 18.8% of the variance of OEE level. The Goodness of Fit test shows a poor model fit, and the significance of the test of Parallel Lines indicates that the assumption of proportional odds is not satisfied.

Tab. 7 – Ordinal Logistic Regression Models M11-M12. Source: own research

Model	Factor	Est.	Std. Error	Odds ratio	Odds ratio CI		Wald	Sig.	Goodness of Fit	Pseudo R	Parallel Lines
					5%	95%					
M11	P_Piece	0.596	0.597	1.814	-0.574	1.765	0.996	0.318	0.013	0.188	0.040
	P_Serial	2.031	0.607	7.622	0.842	3.220	11.211	0.001			
	SMED_Y	0.258	0.499	1.294	-0.719	1.235	0.267	0.605			

M12	P_Piece	0.433	0.601	1.542	-0.745	1.611	0.519	0.471	**0.026**	**0.188**	**0.044**
	P_Serial	2.052	0.607	7.783	0.863	3.241	11.443	0.001			
	TPM_Y	-0.230	0.465	0.794	-1.143	0.682	0.245	0.621			

In model M05, the statistical significance of the Use of SMED and Use of TPM has not been demonstrated. However, factors such as Serial production and Medium-sized companies, Small companies and Micro companies proved statistically significant. These factors proved to be statistically significant in models M06 to M12, confirming the findings in model M05. The results show a statistically significant difference between Serial and Mass production in terms of the effect on the OEE level. Still, there is no statistically significant difference between Piece production and Mass production. Companies with Serial production are 20.567 times more likely to achieve the OEE level of 40-80% than companies with Mass production. In the case of Company size, Micro, Small, and Medium-sized companies show statistically significant differences in the effect on OEE level compared to Large companies. Based on the statistical significance, results and predictions, the model M05 appears to have the best resolution and the most reliable.

5. DISCUSSION AND CONCLUSION

The main objective of this study is to explore the connection and the context of the use of industrial engineering tools, namely TPM and SMED, and to monitor and evaluate OEE in industrial companies in the Czech Republic. In our research, it was found out that only 20.5% of companies implemented and used SMED. This finding corresponds to Gálová et al. (2018) findings, who have found that approximately 18% of companies in the Czech Republic use SMED. Given the benefits of using SMED, a larger share of uses could be expected. In the case of TPM, the present findings confirm that 26.5% of companies implemented and used this tool. This finding is again relatively in line with the research of Gálová et al. (2018) and Rajnoha et al. (2018), who have found that approximately 21% of companies in the Czech Republic use TPM in their practice. However, On the other hand, TPM is more complex and, in terms of implementation, a bit more demanding than SMED; therefore, it is possible to perceive these findings more positively compared to SMED. These tools can increase the OEE level, and OEE can measure the efficiency and performance of SMED and TPM implementation. But the results demonstrate that 54.0% of companies do not monitor and evaluate OEE, which is more than half. On the other hand, Gherghea et al. (2021) stated that OEE is the most frequent Key Performance Indicator without any further specification. Poor et al. (2020) found that 55.0% of companies in the Czech Republic monitor and evaluate OEE. Therefore, in our research, a larger share of companies that monitor and evaluate OEE would be expected because, based on the literature review, it can be assumed that a company that uses SMED and TPM will monitor and evaluate OEE (Mwanza & Mbohwa, 2015; Logesh et al., 2017; Manjunatha et al., 2018; Tsarouhas, 2019; Chikwendu et al., 2020; Suryaprakash et al., 2021; Pattaro Jr. et al., 2022). On the other hand, Rylková et al. (2021) found that only 1% of manufacturing companies in the Czech Republic measure OEE.

Because of the initial findings concerning the imbalances in the structure of companies and their approach to monitoring and evaluation of OEE, the associations between monitoring and evaluation of OEE and use of SMED and use of TPM were further examined. An association between the monitoring and evaluation of OEE and the use of SMED was revealed. This means that companies using SMED are more likely to monitor and evaluate OEE. This finding confirms the theoretical link between OEE and SMED. OEE is used as an indicator of production processes referring to SMED (Slaichova & Marsikova, 2013; Jasial et al., 2014; Zammori et al., 2011). In the case of TPM, an association between the monitoring and evaluation of OEE and the use of TPM was observed. According to the statistical test, companies using TPM are more likely to monitor and evaluate OEE. This finding confirms the theoretical link between OEE and TPM. Monitoring and evaluation of OEE is a part of TPM; it is one of the fundamental pillars of this tool (Ahuja & Khamba, 2008; Ahmad et al., 2018; Krachangchan & Thawesaengskulthai, 2018; Tsarouhas, 2019).

The study focused on examining the effect of selected factors on OEE level within 12 different regression models. In view of the findings, based on the statistical significance, results and predictions, the model M05 appears to have the best resolution and the most reliable. However, it would appear that the Use of SMED and Use of TPM cannot be considered statistically significant. It is not clear whether these factors determine OEE level. The results obtained are pretty surprising. Given the theoretical research and knowledge, it could be assumed that companies using TPM or SMED should achieve higher OEE levels, which should be reflected in greater competitiveness (Mwanza & Mbohwa, 2015; Ahmad et al., 2018; Manjunatha et al., 2018; Krachangchan & Thawesaengskulthai, 2018; Tsarouhas, 2019; Chikwendu et al., 2020; Suryaprakash et al., 2021; Pattaro Jr. et al., 2022). However, this theory was not confirmed in the models.

It is necessary to mention that the role of other factors can also be important. According to Chaurey et al. (2021), the OEE level may depend on a number of different factors; TPM programs make it possible to achieve World Class OEE level, but it is not possible to base it only on systems or technology but also on people (organizational structures, human interactions, etc.). In addition, companies can use SMED and TPM to increase the OEE level. Still, it also depends on the maturity of SMED and TPM programs, i.e., knowledge, education and training, employee attitude and encouragement, top management support and commitment, coordination and team spirit, quality management, equipment ownership, etc. (Chaurey et al., 2021; Rathi et al., 2022; Singh & Gurtu, 2021). However, the research recommends that all companies implement and use SMED and TPM and monitor and evaluate OEE. SMED and TPM are aimed, among other things, at reducing lead time, therefore improving competitiveness, so companies should focus on them and start using them, ideally in combination, with interaction with each other.

Although the study shows exciting and surprising results, it has certain limitations. It is based on data from the online questionnaire survey and analysis of internal data of a selected research sample of companies. Therefore, the subjectivity of data from companies' representatives (because of perception) cannot be excluded. Thus, there is a risk of obtaining biased answers. The non-response bias has not been examined, but we have tried our best to avoid it, as stated in the methodology part of this article. As for the social desirability bias, we do not consider this to be significant in our research, but, of course, there is a possibility of this bias occurring. To acquire more credible results, it would be appropriate to focus on even more detailed qualitative research of selected companies. Another limitation is the research sample, which is limited to industrial companies of different sizes and specializations. The question is then the significance of latent factors such as the period of use and experience with SMED and TPM, level of implementation, or industry specialization. Extending the variables into more latent factors and considering them to detect statistically significant differences would be appropriate. Another way of classification parameters for evaluation will be considered in further research.

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