An empirical analysis of Total Quality Management and Total Productive Maintenance in Industry 4.0

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Abstract

The aim of this study is to investigate the impact of Industry 4.0 adoption and operational performance improvement due to apply Total Quality Management (TQM) and Total Productive Maintenance (TPM). The analyzed sample was collected from 147 Brazilian manufacturers which have been practiced TQM and TPM for at least 10 years and during the past few years have started to adopt Industry 4.0 technologies. Multivariate data analysis was applied into the collected data in order to examine such relationships. Our statistical tests indicate that both TQM and TPM practices act as mediators for the relationship between Industry 4.0 and operational performance improvement. Hence, we mention that the companies which decide to join Industry 4.0 must have properly addressed these practices to entirely benefit from the advances in information and communication systems. This study contributes to threefold. First, it provides evidence to underpin theoretical indications previously argued but lack empirical validation. Second, the identification of relationship in an emerging economy context allows to understand the specific benefits or challenges that Industry 4.0 adoption. Third, comprehending how these approaches interact to help managers to avoid difficulties and set the suitable expectations along their implementation.

Keywords
Total Quality Management, Total Productive Maintenance, Industry 4.0, Operational Performance Improvement.

1. Introduction

To emerge as a leading manufacturer for the world market, companies located in emerging economies' context face a tough competition with global players. While the pressure to compete in their domestic market increases, these companies also struggle to become a global sourcing base (SETH; TRIPATHI, 2005). Hence, they must spend significant efforts to improve operational aspects, such as quality and efficiency performance, compelling them to adopt managerial approaches to support such achievement (TAJ; MOROSAN, 2011; TORTORELLA; FETTERMANN, 2017A).

Two major improvement approaches in the field of production and operations management are Total Quality Management (TQM) and Total Productive Maintenance (TPM) (SHAH; WARD, 2003). TQM is a management approach widely deemed for continuously improving the quality of products, services and processes by focusing on the customers' needs and expectations enhancing customer satisfaction and firm performance (WANG et al., 2012; DALE, 2015). Throughout the years, TQM has been argued as positively impact an organization, although there are mixed results about its relationship with performance (SADIKOGLU; OLCAY, 2014). Similarly, TPM has gained further attention during 1990s as an approach that focuses on maximizing resources utilization through maintenance and basic stability practices (NAKAJIMA, 1988; AHUJA; KHAMBA, 2008B). Specifically in emerging economies' context, where capital expenditure levels are reduced and new machine acquisition is a greater challenge, the proper utilization and maintenance of equipment are vital for an enhanced shop floor efficiency (AHUJA; KHAMBA, 2008A; JAIN et al., 2015). Several researchers (e.g. SETH; TRIPATHI, 2005; SETH; TRIPATHI, 2006; KONECNY; THUN, 2011; KAUR et al., 2012) have examined the effects of association between TQM and TPM on business performance.

Overall, the majority of these studies have pointed to a synergic relationship between both approaches that positively influences operational performance, whose level is much higher when they are simultaneously adopted.
Industry 4.0 denotes an industry whose main characteristics comprehend connected machines, smart products and systems, and inter-related solutions. Such aspects are put together towards the establishment of intelligent production units based on integrated computer and/or digital components that monitor and control the physical devices (KAGERMANN et al., 2013; LASI et al., 2014). Through an internet-based network, these technologies may allow higher levels of flexibility and control, supporting new standards of operational performance (LANDSCHEIDT; KANS, 2016). Nevertheless, the potential benefits of the incorporation of Industry 4.0 into existing management approaches, such as TQM and TPM, were mostly indicated by previous studies (KOLBERG; ZÜEHLKE, 2015; SANDERS et al., 2016; KOLBERG et al., 2016), but based on little empirical evidence to support such arguments. Thus, based on these arguments and the paucity of empirical evidence, two research questions can be raised and described as:

1) *What is the impact of Industry 4.0 on the implementation of TQM and TPM?*
2) *How can all these approaches coexist to improve operational performance in a developing economy context?*

To answer these questions, this study aims at investigating the impact of Industry 4.0 adoption on the relationship between management approaches, such as TQM and TPM, and operational performance improvement. To achieve that, a survey was carried out with 147 manufacturers located in Brazil. These companies have been applying TQM and TPM practices for at least 10 years and during the past few years have started to adopt Industry 4.0 technologies. Multivariate data analysis was applied into the collected data in order to examine such relationships.
The contribution of this study is three-fold. First, it provides evidence to underpin theoretical indications that were previously argued but lack empirical validation. Second, the identification of these relationships in an emerging economy context, such as Brazilian industrial sector, allows to understand the specific benefits or challenges that Industry 4.0 adoption implies over manufacturers that usually do not have the same kind of resources as the ones located in developed economies. Finally, in practical terms, comprehending how these approaches interact helps to anticipate occasional difficulties and sets the proper expectations along their implementation, providing managers the opportunity to curb potential issues and address improvements that catalyze the achievement of performance objectives.
The rest of this paper is structured as follows. Section 2 presents the theoretical background and hypotheses developed to answer our research questions. Section 3 describes the proposed method, with results of its application presented in section 4. Section 5 closes the paper presenting conclusions and future research opportunities.

2. Literature review and hypotheses

2.1 Industry 4.0

Chukwuekwe et al. (2016) suggest the existence of key drivers for Industry 4.0 such as cloud computing, three-dimensional printing technology, Cyber-Physical Systems (CPS), Internet of Things (IoT), Internet of Services (IoS) and Big Data. The adoption of such technologies entails an increased level of automation and changeability, since they focus on information exchange with other entities, control production processes and integrate themselves into their environment (LEE, 2008).
One of the main challenges for manufacturers from emerging economies is related to the high costs entailed by Industry 4.0 technologies adoption (KOLBERG; ZÜEHLKE, 2015). Manufacturing in this socio-economic context is generally featured by high-volume and low value-added products (JAKOVLJEVIC, 2014), which undermines the acquisition of high-tech devices. Further, the inherent low-labor costs usually imply lower skilled employees, which hinders the operationalization of complex cutting-edge technologies (PIRVU et al., 2015). However, some researchers (ZHOU et al., 2015; TORTORELLA; FETTERMANN, 2017b) argue that, if an adequate balance between contextual factors and adoption level is achieved, the benefits of Industry 4.0 can overcome these barriers and provide similar outcomes as the ones observed in developed economies. Thus, to verify the effect of adopting Industry 4.0 technologies in emerging economies' context, we formulated the following hypothesis:
H_1: The adoption of Industry 4.0 technologies positively influences operational performance improvement in manufacturing companies.

2.2 TQM practices and Industry 4.0

TQM is considered a multi-dimensional construct evaluated as a strategic tool which extends beyond the reconstruction of quality standards, techniques and instruments (DALE, 2015). It may also be considered as a systematic approach for developing an expected organizational behavior aimed at people-focused management, fostering employees participation and a collaborative culture to continuously improve and add value for customers (KOBER et al., 2012). Researchers have proposed different measures and nomenclatures that set a similar framework for applying TQM. For instance, Hinckley (2007) and Baudin (2007) have adopted the term *Jidoka* to refer to quality practices and problem-solving skills. Liker and Morgan (2011) and Malmbrandt and Åhlström (2013) have used the term 'Built-in-Quality' to reflect the bundle of practices that aims to support quality enhancement. Additionally, Shah and Ward (2007) defined as 'Controlled Processes' an operational construct comprised by five measures, which ensure that each process will supply defect free units to subsequent process.

It is noteworthy that Industry 4.0 relies heavily on the big data concept, whose essence is determining probabilities with mathematical methods and procedures supporting managers on the decision-making process (TAMÁS et al., 2016). Once machines are interconnected and input real data into virtual clouds, process monitoring tends to become easier, allowing a faster identification of abnormalities which triggers the problem-solving process (SPEAR, 2009). However, this increasing level of automation may lead to process alienation removing responsibility from operators over quality, which is contrary to quality principles; i.e. TQM excels for empowering employees to solve problems. Automation must be implemented in order to avoid that employees become machines' slaves (WOMACK et al., 2007). To better investigate the relationship between Industry 4.0 and TQM, we formulate the following hypotheses:

H_{2a}: The implementation of TQM positively influences operational performance improvement in manufacturing companies.

H_{2b}: The implementation of TQM positively mediates the relationship between Industry 4.0 technologies adoption and operational performance improvement in manufacturing companies.

2.3 TPM practices and Industry 4.0

Maintenance is a critical activity that takes place at the manufacturing shop floor. Machines' failures during production may lead to adverse effects on production schedule, delaying delivery or culminating in employees' overtime to compensate the loss. TPM, which is a concept introduced by Nakajima (1988), aims at addressing equipment downtime through complementary maintenance methods and, thus, achieving a high level of equipment availability. The positive association between the implementation of TPM and companies' operational performance has been extensively validated by previous research (e.g. SHAH; WARD, 2003; FURLAN et al., 2011; NETLAND; FERDOWS, 2014).

Evidence of the integration of Industry 4.0 and current maintenance systems is found in narrow studies, such as Chukwuekwe et al. (2016) which propose concepts for predictive maintenance within an Industry 4.0 environment. Other studies (e.g. ZÜEHLKE, 2010; BOKRANTZ et al., 2017) have only envisioned that through the adoption of CPS and ICT techniques machines are able to diagnose mechanical and electrical failures allowing more assertive corrective interventions and preventive planning (LEE; WANG, 2008), while providing real-time information to managers (ASHTON, 2009). We formulate the following proposition to better investigate the matter:

H_{3a}: The implementation of TQM positively influences operational performance improvement in manufacturing companies.

H_{3b}: The implementation of TQM positively mediates the relationship between Industry 4.0 technologies adoption and operational performance improvement in manufacturing companies.

Therefore, the hypothetical model investigated in this study is summarized in Figure 1. It was tested empirically, as elaborated in the following.

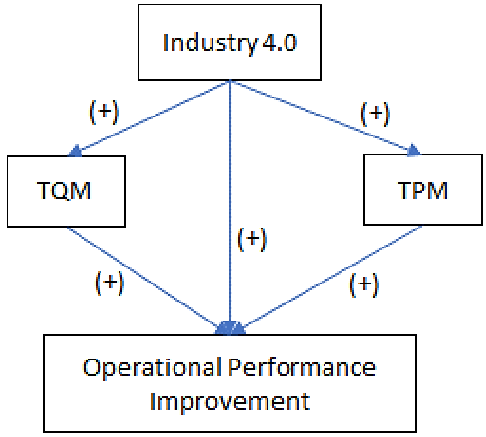

Figure 1. Investigated theoretical model
Note: (+) means a hypothesized positive association between constructs

3. Method

3.1 Sample selection and characteristics

As this study is focused on Brazilian manufacturers' context, the sample was limited to leaders from these companies. Regarding respondents' selection, two criteria were adopted: (*i*) respondents should be aware of Industry 4.0 technologies and their respective companies should have already initiated their adoption; and (*ii*) companies should have a minimum experience (10 years) in implementing TPM and TQM. Our sample included companies from different industrial sectors because of the limited number of companies which have adopted our criteria.
The survey was sent to the leaders, who were former students of four different executive education courses on Industrial Engineering offered by a large Brazilian University during 2017 (in February, April, July and September). Most respondents were from large companies (55.1%) and belonged to the metal-mechanical sector (49.6%). With respect to companies' technological intensity, the Brazilian National Confederation of Industry (2016) categorizes companies according to their industrial sector and, hence, 53.7% were considered as high or medium-high intensity. Regarding respondents' job positions, 42.2% were either engineers or analysts. Finally, all respondents were from companies located in South (70%) and Southeast (30%) of Brazil, which are the most industrialized regions in Brazil (IBGE, 2012).
The questionnaire was structured in four main parts. The first part assessed the observed operational performance improvement during the last three years, according to five indicators: (*i*) productivity, (*ii*) delivery service level, (*iii*) inventory level, (*iv*) quality (scrap and rework) and (*v*) safety (work accidents). A five-point scale ranging from 1 (worsened significantly) to 5 (improved significantly) was used. Then, the second part aimed to collect demographic information of the respondents. The third part of the questionnaire assessed the adoption level of TQM and TPM practices. For that, we applied the instrument empirically validated and proposed by Shah and Ward (2007), which comprises five operational measures related to TQM and four related to TPM (Table 1).
Finally, the fourth part of the questionnaire aimed at measuring the degree of adoption of the Industry 4.0 technologies within the studied companies. For that, 10 digital technologies, which are the most likely ones for adoption within Brazilian industrial sectors (BRAZILIAN NATIONAL CONFEDERATION OF INDUSTRY, 2016), were consolidate (Table 2). The third and the fourth part of questionnaire are described in a statement evaluated according to a Likert scale from 1 (fully disagree/not used) to 5 (fully agree/fully adopted). Furthermore, we provided a statement clarifying that respondents would be kept anonymous and that there was no right or wrong answer.

Table 1. TQM and TPM constructs and measures

Operational constructs	Operational measures
TQM	tqm_1- Large number of equipment/processes on shop floor are currently under SPC tqm_2- Extensive use of statistical techniques to reduce process variance tqm_3- Charts showing defect rates are used as tools on the shop floor tqm_4- We use fishbone type diagrams to identify causes of quality problems tqm_5- We conduct process capability studies before product launch
TPM	tpm_1- We dedicate a portion of everyday to planned equipment maintenance related activities tpm_2- We maintain all our equipment regularly tpm_3- We maintain excellent records of all equipment maintenance related activities tpm_4- We post equipment maintenance records on shop floor for active sharing with employees

Source: Adapted from Shah and Ward (2007)

Table 2. Digital technologies most likely for adoption within Brazilian industrial context

Technology
dt_1- Digital automation without sensors
dt_2- Digital automation with process control sensors
dt_3- Remote monitoring and control of production through systems such as MES* and SCADA**
dt_4- Digital automation with sensors for product and operating conditions identification, flexible lines
dt_5- Integrated engineering systems for product development and product manufacturing
dt_6- Additive manufacturing, rapid prototyping or 3D printing
dt_7- Simulations/analysis of virtual models (finite elements, computational fluid dynamics, etc) for design and commissioning
dt_8- Collection, processing and analysis of large quantities of data (big data)
dt_9- Use of cloud services associated with the product
dt_{10}- Incorporation of digital services into products (Internet of Things or Product Service Systems)

* MES - Manufacturing Execution Systems

** SCADA - Supervisory Control and Data Acquisition

Source: Adapted from Brazilian National Confederation of Industry (2016)

3.2 Sample and method bias

We tested for non-response bias using Levene's test for equality of variances and a t-test for the equality of means among respondents of each class (ARMSTRONG; OVERTON, 1977). Our results indicated no differences in means and variation in the four groups (p-value<5%). Thus, there is no statistical evidence that our sample is significantly different from the rest of the population.

Since single respondents can be a source of common method bias (CMB), especially when the same respondent is answering both the dependent and independent variables with psychometric scales that represent their opinion. To overcome such CMB issue, as suggested by Podsakoff et al. (2003), some techniques were followed. As the question formulation, dependent variables were placed first and physically far from the independent variables in the questionnaire and verbal midpoint labels were added to the scales.

In relation to statistical remedies, we applied Harman's single-factor test with an exploratory factor analysis, which is highly used by researchers to address CMB (MALHOTRA et al., 2006). The Harman's test with all independent and dependent variables resulted into a first factor that included 30.41% of the variance. Consequently, as there was no single factor accounting for most of the variance in the model, common method variance should not be a problem.

3.3 Data analysis

The dataset contains no missing values. To make sure that no influential outliers affect the results, Mahalanobis distance statistic was applied to observed variables using a conservative level of significance (p-value<0.001) as recommended by Kline (2015). Hence, only one response in the sample was excluded. Structural Equation Modelling (SEM) analyses were conducted using the R Package Lavaan (ROSSEEL, 2012). The SEM model was used strictly as Confirmatory Factor Analysis (CFA). Two groups of indices were used to evaluate how the model fits in the data: (*i*) absolute goodness-of-fit (GOF) indices (χ^2, Normed χ^2, Root Mean Square Error of Approximation – RMSEA and Standardized Root Mean Square Residual – SRMSR); and (*ii*) relative GOF indices (Comparative Fit Index – CFI, Normed Fit Index – NFI, Incremental Fit Index – IFI and Tucker-Lewis Index – TLI). GOF is intended to examine how closely the data fit the model through comparing the estimated covariance matrix (theory) and the observed covariance matrix (reality). Hair et al. (2014) suggested that using three or four fit indices provides adequate evidence of model fit, because they are often redundant.

Table 3 shows the GOF results for the proposed SEM model. All fitness measures met the recommendations for at least the reasonable fit, indicating the SEM model fits well in the data. The regression coefficients for the SEM model were estimated using the maximum likelihood method; the statistical significance of the indirect effects was computed using bootstrapping procedures (5,000 bootstrap samples, two-sided CI). The SEM model and all the standardized estimates of the path coefficients (standardized direct effects) and disturbances (proportions of unexplained variance) are presented in Figure 2.

Table 3. Goodness-of-fit (GOF) indices and suggested cut-off (Mulaik et al., 1989; Bentler, 1990; Hooper et al., 2008; Hair et al., 2014)

Fit Index		Value (n=146)	Suggested cut-off (acceptable good fit)
Absolute GOF indices	Chi-square (χ^2)	512.15	
	Normed chi-square (χ^2/df)	2.07	< 5
	RMSEA	0.08	< 0.08
	SRMSR	0.08	< 0.08
Relative GOF indices	CFI	0.89	> 0.90
	NFI	0.90	> 0.90
	TLI	0.90	> 0.90

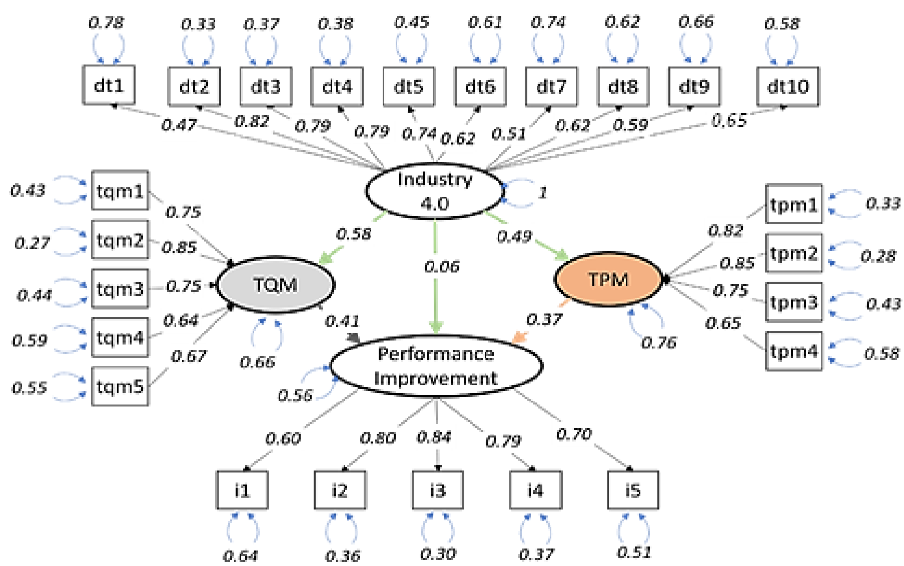

Figure 2. SEM model with all the standardized parameters estimates (path coefficients and disturbances)

3.4 Construct validity and reliability

The verification of constructs validity ensures that the instrument accurately measures what it was supposed to measure (HAIR et al., 2014). In this sense, we checked for convergent and discriminant validity (NAWANIR et al., 2018). Convergent validity was assessed based on factor loading, average variance extracted (AVE) and composite reliability (CR). Table 4 shows that no factor loadings are smaller than 0.35 meaning all observed variables can be considered in the analysis (HAIR et. al, 2014); and AVEs exceed 0.50 (BAGOZZI; YI, 1988). Further, we evaluated

Cronbach's alpha coefficient and CR. As suggested by Nunally (1978), a cut off value of 0.70 indicates an acceptable level of internal consistency. All constructs revealed values above 0.80 for both measures demonstrating a good adequacy of the measurement model.
For discriminant validity, we assessed whether the square root of AVE for each construct is higher than its correlations with any other constructs (FORNELL; LARCKER, 1981). Table 5 displays that all square roots of AVE are higher than the correlation estimates among the latent variables; hence, indicating an adequate level of discriminant validity.

Table 4. Constructs validity and reliability

Constructs	Observed variables	Factor loading	AVE	Cronbach's alpha	CR
TQM	tqm_1	0.753	0.528	0.85	0.85
	tqm_2	0.852			
	tqm_3	0.747			
	tqm_4	0.642			
	tqm_5	0.672			
TPM	tpm_1	0.816	0.590	0.85	0.85
	tpm_2	0.849			
	tpm_3	0.755			
	tpm_4	0.649			
Industry 4.0	dt_1	0.473	0.501	0.89	0.89
	dt_2	0.817			
	dt_3	0.791			
	dt_4	0.789			
	dt_5	0.739			
	dt_6	0.624			
	dt_7	0.508			
	dt_8	0.616			
	dt_9	0.586			
	dt_{10}	0.652			
Performance improvement	i_1	0.600	0.550	0.86	0.85
	i_2	0.797			
	i_3	0.836			
	i_4	0.792			
	i_5	0.700			

Table 5. Discriminant validity

	TQM	TPM	Industry 4.0	Performance improvement
TQM	0.727			
TPM	0.614	0.762		
Industry 4.0	0.542	0.458	0.686	
Performance improvement	0.628	0.613	0.423	0.734

Note: Diagonal values (bolded) are square root of the AVE, whereas the off-diagonals are correlations.

4. Results and discussions

Tables 6 and 7 show the regression coefficients estimates of the SEM model. First, considering the direct effects only (Table 6), our results indicate that the adoption of Industry 4.0 technologies is significant and positively associated with the implementation level of TQM and TPM. However, for hypothesis H_1, which states that Industry 4.0 adoption has a direct positive effect on operational performance improvement at manufacturing companies, no significant association was found; hence, results do not bear such hypothesis. Further, results show that both TQM and TPM implementations are positively associated with operational performance improvement. These findings underpin hypotheses H_{2a} and H_{3a}, indicating that the implementation of both approaches significantly contributes to improving operational performance level at Brazilian manufacturers.
Second, Table 7 shows the indirect effects of Industry 4.0 adoption on the improvement level of operational performance. These indirect effects were estimated statistically as path coefficients in the model (KLINE, 2015),

whose results reveal that TQM and TPM practices positively mediate the relationship between Industry 4.0 and operational performance improvement. Hence, the total effect (direct and indirect) of the adoption of Industry 4.0 technologies on operational performance improvement was positively evidenced; although this effect is mediated by the implementation of TQM and TPM practices, confirming H_{2b} and H_{3b}.

Table 6. Maximum likelihood parameter estimates for direct effects

Predictors	Latent variables								
	TQM			TPM			Performance improvement		
	Estimated effect	Std. Error	Std. effect	Estimated effect	Std. Error	Std. effect	Estimated effect	Std. Error	Std. effect
	0.812	0.211	0.585**						
Industry 4.0				0.743	0.216	0.493*			
							0.070	0.123	0.057
TQM							0.362	0.113	0.411*
TPM							0.298	0.102	0.365*

Note: * *p*-value<0.01; ** *p*-value<0.001

Table 7. Maximum likelihood parameter estimates for Industry 4.0 indirect effects and total effect over Performance improvement (path coefficients)

Path	Performance improvement		
	Estimated indirect effect	Std. Error	Std. indirect effect
Industry 4.0 -> TQM -> Performance improvement	0.294	0.120	0.239*
Industry 4.0 -> TPM -> Performance improvement	0.221	0.095	0.180*
Industry 4.0 total effect (direct + indirect)	0.585	0.159	0.476**

Note: * *p*-value<0.01; ** *p*-value<0.001

Regarding the direct effects, findings converge to most of the studies evidenced in the literature about TQM (e.g. BAUDIN, 2007; DALE, 2015) and TPM (e.g. SHAH; WARD, 2003; FURLAN et al., 2011) practices. Further, the fact that both approaches were found to be significant and positively associated with operational performance improvement indicates that their joint implementation does not entail a concurrent effect. Indeed, results suggest that a combined implementation of both approaches brings out significantly higher improvement levels of operational performance than an isolated one. Moreover, the positive association between Industry 4.0 and both TQM and TPM point that they can also support existing management approaches without conflicting with their practices and underlying principles.

Regarding Industry 4.0's direct effect on operational performance, surprisingly, results did not show any significant association. This outcome is contrary to popular belief, which has widely indicated that the adoption of Industry 4.0 technologies may lead to superior performance standards through the mitigation of traditional managerial and operational barriers (ASHTON, 2009; KOLBERG et al., 2016) and facilitation of problems identification and solution (ZÜEHLKE, 2010; KOLBERG; ZÜEHLKE, 2015). Our results do not underpin that. In turn, the absence of a significant association within our study sample may reflect the actual incipience and lack of awareness with respect to Industry 4.0 and its potential benefits for manufacturers from emerging economies (TORTORELLA; FETTERMANN, 2017). Further, as pointed by Zhou et al. (2015), another justification for this result would be that the managers tend to associate the adoption of Industry 4.0 technologies with prohibitive levels of capital expenditure, undermining any further initiative or providing minimum and shallow solutions.

However, when we analyze the indirect effects, results show that the relationship between Industry 4.0 and operational performance improvement is indeed positively mediated by the implementation of TQM and TPM practices. Such outcome provides empirical evidence to support the discussion raised by Sanders et al. (2016) and Kolberg et al. (2016). Further, they are also aligned with the indications from Tortorella and Fettermann (2017), who suggest that the single incorporation of cutting-edge technologies into ill-structured processes (e.g. quality control and maintenance processes) will not lead manufacturing companies to a significant higher operational performance. Unless proper practices are well-established and the inherent organizational behaviors are observed, Industry 4.0 technologies will provide whimsy gains, causing frustration and wasting resources.

5. Conclusions

This study aimed to investigate the impact of Industry 4.0 technologies adoption on the relationship between TQM, TPM and operational performance improvement. Implications of this research are both from theoretical and practical perspective, and they are detailed in the following sections.

5.1 Theoretical implications

In theoretical terms, this study provides empirical evidence to bear or demystify assumptions that were only hypothesized in previous literature about the relationships among Industry 4.0 technologies, existing management approaches and operational performance improvement. Further, the comprehensions of such relationship intensities in the Brazilian industrial sector provides arguments to identify whether the challenges and benefits of Industry 4.0 adoption may differ from developed economies' context, such as Germany and USA.

In fact, our results pointed that the adoption of Industry 4.0 technologies is still incipient in Brazilian manufacturers, entailing a smaller impact on operational performance as expected. However, findings demonstrated that the effect of Industry 4.0 on operational performance can be much enhanced if manufacturing companies have been properly implementing TQM and TPM practices. Hence, besides contributing directly to operational performance, these practices also positively mediate the relationship between operational performance improvement and Industry 4.0 technologies. This outcome highlights the intrinsic resilience of Industry 4.0, whose benefits are only observed if its technologies adoption is assertively adapted according to companies' context and aim to support existing management practices and routines, such as TQM and TPM.

5.2 Practical contributions

From a practical perspective, a deeper understanding of the combined effects of Industry 4.0, TQM and TPM on operational performance improvement allows managers and practitioners to set proper expectations throughout their implementation processes. Moreover, the identification of synergistic relationships and mediating effects helps leaders to anticipate issues on operational performance improvement, minimizing wasteful decisions and useless investments. Further, our results emphasize the need to extensively work on basic managerial and operational processes improvement through the implementation of traditional approaches, such as TQM and TPM, before the incorporation of innovative technologies.

Nevertheless, contrary to the adoption of Industry 4.0 technologies, an effective implementation of TQM and TPM practices comprises significant lower levels of capital expenditure, which increases the likelihood of succeeding especially in low-cost production scenarios such as emerging economies. Overall, this research suggests companies that, although the pervasiveness of Industry 4.0 technologies in Brazilian manufacturers is still low, a significant improvement in operational performance may be achieved with little effort if TQM and TPM practices are implemented.

5.3 Limitations and future research

Regarding study's limitations, it is noteworthy to highlight a few. First, with respect to study sample, all respondents were from manufacturers located in Brazil. Thus, while this context delimitation increases confidence on describing the examined relationships within this country, it undermines any generalization to other emerging economies. Further, although South and Southeast are the most industrialized regions in Brazil, the expansion of data collection to respondents located in other regions would enrich the sample both in quantitative and qualitative terms.

Second, with regards to the investigated SEM model, manufacturing companies (especially large-sized ones) usually embrace a large set of management approaches besides TQM and TPM. Hence, Industry 4.0 technologies may support differently other approaches, culminating in relationships whose effects may vary over operational performance improvement. Thus, to provide a more holistic perspective, future research should include complementary constructs into the SEM model to verify the actual impact of a multifaceted management together with the adoption of Industry 4.0 technologies. Finally, carrying out similar surveys with respondents from developing and developed countries would allow the establishment of comparative studies, which could raise novel insights about the adequate levels of technologies adoption to maximize performance in each context.

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