Implementation of Big Data Analytics and Manufacturing Execution Systems – an Empirical Analysis in German-Speaking Countries

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Many firms have started Industry 4.0 (I4.0) initiatives in recent years, without having a sound understanding of the effects generated by the technologies introduction. This research provides indications of what to expect from the implementation of two key technologies for I4.0: big data analytics and manufacturing execution systems. The study explores the relationships between these technologies' implementation and a set of performance effects. Additionally, it analyses the influence of the organisational structure. A set of hypotheses derived from literature builds the basis for the quantitative analysis of an industry survey with 116 participants from German-speaking countries. The results show that these technologies have distinct, partially unexpected, performance effects. Furthermore, this research provides evidence that the organisational structure of technology implementation plays no significant role in the attainment of higher technology implementation levels.

Keywords: Industry 4.0; organisational structure; technology implementation; firm performance; internal enablers

1 Introduction

Many companies implement digital technologies to cope with today's multifaceted challenges in production, especially in high-wage or high-cost countries, which are characterised by a 'high Gross Domestic Product (GDP) per capita' (Ketokivi et al. 2017, 20). Companies face a growing competitive pressure caused by globalisation effects, increasing complexity and higher demands for flexibility (Spath 2013; van Laar et al. 2017). The digitalisation of production provides an answer to this growing need for agility (Lu 2017). Overall, numerous scholars (Bauernhansl, ten Hompel, and Vogel-Heuser 2014; Forstner and Dümmler 2014; Kagerman, Wahlster, and Helbig 2013) and practitioners (Brown, Sikes, and Wilmott 2013) associate opportunities and vast performance expectations with the current trend towards digitalisation.

Despite the euphoria, digitalisation related decisions are costly (Y. Chen 2017) and require solid concepts for firms to initiate their 'digital transformation journey' (Berman 2012, 18). Decision-makers in the industry can choose from a broad range of digital technologies such as sensors, cloud computing, manufacturing executions systems (MES), big data analytics (BDA), or robotics. All of these are associated with the Industry 4.0 (I4.0) paradigm (B. Chen et al. 2018; Kang et al. 2016; Lu 2017). Prerequisites, implementation patterns and performance effects may differ for each technology. Hence, it is highly relevant to refer to particular technologies when answering the question of '[…] how typical manufacturers can achieve organisational, operational, technical and legal readiness in preparation for the Industry 4.0' (Ghobakhloo 2018, 930). Empirical evidence for the implementation and effects of I4.0 technologies is available in the literature, but Industry 4.0 is a wide-ranging and ill-defined concept (Rossini et al. 2019; Frank, Dalenogare, and Ayala 2019). Empirical studies focusing on the impacts of specific performance remain limited, despite the broad call for a higher focalisation of Industry 4.0 research (Papadopoulos et al. 2017; Rossini et al. 2019). Hence, the primary objective of our study is to assess if the impacts of technology implementations are technology dependent.

To address the study's primary aim, we developed a research model by adopting the resource-based-view (RBV) (Barney 1991) and dynamic capabilities theoretical lenses (Teece, Pisano, and Shuen 1997). In a recent study, Dubey et al. (2019) have built on the RBV theory to prove the relevance of resources in building capabilities in the use of technology (in their specific case, they were focusing on BDA), thus positively affecting firm performance. However, Torres, Sidorova, and Jones (2018) argue that RBV can be limiting in the study of the dynamic environment typically faced by a company introducing new technologies since the RBV assumes a static view of resources. Hence,

some scholars have proposed considering the dynamic capabilities theory, which is a more dynamic view of resources and capabilities (Torres, Sidorova, and Jones 2018; Wamba et al. 2017). In particular, the dynamic capabilities theory assumes that the 'firm's ability to integrate, build, and reconfigure internal and external competencies to address a rapidly changing environment' allows it to achieve a competitive advantage (Teece, Pisano, and Shuen 1997).

In this study, we decided to focus on the performance effects of BDA and MES, which can be considered key technologies to secure the competitiveness of manufacturing companies (das Neves et al. 2015; Ghobakhloo 2018; Yadegaridehkordi et al. 2018; Seibl and Theobald 2017; Gilchrist 2016).

In the literature, two distinct perspectives on digitalisation impacts exist. On the one hand, several contributions focus on the potential internal improvements in production efficiency and productivity that digitalisation of manufacturing or I4.0 could provide (B. Chen et al. 2018; Kagerman, Wahlster, and Helbig 2013; Kang et al. 2016; Lu 2017; Lee, Kao, and Yang 2014). A study from the Boston Consulting Group, for example, draws an optimistic picture of such productivity gains through I4.0. They estimate an improvement of conversion costs between 15 to 25 per cent for the German manufacturing industry during the next five to ten years (Rüßmann et al. 2015, 7). On the other hand, an external perspective of digitalisation recognises developments of new business models as well as the optimisation of existing products and services (Yoo et al. 2012; Kagerman, Wahlster, and Helbig 2013).

Furthermore, this analysis also investigates the effects of the different organisational structures that firms can apply to introduce digitalisation into their manufacturing entities.

We base our analysis on a survey involving manufacturing companies located in the German-speaking area (Austria, Germany, Liechtenstein, and Switzerland), a region known for its pioneering role in I4.0 (Kagerman, Wahlster, and Helbig 2013). They operate in several industries. The results support managers in their decisions about I4.0 technology investments and provide them with guidance for implementations. Additionally, our research contributes to the theoretical discussion on how to achieve I4.0 readiness (Ghobakhloo 2018), especially concerning the organisational setup. Our statistical analysis complements the yet mainly qualitative discussion on I4.0 technology implementation (Frank, Dalenogare, and Ayala 2019).

We have structured our paper as follows. Section 2 presents the literature related to BDA and MES as selected technologies. It also introduces the hypotheses and model. Section 3 describes the methodological approach, while section 4 presents the results of our research. Finally, section 5 concludes the paper with limitations and outlines future research opportunities.

2   Related literature and hypothesis development

We begin with an introduction to the related literature and present the research hypotheses with the underlying model. In particular, this section consists of four parts. The first part introduces BDA and MES. The second derives the relationships between technology and firm performance. In the third, we provide the literature that considers the effect of organisational structure on technology implementation. Finally, we present the model and the three hypotheses about technology implementation of BDA and MES.

2.1   MES and BDA

Both MES and BDA are key technologies for the digitalisation of manufacturing. The MES provides vital features associated with I4.0 (Seibl and Theobald 2017). It monitors,

optimises, and controls production. Moreover, it can autonomously execute short-term production planning (Sabina Jeschke et al. 2016; Cottyn et al. 2011; Saenz de Ugarte, Artiba, and Pellerin 2009). Although MES are not a new phenomenon and existed before I4.0 (Almada-Lobo 2015; Saenz de Ugarte, Artiba, and Pellerin 2009), several scholars refer to MES as a key or base technology of I4.0 (Frisk and Bannister 2017; Sabina Jeschke et al. 2016; Dalenogare et al. 2018; Mittal et al. 2017; Frank, Dalenogare, and Ayala 2019). Frank et al. (2019), for example, present a framework of adoption patterns for I4.0 and state that companies need to implement MES in the first stage of I4.0. Their framework for MES connects the digital and physical world in the sense of cyber-physical systems (CPS) (Pereira and Romero 2017, 1207) since it combines data gathered at the machine or shop floor level with data from enterprise resource planning (ERP) (Frank, Dalenogare, and Ayala 2019, 16f.). Thus, MES are a prerequisite for other I4.0 technologies such as BDA. Companies should not introduce the latter one before the third (and last) phase of I4.0 implementation (Frank, Dalenogare, and Ayala 2019). Additionally, Almada-Lobo (2015) sees data analytics as one of the four main pillars of future MES.

Scholars define BDA and related applications as a set of methods and technologies to gain valuable information and insights through the analysis of large amounts of data (Zhou, Liu, and Zhou 2016; H. Chen, Chiang, and Storey 2012). Use cases for BDA applications in manufacturing companies stem from quality control, process improvement activities, active maintenance, or product design (B. Chen et al. 2018; Yadegaridehkordi et al. 2018). All in all, researchers widely regard BDA technology as one key supportive element in the context of I4.0 (Pereira and Romero 2017; Zhou, Liu, and Zhou 2016; Lu 2017; Dalenogare et al. 2018; Gilchrist 2016; Kang et al. 2016; Lamba and Singh 2017). As we have seen, big data and advanced analytics are also key drivers

and enablers for the Industrial Internet of Things (IIoT) as they provide for historical, predictive, and prescriptive analysis, which can provide insight into what is happening inside a machine or a process. (Gilchrist 2016, 5). In recent years, BDA has received considerably more attention than MES in the manufacturing-related literature (Bokrantz et al. 2017; Liao et al. 2017; Mittal et al. 2017; Yadegaridehkordi et al. 2018; Lu 2017; Dalenogare et al. 2018; Ghobakhloo 2018; Lamba and Singh 2017).

However, both technologies appear to be mutually related: MES provide the data input for BDA concepts (Seibl and Theobald 2017), and BDA provide information for the planning and optimisation features of MES (Seibl and Theobald 2017; Noh and Park 2014). Decision-makers should consider the effects of and prerequisites for each technology before investing to benefit from the full scope of potentials through implementing both technologies.

2.2   Relationship between technology and performance

We expect both MES and BDA to contribute to firm performance. Studies do not provide a consensus about the performance effects of MES. Several studies indicate a positive effect of MES on operational firm performance (das Neves et al. 2015; Cottyn et al. 2011; Almada-Lobo 2015). 'Manufacturing Execution Systems have been pivotal in the performance, quality and agility needed for the challenges created by globalized manufacturing business and will most likely continue to be' (Almada-Lobo 2015, 18). Similarly, das Neves et al. (2015, 449) find that '[…] the MES significantly contributed to the manufacturing related to improvement of cost, quality, flexibility, conformity and reliability'. In contrast, the findings by Dalenogare et al. (2018) provide evidence that firms do not have high expectations regarding the performance benefits of MES implementations.

On the other hand, more clarity exists concerning the potential performance and productivity effects of BDA applications (Andrew McAffee and Brynjolfsson 2012; Yadegaridehkordi et al. 2018; Addo-Tenkorang and Helo 2016; Côrte-Real et al. 2019; Popovič et al. 2016; Wamba et al. 2017; Dubey et al. 2019). Scholars and practitioners both expect significant operational benefits through the implementation of BDA (Dalenogare et al. 2018; Gupta and George 2016). BDA is associated with cost-saving potential and thus should enhance operational efficiency (Zhou, Liu, and Zhou 2016; Dubey et al. 2019). Furthermore, the application of BDA provides additional information to increase decision quality in manufacturing firms (Popovič et al. 2016; Frisk and Bannister 2017). Scholars also point to the opportunities on the market side – the aforementioned external perspective of digitalisation – through, for example, improved product design or service innovations by BDA (Lee, Kao, and Yang 2014). As such, BDA is (unlike MES) not only associated with internal but also business performance effects (Gupta and George 2016).

Hence, the implication we derive from the literature is a direct relationship between technology implementation and firm performance. This implication leads to the following hypotheses:

H1a. The level of BDA implementation has a significant effect on a firm's performance.
H1b. The level of MES implementation has a significant effect on a firm's performance.

2.3 *Effect of the organisational structure on technology implementation*

Apart from evaluating internal readiness and potential performance effects before an investment (Ghobakhloo 2018), decision-makers also need to consider how to implement a novel technology into a network of globally dispersed manufacturing plants. Scholars

point to the importance of organisational structure in the context of I4.0 (Horlacher, Klarner, and Hess 2016; Cottyn et al. 2011; Ghobakhloo 2018; Hirsch-Kreinsen 2016; Sun et al. 2016; Brown, Sikes, and Wilmott 2013). Sun et al. (2016, 2), for example, state that 'the process of diffusion of information technology is thus not only closely related to its unique ability to solve technical issues but is also associated with the internal organisational structure […]'.

In order to achieve organisational readiness for I4.0 (Ghobakhloo 2018, 930), firms can choose from two forms of organisational structures to implement digital technologies. The implementation can either be guided by a central function (Horlacher, Klarner, and Hess 2016) or by each plant and function autonomously and decentralised. Setting the right degree of centralisation has become an issue since the beginning of the debate on I4.0. Scholars from the domain of global operations have been investigating the question of plant autonomy and responsibility for several decision areas (Feldmann et al. 2013; Olhager and Feldmann 2018; Friedli, Mundt, and Thomas 2014; Maritan, Brush, and Karnani 2004). However, new decision areas have arisen due to I4.0. It is unclear whether each plant should undertake the decision regarding where and how to implement a digital technology autonomously or whether it should be a centrally-located management function which takes the decision. According to Horlacher et al. (2016), centralisation provides the necessary power '[…] to effectively pursue digital transformation initiatives' (Horlacher, Klarner, and Hess 2016, 9). However, there is no consensus about the ideal organisational structure for different I4.0 technologies. Concerning MES, for example, Scholten (2009, 99) states that '[…] it's more logical to install the system locally'. Thus, the implementation responsibility remains decentralised within the local authority of the plant.

As outlined before, technology implementation may influence firm performance. However, the implications for the organisational structure are generally vague. We consider central organisational structures to be moderators for the performance effects of technology implementation. Our second hypothesis is:

> H2. Central (vs decentral) organisational structures moderate the performance
> effects of BDA or MES implementation.

Overall, few sources guide the discussion on the selection of an optimal organisational structure to implement technologies such as BDA or MES in an international manufacturing firm. Additionally, these studies do not provide a consensus regarding the optimal organisational structure. Eventually, we expect an effect of organisational structures on the technology implementation of BDA and MES. Hence, we examine another effect:

> H3. Central (vs decentral) organisational structures influence the degree of
> implementation of BDA and MES.

2.4 *Research model*

We build our research model based on RBV and dynamic capabilities as theoretical lenses. It provides a framework for our research. As recently proposed by Dubey et al. (2019), we rely on the RBV to explain how a company can achieve a competitive advantage (i.e. improved business but also operational performance) by creating bundles of strategic capabilities (i.e. improved implementation of technologies). The dynamic capabilities theory, instead, highlights that in order to achieve a competitive advantage, merely possessing dynamic capabilities is not enough (Helfat et al. 2007; Eisenhardt and Martin 2000; Ambrosini and Bowman 2009). The failure to use them successfully could create a negative impact for the firm due to 'opportunity costs, the cost of maintaining the capability, and the penalty for the selection of an inferior strategy' (Torres, Sidorova,

and Jones 2018, 824). Hence, many elements might influence a firm's ability to exploit dynamic capabilities to create competitive advantages (Torres, Sidorova, and Jones 2018). Previous research focusing on I4.0 attributes a high relevance to the organisation both at the macro-level (i.e. organisational structure) and at the micro-level (i.e. job design and skills) (Cimini et al.; Cagliano et al. 2019). Thus, we decided to explore the role played by the organisational structure in the relationship between technology implementation (i.e. dynamic capabilities) and firm performance (i.e. competitive advantage).
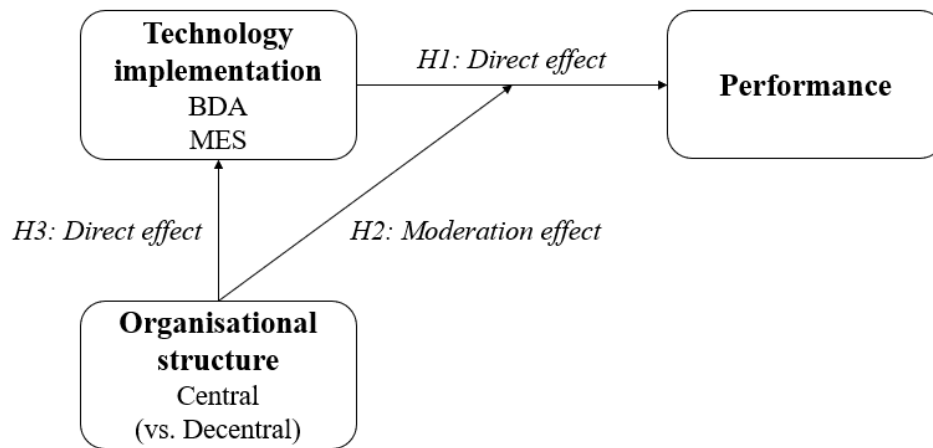

Figure 1**Errore. L'origine riferimento non è stata trovata.** presents the underlying model to test the three hypotheses about technology implementation of BDA and MES. The model integrates the relationship between technology implementation, organisational structure and firm performance. By considering the effect of technology

implementation on performance, it highlights the expected direct effect (H1). Besides,
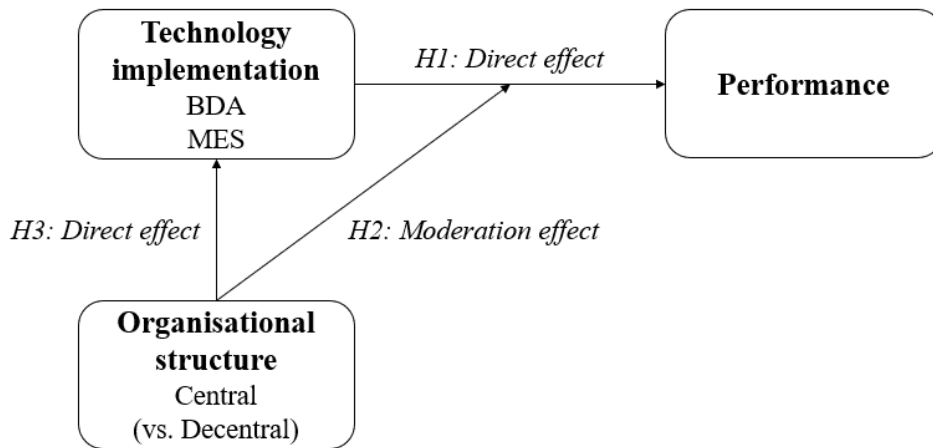

Figure 1 depicts the ambiguous role of organisational structures in technology implementation. On the one hand, the organisational structure moderates the effect of technology implementation on performance (H2). On the other hand, there is a direct effect of the organisational structure on the level of technology implementation (H2).
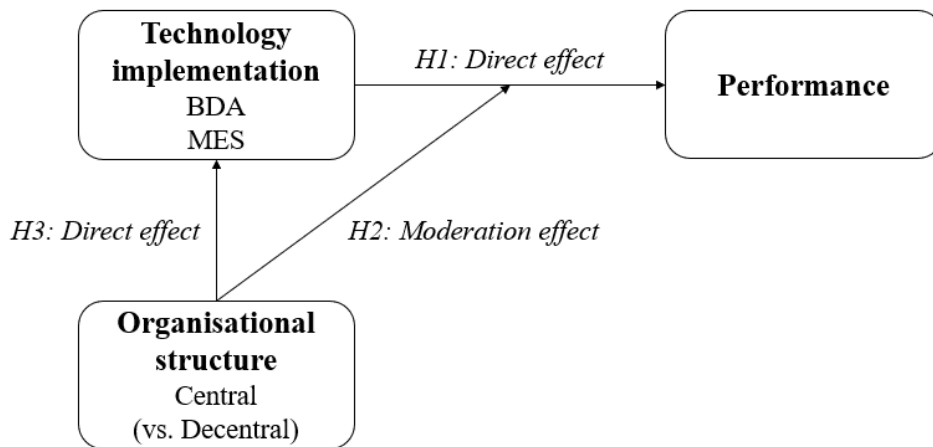

Figure 1. Hypotheses model –implementation of BDA and MES.

3 Methodology

To address the hypotheses, we designed a survey instrument as part of a Swiss-based benchmarking project. The main goal was to investigate the challenges and decisions concerning digitalisation and digital activities of manufacturing companies with plants in

German-speaking high-wage locations (i.e. Austria, Germany, Liechtenstein, and Switzerland). The study assessed the productivity gains and the impacts of digitalisation and new applications on these companies' competitiveness. In the first phase of the study, ten large manufacturing companies from the considered countries provided their support by discussing the survey instrument with the research team. To increase internal validity, we ran a pre-test with these industry partners. Their feedback also provided valuable input for revising the survey instrument. In the end, peer researchers and senior academics reviewed the questionnaire in an iterative process following Forza (2002). This process was of tremendous importance in order to define the specific items connected to the constructs identified from literature (namely, levels of technology implementation, performance and organisational structures). Hence, we derived the items used in this study from discussions with practitioners and other senior academics. This procedure follows the suggestions for exploratory survey research by Forza (2002). Finally, we implemented the questionnaire as an online survey structured into five main sections:

(1) General information: including general data about each participating company, such as the company size, industry, organisational structure and preliminary insights concerning its digitalisation activities;

(2) Technology: assessing the actual status of digitalisation in each company and the adopted technologies;

(3) Strategy: analysing the purposes, approaches, and the short-term as well as long-term strategies;

(4) Stakeholders: evaluating the data exchange with stakeholders, their contribution and their satisfaction with digitalisation practices;

(5) Investment & performance: assessing the economic expenses, contributions and effects of digital technologies within each company in previous years.

In March 2018, we invited potential participants via email. The email included instructions for the survey and explanations of the academic purpose. During data collection, participants had the option to ask questions via e-mail or phone for a better understanding of the questionnaire. In total, 1514 companies received a survey invitation. The sample's geographical focus was the German-speaking area. After a few weeks, we sent two e-mail reminders. In the end, 163 companies clicked on or partly completed the survey. One hundred and twenty-four companies completed the survey, with an overall response rate of 8.19%. The newness of digitalisation in the context of manufacturing companies and the exploratory nature of the research could have caused the rather low response rate. Other recent contributions related to I4.0 have similar response rates (e.g. Arnold and Voigt 2019; Durana et al. 2019). Moreover, the sample size is considered acceptable for our kind of exploratory research (Isaac and Michael 1995). Additionally, we assessed the representativeness of the sample concerning the population in **Errore. L'origine riferimento non è stata trovata.**.

The participants were top management level executives (e.g. Chief Executive Officer (CEO), Chief Financial Officer (CFO), Chief Technology Officer (CTO) and President) as well as representatives of operative functions (such as operations or technical directors, and heads of procurement or manufacturing). Furthermore, participants had to state at the beginning of the questionnaire, whether they were responsible for a single plant, a division or the entire firm. Overall, more than 70% of the replies concerned a single plant level. For the analyses conducted in the course of this work, we take the plant as a unit of analysis, since we assume that even decisions taken at a higher level (i.e. at the division or the overall firm levels) affect each plant. This assumption relates to less than 30% of our sample. In random confirmatory interviews with respondents who answered at the division or overall firm levels, we found that all

these respondents answered specific questions with one of their plants in mind. However, regardless of the unit of analysis level considered, all the single respondents' answers about internal enablers, technology implementation and performance are provided at the same level. Hence, the answers for each participating company are internally consistent. We excluded all responses in which companies stated they were purely providers of digital activities and technologies. Therefore, we focused on companies using digital technologies in manufacturing. We controlled all responses for missing data and transferred them into a distinct database. Depending on the variables considered, we used different numbers of observations for the analyses because of missing data. Missing data in survey answers particularly applies to performance variables, probably because they are considered sensitive data by the replying companies. Due to the limited sample size, we decided to include incomplete responses that only missed the answers to some different variables.

The final sample used for the evaluation in this paper consists of 116 replies from 17 different industries. Large companies (>250 employees) represent most of the sample (62%), but small and medium-sized companies are also part of the sample. In the questionnaire, we asked for the number of employees in full-time equivalents (FTE). **Errore. L'origine riferimento non è stata trovata.** summarises the main characteristics of the sample.

Table 1. Main characteristics of the sample.

	Sample	Population

Size in FTE	N	%	%
Small (less than 50 employees)	19	16.38	83.17
Medium (50 to 249 employees)	22	18.97	10.24
Large (250 and more employees)	72	62.07	2.58
No data	3	2.59	4.01
Total	*116*	*100.00*	*100.00*

Industry (NACE Rev. 2, 10-33)	N	%	%
Food and animal feed	3	2.59	8.93
Textiles	2	1.72	2.02
Pulp and paper products	1	0.86	0.98
Chemical products	2	1.72	2.98
Pharmaceutical	3	2.59	1.02
Rubber and plastic products	5	4.31	3.98
Other non-metallic mineral products	2	1.72	4.03
Metal production and processing	3	2.59	1.50
Metal products	13	11.21	18.83
Computer and electronics	8	6.90	6.22
Electrical equipment	7	6.03	3.86
Mechanical engineering	19	16.38	10.40
Automotive	14	12.07	1.40
Other transport equipment	4	3.45	0.99
Furniture	2	1.72	3.06
Production of other goods	19	16.38	7.94
Other	9	7.76	21.86
Total	*116*	*100.00*	*100.00*

We based the industries on the European industry classification Nomenclature statistique des activités économiques dans la Communauté (NACE) Revision (Rev.) 2[1]. The population includes all active companies in the NACE Rev. 2 industries 10-33 (manufacturing) in the German-speaking area with at least one employee. It was taken from the ORBIS[2] database.

3.1 Measures of dependent and independent variables

We investigated the *technology implementation level* by evaluating the implementation status of selected technologies within the participating companies. The survey participants had to rate their technology implementation level on a Likert scale 1–7 (1 = implementation failed; 2 = not relevant; 3 = observing; 4 = researching and developing, 5 = working on the implementation (prototyping); 6 = already in first use; 7 = fully

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[1] https://ec.europa.eu/eurostat/web/nace-rev2 [Retrieved on 15/06/19]

[2] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis [Retrieved on 15/06/19]

implemented). The option to answer 'I don't know' was also made available to respondents. The questionnaire included 15 technologies supporting manufacturing through I4.0 and digitalisation activities. Most of the respondents perceived some technologies (e.g. drones or blockchain) as irrelevant in the manufacturing context. The technologies selected for this study (BDA and MES), were among the most adopted technologies in our sample.

We use the term *organisational structure* to describe how a company organises its digitalisation activities and responsibilities. The survey question regarding the current organisational structure within each participating company was based on six options (1 = I don't know; 2 = decentralised; 3 = functional; 4 = project team; 5 = centre of excellence (competence); 6 = lead factory). For our analysis, we clustered these answer options into two categories. First, organisational structures with a central authority that organises and coordinates digital activities include the *project team, centre of excellence*, and *lead factory* answer options mentioned above. Second, decentralised organisations with digitalisation specialists spread over different functions or departments include the *decentralised* and *functional* answer options mentioned above. Appendix 1 provides a more detailed overview of the organisational structures presented to the survey participants.

For *performance*, we relied on exploratory factor analysis (a principal component analysis with varimax rotation). We used a set of ten items (cf. **Errore. L'origine riferimento non è stata trovata.**) related to the economic, productive and service performance of the company. The items stem from discussions with practitioners and senior academics. A multiple-item, 7-point Likert-type scale (1 = much worse; 4 = no change; 7 = much better) indicates how the company's performance had changed during the last three years in comparison with its competitors. A factor analysis (a principal

component analysis with varimax rotation) identified four factors. For each factor obtained, we calculated the average of the associated items and used them in the analyses. **Errore. L'origine riferimento non è stata trovata.** shows these factors that we interpreted as *business performance*, *adaptive performance*, *product-enhancing performance*, and *internal process performance*. The four factors explain 76% of the total variance and all the loadings are significantly higher than 0.65.

Cronbach's alpha is higher than 0.7 for the factors that have more than two items (Nunnally, Bernstein, and Berge 1967), while it is lower for *product-enhancing* and *internal process performance*. As the lower value is for two-item constructs, which can lead to lower values of the Cronbach's alpha, we calculated inter-item correlations. For all the two-item factors, the inter-item correlations were significant at the 1% level. Furthermore, we tested other models with a different number of factors, but they proved to be less reliable and hardly interpretable. Therefore, these findings do not represent a concern for the following analyses.

Table 2. Performance factors loadings and Cronbach's alpha.

Variable	Business	Adaptive	Product enhancing	Internal process
Turnover	0.910			
Market share	0.833			
EBIT	0.795			
Flexibility design		0.906		
Flexibility volume		0.838		
Innovative ability		0.667		
Sustainability			0.806	
Services			0.757	
Delivery speed and reliability				0.854
Product quality				0.768
Cronbach's alpha	*0.857*	*0.742*	*0.544[a]*	*0.647[b]*

[a] Inter-item correlation 0.4212 (p-value<0.005)
[b] Inter-item correlation 0.4920 (p-value<0.001)

Additionally, we controlled for common method bias for perceptive measures. We performed a one-factor analysis on all the perceived items applying Harman's single-factor test (Podasakoff et al. 2003). The one-factor solution explains only 21% of the total variance; thus, the test confirms that common method bias is not a cause for concern with our sample data.

3.2 Measurements of control variables

In all the regressions, we considered the company size as a control variable, measured as the logarithm of the number of employees. This procedure is coherent with previous studies that identified company size as a relevant contingent variable when considering technology implementation (Côrte-Real et al. 2019; Beach 2004).

Moreover, the implementation of digital technologies, such as BDA and MES, builds on various firm internal enablers (Côrte-Real et al. 2019; Yadegaridehkordi et al. 2018). We also decided to control for internal enablers to accommodate the possibility that technology implementation is a dependent variable. Several studies identify internal enablers for BDA, such as data management or standardisation (Gölzer and Fritzsche 2017; Yadegaridehkordi et al. 2018; Côrte-Real et al. 2019; B. Chen et al. 2018). Accordingly, Gupta and George (2016, 1055) have referred to a 'data-driven culture' as an intangible resource driving a firm's BDA capability. Furthermore, other scholars have identified similar internal enablers as antecedents for BDA implementation (B. Chen et al. 2018).

For MES, scholars highlight standardisation as an enabling factor as it enforces a '[…] standardised way of working' (Cottyn et al. 2011, 4410). Furthermore, scholars regard organisational and cultural factors as relevant for the implementation of both technologies, BDA and MES (das Neves et al. 2015; Côrte-Real et al. 2019; Yadegaridehkordi et al. 2018). The model by Yadegaridehkordi et al. (2018) also

highlights that enabling factors might directly affect firm performance. Based on a multiple-item, 7-point Likert-type scale (1 = unimportant; 7 = crucially important), the survey participants were asked to rate the importance of several internal enablers for technology implementation. We developed these items through iterative discussions with practitioners and senior academics, aimed at testing and refining the survey instrument. The following eight internal enablers were considered particularly relevant for the conducted analysis on digitalisation: *availability of data*, *fitting infrastructure*, *data harmonisation*, *top management support*, *receptive culture*, *employee commitment*, *established lean concept*, and *high level of standardisation*.

In order to reduce the number of variables, we performed an exploratory factor analysis (a principal component analysis with varimax rotation). The model suggested a three-factor solution (considering eigenvalues above 0.6) that we defined as *data management*, *company's culture*, and *standardisation* (cf. **Errore. L'origine riferimento non è stata trovata.**) in alignment with literature. The reliability of the three-factor solution was assessed by the total variance explained (68%) and by the loadings higher than 0.6. Cronbach's alpha was higher than 0.7 for *data management* and *companies' culture* (Nunnally, Bernstein, and Berge 1967) and equal to 0.6 for *standardisation*. As discussed above, the lower value was for two-item constructs. We also calculated inter-item correlations. For all the two-item factors, the inter-item correlations were significant at the 1% level. Furthermore, we tested other models with a different number of factors but they proved to be less reliable and were hardly interpretable.

Table 3. Enabler factors loadings and Cronbach's alpha.

Variable	Data management	Company's culture	Standardisation
Availability of data	0.847		
Fitting infrastructure	0.830		
Data harmonisation	0.771		
Top management support		0.766	
Receptive culture		0.762	
Employee commitment		0.718	
Established lean concept			0.833
High level of standardisation			0.811
Cronbach's alpha	*0.7940*	*0.686*	*0.586[a]*

[a] Inter-item correlation 0.4185 (p-value<0.001).

4 Results

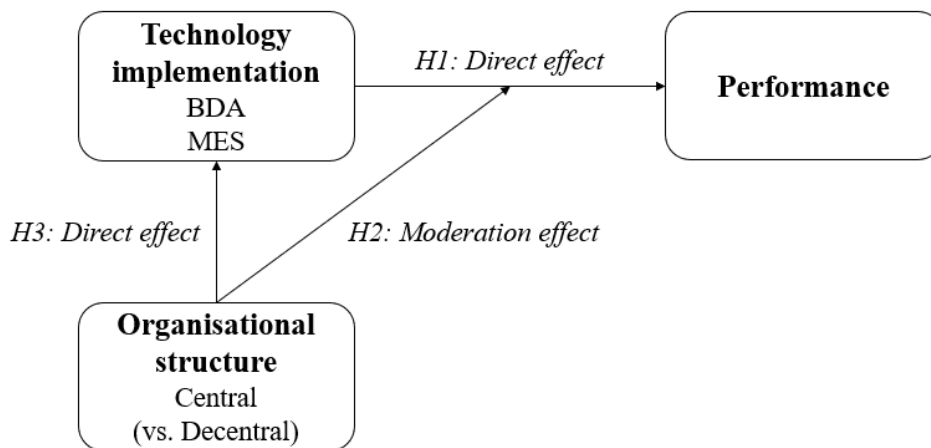Based   on   our   research   framework   in

Figure 1, we divided the analysis into two parts. First, we analysed potential direct effects of the implementation of technology on performance (H1a and H1b) and the potential moderation effects of the organisational structure (H2). Second, we analysed the potential direct effect of organisational structures on technology (*H3*).

4.1 Direct effects of technology on performance (H1a and H1b) and moderation effects of the organisational structure (H2)

In order to identify the direct effect of technology (BDA and MES) on performance and

the moderation effect of organisational structure, we evaluated the coefficients and the corresponding p-values resulting from the Ordinary Least Squares (OLS) regressions for both considered technologies (BDA and MES). We adopted a three-step hierarchical approach by adding the variables one by one in order to isolate the differential effect of each variable on the performance factors (dependent variables). First, we added only the control variable, i.e. the logarithmic transformation of the companies' sizes, as an independent variable. Second, we included the technological variable, i.e. either MES or BDA. Third, we added the interaction effect of the organisational structure evaluated by multiplying the technological variable and the organisational structure dummy variable (cf. **Errore. L'origine riferimento non è stata trovata.**).

To assess the robustness of the result, we also tested the relations by using an ordered logistic regression where the technology variable was the dependent variable since we measured technology adoption on an ordinal scale. However, we did not find different results than the OLS regression solution. Moreover, for each regression, we checked all the assumptions regarding OLS regressions and ensured that we did not violate them.

We also checked the R-squared change from one model to the following in order to assess whether the models with more variables had more explanatory power than the others.

Errore. L'origine riferimento non è stata trovata. presents the overall results of the regression analyses. We indicate the standardised beta coefficients and the corresponding p-values.

Table 4. Results from the regression analyses of technologies on performance.

Independent variables	Dependent variable: business perf.					Hypothesis supported/ not supported
Company size	0.128	0.095	0.097	0.027	0.030	
BDA		0.105	0.085			H1 not supported
BDA*Central org. structure			0.022			H2 not supported
MES				0.299 **	0.266 **	H1 supported
MES*Central org. structure					0.097	H2 not supported
# Observations	*86*	*86*	*85*	*78*	*77*	
R-squared	*0.016*	*0.026*	*0.026*	*0.097*	*0.105*	

Independent variables	Dependent variable: adaptive perf.					Hypothesis supported/ not supported
Company size	0.019	-0.009	0.009	0.042	0.051	
BDA		0.101	0.024			H1 not supported
BDA*Central org. structure			0.146			H2 not supported
MES				0.029	-0.033	H1 not supported
MES*Central org. structure					0.170	H2 not supported
# Observations	*91*	*91*	*89*	*83*	*81*	
R-squared	*0.000*	*0.010*	*0.025*	*0.003*	*0.028*	

Independent variables	Dependent variable: product enhancing perf.					Hypothesis supported/ not supported
Company size	0.234 **	0.151	0.221 **	0.148	0.203 *	
BDA		0.245 **	0.030			H1 supported
BDA*Central org. structure			0.436 ***			H2 supported

						Hypothesis supported/not supported
MES				0.236 *	0.041	H1 supported
MES*Central org. structure					0.448 ***	H2 supported
# Observations	*81*	*81*	*80*	*73*	*72*	
R-squared	*0.055*	*0.108*	*0.254*	*0.110*	*0.278*	

Independent variables	**Dependent variable: internal process perf.**					**Hypothesis supported/ not supported**
Company size	0.005	-0.087	-0.073	-0.086	-0.086	
BDA		0.319 ***	0.254 **			H1 supported
BDA*Central org. structure			0.140			H2 not supported
MES				0.296 **	0.251 **	H1 supported
MES*Central org. structure					0.160	H2 not supported
# Observations	*89*	*89*	*87*	*81*	*79*	
R-squared	*0.000*	*0.093*	*0.107*	*0.076*	*0.105*	

(* $0.05 <$ p-value < 0.10, ** $0.01 <$ p-value < 0.05, *** p-value < 0.01)

If we consider the relationships between the evaluated technologies and performance, it appears that both technologies significantly affect at least two performance factors (cf. **Errore. L'origine riferimento non è stata trovata.**). In particular, we found significant results for BDA on *product-enhancing* and *internal process performance* as well as for MES concerning *business*, *product-enhancing*, and *internal process performance* (cf. **Errore. L'origine riferimento non è stata trovata.**).

Two considerations need to get highlighted in the R-squared analysis. First, the hierarchical process proved to be consistent since the R-squared values increased in the complete models (those which included all the variables) for both technologies. Second, the R-squared values were quite low. Concerning the latter one, we note that literature on

factors potentially influencing both technologies and performance is enormous, and we consider just one variable (i.e. the organisational structure). Low R-squared values mean many other variables may exist that may explain the relationships.

4.2   *Direct effects of the organisational structure (H3)*

In order to consider the effect of the (centralised or decentralised) organisational structure on the constructs identified in the model (cf.
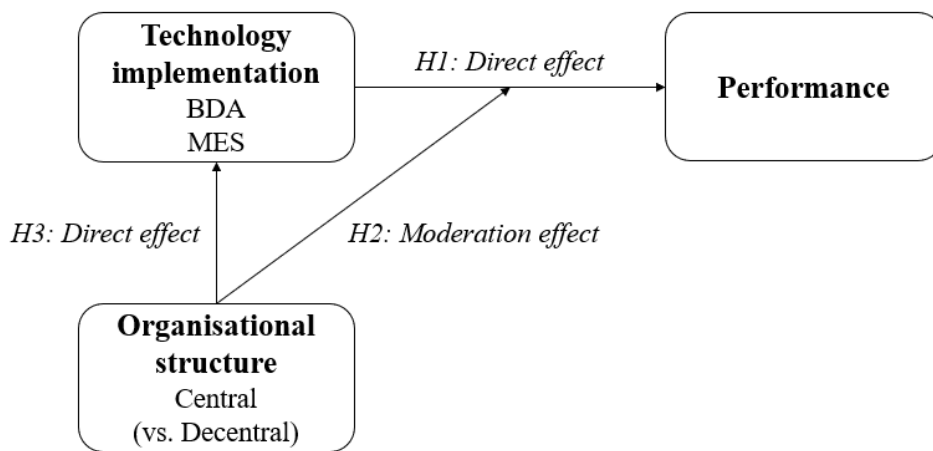

Figure 1), we performed hierarchical regression analyses in which the organisational structure was the independent variable and the technology, either BDA or MES, was the dependent variable (H3). In these analyses, we added company size and internal enabling factors (*data management*, *company's culture*, and *standardisation*) as control variables. **Errore. L'origine riferimento non è stata trovata.** shows the results of the analyses. We indicate the standardised beta coefficients and the corresponding p-values.

Table 5. Results from the regression analyses exploring the direct effect of the organisational structure.

Independent variables	Dependent variable: BDA		Hypothesis supported/ not supported
Company size	0.319 ***	0.294 ***	
Data management	0.303 ***	0.304 ***	

Company's culture	-0.092	-0.072	
Standardisation	0.154	0.179	
Central org. structure		0.152 *	H3 supported
# Observations	*99*	*97*	
R-squared	*0.246*	*0.272*	

Independent variables	Dependent variable: MES		Hypothesis supported/ not supported
Company size	0.336 ***	0.328 ***	
Data management	0.144	0.127	
Company's culture	-0.050	-0.046	
Standardisation	0.147	0.181 *	
Central org. structure		0.075	H3 not supported
# Observations	*90*	*88*	
R-squared	*0.183*	*0.186*	

(* 0.05 < p-value < 0.10, ** 0.01 < p-value < 0.05, *** p-value < 0.01)

We only found slightly significant results for the relationship between a central organisational structure and BDA, suggesting that the implementation of this technology tends to be higher in the case of a centrally managed organisation. The previous observations regarding the R-squared analysis remain valid.

5 Discussion

The conducted analyses show a nuanced picture. The results strongly depend on the considered technology, BDA or MES. Thus, the following discussion considers each technology separately.

The obtained performance results are only partially congruent with other studies in the case of BDA. Our analysis suggests that BDA helps companies achieve both product-enhancing and internal process performance but has no significant effect on business and adaptive performance (cf.
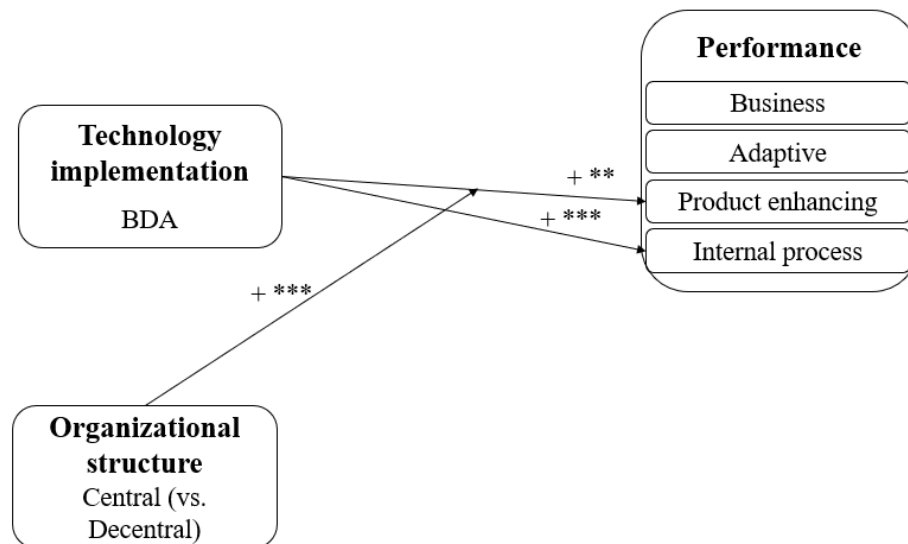

Figure 2). Dubey et al. (2019, 354) focused their investigation on big data and predictive analytics and found '… significant and positive effects on cost and operational performance'. Furthermore, other scholars have indicated that operational and internal benefits from BDA implementation could be expected (Dalenogare et al. 2018; Popovič et al. 2016). However, in order to compare these performance expectations with our study, one needs to carefully examine the performance factors (cf. **Errore. L'origine riferimento non è stata trovata.**).

The positive effect of BDA implementation on the internal process dimension certainly supports the expectations regarding operational and internal performance benefits. It has a significant as well as positive effect on delivery speed and product quality. Flexibility is also an operational performance indicator (Miller and Roth 1994). We assigned two items that measure flexibility to the adaptive performance factor, which, according to our analysis, is not affected by BDA at all. Thus, our findings provide an

equivocal picture. While our study does not confirm that BDA has any effect on the adaptive elements of operational performance, it does substantiate that BDA has a positive effect on internal process performance. The latter implies enhanced delivery speed and quality performance, which leads to cost improvements. Hence, the results confirm, at least indirectly, the positive cost effect of BDA observed by Dubey et al. (2019).
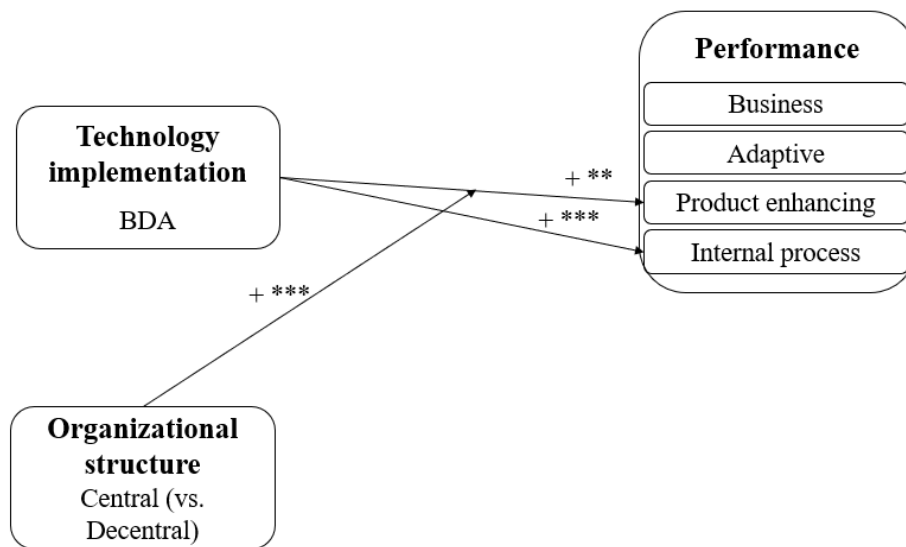
Furthermore,

Figure 2 depicts a positive effect on product-enhancing performance (service and sustainability). Several studies have pointed to the potential of digital technologies in optimising products and services (Yoo et al. 2012; Lee, Kao, and Yang 2014). These findings illustrate that firms can expect to leverage on BDA for this customer-oriented purpose, reflecting an external perspective of digitalisation.

From the RBV perspective, these results support the assertion that BDA implementation capabilities help in creating a competitive advantage through an increase in product-enhancing and internal process performance.

The findings on organisational structure regarding BDA are somewhat surprising. First, the results highlight that a centrally organised technology implementation has a

significant and positive moderating effect on the relationship between technology implementation and product-enhancing performance. This effect means that in the case of BDA implementation, a central organisational structure fosters the performance improvements connected with service and sustainability. However, this result does not hold for internal process performance. Therefore, we can conclude that the role played by the type of organisational structure varies depending on the type of performance a company expects. Thus, the results only partially support hypothesis H2.

One of the most evident findings emerging from this analysis is that the organisational structure does not have any direct effect on technology implementation (H3).

The relevance of these results is enhanced when viewed from the perspective of dynamic capabilities: The results demonstrate that the organisational structure can support the exploitation of BDA implementation capabilities with increased product-enhancing performance if defined correctly. However, this is not supported when considering internal process performance, highlighting that BDA implementation capabilities have a dynamic nature also concerning the surrounding contexts, in this case, the chosen organisational structure.
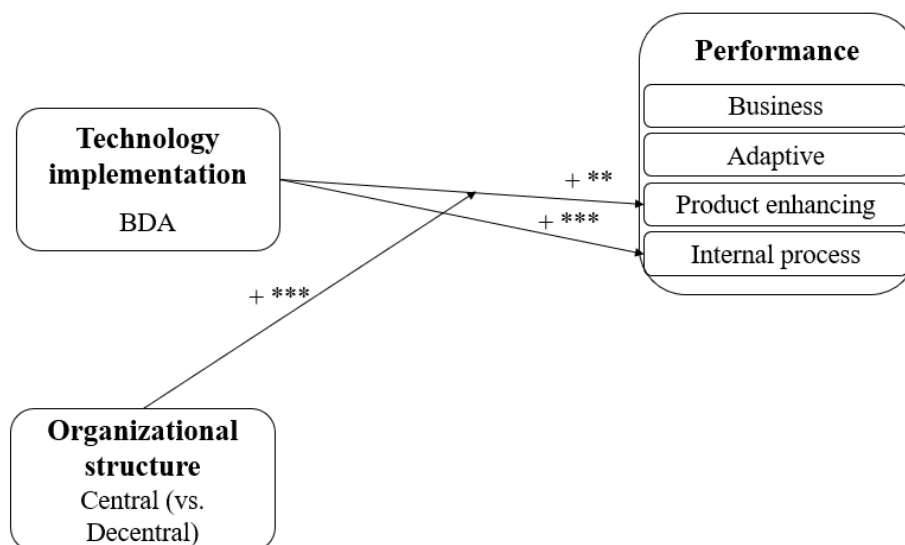
Figure 2 visually reports the results from our analyses conducted with BDA as the investigated technology.
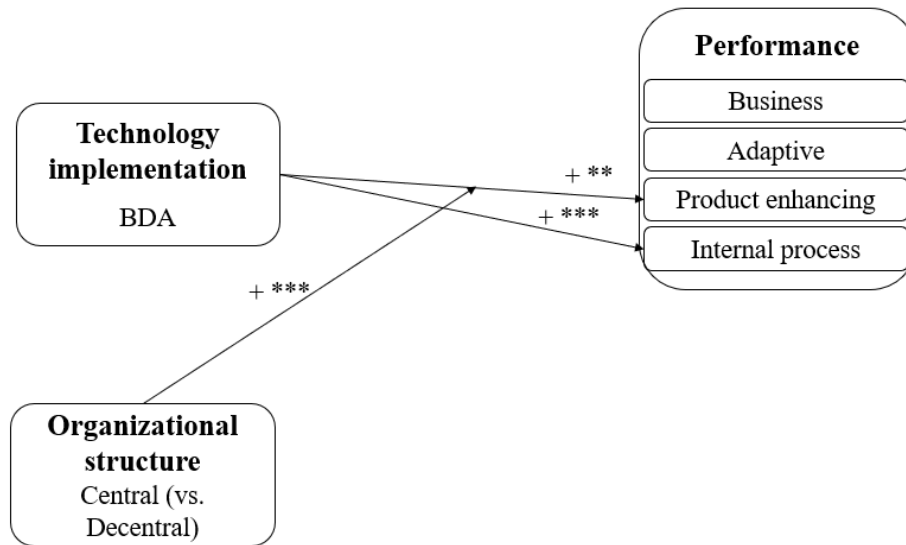

Figure 2. Visual representation of the analysis results for big data analytics (BDA).
+ = positive beta coefficient, - = negative beta coefficient
* 0.05 < p-value < 0.10, ** 0.01 < p-value < 0.05, *** p-value < 0.01

It is important to note that MES generally get adopted on a broader scale than BDA (Frank, Dalenogare, and Ayala 2019; Frisk and Bannister 2017; Sabina Jeschke et al. 2016; Mittal et al. 2017). This fact also becomes evident from the higher level of adoption of MES compared with BDA among the sample companies (cf. Table A2 in Appendix 2).

An MES commonly supports internal processes. It allows real-time visibility of flows and materials as well as a reduction of inventories and scraps. Hence, MES generally contribute to improving 'cost, quality, flexibility, conformity and reliability' (das Neves et al. 2015, 449). Contrary to these expectations, our study did not find any direct relationship between MES implementation and adaptive performance. This finding is consistent with Dalenogare et al. (2018), who observed rather pessimistic expectations about MES investments by Brazilian firms.

Nevertheless, the analysis provides evidence that MES positively and significantly affect internal process performance. These influences include delivery speed and reliability as well as product quality. All relate to the essential tasks of MES, such as scheduling or quality management (Saenz de Ugarte, Artiba, and Pellerin 2009; Helo et al. 2014).

As stated above, MES are mainly associated with internal performance expectations. Therefore, one unanticipated finding of MES was a positive effect on business performance. To explain this result, we can consider that the impact on business performance might be an indirect result of internal process effects, which can lead to business performance improvements in the long run. Finally, we found a slightly significant relationship with product-enhancing performance.

Once again, the RBV perspective allows the development of a more valuable explanation for the results. In this case, MES implementation capabilities allow the achievement of competitive advantage through increased business, product-enhancing and internal process performance. Of course, when considering a different technology, the results change, because the capabilities required to implement it properly, differ.

Scholten (2009) stated that a centralised organisational structure best implements MES. However, the results do not support a direct effect of organisational structure on the level of technology implementation (H3 is not supported). A rather significant moderation effect on the relationship between MES implementation and performance only exists when considering product-enhancing performance (H2 is partially supported).

As in the case of BDA, the chosen organisational structure moderates the relationship between MES implementation and firm performance only in specific cases. In particular, a central organisation fosters the positive effect of MES implementation capabilities on product-enhancing performance. Instead, the organisational structure does

not appear to be relevant as a booster of competitive advantages as a result of business and internal processes.

Figure 3 visually reports the results from our analyses conducted with MES as the investigated technology.
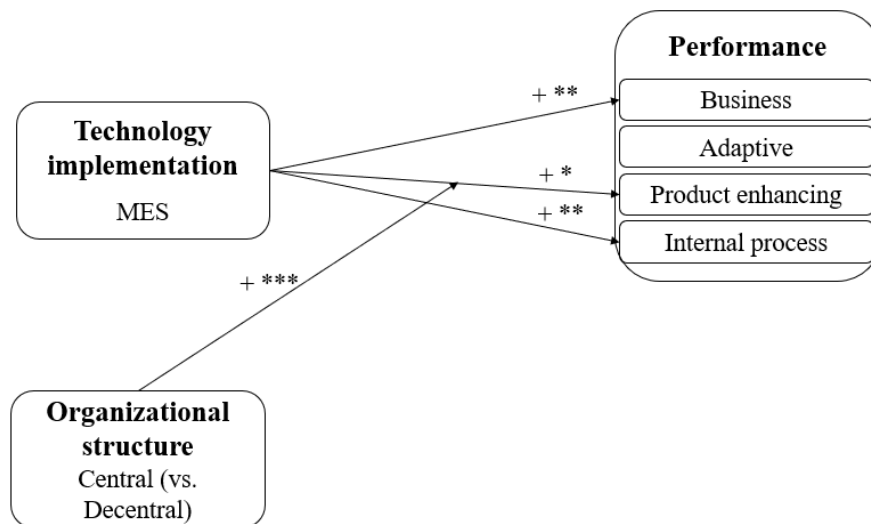

Figure 3. Visual representation of the analysis results for manufacturing execution system (MES).
+ = positive beta coefficient, - = negative beta coefficient
* 0.05 < p-value < 0.10, ** 0.01 < p-value < 0.05, *** p-value < 0.01

What stands out from the results of both I4.0 related technologies, BDA and MES, is their similarity regarding two points. First, the results for both technologies showed no effect on adaptive performance. It is somewhat surprising that both technologies seem not to be related to operational flexibility, which is the main component within the adaptive performance factor (cf. **Errore. L'origine riferimento non è stata trovata.**). A note of caution is necessary here since innovation ability is also part of the adaptive performance factor and possibly interferes with the effects on flexibility. Hence, one needs to interpret these results carefully.

Second, for both technologies, no relation between organisational structure and the level of technology implementation was found. Therefore, our study contributes to

the substantial research undertaken on the role of organisational structure in the context of digitalisation (Horlacher, Klarner, and Hess 2016; Cottyn et al. 2011; Ghobakhloo 2018; Hirsch-Kreinsen 2016). The findings point out that the I4.0 implementation progress of technologies is not related to the setup of the organisational structure.

All in all, we tested three hypotheses. Our findings support the first hypothesis depending on the technology and performance factor considered. Furthermore, our findings partially support the second hypothesis. Finally, our findings do not support the third hypothesis. Thus, we can only partially confirm the proposed model based on evidence in the literature. However, it is notable that the results differ significantly for each technology. Our research demonstrates that it is crucial to treat each technology individually and on its own instead of treating all I4.0 technologies as a homogenous group. Future research may continue exploring effects related to specific I4.0 technologies and their corresponding use cases.

6 Conclusions

I4.0, the fourth industrial revolution, is on everyone's lips. Practitioners and academics face a multitude of digital technologies associated with the concept of I4.0. Expectations regarding the performance effects of these technologies are high. However, it remains unclear exactly what to expect performance-wise. Our investigation, based on a survey of 116 participants, aimed to answer these questions with a focus on two important I4.0 related technologies, BDA and MES. In conclusion, our analyses of the two technologies indicate that:

- BDA and MES have a positive impact on distinct performance categories.

- Results sharply differ for each considered technology (either BDA or MES).

- The organisational structure does not influence technology implementation.

- The organisational structure has a positive moderating effect on specific technology-performance relationships.

6.1 Managerial implications

This research combines quantitative results with the existing knowledge base in literature, suggesting some managerial implications. First, it enhances the understanding of managers and decision-makers in manufacturing firms and equips them with some basic guidelines for action. Apart from action recommendations, managers can also utilise our analysis to support their decision-making processes. This evaluation of selected technologies proves a positive effect on performance in general. However, the results highlight that managers should not expect any adaptive performance improvements and should maintain realistic expectations regarding the business effects. Finally, we provide some guidance for firms that are unclear about their organisational setup for technology implementations. Based on our findings, it seems that the question of how to organise technology implementation is negligible.

6.2 Limitations, scientific implications and outlook

This research is subject to some inherent limitations. First, the response rate was relatively low. It may be that the length of the questionnaire deterred several participants. The survey was composed of five comprehensive sections to answer questions beyond the content of this analysis. However, as participants were mainly top-level managers or responsible for manufacturing-related functions, the sample complies with the quality demands and meets the target audience. Besides, the newness of the I4.0 topic might explain the reluctance of respondents in completing the survey.

A potential source of bias for the study is the geographic focus on individuals and firms from German-speaking countries. Given that some scholars see the cradle of I4.0

in Germany (Lu 2017; Zhou, Liu, and Zhou 2016; Liao et al. 2017; Ghobakhloo 2018), openness towards this topic and maturity in implementation of respective technologies might be higher there than in other regions. However, this focus also limits the study's comparability with evidence from quantitative research conducted globally or in other regions. Nevertheless, we encourage other scholars to conduct similar research in other countries to gain a better understanding of differences and similarities; a similar exploration of emerging economies might be particularly interesting.

This research enriches the current discussion in academia on digital technologies in the context of I4.0. First, it provides empirical evidence for the widespread expectation that I4.0 technologies have a positive performance effect. At the same time, our findings challenge the assumption that I4.0 technologies, such as BDA and MES, improve operational performance per se. Though our analysis confirmed a positive effect on, for example, internal process performance, it does not provide evidence for any effect on adaptive performance. Further research is necessary to understand these performance effects in a better way. Qualitative cases might provide a deeper understanding of the performance effects that can stem from implementing I4.0 technologies.

Our research also highlights why there is a lack of consensus in the literature about the ideal organisational structure to implement I4.0 technologies. Both centralised and decentralised organisations show no significant effect on technology implementation. However, centralised organisations moderate the relationship between technology implementation and product-enhancing performance.

However, although the MES-related literature prefers a centralised approach to implementing such systems, our analysis does not find empirical evidence to support this assumption. The choice for an organisational structure to implement digital technologies remains highly relevant, especially for manufacturing firms that operate globally

dispersed plants. These firms are currently investing significantly in I4.0 technologies. If research continues to investigate the organisational questions linked to technology implementation, it could provide them with highly relevant results for practice.

Acknowledgements

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Appendix 1   Organisational structures in the survey questionnaire

When asked for the organisational structure of their digitalisation activities, we provided the survey participants with the graphical representation shown in Figure A1 and the following definitions in the questionnaire:

- Decentralised = integrated into functional units (specialists are scattered over different departments and work exclusively for their department)

- Functional = integrated into a single functional unit (specialists are part of one functional area, which is responsible for all digitalisation related topics)

- Project / Lead Team = organised as a project or lead team (team of digitalisation specialists with members from different departments, which is responsible for all digitalisation related topics)

- Centre of Excellence (Competence) = organised as a centre of excellence (digitalisation specialists are allocated to functional units, and their activities are centrally coordinated)

- Lead Factory = organised as a lead factory (one plant fulfils all digitalisation activities and provides solutions to other sites. It leads in terms of knowledge, competency and technology)
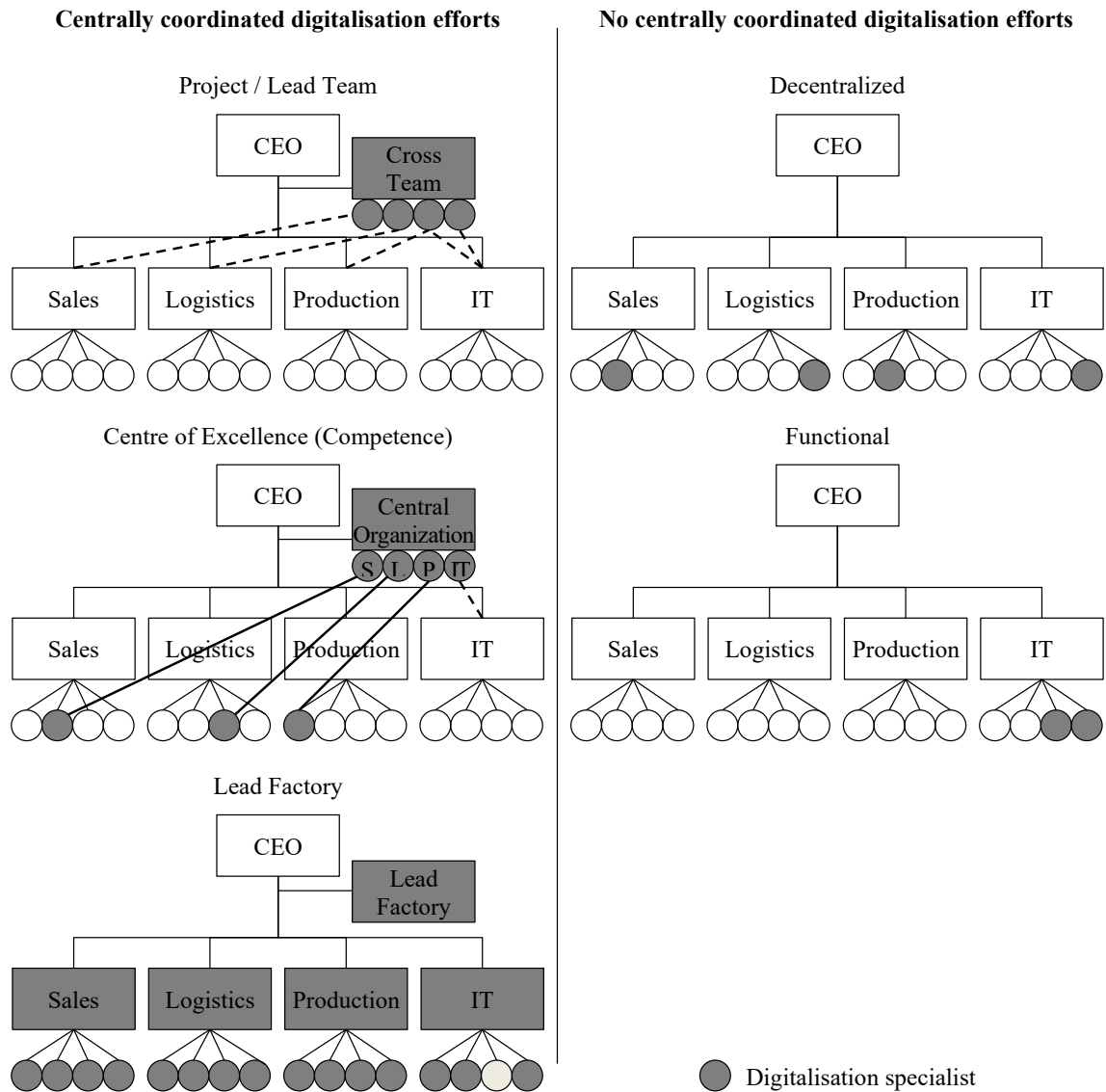
Figure A1. Graphical representation of the organisation structures that we presented to the survey participants.

As seen in Figure A1, we grouped the five different organisational structures into two categories: those that provide central coordination and those that do not provide central coordination of digitalisation activities, i.e. are decentralised. We characterise centralised coordination by at least one function with digitalisation responsibility above the level of individual departments.

Appendix 2   Descriptive statistics of the variables used in the analysis

Table A2. Descriptive statistics of the variables used in the analysis: internal enablers, technologies, performance.

Variable	No. of observations	Mean	Std. Dev.	Min.	Max.
BDA	114	3.394	1.392	2	6
MES	107	4.037	1.742	1	6
Business	87	4.978	1.013	2.33	7
Adaptive	93	5.012	0.9537	3	8
Product-enhancing	81	4.771	0.8102	3	6.5
Internal process	90	4.883	0.8212	2	6.5
SizeLn	113	6.074	2.093	0	10.9
Data management	104	5.841	0.7877	3.33	7
Company's culture	104	5.839	0.8564	2.67	7
Standardisation	104	5.293	1.137	2.5	7

Appendix 3 Relevant questions from the survey

A3.1 Industry

Which industry does your company operate in?

Please tick the industrial sector in which your company is operating. If more than one category is correct, please choose the most dominant one.

○ 10 - Manufacture of food and animal feed

○ 11 - Manufacture of beverages

○ 12 - Manufacture of tobacco products

○ 13 - Manufacture of textiles

○ 14 - Manufacture of clothes

○ 15 - Manufacture of leather and related products and shoes

○ 16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials

○ 17 - Manufacture of pulp, paper and paper products

○ 18 - Publishing, printing and reproduction of recorded media

○ 19 - Manufacture of coke and refined petroleum products

○ 20 - Manufacture of chemical products

○ 21 - Manufacture of pharmaceuticals

○ 22 - Manufacture of rubber and plastic products

○ 23 - Manufacture of other non-metallic mineral products

○ 24 - Metal production and metal processing

○ 25 - Manufacture of metal products

○ 26 - Manufacture of computer, electronic and optical products

○ 27 - Manufacture of electrical equipment

- ○ 28 - Mechanical engineering

- ○ 29 - Manufacture of automotive and automotive components

- ○ 30 - Manufacture of other transport equipment

- ○ 31 - Manufacture of furniture

- ○ 33 - Repair and installation of machinery and equipment

- ○ 32 - Production of other goods, namely: _____

A3.2 Company classification

How would you classify your company? Are you user or provider (or both) of digital technologies/solutions?

Please choose the appropriate answer.

- ☐ Provider

- ☐ User

A3.3 Size / employees

How many people are employed by your company as measured in full-time equivalents? If you do not have the exact number, please give your best estimate. Please provide a whole number and do not make use of a separator for thousands.

_____ [FTEs]

A3.4 Organisational structure

How has your company primarily organised its digitalisation activities/responsibilities and how does it plan to adapt it? What do you think is the optimal organisational structure? You can find an explanation for the organisational structures here (cf. information provided in Appendix 1). If no changes are planned, please select the same organisational structure for 'current' and 'planned'.

Current

Organisational Structure

- ○ I don't know
- ○ Decentralised
- ○ Functional
- ○ Project Team
- ○ Centre of Excellence (Competence)
- ○ Lead Factory

A3.5 Technology implementation

What is the current status of your company regarding the following technologies, which can be used for Industry 4.0 and digitalisation activities?

Please choose one or more options from the list.

	Implementation failed	Not relevant	Observing	Researching and developing	Working on the implementation (prototyping)	Already in first use	Fully implemented	I don't know
Big data analytics	○	○	○	○	○	○	○	○
Manufacturing execution systems (MES)	○	○	○	○	○	○	○	○
…	○	○	○	○	○	○	○	○

A3.6 Performance

How has the performance of your company changed in comparison to one of its competitors during the last three years?

Please indicate development with respect to the following factors.

	Much worse	Worse	Slightly worse	No change	Slightly better	Better	Much better	I don't know
Turnover	○	○	○	○	○	○	○	○
EBIT	○	○	○	○	○	○	○	○
Market share	○	○	○	○	○	○	○	○
Manufacturing/ operations cost	○	○	○	○	○	○	○	○
Product quality	○	○	○	○	○	○	○	○
Delivery speed and reliability (on-time)	○	○	○	○	○	○	○	○
Flexibility (design)	○	○	○	○	○	○	○	○
Flexibility (volume)	○	○	○	○	○	○	○	○
Innovative ability (product)	○	○	○	○	○	○	○	○
Image / brand recognition	○	○	○	○	○	○	○	○
Services (e.g. after-sales-service)	○	○	○	○	○	○	○	○
Sustainability	○	○	○	○	○	○	○	○