UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL

ESCOLA DE ENGENHARIA

PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

Lucas Santos Dalenogare

A INDÚSTRIA 4.0 NO BRASIL: UM ESTUDO DOS BENEFÍCIOS ESPERADOS E TECNOLOGIAS HABILITADORAS

Porto Alegre

2018

Lucas Santos Dalenogare

A Indústria 4.0 no Brasil: um estudo dos benefícios esperados e tecnologias habilitadoras

Dissertação submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul como requisito parcial à obtenção do título de Mestre em Engenharia de Produção, modalidade Acadêmica, na área de concentração em Sistemas de Produção.

Orientador: Alejandro Germán Frank, Dr.

Porto Alegre

2018

Lucas Santos Dalenogare

A Indústria 4.0 no Brasil: um estudo dos benefícios esperados e tecnologias habilitadoras

Esta dissertação foi julgada adequada para a obtenção do título de Mestre em Engenharia de Produção na modalidade Acadêmica e aprovada em sua forma final pelo Orientador e pela Banca Examinadora designada pelo Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul.

Prof. Dr. Alejandro Germán Frank
Orientador PPGEP/UFRGS

Prof. Flávio Sanson Fogliatto, *PhD*.
Coordenador PPGEP/UFRGS

Banca Examinadora:

Professor Glauco Henrique de Sousa Mendes, Dr (PPGEP/UFSCAR)

Professor Michel José Anzanello, *Ph.D*. (PPGEP/UFRGS)

Professor Tarcisio Abreu Saurin, Dr. (PPGEP/UFRGS)

"We live in a society exquisitely dependent on science and technology, in which hardly anyone knows anything about science and technology." (Carl Sagan)

AGRADECIMENTOS

Primeiramente, meus agradecimentos ao Prof. Alejandro Frank, orientador deste trabalho, pelo direcionamento e no auxílio da compreensão do tema e dos métodos aplicados no artigo. Mais que tudo, agradeço pela grande paciência, o incentivo, a confiança e por tudo que aprendi na elaboração desta dissertação.

Agradeço também ao Prof. Néstor Ayala pelos direcionamentos, as contribuições nos artigos e na dissertação como um todo, e também pela paciência e confiança. Seu apoio foi fundamental.

Aos dois professores, Alejandro e Néstor, gostaria de agradecer também por incentivar e inspirar a excelência, sempre motivando ótimos trabalhos.

Meu agradecimento especial a meus pais, José Rui e Rosane, e minha irmã Bruna, que me apoiaram e estiveram ao meu lado, sempre!

Meus agradecimentos aos amigos, especialmente ao Ivan Dal Bosco, que me ajudou nos problemas técnicos.

Agradeço ao Me. Guilherme Benitez, que além de co-autor do primeiro artigo, dispôs do seu tempo para me ajudar com a pesquisa acadêmica.

Minha gratidão a toda equipe do NEO UFRGS pelo apoio, tornando as rotinas melhores.

Meus agradecimentos a todo o Departamento de Engenharia de Produção UFRGS.

Por fim, agradeço aos professores da banca examinadora por aceitarem o convite e se dedicarem à leitura desta dissertação.

CRÉDITOS

A pesquisa apresentada nesta dissertação foi desenvolvida no Núcleo de Engenharia Organizacional da Universidade Federal do Rio Grande do Sul (NEO/UFRGS), como parte integrante do Programa de Pós-graduação em Engenharia de Produção da mesma universidade (PPGEP/UFRGS).

A presente pesquisa forma parte do projeto "*Gerenciamento de stakeholders para implementação da Indústria 4.0 em empresas gaúchas: uma análise focada na transformação dos modelos de negócios industriais*" financiado pela Fundação de Amparo à Pesquisa do Estado do Rio Grande do Sul mediante o edital FAPERGS/Pq-G 2017.

O desenvolvimento da dissertação também foi possível graças à bolsa de mestrado que o candidato recebeu da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) do Ministério de Educação – Governo Federal do Brasil.

Parte da coleta de dados foi possível graças à parceria do NEO/UFRGS com a Associação Brasileira da Indústria de Máquinas e Equipamentos (ABIMAQ), Regional Sul, mediante o projeto de pesquisa industrial intitulado "*Mapeamento das demandas e ofertas tecnológicas da ABIMAQ-RS para a Indústria 4.0*".

RESUMO

A Indústria 4.0 surge com o objetivo de desenvolver fábricas inteligentes, com alto grau de autonomia e flexibilidade, através da adoção de tecnologias digitais de forma integrada nas empresas e suas cadeias de valor. Ao mesmo tempo, a Indústria 4.0 promove benefícios que vão além da performance operacional, como o desenvolvimento de novas ofertas e novos modelos de negócios para as empresas. A Indústria 4.0 é originada na Alemanha, país com alta performance tecnológica, e rapidamente inspira outras iniciativas no mundo inteiro, inclusive em países emergentes como o Brasil. Estes países possuem maiores barreiras para a adoção das tecnologias relacionadas ao conceito, principalmente devido à atual situação tecnológica dos seus parques industriais. Embora a Indústria 4.0 seja um tema crescente na literatura, ainda existem grandes lacunas de estudo sobre a adoção de tecnologias relacionadas ao conceito no contexto de países emergentes, principalmente por se tratar de uma iniciativa recente. Logo, o objetivo desta dissertação é estudar o conceito da Indústria 4.0 no Brasil, de forma a entender quais são os benefícios do conceito para a performance industrial e as tecnologias habilitadoras. O trabalho tem uma abordagem quantitativa, com análises estatísticas aplicadas em dados de pesquisas *surveys* conduzidas em nível nacional. Os principais resultados obtidos foram: (i) identificação da relação entre as tecnologias e os benefícios esperados do conceito, (ii) identificação de disparidades entre a percepção industrial brasileira e a literatura sobre os benefícios da Indústria 4.0, (iii) identificação da abrangência do conceito da Indústria 4.0, compreendendo elementos que transcendem a manufatura avançada, e (iv) identificação de tecnologias habilitadoras para a implantação do conceito. Sob a perspectiva acadêmica, esta dissertação traz importantes contribuições para o entendimento do conceito e das tecnologias da Indústria 4.0, assim como o impacto destas na performance industrial. Do ponto de vista prático, os resultados auxiliam na compreensão de um tema de alta relevância empresarial, contribuindo com perspectivas para a diretriz estratégica das empresas à Indústria 4.0.

Palavras Chaves: Indústria 4.0, quarta revolução industrial, adoção de tecnologias, performance industrial,.

ABSTRACT

Industry 4.0 arises with the goal to develop smart factories, with advanced autonomy and flexibility, through the adoption of digital technologies in an integrated manner in companies and in their value chains. The Industry 4.0enables benefits beyond operational performance, as the development of new offerings and new business models for companies. Industry 4.0 was developed in Germany, a country with high technological performance, and quickly inspires other initiatives in the whole world, in developed and emergent countries such as Brazil. These countries face major barriers for the adoption of technologies related to the concept, mainly due to the current technological level of their industrial sites. Even though Industry 4.0 is a growing field in literature, there are still considerable gaps of studies about the adoption of technologies related to the concept in the context of emergent countries, mostly due to its novelty. Therefore, this dissertation aims to study the concept of Industry 4.0 in Brazil, in order to understand its benefits for industrial performance and its enabling technologies. This study has a quantitative approach, with statistical analysis of data from national surveys. The main outcomes obtained were: (i) the identification of a relation between technologies and the expected benefits of the concept, (ii) the identification of disparities between Brazilian industrial perception and the literature about Industry 4.0 benefits, (iii) the identification of a wide scope of Industry 4.0 concept, comprising elements that transcends smart manufacturing, and (iv) the identification of enabling technologies for the implementation of the concept. Under academic perspective, this dissertation brings important contributions to understand the Industry 4.0 concept and technologies, and its impact on industrial performance. As practical contributions, the results contribute for the understandings of a high relevant theme for companies, contributing with perspectives for their strategical orientation towards Industry 4.0.

Key words: Industry 4.0, fourth industrial revolution, adoption of technologies, industrial performance.

SUMÁRIO

LISTA DE FIGURAS

LISTA DE TABELAS

1 INTRODUÇÃO

1.1 Contexto da pesquisa

A Indústria 4.0 começou como uma iniciativa do governo alemão para desenvolver o conceito de fábricas inteligentes – fábricas com alto grau de autonomia e flexibilidade, integradas em toda a cadeia de valor e no ciclo de vida do produto (WANG et al., 2016; TAO et al., 2018) –, visando a maior produtividade e eficiência do setor industrial do país e novas oportunidades de mercados. A iniciativa conta com uma parceria com universidade e empresas, de forma a desenvolver as competências necessárias e difundir as tecnologias que possibilitam as fábricas inteligentes (KAGERMANN et al., 2013).

O objetivo da Indústria 4.0 deveria ser alcançado com a adoção de tecnologias digitais em dimensões operacionais e administrativas, de forma integrada (ADOLPHS et al., 2015; GILCHRIST; 2016). Mesmo que algumas tecnologias compreendidas pelo conceito já estão sendo implementadas em âmbito industrial, suas aplicações têm alcance limitado, geralmente dando suporte apenas às atividades específicas e isoladamente nas funções de uma empresa, enquanto o conceito ideal visa a uma aplicação integrada em toda a empresa e na cadeia de valor em que esta está situada (LU; WENG, 2018; KAGERMANN et al., 2013; JESCHKE et al., 2017). A aplicação integrada implica em uma grande mudança de paradigma no funcionamento dos novos sistemas produtivos, que poderão responder às flutuações de demandas de consumidores, incluindo a produção de produtos customizados em larga-escala, com maior agilidade (BRETTEL et al., 2014).

As tecnologias consideradas no conceito da Indústria 4.0 também habilitam o desenvolvimento de novos produtos com maior valor agregado (KAGERMANN et al., 2013). Estes produtos possuem capacidades digitais que comportam serviços complementares à oferta do produto, que também pode ser oferecido como um serviço através de product-service systems (PSS), resultando em novos modelos de negócio para as empresas (PORTER; HEPPELMANN, 2015; ZHONG et al., 2017).

Rapidamente, a iniciativa da Indústria 4.0 tem chamado atenção de grandes empresas de consultoria, que enxergam grandes oportunidades de negócios e um forte impacto econômico em nível global com a adoção das tecnologias habilitadoras do conceito (RÜßMANN et al., 2015; WEE et al., 2015; BERGER, 2014; SNIDERMANN et al., 2016). Ainda, o impacto dessa adoção é corroborado com o desenvolvimento de iniciativas por outros países com objetivos semelhantes aos da Indústria 4.0, como a parceria *Advanced Manufacturing* nos Estados Unidos e a iniciativa *La Nouvelle France Industrielle* na França (LIAO et al., 2017). Com a Indústria 4.0 como base, iniciativas foram desenvolvidas também em países emergentes, como o *Made in China 2025*, na China (LU, 2017), e o Rumo à Indústria 4.0, no Brasil (ABDI, 2017).

Desta forma, a Indústria 4.0 é considerada como o início da quarta revolução industrial, na qual pesquisadores, agências governamentais e empresas preveem grandes alterações de paradigmas que vão além da tecnologia empregada na manufatura, envolvendo também alterações nas abordagens de gestão, características mercadológicas e capital humano, conforme percebido nas três revoluções anteriores (YIN et al., 2018; DRATH; HORCH, 2014; STOCK et al., 2018).

1.2 Problema de pesquisa, tema e objetivos

1.2.1 Problema de pesquisa

A Indústria 4.0 surge com o objetivo de desenvolver fábricas inteligentes, que visam a solucionar problemas enfrentados pelo setor industrial e trazer novos benefícios que vão além da maior produtividade das fábricas (KAGERMANN et al., 2013; LU, 2017). Este objetivo será realizado através da adoção de tecnologias digitais nas empresas, cuja implementação holística em um sistema produtivo ainda é objeto de estudos para a sua viabilização, uma vez que é caracterizada por alta complexidade (LEE et al., 2015; ZHONG et al., 2017; GILCHRIST, 2016). Porém, algumas aplicações das fábricas inteligentes já são possíveis, as quais algumas empresas já se beneficiam com a adoção destas tecnologias, principalmente em países desenvolvidos.

Países desenvolvidos como a Alemanha e EUA efetivamente desenvolveram parques industriais sobre o preceito da automação da terceira revolução industrial, que serve como base para as fábricas inteligentes da quarta revolução industrial (KAGERMANN et al., 2013). Enquanto isso, em países emergentes como o Brasil, alguns setores industriais ainda estão no processo de automação, tornando estes países menos preparados para a Indústria 4.0 (CNI, 2016). Ainda, considerando o alto grau de inovação tecnológica do conceito, a disparidade entre países desenvolvidos e emergentes é acentuada, uma vez que países desenvolvidos realizam maiores investimentos em pesquisa e desenvolvimento (GUAN et al., 2006).

Considerando que o conceito da Indústria 4.0 é caracterizado por alta inovação tecnológica e por uma abrangência que transcende a manufatura, existem muitas lacunas sobre as tecnologias habilitadoras, assim como o impacto destas na competitividade das empresas. Por se tratar de um conceito muito recente, os primeiros estudos provêm de áreas de consultoria ou pesquisas industriais (e.g. RÜßMANN et al., 2015; WEE et al., 2015; BERGER, 2014). As principais pesquisas acadêmicas em periódicos científicos de alto fator impacto têm aparecido somente a partir de 2017 (e.g. SANTOS et al., 2017; QUEZADA et al., 2017; BOKRANTZ et al., 2017), destacando-se as edições especiais de periódicos tais como o *International Journal of Production Economics*. Contudo, a maior parte desses estudos tratam aspectos específicos da implementação de algumas tecnologias da Indústria 4.0, sem avaliar esta como um conceito abrangente com suas implicações para a gestão de operações. Nesse sentido, um dos problemas que se destacam é a ausência de evidências empíricas sobre os impactos que as tecnologias da Indústria 4.0 podem trazer sobre o desempenho operacional das empresas. Ao invés desta nova tendência ser aceita como um dogma, é necessário comprovar empiricamente os seus efeitos nas empresas. Isto torna-se mais necessário quando considerado o contexto específico do Brasil como um país emergente, o qual enfrenta diversas dificuldades estruturais para a implantação de inovações tecnológicas, tal como já o apontou no passado uma pesquisa de larga escala conduzida por Frank et al. (2016). Portanto, propõe-se a seguinte questão de pesquisa: *Existem benefícios para a performance industrial vindos da implementação da Indústria 4.0 no Brasil?* No caso afirmativo*, quais esses benefícios e de quais tecnologias que compõem esse grande* *conceito eles provêm?* E, além disso, *como essas tecnologias são e podem ser implantadas para obter os benefícios esperados?*

1.2.2 Tema e objetivos

O tema desta dissertação é a adoção de tecnologias digitais difundidas pelo conceito da Indústria 4.0 em países emergentes, considerando o impacto destas na performance industrial.

O *objetivo geral* deste trabalho consiste em estudar o conceito da Indústria 4.0 no contexto do Brasil, de forma a entender quais são os benefícios da Indústria 4.0 e as tecnologias habilitadoras.

O objetivo geral pode ser desdobrado nos seguintes *objetivos específicos*:

(i) Entender os benefícios esperados com o conceito da Indústria 4.0 na indústria brasileira.

(ii) Estudar quais tecnologias relacionadas ao conceito de Indústria 4.0 permitem tais benefícios; e

(iii) Definir o(s) padrão(es) de adoção de tecnologias da Indústria 4.0 no contexto das empresas brasileiras.

1.3 Justificativa do tema e dos objetivos

A Indústria 4.0 surgiu como conceito de um novo estágio industrial em que empresas manufatureiras precisam se adaptar para se manterem competitivas, afetando também outros setores da economia (CNI, 2016). Este estágio é caracterizado pela adoção de tecnologias digitais avançadas, de forma integrada (LU, 2017; SCHUH et al., 2017; GILCHRIST, 2016). Ainda que alguns estudos citem as tecnologias necessárias para a Indústria 4.0 (ZHONG et al., 2017; LU, 2017), existem lacunas sobre os benefícios promovidos pela adoção e a implementação destas em um sistema produtivo (STOCK et al., 2018). Estas lacunas trazem desafios para outras dimensões além da tecnológica: desenvolvimento do capital humano multidisciplinar, cadeias produtivas, infraestrutura e regulação (STOCK et al., 2018). De modo a contornar estes desafios, o governo brasileiro lançou uma iniciativa em cooperação com agentes governamentais, academia e empresas, de forma similar a outros países mais avançados no conceito. Porém, conforme estudos conduzidos pela CNI, existe um grande desconhecimento do conceito pelo setor industrial brasileiro, no qual mais da metade das empresas desconhecem as tecnologias compreendidas pela Indústria 4.0. Ainda, considerando a heterogeneidade tecnológica no setor industrial brasileiro, o *roadmap* para a implantação da Indústria 4.0 no país deve considerar a disparidade entre os diferentes setores, aumentando as dificuldades para adaptação do país ao conceito, de forma geral (CNI, 2016). Logo, de forma a orientar a adoção das tecnologias da Indústria 4.0 pelas empresas brasileiras, torna-se necessário identificar qual a infraestrutura tecnológica mínima para a Indústria 4.0, de forma a preparar as empresas para a disrupção final do conceito. Ainda, tendo em vista que as tecnologias 4.0 permitem diferentes aplicações e benefícios, tal relação deve ser entendida considerando as diferentes dimensões de performance industrial no contexto brasileiro. Dessa maneira, destaca-se a importância do tema para os propósitos práticos da sua implantação nas empresas.

Por outro lado, do ponto de vista acadêmico, a Figura 1 apresenta o relatório do Web of Science ® de uma própria pesquisa realizada em 31/08/2018 sobre artigos em periódicos científicos internacionais com os tópicos “Industry 4.0” ou “Industrie 4.0”. Observa-se que somente a partir de 2015 o tema começou a surgir e seu crescimento tende a ser crescente (observa-se que 2018 apresenta resultados só até agosto e estes já ultrapassaram o total do ano anterior), marcando uma destacada importância acadêmica para o assunto. Além disso, recentemente os principais periódicos científicos da área de gestão de operações têm realizado chamadas especiais para publicações de edições específicas sobre o tema, dentre eles destacam-se: “Industry 4.0 and Production Economics” (*I.J. of Production Economics,* 2019), “Operational Excellence towards Sustainable Development Goals through Industry 4.0” (*I.J. of Production Economics,* 2017), “Industry 4.0 and Smart Manufacturing” (*Manufacturing Letters*, 2018), “Industry 4.0 – Smart production systems, environmental protection and process safety” (Process Safety and Environmental Protection, 2018), “Implementation and acceleration of Industry 4.0” (J.*of Manufacturing Technology Management*, 2019), entre outros. A novidade do tema faz com que existam ainda diversas lacunas na literatura que precisem de uma melhor e maior compreensão, dentre elas as apontadas na problemática da presente dissertação.

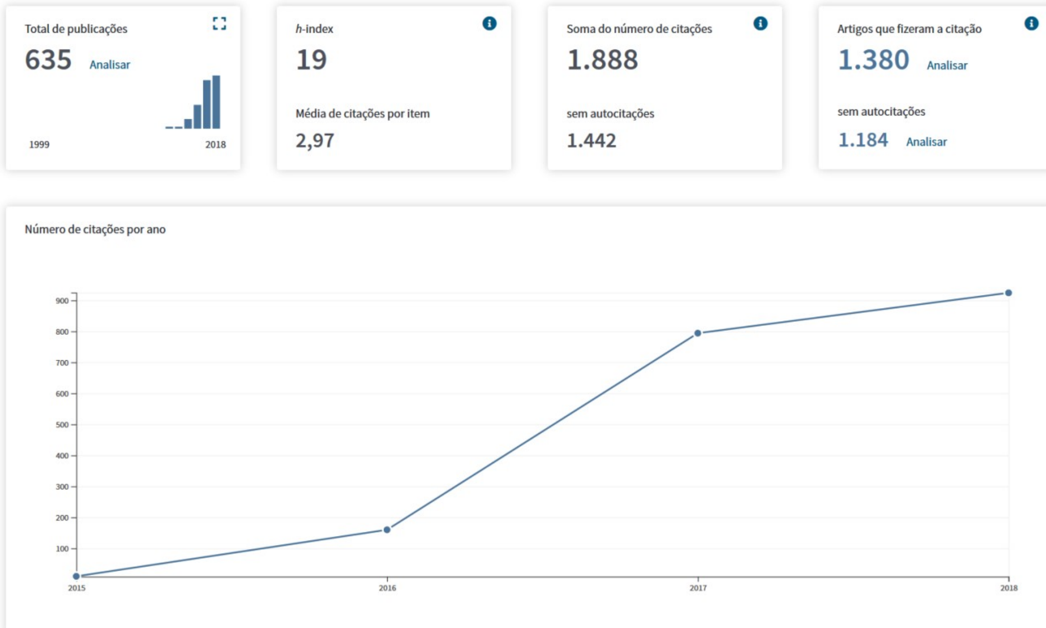

Figura 1 – Relatório de citações do Web of Science ® para os tópicos "*Industry 4.0*" OR "*Industrie 4.0*" realizado em 31/08/2018.

1.4 Método

De acordo com as definições de projetos de pesquisa de Gil (2002), este trabalho é preponderantemente de natureza aplicada, pois visa gerar conhecimentos específicos sobre aplicações práticas, envolvendo problemas indústrias reais e atuais. A pesquisa é caracterizada com uma abordagem quantitativa, pois são utilizados métodos estatísticos para analisar dados de amostras de empresas, buscando identificar padrões explicativos para o fenômeno estudado. Referente aos objetivos, o trabalho pode ser classificado como explicativo e em parte exploratório, pois busca entender relações entre variáveis (tipos de tecnologias e desempenho) e entender padrões de adoção tecnológica, através da análise de dados coletados. Por fim, uma vez que se trata de um fenômeno já iniciado, mas ainda em desenvolvimento e com alto grau de inovação, diversos procedimentos foram utilizados a fim de analisá-lo com o maior detalhamento possível. Os métodos são detalhados na Figura 2 e explicados a seguir.

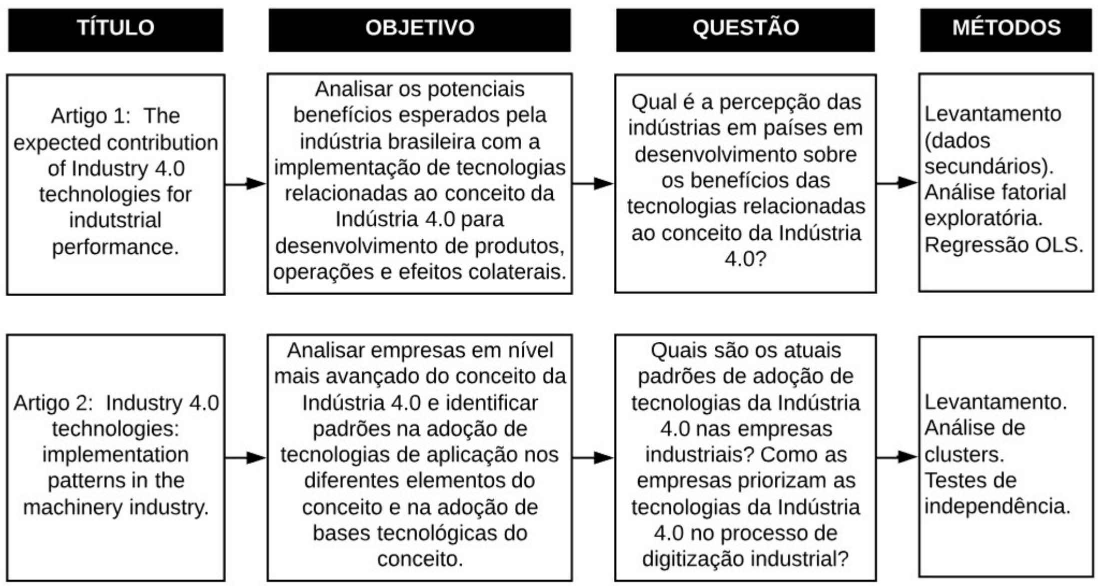

Figura 2 - Divisão da estrutura do trabalho segundo os objetivos específicos.

No Artigo 1 – "The expected contribution of Industry 4.0 technologies for industrial performance" – foi utilizada uma base de dados secundários levantada a partir de uma pesquisa de levantamento (*survey*) conduzida pela Confederação Nacional da Indústria (CNI) no Brasil, sobre Indústria 4.0. O objetivo desse artigo é identificar quais os benefícios esperados pelas empresas brasileiras do setor industrial com a adoção de tecnologias específicas do conceito da Indústria 4.0, relacionando os achados com a literatura. Para tanto, utilizou-se um método de regressão linear simples para avaliar a relação entre as tecnologias e os benefícios esperados. O método utilizado tem objetivo explicativo, pois identifica os fatores que determinam a ocorrência de fenômenos, neste caso, quais tecnologias devem ser empregadas para determinados benefícios. O procedimento realizado é do tipo expost-facto, pois através de regressão linear, analisa a existência de relações entre variáveis independentes e dependentes, sem ter o controle sobre as variáveis.

No Artigo 2 – "*Industry 4.0 technologies: implementation patterns in the machinery industry*" – foi conduzida uma pesquisa de levantamento (*survey*) em empresas nacionais do setor de máquinas e equipamentos industriais. A partir dos resultados, foi realizada uma análise de cluster e testes de independência, de forma a identificar grupos com diferentes maturidades no conceito da Indústria 4.0 e, no grupo com maior maturidade, identificar padrões de adoção das tecnologias do conceito – tecnologias de aplicação e tecnologias habilitadoras. O método utilizado tem objetivo exploratório, no qual após levantamento, foi realizada uma análise de cluster para identificar empresas com maior maturidade no conceito e realizados testes de independência para maior compreensão da adoção de tecnologias da Indústria 4.0 nestas empresas.

1.5 Delimitações do trabalho

A maior limitação desta pesquisa é a sua contextualização em países em emergentes, uma vez que o conceito analisado está em um estágio mais avançado em países em desenvolvimento, embora existam iniciativas e empresas mais avançadas no conceito em países em desenvolvimento.

Embora sejam consideradas algumas limitações técnicas referentes as tecnologias em estudo, estas limitações não são estudadas com profundidade neste trabalho, considerando o foco principal de performance industrial.

Outra limitação é que as tecnologias estudadas no Artigo 1 não são completamente correspondentes às tecnologias da Indústria 4.0 utilizadas no Artigo 2. Isso se deve ao fato que os pesquisadores não tiveram controle sobre a condução da primeira pesquisa, sendo esta de dados secundários. Nessa pesquisa, a CNI optou por considerar algumas tecnologias tradicionais da indústria dentro do conceito de Indústria 4.0 (por exemplo CAD/CAE). Por outro lado, na segunda pesquisa (Artigo 2), conduzida pelo pesquisador e colaboradores, optou-se por priorizar as tecnologias consagradas na literatura acadêmica recente sobre o tema, de maneira que haja uma maior ênfase em conceitos emergentes (por ex. inteligência artificial e realidade aumentada). Contudo, os conceitos e entendimentos trazidos por ambos os artigos continuam sendo complementares.

Outras limitações específicas de cada um dos artigos abordados são tratados diretamente nos mesmos, visando facilitar a compreensão do leitor enquanto se acompanham os resultados.

1.6 Estrutura do trabalho

Esta dissertação está estruturada em quatro capítulos. Neste primeiro capítulo introdutório foi apresentado o problema de pesquisa, a justificativa e métodos utilizados. O Capítulo 2 consiste no primeiro artigo da dissertação, voltado aos objetivos específicos (i) e (ii). O Capítulo 3 apresenta o segundo artigo da dissertação, busca atender o objetivo específico (iii). Por fim, no Capítulo 4 são apresentadas as conclusões do trabalho e sugestões de trabalhos futuros.

1.7 Referências

ABDI - Agência Brasileira de Desenvolvimento Industrial. Inovação, Manufatura Avançada e o Futuro da Indústria. 2017. Available at: (www.abdi.com.br/Estudo/ABDI_Inovacao_Manufatura_Vol01.pdf).

ADOLPHS, Peter et al. Reference architecture model industrie 4.0 (rami4. 0). **ZVEI and VDI**, Status Report, 2015.

AHUETT-GARZA, H.; KURFESS, T. A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing. **Manufacturing Letters**, v. 15, p. 60-63, 2018.

BERGER, Roland. Industry 4.0: The new industrial revolution–How Europe will succeed. **Roland Berger strategy consultants**, maart, 2014.

BOKRANTZ, Jon et al. Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030. **International Journal of Production Economics**, v. 191, p. 154-169, 2017.

CNI - Confederação Nacional da Indústria, 2016. Industry 4.0: a new challenge for Brazilian industry. Disponível em: (https://bucket-gw-cni-static-cms-si.s3.amazonaws.com/media/filer_public/54/02/54021e9b-ed9e-4d87-a7e5-3b37399a9030/challenges_for_industry_40_in_brazil.pdf).

DRATH, Rainer; HORCH, Alexander. Industrie 4.0: Hit or hype?[industry forum]. **IEEE industrial electronics magazine**, v. 8, n. 2, p. 56-58, 2014.

FRANK, Alejandro Germán et al. The effect of innovation activities on innovation outputs in the Brazilian industry: Market-orientation vs. technology-acquisition strategies. **Research Policy**, v. 45, n. 3, p. 577-592, 2016.

GIL, A. C. Como classificar as pesquisas. **Como elaborar projetos de pesquisa**, v. 4, p. 44-45, 2002.

GILCHRIST, Alasdair. **Industry 4.0: the industrial internet of things**. Apress, 2016.

GUAN, Jian Cheng et al. Technology transfer and innovation performance: Evidence from Chinese firms. **Technological Forecasting and Social Change**, v. 73, n. 6, p. 666-678, 2006.

JESCHKE, Sabina et al. Industrial internet of things and cyber manufacturing systems. In: **Industrial Internet of Things**. Springer, Cham, 2017. p. 3-19.

KAGERMANN, Henning et al. **Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group**. Forschungsunion, 2013.

LASI, Heiner et al. Industry 4.0. **Business & Information Systems Engineering**, v. 6, n. 4, p. 239-242, 2014.

LIAO, Yongxin et al. Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. **International Journal of Production Research**, v. 55, n. 12, p. 3609-3629, 2017.

LEE, Jay; BAGHERI, Behrad; KAO, Hung-An. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. **Manufacturing Letters**, v. 3, p. 18-23, 2015.

LU, Yang. Industry 4.0: A survey on technologies, applications and open research issues. **Journal of Industrial Information Integration**, v. 6, p. 1-10, 2017.

LU, Hsi-Peng; WENG, Chien-I. Smart manufacturing technology, market maturity analysis and technology roadmap in the computer and electronic product manufacturing industry. **Technological Forecasting and Social Change**, v. 133, p. 85-94, 2018.

PORTER, Michael E.; HEPPELMANN, James E. How smart, connected products are transforming companies. **Harvard Business Review**, v. 93, n. 10, p. 96-114, 2015.

QUEZADA, Luis E. et al. Operational Excellence towards Sustainable Development Goals through Industry 4.0. **International Journal of Production Economics**, v. 190, p. 1-2, 2017.

SANTOS, Maribel Yasmina et al. A Big Data system supporting Bosch Braga Industry 4.0 strategy. **International Journal of Information Management**, v. 37, n. 6, p. 750-760, 2017.

RÜßMANN, Michael et al. Industry 4.0: The future of productivity and growth in manufacturing industries. Boston Consulting Group, v. 9, 2015.

SCHEER, A. W. Industry 4.0: from vision to implementation. **Whitepaper,[Online]**, n. 9, 2015.

SCHUH, Günther et al. Industrie 4.0 Maturity Index. **Managing the Digital Transformation of Companies. Munich: Herbert Utz**, 2017.

SNIDERMAN, Brenna; MAHTO, Monika; COTTELEER, Mark J. Industry 4.0 and manufacturing ecosystems: Exploring the world of connected enterprises. **Deloitte Consulting**, 2016.

STOCK, Tim et al. Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. **Process Safety and Environmental Protection**, v. 118, p. 254-267, 2018.

WANG, Shiyong et al. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. **Computer Networks**, v. 101, p. 158-168, 2016.

WEE, D. et al. Industry 4.0-how to navigate digitization of the manufacturing sector. **McKinsey & Company**, v. 58, 2015.

YIN, Yong; STECKE, Kathryn E.; LI, Dongni. The evolution of production systems from Industry 2.0 through Industry 4.0. **International Journal of Production Research**, v. 56, n. 1-2, p. 848-861, 2018.

ZHONG, Ray Y. et al. Intelligent manufacturing in the context of industry 4.0: a review. **Engineering**, v. 3, n. 5, p. 616-630, 2017.

2 ARTIGO 1 – THE EXPECTED CONTRIBUTION OF INDUSTRY 4.0 TECHNOLOGIES FOR INDUSTRIAL PERFORMANCE*

Lucas Santos Dalenogare[1]; Guilherme Brittes Benitez[1]; Néstor Fabián Ayala[2]; Alejandro Germán Frank[1]

***This paper was accepted for publication at the International Journal of Production Economics: https://doi.org/10.1016/j.ijpe.2018.08.019.**

[1] Department of Industrial Engineering, Universidade Federal do Rio Grande do Sul, Brazil

[2] Department of Service Engineering, Universidade Federal do Rio Grande do Sul, Brazil

Abstract

Industry 4.0 is considered a new industrial stage in which vertical and horizontal manufacturing processes integration and product connectivity can help companies to achieve higher industrial performance. However, little is known about how industries see the potential contribution of the Industry 4.0 related technologies for industrial performance, especially in emerging countries. Based on the use of secondary data from a large-scale survey of 27 industrial sectors representing 2,225 companies of the Brazilian industry, we studied how the adoption of different Industry 4.0 technologies is associated with expected benefits for product, operations and side-effects aspects. Using regression analysis, we show that some of the Industry 4.0 technologies are seen as promising for industrial performance while some of the emerging technologies are not, which contraries the conventional wisdom. We discuss the contextual conditions of the Brazilian industry that may require a partial implementation of the Industry 4.0 concepts created in developed countries. We summarize our findings in a framework, that shows the perception of Brazilian industries of Industry 4.0 technologies and their relations with the expected benefits. Thus, this work contributes by discussing the real expectations on the future performance of the industry when implementing new technologies, providing a background to advance in the research on real benefits of the Industry 4.0.

Keywords: Industry 4.0; digitization; advanced manufacturing; industrial performance; emerging countries.

2.1 Introduction

Industry 4.0 is understood as a new industrial stage in which there is an integration between manufacturing operations systems and information and communication technologies (ICT) – especially the Internet of Things (IoT) – forming the so-called Cyber-Physical Systems (CPS) (JESCHKE et al., 2017; WANG; TÖRNGREN; ONORI, 2015). This new industrial stage is affecting competition rules, the structure of industry and customers' demands (BARTODZIEJ, 2017; GILCHRIST, 2016). It is changing competition rules because companies business models are being reframed by the adoption of IoT concepts and digitization of factories (DREGGER et al., 2016; LASI et al., 2014; WANG; TÖRNGREN; ONORI, 2015). From the market point of view, digital technologies allow companies to offer new digital solutions for customers, such as internet-based services embedded in products (AYALA et al., 2017; COREYNEN; MATTHYSSENS; VAN BOCKHAVEN, 2017). From the operational perspective, digital technologies, such as CPS, are proposed to reduce set-up times, labor and material costs and processing times, resulting in higher productivity of production processes (Brettel et al., 2014; Jeschke et al., 2017).

Several countries have recently created local programs to enhance the development and adoption of Industry 4.0 technologies. In Germany – where this concept was born – this program was called "High-Tech Strategy 2020", in the United States was established the "Advanced Manufacturing Partnership", in China the "Made in China 2025" and in France the "*La Nouvelle France Industrielle*" (KAGERMANN et al., 2013; RAFAEL et al., 2014; WAHLSTER, 2013; ZHOU, 2017; CNI, 2013; LIAO et al., 2017). In Brazil, the program called "Towards Industry 4.0" (*Rumo à Indústria 4.0*) was created by the Brazilian Agency for Industrial Development (ABDI – *Agência Brasileira de Desenvolvimento Industrial*) together with other initiatives of the Ministry of Industry, Foreign Trade and Services (MDIC – *Ministério da Indústria, Comércio Exterior e Serviços*) (ABDI, 2017). All these programs, in both developed and emerging countries aim to disseminate the Industry 4.0 concepts and technologies in local firms.

Nevertheless, it is well-known that the adoption of advanced technologies can be more challenging for emerging countries (HALL; MAFFIOLI, 2008; KUMAR; SIDDHARTHAN, 2013). Since the economies of emerging countries have been historically more focused on the extraction and commercialization of commodities, companies in these countries are frequently behind in terms of technology adoption, when compared to their counterparts in developed countries (CASTELLACCI, 2008). Other factors such as ICT infrastructure, culture, level of education and economic and political instability can also interfere in the value perception and in the consequent level of investments in advanced technologies (FRANK et al., 2016). Thus, even when the Industry 4.0 related technologies are presented by the literature as beneficial for firms, given the particular characteristics of developing economies, an important question emerges: *what is the perception of industries in developing countries about the benefits of Industry 4.0 related-technologies for industrial performance*?

We aim to answer this question by analyzing the potential benefits for product development, operations and side-effects aspects expected by the Brazilian industry when implementing the Industry 4.0 related technologies. We analyze secondary data from a large survey recently applied in Brazil by the National Confederation of the Industries (*Confederação Nacional das Indústrias* – CNI), which comprises a sample of 2,225 companies from different industrial segments of this emerging country. Our findings indicate that only some of the Industry 4.0 related technologies are expected as beneficial by the Brazilian industry and that it depends on the focus of the industrial sectors, i.e. focus in differentiation or cost. We also discuss some unanticipated findings regarding advance technologies with negative expected results on industrial performance.

The remaining sections of this paper are structured as follows. In Section 2, we provide the theoretical background for Industry 4.0 technologies and the expected benefits of their implementation, as well as their usefulness in emerging countries. Section 3 introduces the research method where we discuss the secondary data source and our methodological procedures for the data treatment and analysis. The results are presented in Section 4, followed by the discussions of the findings in Section 5 and the conclusions in Section 6.

2.2 Theoretical background

2.2.1 Industry 4.0 and the international technology diffusion-adoption theories

Some scholars and practitioners have considered four main industry changes throughout the history, while the Industry 4.0 is the last one and an ongoing industry transformation (QIN; LIU; GROSVENOR, 2016). The steam machine – between 1760 and 1840 – characterized the first industry revolution; the second was defined by the utilization of electricity in industrial processes in the end of the XIX century; the third revolution started in the decade of 1960 with the use of ICT and industrial automation. The fourth industrial revolution – or Industry 4.0 – emerged from several developed countries and it was consolidated in a German public-private initiative to build smart factories by the integration of physical objects with digital technologies (BRETTEL et al., 2014; HERMANN; PENTEK; OTTO, 2016). The key element that characterizes this new industrial stage is the deep change in the manufacturing systems connectivity due to the integration of ICT, IoT and machines in cyber-physical systems (CPS) (KAGERMANN; WAHLSTER; HELBIG, 2013; SCHWAB, 2016). As a result, the Industry 4.0 can be considered nowadays as a new industrial age based on the connectivity platforms used in the industry (LASI et al., 2014; PARLANTI, 2017; REISCHAUER, 2018). It considers the integration of several different dimensions of the business, with a main concern on manufacturing issues, based on advance manufacturing technologies (SALDIVAR et al., 2015; FATORACHIAN and Kazemi, 2018). In such a sense, Industry 4.0 can be understood as a result of the growing digitization of companies, especially regarding to manufacturing processes (KAGERMANN, 2015; SCHUMACHER; EROL; SIHN, 2016).

Following this concept, Industry 4.0 can be seen as a matter of technology diffusion and adoption. Emerging technologies of this new industrial age have been conceived in developed countries such as Germany, which is nowadays leading the diffusion of the concept to other countries interested in its adoption (ARBIX et al., 2017; BERNAT; KARABAG, 2018). However, the diffusion-adoption process tends to be slow and it usually flows from developed countries to developing countries (COMIN; HOBIJN, 2004; EATON; KORTUM, 1999; PHILLIPS; CALANTONE;

LEE, 1994). Therefore, different behavior patterns could be seen when analyzing digital technologies in an emerging country such as Brazil comparing to the leading countries on this issue such as Germany. According to the diffusion-adoption theories, different aspects can produce such gaps between economies. Barriers to the diffusion and adoption are frequently present (PARENTE; PRESCOTT, 1994) and the competitive environment of both the supplier side and the adopter industry also create differences (ROBERTSON; GATIGNON, 1986). As a consequence, emerging countries can have a different value perception of the diffused technologies (ALEKSEEV et al., 2018; LUTHRA; MANGLA, 2018) which may be based on different needs compared to developed countries (KAGERMANN, 2015).

Our study is based on the fact that the perceived value of technologies can be different in emerging countries, which can also change their adoption of these technologies (CASTELLACCI, 2008; CASTELLACCI; NATERA, 2013). Instead of studying the technology diffusion-adoption flow, as previously done by several other scholars (e.g. PHILLIPS et al., 1994; COMIN and HOBIJN, 2004), we focus on the current adoption and its expected benefits in the Brazilian industry. We first address the general benefits proposed by those enthusiastic on Industry 4.0. Second, we consider the Brazilian industrial context and the possible difficulties for the implementation of Industry 4.0 concepts. Then, we use empirical data to investigate the adoption levels and the expected benefits. We use the diffusion-adoption theory in order to understand better our findings.

2.2.2 Industry 4.0 and its expected benefits

The Industry 4.0 concepts are proposed to enable companies to have flexible manufacturing processes and to analyze large amounts of data in real time, improving strategic and operational decision-making (KAGERMANN; WAHLSTER; HELBIG, 2013; PORTER; HEPPELMANN, 2014; SCHWAB, 2016). This new industrial stage has been possible due to the use of ICTs in industrial environments (KAGERMANN; WAHLSTER; HELBIG, 2013) and due to the cheapening of sensors, increasing their installation in physical objects (BANGEMANN et al., 2016; BRETTEL et al., 2014; PORTER; HEPPELMANN, 2014). The advancements in these technologies allowed the development of embedded and connected systems (BRETTEL et al., 2014; JAZDI, 2014; KAGERMANN; WAHLSTER; HELBIG, 2013). These systems aim to monitor and control the equipment, conveyors and products through a cycle of feedbacks that collect a great quantity of data (big data) and update the virtual models with the information of the physical processes, resulting in a smart factory (GILCHRIST, 2016; WANG; TÖRNGREN; ONORI, 2015; WANG et al., 2016a). Therefore, since the development of digital manufacturing in the 1980s, different technologies have emerged and have been applied in production systems, such as cloud computing for on-demand manufacturing services (YU; XU; LU, 2015), simulation for commissioning (SALDIVAR et al., 2015), additive manufacturing for flexible manufacturing systems (KAGERMANN; WAHLSTER; HELBIG, 2013; WANG et al., 2016a), among others. Table 1 presents a list of ten types of technologies frequently associated to the Industry 4.0 concept (CNI, 2016; GILCHRIST, 2016; JESCHKE et al., 2017).

The technologies presented in Table 1 support the three main advantages that characterize Industry 4.0: vertical integration, horizontal integration and end-to-end engineering (KAGERMANN; WAHLSTER; HELBIG, 2013; WANG; TÖRNGREN; ONORI, 2015). The vertical integration refers to the integration of ICT systems in different hierarchical levels of an organization, representing the integration between the production and the management levels in a factory (KAGERMANN; WAHLSTER; HELBIG, 2013). On the other hand, the horizontal integration consists in the collaboration between enterprises inside a supply chain, with resource and real time information exchange (BRETTEL et al., 2014). End-to-end engineering is the integration of engineering in the whole value chain of a product, from its development until after-sales (BRETTEL et al., 2014; GILCHRIST, 2016; KAGERMANN; WAHLSTER; HELBIG, 2013).

Table 1: Technologies of the Industry 4.0

Technologies	Definition
Computer-Aided Design and Manufacturing [CAD/CAM]	Development of projects and work plans for product and manufacturing based on computerized systems (SCHEER, 1994).
Integrated engineering systems [ENG_SYS]	Integration of IT support systems for information exchange in product development and manufacturing (ABRAMOVICI, 2007; BRUUN et al., 2015; KAGERMANN; WAHLSTER; HELBIG, 2013).
Digital automation with sensors [SENSORING]	Automation systems with embedded sensor technology for monitoring through data gathering (SALDIVAR et al., 2015).
Flexible manufacturing lines [FLEXIBLE]	Digital automation with sensor technology in manufacturing processes (e.g. radio frequency identification – RFID – in product components and raw material), to promote Reconfigurable Manufacturing Systems (RMS) and to enable the integration and rearrangement of the product with the industrial environment in a cost-efficient way (ABELE et al., 2007; BRETTEL et al., 2014).
Manufacturing Execution Systems (MES) and Supervisory control and data acquisition (SCADA) [MES/SCADA]	Monitoring of shop floor with real time data collection using SCADA and remote control of production, transforming long-term scheduling in short term orders considering restrictions, with MES (JESCHKE et al., 2017).
Simulations/analysis of virtual models [VIRTUAL]	Finite Elements, Computational Fluid Dynamics, etc. for engineering projects and commissioning model-based design of systems, where synthesized models simulates properties of the implemented model (BABICEANU; SEKER, 2016; SALDIVAR et al., 2015).
Big data collection and analysis [BIG_DATA]	Correlation of great quantities of data for applications in predictive analytics, data mining, statistical analysis and others (GILCHRIST, 2016).
Digital Product-Service Systems [DIGITAL_SERV]	Incorporation of digital services in products based on IoT platforms, embedded sensors, processors, and software enabling new capabilities (PORTER; HEPPELMANN, 2014).
Additive manufacturing, fast prototyping or 3D impression [ADDITIVE]	Versatile manufacturing machines for flexible manufacturing systems (FMS), transforming digital 3D models into physical products (GARRETT, 2014; WELLER; KLEER; PILLER, 2015).
Cloud services for products [CLOUD]	Application of cloud computing in products, extending their capabilities and related services (PORTER; HEPPELMANN, 2014).

The extant literature has suggested that this integration achieved by digital technologies can promote several benefits to the industry (KAGERMANN; WAHLSTER; HELBIG, 2013). For business operations, the communication between machines and products enables reconfigurable and flexible lines for production of customized products, even for small batches (BRETTEL et al., 2014; WANG et al., 2016b). In addition, with the CPS for information processing, companies have more support for decision-making processes and have faster adaptation for several kinds of events, like production line breakdowns (SCHUH; ANDERI; GAUSEMEIER, 2017). Therefore, these systems can increase the productivity of the companies, with better efficiency of resources utilization, through the combination of production with smart grids for energy savings, for example (ALI; AZAD, 2013; JESCHKE et al., 2017). Industry 4.0 also has opportunities and benefits for business growth. Through the horizontal integration concept, collaborative networks among enterprises combine resources, divide risks and quickly adapt to changes in the market, seizing new opportunities (BRETTEL et al., 2014). Collaboration is extended to customers also, through digital channels and smart products that integrate the firm with the customers, allowing also the delivery of higher value to the latter (KIEL, D., ARNOLD, C., COLLISI, M., VOIGT et al., 2016; PORTER; HEPPELMANN, 2014). Using additive manufacturing technology, enterprises can co-design products with customers, resulting in highly customized products, increasing their perceived value (WELLER; KLEER; PILLER, 2015). Finally, with the service orientation of Industry 4.0 (GILCHRIST, 2016) and horizontal integration, new business models can be developed, with new ways to deliver and capture value from customers (CHRYSSOLOURIS et al., 2009; KAGERMANN; WAHLSTER; HELBIG, 2013).

From a socio-technical perspective (HENDRICK; KLEINER, 2001), it is acknowledged that the adoption of the aforementioned emerging technologies of the Industry 4.0 are not supported by themselves. There are at least three complementary socio-technical dimensions to the technological one to consider the digitization process towards the Industry 4.0 implementation (FRANK; RIBEIRO; ECHEVESTE, 2015): (i) organization of work - new technologies need to rethink how the organization will operate (BRETTEL et al., 2014); (ii) human factors – new technologies require new competences and skills from the workers (RAS et al., 2017; WEI; SONG; WANG, 2017); and (iii) external environment – adoption of new technologies are dependent of the maturity where they are implemented (SCHUMACHER; EROL; SIHN, 2016). We focus on two of them, the *technological* opportunities and its relation with a specific *external environment* (i.e. an emerging country). Human factors and the organization of work can be enablers that potentialize the benefits of these technologies for business performance, as previously shown in the broader literature of technology management (WESTERMAN; BONNET; MCAFEE, 2014). Thus, we consider only the first step, which is to verify the expected contribution of the technologies for industrial performance, being aware that such technologies may need a complementation of these other dimensions in a specific context.

2.2.3 Industry 4.0 in the context of emerging countries

As stated, Industry 4.0 was born in developed countries, where prior industrial stages are already mature regarding automation and ICT usage, two concepts of the third industrial revolution that converge in the Industry 4.0 (KAGERMANN; WAHLSTER; HELBIG, 2013). In this sense, emerging countries may face an important gap for the Industry 4.0 adoption due to the low maturity of prior industrial stages (GUAN et al., 2006; KRAWCZYŃSKI; CZYZEWSKI; BOCIAN, 2016). In the case of Brazil, the ICT adoption has significantly grown improving work productivity (CORTIMIGLIA; FRANK; MIORANDO, 2012; MENDONÇA; FREITAS; DE SOUZA, 2008). However, as shown in the findings of Frank et al. (2016) in a large-scale survey of Brazilian industry, the investments on software acquisition has not leaded to good results in terms of market benefits or internal manufacturing process improvement. The authors suggest that companies are investing in software acquisition simply to automatize their operational routines instead of seeking advanced ICT tools that could give them a real competitive advantage in innovation development (FRANK et al., 2016).

On the other hand, regarding manufacturing technologies, the same work of Frank et al. (2016) shows that machinery and equipment acquisition strategy resulted in poor results for innovation outcomes when compared to other innovation activities of industries in Brazil. As argued by these authors, one of the reasons is that most of the companies do not acquire leading technologies – as those from the Industry 4.0 –, but only those basics to update old industrial equipment, which is also in line with other prior works in emerging markets (e.g. FRANCO; RAY; RAY, 2011; ZUNIGA; CRESPI, 2013). In this sense, the work of Nakata and Weidner (2012) showed that most population in emerging countries has lower incomes than in developed countries, what implies that the most consumed product are low cost, making lower price a more relevant factor in competitiveness than innovativeness. This market behavior can clearly influence technology investments. Usually, firms in developing countries are focused on making investments in well-established technologies for the increase of productivity than in advanced technologies for the differentiation of products, as evidenced in prior studies, cited above. Thus, the two main pillars of Industry 4.0 – processing technologies and ICT – still seems weak in order to advance toward the fourth industrial revolution.

In addition, there are structural challenges that emerging economies may face and that can be a barrier for the Industry 4.0 establishment. One of them is that emerging economies growth are based on the low-cost workforce, especially for manufacturing activities, and it can discourage or delay investments in automation and other technologies, which usually are more expensive in these countries (CASTELLACCI, 2008; RAMANI; THUTUPALLI; URIAS, 2017). The supply chain of the manufacturing industry may be another constraint, which tend to be less integrated when compared to developed countries (MARODIN et al., 2016, 2017b). Besides, the few investments in R&D (OLAVARRIETA; VILLENA, 2014), added to the economic and political instabilities and low quality of education and research institutions (CRISÓSTOMO; LÓPEZ-ITURRIAGA; VALLELADO, 2011; FRANK et al., 2016; HALL; MAFFIOLI, 2008), configure a hard scenario for the adoption of Industry 4.0 technologies.

Finally, based on this prior research, it is clear that challenges for the adoption of Industry 4.0 technologies in emerging countries are different from those in developed countries, as it is proposed in the technology diffusion-adoption literature (PHILLIPS; CALANTONE; LEE, 1994). As the concept of Industry 4.0 is relatively new, there is a high uncertainty and lack of knowledge about the real impact and contribution of the

Industry 4.0 related technologies in the context of emerging countries in general. In order to fill this gap, our study focuses on the contribution of these technologies in the Brazilian industry, as one representative of the emergent economies which has significantly increased the industrial activities in the recent years (FRANK et al., 2016). Few studies have been conducted in this country on Industry 4.0 initiatives, while most of them come from consulting research and presents only descriptive information of this scenario. One of them is the survey conducted by Price Waterhouse Coopers (PWC) in 32 Brazilian industries (PWC, 2016), which shows a low level of digitization in several business processes. However, despite the low level of digitization, this survey shows that Brazilian enterprises expect bigger investments in digital technologies for the next years, with return in efficiency improvement, reduction of operational costs and additional business income (PWC, 2016). Other important source of information is the industrial survey conducted by the National Confederation of the Industry of Brazil (CNI, 2016), where a set of Industry 4.0 related technologies were considered and analyzed in the Brazilian industry. This survey shows that the level of implementation is still low, but that there are already some industrial sectors investing in these technologies and that an important part of the industry is concerned with this issue and is expecting new benefits from such investments. Following this last survey, we aim to deepen such analysis by investigating the association between the considered technologies and expected benefits in the CNI (2016) large-scale survey.

2.3 Research method

2.3.1 Sampling and measures

Our study focuses on a secondary data analysis of the dataset collected by the 'Special survey on Industry 4.0 in Brazil', conducted by the National Confederation of the Industries (CNI, 2016). CNI is an entity that represents the Brazilian industry and comprises 1,250 employers' unions and almost 700,000 industrial businesses affiliated. CNI promotes the interests of the industry in Brazil and as well as research and development studies[1]. This large-scale industrial survey had the purpose of obtaining a current technological overview on Industry 4.0 in Brazilian industry. CNI elaborated a questionnaire and sent it by e-mail to operations managers of 7,836 companies random selected from the population. The population of the survey is composed only by companies related to production activities (i.e. extractive and transformation sectors). The total amount of useful responses obtained was 2,225 which represents a response rate of 28.39% (CNI, 2016). The final sample represents 40,8% small, 36,6% medium and 22,6% large industrial companies from 27 sectors in Brazil (see demographic details in Table 2). Given the demographic distribution of the complete responses (questionnaires) regarding companies' size, the industrial sectors, and the regional distribution of the data collected (which included all the industrialized States of the country), we have no reasons to believe the existence of biased patterns when compared to the incomplete responses, which were not included in the final sample (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009, p.42-45). However, such level of details is not provided in the available secondary data from (CNI, 2016).

Table 2 : Demographic characteristics of the industrial sectors considered in the sample

Industrial sectors considered in the study	Mining Food products Beverages Textiles products Wearing apparel Leather and related products Footwear and parts Wood products Pulp and Paper Printing and recorded media Coke and refined petroleum products Chemicals Soap and detergents Chemicals and pharmaceuticals	Rubber products Plastics produtcs Non-metallic mineral products Basic metals Metal products (not machinery and equipment) Computers, electronics and opticals products Electrical equipment Machinery and equipment Motor vehicles, trailers and semi-trailers Other transport equipment Furniture Repair and installation Other manufacturing
Sample distribution	Total of companies in the 27 sectors: 2,225	Large companies: 500 (22.6%) Medium companies: 815 (36.6%) Small companies: 910 (40.8%)

The questionnaire used in the survey is composed by six group of main questions[2]: (i) *Key-technologies*: a list of 11 digital technologies related to the Industry

[1] Information source http://www.portaldaindustria.com.br/cni/en/about/about-cni/

2 The complete questionnaire is available at http://www.portaldaindustria.com.br/estatisticas/sondesp-66-industria-4-0/

4.0 where the companies indicate the technologies that they consider the most potential to enhancing the competitiveness of the Brazilian industry in the next five years; (ii) *Adopted technologies*: the same list of technologies where the companies indicate those technologies they are already using (iii) *Expected benefits*: a list of benefits expected from digital technologies where the companies indicate up to five benefits they expect to obtain with the technologies adopted; (iv) *Internal barriers*: a list of internal barriers the companies face in order to acquire digital technologies; (v) *External barriers*: a list of external barriers the companies face in order to acquire digital technologies (vi) *Industrial policy*: a list of possible actions the government should make to accelerate the digital technologies adoption by the Brazilian industries. For the purpose of this paper, we used data from the questions (ii) and (iii) of this survey, i.e. the digital technologies adopted and the expected benefits. Question (ii) asks: "*Indicate the digital technologies that your company already uses*". For this question, a list of 11 digital technologies are provided (see Section 3.2). Question (iii) asks "*Indicate the main benefits that your company expects to obtain by adopting digital technologies: (Indicate up to five items)"*. Here, a list of 14 benefits are provided (see Section 3.2). For both set of variables, the scale provided by the CNI database is in percentage (0% to 100%), representing the relative amount of companies of each industrial sector that have adopted a specific technology (Question ii) or that are expecting a specific benefit (Question iii).

2.3.2 Variables Selection

Since our main purpose is to understand the expected benefits of Industry 4.0 related technologies for industrial performance in Brazil, we defined as independent variables the technologies of Industry 4.0 adopted by the industrial sectors and as dependent variables the benefits expected by industrial sectors that are applying these technologies, which are both provided by the CNI (2016) survey. As presented in Table 2, the Industry 4.0 technologies are represented by 11 technologies and the expected benefits by 14 main benefits aligned with those highlighted in the literature. From the independent variables of our regression model, we did not include two technologies that are considered in the CNI survey. The first one was 'digital automation without sensors', that was excluded because it is exclusively related to the classic automation of the third Industrial Revolution. The second variable excluded was Simulation/virtual models [VIRTUAL], because it did not follows a normal distribution in the data, presenting a high value of Kurtosis (4.269) (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009), although it is directly related to the Industry 4.0 and was considered in Table 2. The data for the considered variables of our study are provided by CNI (2016) at an aggregate-level, as the percentage of companies in each industrial sector that indicated the adoption of a specific technology and the expectation for a specific benefit. Therefore, our study considers the analysis at the industrial sector level. Besides these variables, we also included two dummies as potential control variables in order to represent the three levels of technology intensity of the 27 industrial sectors under analysis (low, medium and high). These technological intensity levels are described in the CNI (2016) report. Table 3 summarizes the dependent and independent variables used in our regression model.

Table 3 : Technologies and expected benefits considered in the research model

Technologies (Independent Variables)	**Expected benefits (Dependent variables)**
Computer-Aided Design integrated with Computer-Aided Manufacturing [CAD/CAM]	Y1: Improvement of product customization
Integrated engineering systems [ENG_SYS]	Y2: Optimize automation processes[1]
Digital automation with sensors [SENSORING]	Y3: Increase energy efficiency[1]
Flexible manufacturing lines [FLEXIBLE]	Y4: Improvement of product quality
MES and SCADA systems [MES/SCADA]	Y5: Improve decision-making process[1]
Big data [BIG_DATA]	Y6: Reduction of operational costs
Digital Product-Services [DIGITAL_SERV]	Y7: Increase productivity
Additive manufacturing [ADDITIVE]	Y8: Increase worker safety[1]
Cloud services [CLOUD]	Y9: Create new business models[1]
	Y10: Reduction of product launch time
	Y11: Improving of sustainability
	Y12: Increase of processes visualization and control
	Y13: Reduce of labor claims
	Y14: Compensate for the lack of a skilled worker[1]

[1] These dependent variables were deleted from the model during the EFA procedure of variables reduction as explained in Section 3.3.

2.3.3 Variables reduction for regression analysis

To understand how the different Industry 4.0 related technologies are seen as beneficial for the industrial performance, we kept all Industry 4.0 technologies (Table 2) as single variables (not constructs) in order to differentiate the association of each of them to the expected performance outputs. We tested multicollinearity using the Variance Inflator Factor (VIF) to avoid potential mulicollinearity among these independent variables in the regression model. On the other hand, we synthesized the 14 expected benefits presented in Table 2 (i.e. industrial performance) into main categories using a Exploratory Factor Analysis (EFA)[3]. EFA technique allowed us to obtain broader performance metrics based on the partial contribution of different but correlated measures (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). Such a strategy was also used in other prior works in the operations management field (e.g. MARODIN et al., 2017a) and innovation field (e.g. FRANK et al., 2016). This helped us to study the potential contribution of the technologies for the benefits of overall performance metrics when strong correlated outputs are considered. Based on Hair et al. (2009), we divided this procedure in two steps, the validation of EFA adequacy to the sample and the reduction of variables by means of the EFA technique, as explained next.

We used three criteria to evaluate the adequacy of the data to the EFA technique: the Kaiser-Meyer-Olkin (KMO) test for measure of sampling adequacy, Bartlett's test of sphericity, and the measure of sampling adequacy (MSA)[4] (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). All these tests suggested that the dependent variables can be reduced using EFA, since the KMO test was 0.501 (i.e. it equals the threshold value recommended), while the Barlett's test of sphericity presented a p-value < 0.001 (i.e. lower than the suggested $p < 0.05$ significance level)

---

[3] EFA has been proposed as suitable also for small sample sizes (aggregated data, in our case), when the validation tests and the outputs are robust enough as those obtained in our results. For more details see MacCallum et al. (2001) and Dochtermann and Jenkins (2011).

[4] The statistical tests for both EFA and regression analysis were performed by using IBM® SPSS® Statistics version 20.

and the MSA test indicated that 75% of the variables had values higher than 0.5, as required by this test (Hair et al., 2009).

Then, we performed the EFA for the dependent variables (Table 4). We used a Varimax orthogonal rotation factor solution in order to reduce ambiguities often related to non-rotated analysis and achieve clearer and more meaningful factor solution from the EFA (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). We followed an iterative process to achieve the optimized solution where the optimal number of components were selected based on the eigenvalues, which should be higher than 1.0 (latent root criterion) and on the the percentage of variance criterion, which considers that the optimal number of components are those that exceed 60% of the total variance and ideally more than 70%; in our case we used the latter percentage (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). In the initial solution, 6 of the 14 output variables (Y2, Y3, Y5, Y8, Y9 and Y14) showed no relation to any principal components (these variables are indicated in Table 3). Therefore, they were deleted from the outputs. Then, the EFA with Varimax was performed again for the eight remaining dependent variables, which were represented in three components that explain 75.49% of the variance, as shown in Table 4. The three main components were defined according to the variables with high factor loading (>0.5) represented in them. The factorial scores for these new three outputs were obtained by means of the Thurnstones' method. Table 3 also shows the reliability analysis of the three constructs using Cronbach's alpha, being all them above the threshold value of 0.7 (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). Hence, the final three factors are: Product expected benefits [PRODUCT], Operational expected benefits [OPERATION] and Side-effects expected benefits [SIDE-EFFECTS]. The first one (PRODUCT), includes all benefits regarding the product offered, measurement of customization, quality and launch time as dimensions of the product performance. The second construct (OPERATION) considers all the metrics regarding the internal industrial activity of the factory, including costs, productivity and process control of the factory.

Lastly, we called the third component as Side-effects expected benefits [SIDE-EFFECTS] because it considers the collateral effects related to the use of digital technologies of Industry 4.0. In this third component, two benefits are included: the improvement in sustainability (or reduction of externalities) and the reduction of labor claims. Despite the main goal of Industry 4.0, which is to increase productivity, the initiative aims to reach this goal with more efficient resources utilization, possible by the use of technologies such as additive manufacturing (DE SOUSA JABBOUR et al., 2018b; KAGERMANN; WAHLSTER; HELBIG, 2013). In addition, labor claims can be reduced due to different reasons in this initiave, as this new paradigm relies less on the human force (i.e. fewer workers with potential claims) and also because some technologies aims to help workers to perform their taks (i.e. workers more assisted to do their job), e.g. human-machine collaboration systems (GILCHRIST, 2016; WANG; TÖRNGREN; ONORI, 2015). Both benefits, improving sustainability and reducing labor claims, can be related into one component as they are usually not the primary objectives expected from industries when investing in digital technologies, so these benefits can be seen as derivative from the expected primary benefits from the Industry 4.0 (CNI, 2016). Table 5 presents the correlation matrix of the final set of variables used in our analysis. This table also shows the descriptive statistics such as mean, standard deviation and the skewness and kurtosis test to verify normality of the data.

Table 4: Rotated Factor-Loading Matrix from EFA procedure

List of expected benefits from the Industry 4.0	**Factor loadings [a]**			
	PRODUCT	**OPERATIONAL**	**SIDE-EFFECTS**	**Commu-nalities**
Improvement of product customization	**0.797**	0.251	-0.171	0.727
Improvement of product quality	**0.766**	0.167	-0.309	0.711
Reduction of operational costs	0.306	**0.865**	0.026	0.843
Increase productivity	0.461	**0.609**	0.071	0.588
Reduction of product launch time	**0.868**	0.028	0.202	0.796
Improving of sustainability (externalities)	0.079	-0.076	**0.935**	0.886
Increase of processes visualization and control	-0.035	**0.818**	0.06	0.675
Reduce of labor claims (worker satisfaction)	-0.311	0.357	**0.767**	0.813
Eigenvalue	**2.986**	**1.919**	**1.135**	
% of variance explained (cumulative)	**37.32%**	**61.31%**	**75.49%**	
Cronbach's alpha	**0.807**	**0.750**	**0.720**	

[a] High factorial loadings (>0.5) are represented in bold and underlined

Table 5: Correlation matrix and descriptive analysis

		MEAN (%)	S.D.	Skweness	Kurtosis	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	**PRODUCT**	0.24	0.06	0.402	0.596	--													
2	**OPERATIONAL**	0.36	0.05	-0.639	-0.112	0.000	--												
3	**SIDE-EFFECTS**	0.07	0.02	-0.284	-0.328	0.000	0.000	--											
4	**CAD_CAM**	0.27	0.17	0.542	-0.771	0.648**	0.402*	0.080	--										
5	**ENG_SYS**	0.14	0.08	0.352	-0.683	0.597**	0.446*	0.215	0.749**	--									
6	**SENSORING**	0.20	0.09	-0.080	-0.400	-0.191	0.335	0.281	-0.157	0.229	--								
7	**FLEXIBLE**	0.06	0.04	0.343	-0.327	0.191	0.207	0.062	-0.069	0.303	0.699**	--							
8	**MES-SCADA**	0.05	0.03	0.347	-0.747	-0.305	0.297	0.234	-0.113	0.300	0.714**	0.505**	--						
9	**BIG_DATA**	0.07	0.04	0.795	0.970	-0.279	0.487*	0.187	0.045	0.246	0.256	0.109	0.516**	--					
10	**DIGITAL_SERV**	0.03	0.02	1.054	2.517	0.381	0.306	-0.104	0.226	0.363	-0.020	0.256	0.073	0.353	--				
11	**ADDITIVE**	0.04	0.04	1.415	1.308	0.625**	0.124	0.356	0.522**	0.669**	0.107	0.314	0.139	0.323	0.463*	--			
12	**CLOUD**	0.06	0.03	0.043	0.069	0.064	-0.020	0.050	-0.191	-0.207	0.409*	0.418*	0.115	-0.078	0.041	0.042	--		
13	**Control_tech_low**	0.48	0.51	0.079	-2.160	0.014	-0.395*	-0.228	-0.348	-0.298	-0.465*	-0.239	-0.244	-0.345	-0.229	-0.264	-0.114	--	
14	**Control_tech_high**	0.26	0.45	1.164	-0.702	0.279	0.415*	0.045	0.496**	0.444*	0.173	0.283	0.049	0.087	0.491**	0.356	0.225	-0.570**	--

** p< 0.01; * p<0.05.

2.4 Results

We used an ordinary least square (OLS) regression[5] to understand the association of Industry 4.0 related-technologies to three types of expected benefits: Product expected benefits [PRODUCT], Operational expected benefits [OPERATIONAL] and Side-effects expected benefits [SIDE-EFFECTS]. OLS regression should be used only if some standard requirements of the database are achieved, such as normality, linearity, and homoscedasticity (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). The skewness and kurtosis values reported in Table 5 suggest that the variables can be assumed as normal distributed, since they are below the threshold of 2.58 (α=0.01) (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). We also assessed data normality graphically by means of an examination of the residuals. We analyzed collinearity by plotting the partial regressions for the independent variables while homoscedasticity was visually examined in plots of standardized residuals against predicted value. All these requirements were met in our dataset. Moreover, multicollinearity could be also a problem for OLS regression (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009). Therefore, we tested the variance inflation factor (VIF) among the independent variables, resulting in VIF<3.5 for the independent variables and control variables, excepting for CAD/CAM, ENG_SYS and SENSORING which resulted in VIF<8.14. As all these values were below the threshold VIF=10.0, multicollinearity may not be a concern in our regression model (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009).

We performed three independent regression models, one for each of the expected benefits (i.e. PRODUCT, OPERATIONAL and SIDE-EFFECTS). The results of the regression models for the three industrial expected benefits metrics are shown in Table 6. Two of the three models were significant at $p<0.05$ and one did not show statistical significance. The first regression model ($F= 14.245$, $p<0.001$) explained 84.9% of the variance of PRODUCT; while the second model ($F=3.042$, $p = 0.024$) explained 46.3% of the OPERATIONAL variance. Lastly, we identified that SIDE-EFFECTS was not significant ($F= 0.751$, $p = 0.679$).

[5] OLS regression was performed using IBM SPSS Statistics ® version 20.

Regarding the association of the specific Industry 4.0 related technologies with the expecting PRODUCT, the following technologies presented positive and significant effects: integrated engineering systems for product development and manufacturing [ENG_SYS] (β = 0.438, p = 0.063); incorporation of digital services into products [DIGITAL_SERV] (β = 0.286, p = 0.022); additive manufacturing [ADDITIVE] (β = 0.261, p = 0.050); and Cloud Services [CLOUD] (β = 0.255, p = 0.043). In addition, one technology is negatively associated to the expected outcome of this expected benefits metric: big data analysis [BIG_DATA] (β = -0.388, p = 0.004).

In the second expected benefits metric, OPERATIONAL, the technologies with positive and significant association were: Computer-Aided Design with Computer-Aided Manufacturing [CAD/CAM] (β = 0.774, p = 0.046); digital automation with sensors for process control [SENSORING] (β = 0.778, p = 0.064) and Big Data [BIG_DATA] (β = 0.658, p = 0.008). On the other hand, additive manufacturing [ADDITIVE] had a negative association (β = -0.529, p = 0.036) to this expected benefits metric. ADDITIVE also showed a positive association to SIDE-EFFECTS (β = 0.622, p = 0.081), although the complete model for SIDE-EFFECTS was not statistical significant.

Table 6: Results of the regression analysis[(a)]

	Expected benefits for…		
	PRODUCT	**OPERATIONAL**	**SIDE-Effects**
CAD_CAM	0.310	**0.774****	-0.306
ENG_SYS	**0.438***	-0.129	0.118
SENSORING	-0.189	**0.778***	0.303
FLEXIBLE	0.212	0.062	-0.409
MES-SCADA	-0.246	-0.345	0.078
BIGDATA	**-0.388*****	**0.658*****	-0.040
DIGITAL_SERV	**0.286****	0.192	-0.308
ADDITIVE	**0.261****	**-0.529****	**0.622***
CLOUD	**0.255****	-0.149	0.009
Control_tech_low	0.257	0.379	-0.300
Control_tech_high	**0.426***	0.241	-0.126
F-value	14.245***	3.042**	0.751
R^2	0.913	0.690	0.355
Adjusted R^2	0.849	0.463	-0.118

[(a)] Significant effects are represented in bold and underlined; *p<0.1; **p<0.05; ***p<0.01.

Furthermore, we performed a statistical power analysis of our two significant models (PRODUCT and OPERATION) based on (COHEN; COHEN; STEPHEN, 2003). We first estimated the population effect size of R^2 using Cohen's f^2 estimation[6]. For the PRODUCT model we obtained a $f^2 = 10.45$, which represents a statistical power of > 0.99 at $\alpha = 0.01$, while for the OPERATION regression model the f^2 was 2.23, which represents a statistical power of ≈ 0.93 at $\alpha = 0.01$. We also considered the statistical power of the partial coefficients using Cohen's f^2 estimation for the predictors[7] and the range of effects suggested by them: 0.02– small effect, 0.15 – medium effect, and 0.35 – large effect (COHEN; COHEN; STEPHEN, 2003, p. 95). Considering the statistical significant independent variables in the PRODUCT model, two of them showed large effects: BIGDATA (0.78) and DIGITAL_SERV (0.44), while all the others showed medium effect (≥0.27). For the significant regressors in the OPERATION model, two technologies indicate large effect: BIGDATA (0.63) and ADDITIVE (0.35), while the other two CAD_CAM and SENSORING presented medium effects (0.32 and 0.27 respectively). Therefore, we can conclude that the significant effects have also satisfactory statistical power in our sample.

2.5 Discussions

We summarized our findings in Figure 1, aiming to illustrate the connections between the different Industry 4.0 related technologies and the expected benefits. We use this framework (Figure 1) to guide the discussion of our findings and to clarify how these Industry 4.0 technologies can be understood in the Brazilian context. Firstly, we divided our framework (Figure 1) in two set of technologies as our findings showed in Table 6. The first set is related to (i) *Product Development Technologies* of the Industry 4.0 while the second set is related to (ii) *Manufacturing Technologies* of the Industry 4.0. We divided technologies in these two groups because, as we shown in our results, the industrial sectors have different expectations for them. According to our findings of

---

[6] According to Cohen et al. (2003, p. 92): $f^2 = \frac{R^2}{(1-R^2)}$

[7] According to Cohen et al. (2003, p. 94): $f^2 = \frac{sr^2}{(1-R^2)}$; where sr^2 represents the squared semipartial correlation coefficient for the predictor of interest.

Table 6, technologies that are expected to contribute for Product Performance (i.e. *Product Development Technologies*) are ENG_SYS, DIGITAL_SERV, ADDITIVE and CLOUD, while the technologies expected to bring benefits for operational performance (i.e. *Manufacturing Technologies*) are CAD_CAM, SENSORING and BIGDATA. Two technologies, integrated engineering systems [ENG_SYS] and Computer-Aided Design and Manufacturing [CAD/CAM] are considered integration systems in the interface between product and operational processes, as shown in Figure 1 (TAO et al., 2018a). Next, we discuss in detail the configuration of this framework based on our findings and on prior evidences from the literature.

Firstly, regarding the *Product Development Technologies* (Figure 1), *additive manufacturing* [ADDITIVE], which in product development is represented by 3D-printing, is associated with the expected benefits for new product development. This expectation is aligned with the literature, which highlights that the use of additive technology brings several advantages since products can be digitally modified before their physical production, reducing the processing times, resources and tools needed. This technology accelerates product innovation and assists co-design activities, promoting more customized products (YIN; STECKE; LI, 2017). While additive manufacturing (3D-printing) promotes customization of the products, our findings (Table 6) show that the industry also expects *digital services in products* [DIGITAL_SERV] and *Cloud Services [CLOUD]* to increase the value perceived by the customers (Figure 1). According to Porter and Heppelmann (2014) digital services connected in the cloud are a global trend in companies, allowing them to launch smart products with embedded sensors, processors, software and connected via internet, which enables new functions and capabilities related to their monitoring, control, optimization and autonomy. With the Internet of Things (IoT), products can communicate with other products and systems of products, optimizing overall results and enabling after-sales service solutions. These technologies should improve the performance of extant products and the development of new products, and its utilization shows some degree of differentiation strategies expected by Brazilian industrial sectors. However, as the (CNI, 2016) report state, there are still few industrial sectors that incorporate digital services in their products with cloud systems and that use additive manufacturing.

On the other hand, the use of Big Data collection and analysis [BIG_DATA] showed a negative association to the benefits expected for product performance. This is a surprising result for us, since the literature describes this technology as of great potential to leverage innovation, competition and productivity in business processes (WAMBA et al., 2015). While the industry is expecting positive outcomes for integrating data in the cloud (i.e. CLOUD was positive), they do not present an optimistic perspective for the latter technology. In other words, IoT technologies are perceived as useful for real-time processing but not for data storage and analysis. This may suggest that the Brazilian industry still lags in the implementation of one of the most promising tools in the Industry 4.0 for product improvement and innovation (WAMBA et al., 2015). Therefore, even though these technologies have been widely diffused in developed countries, their diffusion and adoption in Brazil is still behind the competitive level expected. Such problem can be corroborated with a recent industrial survey conducted by PwC consulting (PWC, 2016) that indicates that around 63% of Brazilian companies considered themselves in a weak maturity level for Big data analytics, 30% in a middle maturity level and those that represented the remaining 7% outsourced data analytics competencies. As most industrial sectors do not have the capacity to properly analyze the large amount of data they generate, we conclude that this lack of knowledge might impair the perception of usefulness for the development of new products, which represents a diffusion-adoption gap for the Industry 4.0 in Brazil.

Regarding the interface between the (i) *Product Development Technologies* and (ii) *Manufacturing Technologies*, our findings (Table 6) showed that there are two complementary integration technologies: ENG_SYS, which is positively associated to PRODUCT expected benefits, and CAD/CAM, which is positively associated to OPERATIONAL expected benefits (Figure 1). We argue that based on the findings and on the fact that ENG_SYS work with the integration of the whole product lifecycle data, from the product conception to its production and commercialization (ABRAMOVICI, 2007; BRUUN et al., 2015; STARK, 2011). This technology can aid different industrial sectors to overcome the well-known communication and coordination barriers they face when involving suppliers in a collaborative NPD for complex products (LANGNER; SEIDEL, 2009; PENG; HEIM; MALLICK, 2014). Moreover, as horizontal integration is one of the main Industry 4.0 characteristics, integrated engineering systems also have an important role for connecting people, objects and systems through digital platforms, what clearly simplify the orchestration of services and applications in industrial activities (KAGERMANN; WAHLSTER; HELBIG, 2013). On the other hand, CAD/CAM can help the operational aspects for vertical integration, since it can help to translate the product lifecycle data from end-to-end engineering into product design specifications, enhancing the visibility of manufacturing processes still in the design phase (JESCHKE et al., 2017).

Following the *Manufacturing Technologies* dimension, surprisingly neither MES/SCADA nor flexible manufacturing lines [FLEXIBLE] were significantly associated to the OPERATIONAL expected benefits. Based on the extant literature, we were expecting a positive association of them, jointly with the integration systems (ENG_SYS and CAD/CAM) and the digital automation with sensors [SENSORING], as a set of standard technologies for the Industry 4.0 manufacturing system. While ENG_SYS and CAD/CAM integrate product development data with manufacturing processes (MIRANDA et al., 2017), SENSORING enables data collection in the manufacturing process (KONYHA; BÁNYAI, 2017), which could be used by the flexible manufacturing lines [FLEXIBLE] to reconfigure or adapt the processing sequence, schedule, etc. (WANG; TÖRNGREN; ONORI, 2015) with MES/SCADA support (JESCHKE et al., 2017). In other words, these technologies should form a system that enables both, horizontal and vertical integration (ZHOU et al., 2015). ENG_SYS contributes for information sharing among functional areas in the factory, both internally and externally, which in the latter constitutes the horizontal integration. FLEXIBLE and MES/SCADA contribute to the integration among process stages in the hierarchical areas. The first aims to build reconfigurable lines with sensor technology, in order to ease the change the product types in the production lines (BRETTEL et al., 2014; STEIMER et al., 2016), while MES/SCADA generate daily production orders from the ERP, considering several restrictions from machine data (Jeschke et al., 2017), SENSORING acts at the most basic levels of the equipment operation (GERBER; BOSCH; JOHNSSON, 2013). One reason because MES/SCADA and FLEXIBLE might be not statistically associated to the OPERATIONAL expected benefits is because they are in very early stage of adoption in the Brazilian industry, since only around 8% of the industry has adopted these technologies for operational processes, according to the CNI report (CNI, 2016). Thus, several industrial sectors may not be aware of their contribution for operational benefits.

Digital automation with sensors for process control [SENSORING] showed a significant association to the OPERATIONAL expected benefits, being one of the most implemented technologies (around 27%) in the industries of the survey (CNI, 2016). Even though this is one of the less advanced technologies in the Industry 4.0 concept (YU; XU; LU, 2015), it provides the basis for production cells control and data collection of manufacturing flow and cells demand, aiming to provide inputs for the flexible lines and the MES/SCADA, as shown in Figure 1. SENSORING also allows to create operational big data [BIG_DATA] – also positively significant in our findings – for further analysis aiming for predicting maintenance, machine-learning (self-adapting), scheduling for the Manufacturing Execution System (MES) and to provide information for new design and manufacturing in the CAD/CAM system (TAO et al., 2018b), as we show in the framework of Figure 1. On the other hand, it is worth noticing that cloud services [CLOUD] did not show significant association to the OPERATIONAL expected benefits while BIG_DATA did, as we explained before. Based on prior studies (e.g. GILCHRIST, 2016; JESCHKE et al., 2017) we expected a joint contribution of these technologies. One possible reason is that CLOUD is associated with external data warehousing and this is still a concern in the industry due to data security, which represent a barrier for its implementation (WANG; TÖRNGREN; ONORI, 2015).

The last Industry 4.0 technology at the operational level is additive manufacturing [ADDITIVE] which we represented in Figure 1 as overlapped with different manufacturing operations. This means that ADDITIVE could be used in different operation stages and for different production purposes. However, our findings showed a negative association of this technology with OPERATIONAL expected benefits. According to Weller et al. (2015), additive manufacturing still has several restrictions for its application in manufacturing processes, such as the availability of materials and lack of defined quality standards. Moreover, although this technology can improve product development, this equipment has still low production throughput speed, when compared to conventional manufacturing, which may affect larger-scale production levels with cost efficiency, as suggested by our results.

Finally, regarding the SIDE-EFFECTS expected benefits, Figure 1 represents it as a possible secondary perceived benefit from the Industry 4.0. Our results indicated a positive association with additive manufacturing. However, the complete model for SIDE-EFFECTS was not statistically significant – even when ADDITIVE has a positive association to this output – suggesting that this performance is not expected with the use of most of the Industry 4.0-related technologies. This is an unexpected finding, since the improvement of resource consumption efficiency is one of the main areas of Industry 4.0 (KAGERMANN; WAHLSTER; HELBIG, 2013), and the technologies analysed in this paper are suggested to contribute to sustainability (e.g. DE SOUSA JABBOUR et al., 2018a; KIEL, D., ARNOLD, C., COLLISI, M., VOIGT et al., 2016; MAN; STRANDHAGEN, 2017; STOCK; SELIGER, 2016), and indirectly for labor claim reduction, by automatizing the production process which reduces the need for manpower (e.g. HOZDIĆ, 2015). The concern with Industry 4.0 as a way to deal with these side-effects aspects has been addressed in studies of developed economies. However, when considering emerging economies such as Brazil, other aspects may be priority in the industry's concern. As acknowledged by the CNI report (CNI, 2016), the main efforts of Brazilian industries with digital technologies has been to increase productivity, while the side-effects benefits are not yet a clear objective of the industry when investing in Industry 4.0 technologies. Therefore, they could be a secondary benefit only perceived after the achievement of product and operational benefits. This is also in line with the general literature about sustainability in industry, which evidences differences in such concern between developed and emerging countries (HANSEN et al., 2018; VIOTTI, 2002).

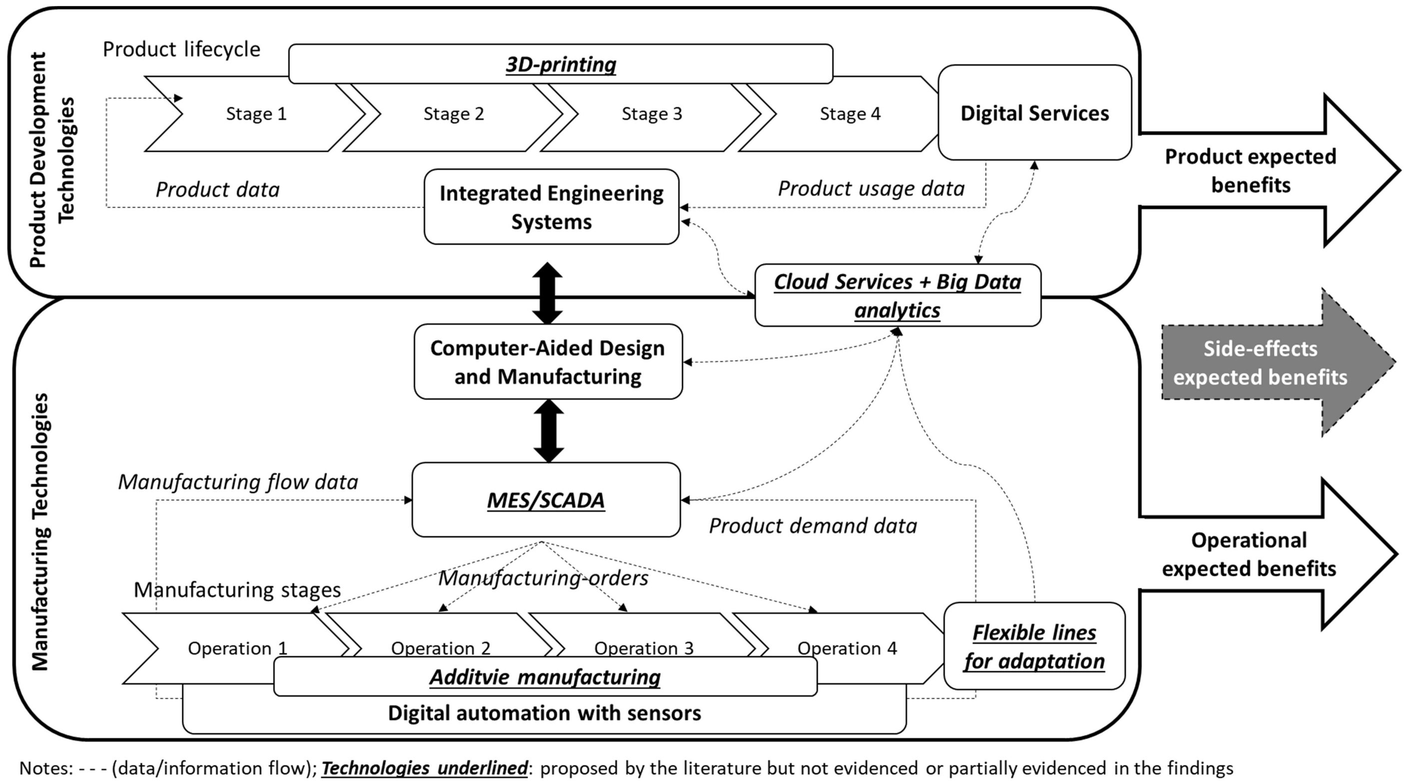

Figure 1 – Framework summarizing the findings and discussions of the paper

2.6 Conclusions

In this paper we analyzed the perception of the Brazilian Industry about the benefits of Industry 4.0 related-technologies for three industrial performance metrics: product, operational and side-effects. Our results showed that some of these technologies are positively associated to the expected industrial benefits while others are still at a very early stage of adoption and, thus, without clear expected benefits. We discussed reasons for the lack of expectation of benefits for some of the promising technologies of the Industry 4.0 in this specific emerging industry.

Our main contribution to the state-of-the-art is that we show how these technologies are used and seen in an emerging economy, since most of the studies on this matter have been conducted in developed countries. In this sense, we showed how different set of technologies are associated with different expected benefits. We showed that the Brazilian industry has not yet taken advantage from some promising technologies such as product big data analysis, cloud services for manufacturing, among other technologies for the digitalization of the factory and for the analysis of the product performance. A further contribution is that we could not find any relation between the Industry 4.0 and the expected benefits for sustainability and labor claims [SIDE-EFFECTS], which represents a different pattern when comparing to developed economies. Based on prior evidences from developed countries, we argued that since side-effects tend to be at the second level of priority in the industries, after achieving operational and product performance benefits, the Brazilian industry is still not focused on this aspect, but this deserves future investigation.

2.6.1 Practical implications

Our results can be useful for both, operations managers and industrial policy-makers. For operations management, our results showed which are expected to be the most powerful technologies to enhance product and operational performance in the Brazilian context, according to the industry perception. Companies that want to initiate their digitalization journey towards the Industry 4.0 should first think, before implementing any technology, what are their strategic goals. Thus, companies with a focus on differentiation should prioritize the implementation of those technologies pointed as significantly associated to the Product Development Technologies dimension (Figure 1), according to what is expected by the industry and the literature; while companies with a focus on low cost, productivity or operational flexibility should prioritize those Industry 4.0 technologies that have significant contribution for the Manufacturing Technologies dimension. On the other hand, industrial policy-makers in emerging countries can use our findings as a guideline about what technologies still need to be developed for the industry to achieve the competitiveness standards of developed countries. For instance, big data, cloud services and additive manufacturing (e.g. 3D printing) are strong industrial trends in developed countries that should be considered for the future of the emerging countries. However, this field needs further debates regarding the industrial policy approaches to foster the national competitiveness of the country.

2.6.2 Limitations and future research

The use of a secondary dataset for our analysis allowed us to obtain a broad overview of a still little explored emerging industry. However, some limitations are present due to this kind of research. Firstly, our results have limitations on the statistical inferences since we considered expecting benefits from the industry 4.0 technologies and not current benefits obtained from them. This is because the implementation of many of these technologies are recent and the benefits are not feasible to be obtained in the short-term. Future works can use our findings to advance in the study of real improvements, which could be done only in the middle or long-term of this new industrial trend. Experimental studies can provide quicker answers to these aspects when compared with survey studies. However, it is well known that experimental studies have also limitations regarding the generalization of the results.

Furthermore, we used aggregated-level data analysis and thus we studied the industrial sector behavior. In this sense, we call the attention to the risk of ecological fallacy, when macro-level analysis using aggregate data is used in micro-level conclusions (firm-level) (CLARK; AVERY, 1975). In this sense, our results are only valid at the industry-level behavior. Other future studies could, therefore, deepen our research by conducting company-level surveys. We also studied a cross-sectional sample, thus future longitudinal studies on the effect of the Industry 4.0 technologies could evidence patterns and maturity levels of the adoption of such technologies. We know that future research is called to address the endogeneity problems that can be present in large-scale survey studies (BASCLE, 2008), especially because the adoption of technologies might depend not only on internal decisions but on the access to public funds and other kind of governmental incentives (FRANK et al., 2016). There are other inherent aspects regarding endogeneity in operations management that we did not addressed in this work and are part of an emerging discussion in this field (KETOKIVI; MCINTOSH, 2017). We were aware about these limitations, but due to the limitation of information in our dataset we cannot include instrumental variables that may be helpful to test alternative models to the OLS models used in this paper. Finally, we mentioned in our work that, from a sociotechnical perspective, organizational and human factors are very relevant to the implementation of technologies. Since we delimited our research only to technological factors in a specific environment, future studies could expand to these other two factors, in order to consider how they facilitate or not the implementation of the technologies addressed in our work.

2.7 References

ABDI - AGÊNCIA BRASILEIRA DE DESENVOLVIMENTO INDUSTRIAL. **Inovação, Manufatura Avançada e o Futuro da Indústria**. [s.l.] Available at: (www.abdi.com.br/Estudo/ABDI_Inovacao_Manufatura_Vol01.pdf), 2017.

ABELE, E. et al. Mechanical module interfaces for reconfigurable machine tools. **Production Engineering**, v. 1, n. 4, p. 421–428, nov. 2007.

ABRAMOVICI, M. Future Trends in Product Lifecycle Management (PLM). In: **The Future of Product Development**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007. p. 665–674.

ALEKSEEV, A. et al. Financial Strategy of Development of Industry 4.0 in the Countries with Developing Economy. **Revista ESPACIOS**, v. 39, n. 12, 2018.

ALI, A. B. M. S.; AZAD, S. Demand Forecasting in Smart Grid. In: [s.l: s.n.]. p. 135–150.

ARBIX, G. et al. Advanced Manufacturing: What Is to Be Learnt from Germany, the US, and China. **Novos Estudos CEBRAP**, v. 36, n. 3, p. 29–49, 2017.

AYALA, N. F. et al. Knowledge sharing dynamics in service suppliers' involvement for servitization of manufacturing companies. **International Journal of Production Economics**, v. 193, n. June, p. 538–553, nov. 2017.

BABICEANU, R. F.; SEKER, R. Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. **Computers in Industry**, v. 81, p. 128–137, set. 2016.

BANGEMANN, T. et al. Integration of Classical Components Into Industrial Cyber–Physical Systems.

Proceedings of the IEEE, v. 104, n. 5, p. 947–959, maio 2016.

BARTODZIEJ, C. J. C. J. The concept Industry 4.0. In: [s.l.] Springer Fachmedien Wiesbaden, 2017. p. 27–50.

BASCLE, G. Controlling for endogeneity with instrumental variables in strategic management research. **Strategic Organization**, v. 6, n. 3, p. 285–327, ago. 2008.

BERNAT, S.; KARABAG, S. F. Strategic alignment of technology: Organising for technology upgrading in emerging economy firms. **Technological Forecasting and Social Change**, maio 2018.

BRETTEL, M. et al. How Virtualization , Decentralization and Network Building Change the Manufacturing Landscape : **International Journal of Mechanical, Industrial Science and Engineering**, v. 8, n. 1, p. 37–44, 2014.

BRUUN, H. P. L. et al. PLM system support for modular product development. **Computers in Industry**, v. 67, p. 97–111, 2015.

CASTELLACCI, F. Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. **Research Policy**, v. 37, n. 6–7, p. 978–994, jul. 2008.

CASTELLACCI, F.; NATERA, J. The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. **Research Policy**, v. 42, n. 3, p. 579–594, 2013.

CHRYSSOLOURIS, G. et al. Digital manufacturing: History, perspectives, and outlook. **Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture**, v. 223, n. 5, p. 451–462, maio 2009.

CNI - CONFEDERAÇÃO NACIONAL DA INDÚSTRIA. **Industry 4.0: a new challenge for Brazilian industry**. [s.l.] Available at: (https://bucket-gw-cni-static-cms-si.s3.amazonaws.com/media/filer_public/54/02/54021e9b-ed9e-4d87-a7e5-3b37399a9030/challenges_for_industry_40_in_brazil.pdf), 2016.

COHEN, J.; COHEN, P.; STEPHEN, G. **Applied multiple regression/correlation analysis for the behavioral sciences**. 3. ed. [s.l.] UK: Taylor & Francis, 2003.

COMIN, D.; HOBIJN, B. Cross-country technology adoption: making the theories face the facts. **Journal of monetary Economics**, v. 51, n. 1, p. 39–83, 2004.

CONSEIL NATIONAL DE L'INDUSTRIE. **The New Face of Industry in France. Paris: French National Industry Council**, 2013.

COREYNEN, W.; MATTHYSSENS, P.; VAN BOCKHAVEN, W. Boosting servitization through digitization: Pathways and dynamic resource configurations for manufacturers. **Industrial Marketing Management**, v. 60, p. 42–53, 2017.

CORTIMIGLIA, M. N.; FRANK, A. G.; MIORANDO, R. F. ICT Trends in Brazil. **IT Professional**, v. 14, n. 4, p. 31–38, jul. 2012.

CRISÓSTOMO, V. L.; LÓPEZ-ITURRIAGA, F. J.; VALLELADO, E. Financial Constraints for Innovation in Brazil. **Latin American Business Review**, v. 12, n. 3, p. 165–185, jul. 2011.

DE SOUSA JABBOUR, A. et al. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. **Technological Forecasting and Social Change**, v. 132, p. 18–25, 2018a.

DE SOUSA JABBOUR, A. B. L. et al. When titans meet – Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. **Technological Forecasting and Social Change**, v. 132, n. January, p. 18–25, 2018b.

DOCHTERMANN, N. A.; JENKINS, S. H. Multivariate Methods and Small Sample Sizes. **Ethology**, v. 117, n. 2, p. 95–101, fev. 2011.

DREGGER, J. et al. **The digitization of manufacturing and its societal challenges: A framework for the future of industrial labor**. 2016 IEEE International Symposium on Ethics in Engineering, Science and Technology (ETHICS). **Anais**...Institute of Electrical and Electronics Engineers Inc., set. 2016

EATON, J.; KORTUM, S. International Technology Diffusion: Theory and Measurement. **International Economic Review**, v. 40, n. 3, p. 537–570, ago. 1999.

FATORACHIAN, H.; KAZEMI, H. A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework. **Production Planning & Control**, p. 1–12, jan. 2018.

FRANCO, E.; RAY, S.; RAY, P. K. Patterns of Innovation Practices of Multinational-affiliates in Emerging Economies: Evidences from Brazil and India. **World Development**, v. 39, n. 7, p. 1249–1260, jul. 2011.

FRANK, A. G. et al. The effect of innovation activities on innovation outputs in the Brazilian industry: Market-orientation vs. technology-acquisition strategies. **Research Policy**, v. 45, n. 3, p. 577–592, abr. 2016.

FRANK, A. G.; RIBEIRO, J. L. D.; ECHEVESTE, M. E. Factors influencing knowledge transfer between NPD teams: a taxonomic analysis based on a sociotechnical approach. **R&D Management**, v. 45, n. 1, p. 1–22, jan. 2015.

GARRETT, B. 3D Printing: New Economic Paradigms and Strategic Shifts. **Global Policy**, v. 5, n. 1, p. 70–75, fev. 2014.

GERBER, T.; BOSCH, H.; JOHNSSON, C. Vertical Integration of Decision-Relevant Production Information into IT Systems of Manufacturing Companies. p. 263–278, 2013.

GILCHRIST, A. **Industry 4.0: the industrial internet of things**. Berkeley: Apress, 2016.

GUAN, J. C. et al. Technology transfer and innovation performance: Evidence from Chinese firms. **Technological Forecasting and Social Change**, v. 73, n. 6, p. 666–678, jul. 2006.

HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, R. E. **Multivariate data analysis: A global perspective**. [s.l.] Upper Saddle River: Prentice Hall, 2009.

HALL, B.; MAFFIOLI, A. Evaluating the impact of technology development funds in emerging economies: evidence from Latin America. **The European Journal of Development Research**, v. 20, n. 2, p. 172–198, jun. 2008.

HANSEN, U. et al. Sustainability transitions in developing countries: Stocktaking, new contributions and a research agenda. v. 84, p. 198–203, 2018.

HENDRICK, H.; KLEINER, B. **Macroergonomics: An introduction to work system design**. [s.l.] Santa Monica, CA: Human Factors and Ergonomics Society, 2001.

HERMANN, M.; PENTEK, T.; OTTO, B. **Design Principles for Industrie 4.0 Scenarios**. [s.l.] IEEE, 2016. v. 2016–March

HOZDIĆ, E. Smart factory for industry 4.0: A review. **International Journal of Modern Manufacturing Technologies**, v. 7, n. 1, p. 28–35, 2015.

JAZDI, N. **Cyber physical systems in the context of Industry 4.0**. 2014 IEEE International Conference on Automation, Quality and Testing, Robotics. **Anais**...maio 2014

JESCHKE, S. et al. **Industrial Internet of Things and Cyber Manufacturing Systems**. [s.l.] Springer, 2017.

KAGERMANN, H. Change Through Digitization—Value Creation in the Age of Industry 4.0. In: **Management of Permanent Change**. Wiesbaden: Springer Fachmedien Wiesbaden, 2015. p. 23–45.

KAGERMANN, H.; WAHLSTER, W.; HELBIG, J. **Recommendations for implementing the strategic initiative INDUSTRIE 4.0Final report of the Industrie 4.0 WG**. [s.l: s.n.].

KETOKIVI, M.; MCINTOSH, C. N. Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. **Journal of Operations Management**, v. 52, p. 1–14, maio 2017.

KIEL, D., ARNOLD, C., COLLISI, M., VOIGT, K. et al. **The impact of the industrial internet of things on established business models**. Proceedings of the 25th international association for management of technology (IAMOT) conference. **Anais**...2016

KONYHA, J.; BÁNYAI, T. Sensor Networks for Smart Manufacturing Processes. **Solid State Phenomena**, v. 261, p. 456–462, ago. 2017.

KRAWCZYŃSKI, M.; CZYZEWSKI, P.; BOCIAN, K. Reindustrialization: A challenge to the economy in the first quarter of the twenty-first century. **Foundations of Management**, v. 8, n. 1, p. 107–122, 2016.

KUMAR, N.; SIDDHARTHAN, N. Technology, Market Structure and Internationalization: Issues and Policies for Developing Countries. 2013.

LANGNER, B.; SEIDEL, V. P. Collaborative concept development using supplier competitions: Insights from the automotive industry. **Journal of Engineering and Technology Management**, v. 26, n. 1–2, p. 1–14, mar. 2009.

LASI, H. et al. Industry 4.0. **Business and Information Systems Engineering**, v. 6, n. 4, p. 239–242, 2014.

LIAO, Y. et al. Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. **International Journal of Production Research**, v. 55, n. 12, p. 3609–3629, jun. 2017.

LUTHRA, S.; MANGLA, S. Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. **Process Safety and Environmental Protection**, v. 117, p. 168–179, 2018.

MACCALLUM, R. C. et al. Sample Size in Factor Analysis: The Role of Model Error. **Multivariate Behavioral Research**, v. 36, n. 4, p. 611–637, out. 2001.

MAN, J. C. DE; STRANDHAGEN, J. O. An Industry 4.0 Research Agenda for Sustainable Business Models. **Procedia CIRP**, v. 63, p. 721–726, 2017.

MARODIN, G. A. et al. Contextual factors and lean production implementation in the Brazilian automotive supply chain. **Supply Chain Management: An International Journal**, v. 21, n. 4, p. 417–432, jun. 2016.

MARODIN, G. A. et al. Lean production and operational performance in the Brazilian automotive supply chain. **Total Quality Management & Business Excellence**, p. 1–16, mar. 2017a.

MARODIN, G. A. et al. The moderating effect of Lean supply chain management on the impact of Lean shop floor practices on quality and inventory. **Supply Chain Management: An International Journal**, v. 22, n. 6, p. 473–485, set. 2017b.

MENDONÇA, M. A. A.; FREITAS, F.; DE SOUZA, J. M. Information technology and productivity: Evidence for Brazilian industry from firm-level data. **Information Technology for Development**, v. 14, n. 2, p. 136–153, abr. 2008.

MIRANDA, J. et al. Sensing, smart and sustainable product development (S ^{3} product) reference framework. **International Journal of Production Research**, p. 1–22, nov. 2017.

NAKATA, C.; WEIDNER, K. Enhancing New Product Adoption at the Base of the Pyramid: A Contextualized Model. **Journal of Product Innovation Management**, v. 29, n. 1, p. 21–32, jan. 2012.

OLAVARRIETA, S.; VILLENA, M. G. Innovation and business research in Latin America: An overview. **Journal of Business Research**, v. 67, n. 4, p. 489–497, abr. 2014.

PARENTE, S. L.; PRESCOTT, E. C. Barriers to Technology Adoption and Development. **Journal of Political Economy**, v. 102, n. 2, p. 298–321, abr. 1994.

PARLANTI, R. Smart shopfloors and connected platforms in Industry 4.0. **Electronics World**, v. 123, n. 1975, p. 26–28, 2017.

PENG, D. X.; HEIM, G. R.; MALLICK, D. N. Collaborative Product Development: The Effect of Project Complexity on the Use of Information Technology Tools and New Product Development Practices. **Production and Operations Management**, v. 23, n. 8, p. 1421–1438, ago. 2014.

PHILLIPS, L. A.; CALANTONE, R.; LEE, M. International Technology Adoption. **Journal of Business & Industrial Marketing**, v. 9, n. 2, p. 16–28, jun. 1994.

PORTER, M.; HEPPELMANN, J. How smart, connected products are transforming competition. **Harvard Business Review**, v. 92, n. 11, p. 64–88, 2014.

PWC - PRICEWATERHOUSECOOPERS. **Indústria 4.0: Digitização como vantagem competitiva no Brasil**. [s.l.] Available at: (https://www.pwc.com.br/pt/publicacoes/servicos/assets/consultoria-negocios/2016/pwc-industry-4-survey-16.pdf), 2016.

QIN, J.; LIU, Y.; GROSVENOR, R. A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. **Procedia CIRP**, v. 52, p. 173–178, 2016.

RAFAEL, R., SHIRLEY, A.J., LIVERIS, A. **Report To The President Accelerating U.S. Advanced Manufacturing. Washington, DC: The President's Council of Advisors on Science and Technology.**, 2014.

RAMANI, S. V.; THUTUPALLI, A.; URIAS, E. High-value hi-tech product introduction in emerging countries. **Qualitative Market Research: An International Journal**, v. 20, n. 2, p. 208–225, abr. 2017.

RAS, E. et al. **Bridging the skills gap of workers in Industry 4.0 by Human Performance Augmentation Tools: Challenges and Roadmap**. Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments. **Anais**...2017

REISCHAUER, G. Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. **Technological Forecasting and Social Change**, v. 132, p. 26–33, jul. 2018.

ROBERTSON, T.; GATIGNON, H. Competitive effects on technology diffusion. **Journal of Marketing**, v. 50, n. 3, p. 1–12, 1986.

SALDIVAR, A. A. F. et al. **Industry 4.0 with cyber-physical integration: A design and manufacture perspective**. 2015 21st International Conference on Automation and Computing (ICAC). **Anais**...IEEE, set. 2015

SCHEER, A.-W. **Cim: Computer Integrated Manufacturing Towards the Factory of the Future**. [s.l.] Secaucus, New Jersey, U.S.A.: Springer Verlag, 1994.

SCHUH, G.; ANDERI, R.; GAUSEMEIER, J. **Industrie 4.0 maturity index. Managing the Digital Transformation of Companies (acatech STUDY)**. [s.l.] Available at: (http://www.acatech.de/fileadmin/user_upload/Baumstruktur_nach_Website/Acatech/root/de/Publikationen/Projektberichte/acatech_STUDIE_Maturity_Index_eng_WEB.pdf), 2017.

SCHUMACHER, A.; EROL, S.; SIHN, W. A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. **Procedia CIRP**, v. 52, p. 161–166, 2016.

SCHWAB, K. **The Fourth Industrial Revolution. 1st Edition, World Economic Forum.** [s.l: s.n.].

STARK, J. **Product Lifecycle Management**. London: Springer, 2011.

STEIMER, C. et al. Approach for an Integrated Planning of Manufacturing Systems Based on Early Phases of Product Development. **Procedia CIRP**, v. 57, p. 467–472, 2016.

STOCK, T.; SELIGER, G. Opportunities of Sustainable Manufacturing in Industry 4.0. **Procedia CIRP**, v. 40, p. 536–541, 2016.

TAO, F. et al. Digital twin-driven product design, manufacturing and service with big data. **International Journal of Advanced Manufacturing Technology**, v. 94, n. 9–12, p. 3563–3576, 2018a.

TAO, F. et al. Data-driven smart manufacturing. **Journal of Manufacturing Systems**, n. January, 2018b.

VIOTTI, E. B. National Learning Systems: A new approach on technological change in late industrializing economies and evidences from the cases of Brazil and South Korea. **Technological Forecasting and Social Change**, v. 69, n. 7, p. 653–680, set. 2002.

WAHLSTER, W. **SemProM : foundations of semantic product memories for the internet of things**. [s.l.] Springer Science & Business Media, 2013.

WAMBA, F. S. et al. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. **International Journal of Production Economics**, v. 165, p. 234–246, jul. 2015.

WANG, L.; TÖRNGREN, M.; ONORI, M. Current status and advancement of cyber-physical systems in manufacturing. **Journal of Manufacturing Systems**, v. 37, p. 517–527, 2015.

WANG, S. et al. Towards smart factory for industry 4.0: A self-organized multi-agent system with big data based feedback and coordination. **Computer Networks**, v. 101, p. 158–168, 2016a.

WANG, S. et al. Implementing Smart Factory of Industrie 4.0: An Outlook. **International Journal of Distributed Sensor Networks**, v. 2016, 2016b.

WEI, Z.; SONG, X.; WANG, D. Manufacturing flexibility, business model design, and firm performance. **International Journal of Production Economics**, v. 193, p. 87–97, nov. 2017.

WELLER, C.; KLEER, R.; PILLER, F. T. Economic implications of 3D printing: Market structure models in light of additive manufacturing revisited. **International Journal of Production Economics**, v. 164, p. 43–56, jun. 2015.

WESTERMAN, G.; BONNET, D.; MCAFEE, A. **Leading digital: Turning technology into business transformation**. [s.l.] Harvard Business Press, 2014.

YIN, Y.; STECKE, K. E.; LI, D. The evolution of production systems from Industry 2.0 through Industry 4.0. **International Journal of Production Research**, p. 1–14, nov. 2017.

YU, C.; XU, X.; LU, Y. Computer-Integrated Manufacturing, Cyber-Physical Systems and Cloud Manufacturing - Concepts and relationships. **Manufacturing Letters**, v. 6, p. 5–9, 2015.

ZHOU, J. Intelligent mannfacturing-main direction of " made in China 2025 ". p. 3969, 2017.

ZHOU, K. et al. **Industry 4.0: Towards future industrial opportunities and challenges**. 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD). **Anais**...2015

ZUNIGA, P.; CRESPI, G. Innovation strategies and employment in Latin American firms. **Structural Change and Economic Dynamics**, v. 24, p. 1–17, mar. 2013.

3 ARTIGO 2 – INDUSTRY 4.0 TECHNOLOGIES: IMPLEMENTATION PATTERNS IN THE MACHINERY INDUSTRY

Lucas Santos Dalenogare[1]; Néstor Fabián Ayala[2]; Alejandro Germán Frank[1]

[1] Department of Industrial Engineering, Universidade Federal do Rio Grande do Sul, Brazil

[2] Department of Service Engineering, Universidade Federal do Rio Grande do Sul, Brazil

Abstract

Industry 4.0 has been considered as a new industrial stage in which several emergent technologies are converging to provide new solutions for manufacturing and product development. However, the growing set of technologies proposed for the Industry 4.0 can follow different patterns of adoption in manufacturing companies. In this sense, the literature lacks understanding on how these technologies are implemented. In this paper, we aim to understand two aspects: firstly, we study whether smart manufacturing technologies (the core of the Industry 4.0) can show different patterns of implementation, providing different levels of maturity and behavior in the Industry 4.0 implementation; and, secondly, we study whether the higher levels of adoption of smart manufacturing technologies are complemented by other support technologies (smart supply chain and smart working technologies) as well as by the base technologies of the Industry 4.0 (IoT, cloud, big data and analytics). We performed a survey in 92 manufacturing companies of the Machinery and Equipment Builders industry to study 25 technologies of the Industry 4.0 which we classified in three main technology groups: appliance technologies, support technologies and base technologies. Our findings show that the maturity levels of the Industry 4.0 are related to a growing implementation of all the appliance technologies (smart manufacturing and smart product and services) but that companies are still weak in the adoption of base technologies that provide connectivity to those appliance technologies. We show that the growth in the intelligence that companies can obtain based in the base-technologies is the cutting edge for the competitiveness in the Industry 4.0 implementation.

Keywords: Industry 4.0; smart manufacturing; survey; manufacturing companies; maturity.

3.1 Introduction

Historically, industrial revolutions aimed a common objective: to increase production volume and to reduce costs (DRATH; HORCH, 2014). This goal changed production systems in many aspects, from energy consumption and employed technologies to companies' organizational arrangements (YIN; STECKE; LI, 2018). Even though the cost concerns sustain until today, now companies face new challenges. Product customization demand has been growing, originating the mass customization strategy in the past decades (FOGLIATTO; DA SILVEIRA; BORENSTEIN, 2012). However, despite many technological advances, companies frequently struggle to find a balance between the diversification of products and the impact in production costs (EL MARAGHY, 2006). Consequently, since the third industrial revolution, innovative concepts and technologies have been developed and pointed as possible solutions to overcome these manufacturing challenges, leading to the so-called fourth industrial revolution (LIAO et al., 2017; LU, 2017).

The fourth industrial revolution – also named as Industry 4.0 – is one of the most trending topics in businesses and academic fields (CHIARELLO; TRIVELLI, LEONELLO BONACCORSI; FANTONI, 2018). This concept has smart manufacturing as a key element (KAGERMANN; WAHLSTER; HELBIG, 2013) but it extends factory borders (DRATH; HORCH, 2014), expanding to entire lifecycle of product development – from concept design to logistics (DALENOGARE et al., 2018; WANG et al., 2016a) and changing the way people work (STOCK et al., 2018). This new paradigm mainly relies on the adoption of digital technologies to gather data in real time, with advanced tools to analyze and provide useful information through cyber physical systems (LEE; BAGHERI; KAO, 2015; WANG et al., 2016b). The advent of Internet of Things (IoT), cloud computing, big data and analytics, made the cyber-physical systems possible, being considered as base technologies for other application technologies in smart manufacturing (LU, 2017; WANG; TÖRNGREN; ONORI, 2015).

With the adoption of the Industry 4.0, a company could produce different types of products without large increases in operations costs, due to its autonomy and flexibility (WANG et al., 2016a). The outcome should be a more reliable, flexible and efficient production system and new business opportunities for many industrial sectors and service providers (GILCHRIST, 2016). However, the Industry 4.0 manufacturing system has a very complex architecture (LEE; BAGHERI; KAO, 2015), which is one of the main concerns in this new industrial stage. Furthermore, the effective architecture implementation of Industry 4.0 technologies is still subject of ongoing researches, but studies indicate major potential enabled from it, in which some applications are already possible (BABICEANU; SEKER, 2016; DALENOGARE et al., 2018; LEE; BAGHERI; KAO, 2015). However, despite the hype of the Industry 4.0 concept, there are still some uncertainties about the implementation of the Industry 4.0 technologies. Some prior works have proposed theoretical maturity models and implementation stages of the Industry 4.0 technologies (e.g. LEE; BAGHERI; KAO, 2015; LU; WENG, 2018; SCHUH; ANDERI; GAUSEMEIER, 2017). Other works have studied the impact of some technologies on industrial performance, at the industry-level (DALENOGARE et al., 2018). However, there is a lack of studies providing empirical evidence from the firm-level about the way such technologies are adopted in manufacturing companies, leading to two important questions: *what are the current technology adoption patterns of the Industry 4.0 in manufacturing companies? How companies prioritize Industry 4.0 technologies in the industrial digitization process?*

In order to answer these questions, this paper presents an exploratory quantitative analysis from a survey of 92 manufacturing companies from the machinery and equipment building sector in Brazil. We aim to understand whether manufacturing companies can be organized based on common patters of Industry 4.0 related technologies adoption and if these patterns are complemented by support technologies that allow to define configuration types of Industry 4.0. Such analysis helps us to better understand what is needed for an effective implementation of the Industry 4.0 technologies in manufacturing companies. Aiming this, we use a cluster analysis method with independence tests to define patterns of technology adoption. These techniques allow us to identify the extension of the adoption of the Industry 4.0 concept and the association of its central elements with other supported technologies and practices. As a key-finding, we propose a structure of technology layers (base, support and appliance technologies) and the level of adoption of such technologies in the Industry 4.0 transition of the sample studied. Our findings are summarized in a final framework showing how technologies are adopted following a maturity pattern of implementation.

3.2 Defining the Industry 4.0 concept

Industry 4.0 was coined in 2011 in a German public-private initiative with governmental agencies, private companies and universities, as a strategy program with the main goal to develop advanced production systems, for higher productivity and efficiency of the national industry (KAGERMANN; WAHLSTER; HELBIG, 2013). This concept represents a new industrial stage of the nowadays manufacturing companies formed by a set of emerging and convergent technologies (DALENOGARE et al., 2018). It has the main purpose to enhance every necessary activity throughout all functions in an integrated industrial value chain and comprehended in the whole product lifecycle, in which all stages, from design to after-sale, are improved with digital technologies (LIAO et al., 2017; WANG et al., 2016a). This new industrial stage demands a socio-technical evolution of the human role in production systems, in which all working activities in the value chain will be performed with smart approaches (PARK; LEE; LEE, 2014) and grounded with information and communication technologies (ICTs) (RAGUSEO; GASTALDI; NEIROTTI, 2016).

Therefore, Industry 4.0 is a broader concept, with its core in smart manufacturing. The concept of smart manufacturing considers an adaptable system where flexible lines adjust production processes for multiple types of products and changing conditions (SCHUH; ANDERI; GAUSEMEIER, 2017; WANG et al., 2016b), making possibly customized products at a large scale and in a sustainable way with better resource consumption (DE SOUSA JABBOUR et al., 2018; SCHEER, 2015). This requires a vertical integration within companies, where shop floor activities and business management are intertwined with information exchange of production planning, monitoring and control. The exchange of information also transcends horizontally in the whole business supply chain, synchronizing production with logistics activities with more agility (BRETTEL et al., 2014; WANG et al., 2016a). This comprehends the horizontal integration feature of Industry 4.0 that enables companies to combine resources in collaborative manufacturing (CHIEN; KUO, 2013; LIN et al., 2012), allowing them to focus on their core competencies by outsourcing other activities, without losing their bond in the value chain (CHRISTOPHER, 2000).

In addition, with horizontal integration companies can share capabilities for product innovation in industry platforms, a joint effort to develop products and complementary assets and services, with more value-added (GAWER; CUSUMANO, 2014; KORTMANN; PILLER, 2016). Thus, by integrating value networks, horizontal integration also has an interface with end-to-end digital engineering feature. The product lifecycle integration has the purpose to shorten innovation cycles of new product development, quickly launching them to the market due to smart approaches in design and manufacturing, and also with smart products. Smart products have embedded smart and connectivity components that enable digital capabilities of physical products, which generates data that can be obtained from manufacturers (PORTER; HEPPELMANN, 2014). This data is then used to understand product's usage, providing feedback information for new product development (TAO et al., 2018a). The new capabilities of smart products can promote changes in every activity in an industrial value chain (PORTER; HEPPELMANN, 2015), and its development is considered the second main objective of Industry 4.0, as it grounds new business models based on product-service systems (PSS) (ZHONG et al., 2017), bringing opportunities for manufacturers and service providers (KAGERMANN; WAHLSTER; HELBIG, 2013).

Industry 4.0 has two main focus: development of an advanced production system and development of smart products. At the core of the concept, smart manufacturing represents the evolution of manufacturing, an advanced and intelligent system capable to adapt shop floor for fluctuating demands of types of products and respond to downtime events (SCHUH; ANDERI; GAUSEMEIER, 2017; WANG et al., 2016b). However, to achieve an entire smart and integrated production system, supporting elements are necessary. Smart supply chain must be considered for horizontal integration, while smart working must be grounded with digital technologies throughout different stages of product lifecycle (KAGERMANN; WAHLSTER; HELBIG, 2013; TAO et al., 2018b). Furthermore, the new production system requires base technologies to develop the necessary capabilities that make it smart and integrated. These elements are presented next based on a theoretical model proposed for the Industry 4.0 technologies.

3.3 A technological framework of the Industry 4.0

Although most of the Industry 4.0 related technologies are interrelated, they can be separated in at least three main dimensions according to their main objective, as we propose in our theoretical framework of Figure 1. At the top of this framework we placed the central focus of the Industry 4.0 which is the transformation of the manufacturing activities based on emerging technologies (Smart Manufacturing) and on the way product and services are offered (DALENOGARE et al., 2018). We called this dimension as '*appliance technologies*' due to its end-application purpose of producing goods with the use of such technologies. These two dimensions rely on the other two: support and base technologies. The so called '*support technologies*' considers the integration of smart supply chain with the manufacturing system and the use of smart working technologies to support new working methods. The ground level considers the '*base technologies*' which are the technologies that provide connectivity and intelligence for the appliance and supporting technologies. This last dimension is the one which enables the Industry 4.0 concept and differentiates it from previous industrial stages since it makes that the other technologies can be interconnected and adaptative to the manufacturing requirements.

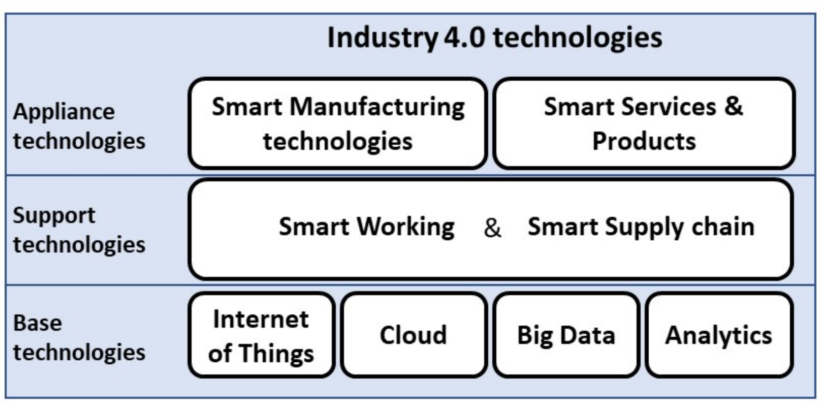

Figure 1 : Theoretical framework of the Industry 4.0 technologies

In the following subsections, we define each technological level proposed in our framework of Figure 1. We aim to understand how these technologies are used in manufacturing firms and if they follow implementation patterns.

3.3.1 Appliance technologies of the Industry 4.0

In the core of the Industry 4.0, *smart manufacturing* technologies work as the central pillar of the internal value-added of the factory (AHUETT-GARZA; KURFESS, 2018), while *smart products* consider the external value-added of the factory when the customer is integrated to the production system (DALENOGARE et al., 2018).

Regarding the smart manufacturing dimension, we subdivided the related technologies to seven main purposes: (i) Factory's vertical integration, (ii) Factory virtualization, (iii) Work automation, (iv) Intelligent decision-making, (v) Internal traceability, (vi) Flexibility and (vii) Smart energy, as summarized in Table 1. Factory's vertical integration comprises factories capable to integrate their processes with advanced IT systems in all hierarchical areas – vertical integration –, which may take decision-making actions with less need of human action (SCHUH; ANDERI; GAUSEMEIER, 2017). To reach vertical integration, the first step at shop floor is the digitalization of all physical objects and parameters with sensors, actuators and Programmable Logic Controllers (PLC) (JESCHKE et al., 2017; LEE; BAGHERI; KAO, 2015). The data is then gathered with Supervisory Control and Data Acquisition (SCADA), for production control and diagnosis at the shop floor. Towards managerial layer, Manufacturing Execution Systems (MES) obtain data from SCADA, providing production status to Enterprise Resource Planning (ERP), a commercial and operational system for control of supplies acquisition and production orders determination. When all systems properly integrated, the information of production orders also flows from ERP to MES and then SCADA (JESCHKE et al., 2017; TELUKDARIE et al., 2018). Vertical integration gathers managerial layer to shop floor, creating more transparency for all processes within a factory and also ease its adaptability to different product types.

To enhance adaptability for different types of products, smart manufacturing comprises networked machines at shop floor, through machine-to-machine communication (M2M) (KAGERMANN; WAHLSTER; HELBIG, 2013). M2M consist on a communication system with interoperability, which makes machines capable to understand each other and ease setup procedures, facilitating their adaptation in manufacture lines (GILCHRIST, 2016). This capability is supported with virtual commissioning, that emulates the different PLC-codes of machines and virtually validates setup procedures, avoiding extended downtime due to the actual setups of machinery (ADOLPHS et al., 2015; MORTENSEN; MADSEN, 2018). This simulation is more advanced with digital manufacturing, which besides PLC-codes, also considers data from all virtualized objects of the shop floor and then simulates operations' processes, considering several parameters that can affect production (JESCHKE et al., 2017).

Smart manufacturing also promotes an enhanced automation of the third industrial revolution, with productivity gains through work automation and analytical capabilities of the factory (KAGERMANN; WAHLSTER; HELBIG, 2013). Smart robots can work alongside humans, executing tasks with self-coordination in an autonomous matter (GILCHRIST, 2016). Robots can perform tasks with more precision, increased productivity and much less prone to fatigue (THOBEN; WIESNER; WUEST, 2017). In addition, artificial intelligence gives support for smart manufacturing in many dimensions. In machines, advanced analytical tools can analyze sensor data from their usage monitoring and forecast machinery failure for fatigue or overload. This enables predictive maintenance of machines, avoiding downtimes due to unexpected failures or corrective maintenance (JANAK; HADAS, 2015). Machines with artificial intelligence and sensors can also automatically identify nonconformities in products in earlier stages of the production processes, increasing quality control and reducing costs due to production of defective batches (ADOLPHS et al., 2015). Furthermore, artificial intelligence also complements systems like ERP, predicting long-term production demands and transforming them into daily production orders, considering last-minute orders and operations' restrictions (GILCHRIST, 2016; JESCHKE et al., 2017).

For internal traceability, sensors are applied in raw materials and finished products in the factory's warehouse. This optimized inventory control give support for recall actions, through identification of components in defective batches of finished products. Internal traceability can also give support to adaptable systems with flexible lines (ANGELES, 2009; WANG et al., 2016a), in which machines read products requirements in the sensors embedded on it, and perform the necessary actions to manufacture it. Flexible lines can also comprise modular machines that are easily plugged into a manufacturing line, with minimum setup time. This enables the production of different types of products at small batches, with minimum productivity reduction (BALOGUN; POPPLEWELL, 1999; WANG et al., 2016a). In addition, to reach the production of even customized products, additive manufacturing is a promising technology within Industry 4.0 concept. Additive manufacturing uses 3D printing of digital models that can be altered for customization, using the same resources to manufacture different goods. The printer produces the whole product based on the digital model, requiring no setup time. Therefore, additive manufacturing also promotes a sustainable production, as only requires one process that generates less waste than traditional manufacturing. However, for large-scale productions, the use of additive manufacturing is still not viable due to its low throughput speed (D'AVENI, 2015; WELLER; KLEER; PILLER, 2015).

Lastly, to enhance factory's efficiency, smart manufacturing also comprises smart energy (KAGERMANN; WAHLSTER; HELBIG, 2013). Smart energy rids aims to increase energy savings and consist of energy efficiency monitoring and improving systems. Efficiency monitoring relies on data collection of energy consumption in electrical power grids, while its improvement is achieved through intelligent systems for energy management, which schedules energy intensive stages of production in times with favorable electricity rates (GILCHRIST, 2016; JESCHKE et al., 2017).

Manufacturing companies can focus on different needs they may have when they prioritize the implementation of the aforementioned smart manufacturing technologies. Ideally, it would be expected that the adoption of the Industry 4.0 may lead to a high level of implementation of all these technologies. However, recent findings of the literature have shown that the industry varies in the benefits expected by those technologies for industrial performance (Dalenogare et al., 2018). Therefore, we assume the following hypothesis regarding the adoption of Smart Manufacturing technologies:

H1: Different patterns of Industry 4.0 can be defined based on the type of smart manufacturing technologies adopted by the manufacturing companies.

Table 1: Smart manufacturing technologies and Smart Products

Categories	Technologies for Smart Manufacturing	Reference
Vertical integration	Sensors, actuators and Programmable Logic Controllers (PLC)	(JESCHKE et al., 2017; LEE; BAGHERI; KAO, 2015)
	Supervisory Control and Data Acquisition (SCADA)	(JESCHKE et al., 2017)
	Manufacturing Execution System (MES)	(JESCHKE et al., 2017; TELUKDARIE et al., 2018)
	Enterprise Resource Planning (ERP)	(JESCHKE et al., 2017)
	Machine-to-machine communication (M2M)	(GILCHRIST, 2016)
Virtualization	Virtual commissioning	(ADOLPHS et al., 2015; MORTENSEN; MADSEN, 2018)
	Simulation of processes (e.g. digital manufacturing)	(JESCHKE et al., 2017)
	Artificial Intelligence for predictive maintenance	(JANAK; HADAS, 2015)
	Artificial Intelligence for planning of production	(GILCHRIST, 2016)
Automation	Machine-to-machine communication (M2M)	(GILCHRIST, 2016)
	Industrial robots	(GILCHRIST, 2016)
	Automatic nonconformities identification in production	(GILCHRIST, 2016; JESCHKE et al., 2017)
Traceability	Identification and traceability of raw materials	(ANGELES, 2009)
	Identification and traceability of final products	
Flexibility	Additive manufacturing	(D'AVENI, 2015; WELLER; KLEER; PILLER, 2015)
	Flexible and autonomous lines	(BALOGUN; POPPLEWELL, 1999; WANG et al., 2016b)
Energy management	Energy efficiency monitoring system	(GILCHRIST, 2016; KAGERMANN; WAHLSTER; HELBIG, 2013)
	Energy efficiency improving system	(JESCHKE et al., 2017; KAGERMANN; WAHLSTER; HELBIG, 2013)
Categories	**Technologies for Smart Product and Services**	**Reference**
Capabilities of smart, connected products	Product's connectivity	(PORTER; HEPPELMANN, 2014)
	Product's monitoring	
	Product's control	
	Product's optimization	
	Product's autonomy	

On the other hand, the appliance technologies for smart product comprise smart components that enable digital capabilities and services with products' offering, as shown in Table 1. Embedded sensors allow the connectivity of products in a network with other objects and systems. Sensors also add a monitoring capability in physical products, allowing customers to know the product condition and usage parameters.

Products with embedded software enable their control through digital interface, possibly in a remote way when the software is embedded in a product cloud. With analytical algorithms, the product can have optimization functions, enhancing products' performance and with predictive diagnoses that informs necessary corrections. Finally, with artificial intelligence, the product can autonomously optimize itself. These capabilities extend products functions for customers, and also bring opportunities for manufacturers. Product monitoring also provides useful information for manufacturers, which can gather this data and identify patterns of product usage, for market segmentation and new product development, enabling digital product-service-systems (PSS), in which manufacturers can offer additional services with the product and even offer the product as a service (ZHONG et al., 2017). Although some companies can be focused on the external aspect of the digital technologies - smart products and services for the end customer, the Industry 4.0 concept assumes that both, internal smart manufacturing and external product and services should be connected and integrated (KAGERMANN; WAHLSTER; HELBIG, 2013; PORTER; HEPPELMANN, 2015; TAO et al., 2018b). Such an approach was previously studied by Kamp et al., (2017) and Rymaszewska et al. (2017) who worked on the connections of the digital services with the internal processes. Therefore, we propose the following hypothesis:

H2: The level of adoption of smart product technologies are associated to the maturity levels in the Smart Manufacturing technologies of the Industry 4.0.

3.3.2 Support technologies of the Industry 4.0

Support technologies consider the technologies to assist the production flow inside and outside the factory, summarized in Table 2. Outside the factory, it considers the technologies supporting the horizontal integration of the factory with the supply chain, while inside the factory the technologies to support working activities. Considering the broader concept of Industry 4.0, smart working technologies also assist activities prior manufacturing phase of the product lifecycle.

The horizontal integration, supported by the smart supply chain technologies, comprises the exchanging real-time information about production orders with suppliers and distribution centers aiming to provide a better reliability of deliveries, considering logistics bottlenecks issues (BRETTEL et al., 2014; PFOHL; YAHSI; KURNAZ, 2017). While smart manufacturing includes intra-logistics processes with technologies for internal traceability of materials (TAO et al., 2018b; ZHOU, 2017), other technologies must be comprehended to connect the factories to inter-logistics processes (PFOHL; YAHSI; KURNAZ, 2017). Considering information sharing and its visibility among all actors of supply chain a paramount (BARRATT; OKE, 2007), especially due to the tendency of supply chains to become more complex (PFOHL; KÖHLER; THOMAS, 2010), a reliable ICTs infrastructure is required (ANGELES, 2009). Digital platforms meet this requirement, as it provides easy on-demand access to information displayed in a cloud, integrating suppliers and manufacturers (ANGELES, 2009; BRETTEL et al., 2014; PFOHL; YAHSI; KURNAZ, 2017). This way, the tracking goods can be remotely monitored, maintaining warehousing at its optimized level due to real-time communication to suppliers of materials' consumption. In addition, when digital platforms connected to meteorological systems and with analytical capabilities, delivery delays can be avoided. These digital platforms can also reach customers, which can track its finished product (PFOHL; YAHSI; KURNAZ, 2017), resulting in an improved customer satisfaction (BRETTEL et al., 2014). Digital platforms can also integrate factories in different company's units, for information exchange among them, also providing operations status to central administrations (SIMCHI-LEVI; KAMINSKY; SIMCHI-LEVI, 2004).

On the other hand, technologies for smart working aim to provide better conditions to the workers in order to enhance their productivity (KAGERMANN; WAHLSTER; HELBIG, 2013) and to connect them to the information and data flow from the shop floor (WANG et al., 2016b) as an integrated mechanism between human and machines (THOBEN; WIESNER; WUEST, 2017). By means of connectivity, virtual capabilities and smart automation, these technologies are focused on providing remote control of the activities, improving the decision-making processes and enhanced information visibility and manufacturing activities (AHUETT-GARZA; KURFESS, 2018; TAO et al., 2018b; THOBEN; WIESNER; WUEST, 2017). Through digital platforms, the information obtained from operations in smart manufacturing enable a remote monitoring and operation of production. This allows managers to know production status in real-time and from anywhere, possibly through mobiles such as smartphones and tablets, facilitating decision-making for changes in operations (EL KADIRI et al., 2016; WANG et al., 2016b; ZHONG et al., 2017). Virtual tools also promote decision-making activities in manufacture and product design phase, with better visualization of information. Augmented and virtual reality are two state-of-the-art technologies comprised in the concept of Industry 4.0 that generate, respectively, partial and complete virtual environments (ELIA; GNONI; LANZILOTTO, 2016; GILCHRIST, 2016). In manufacturing maintenance, virtual reality accelerates workers trainings with an immersive simulation of the maintenance routines (GORECKY; KHAMIS; MURA, 2017), while augmented reality assists workers with an interactive and real-time guidance for the necessary steps of machinery inspection (SCURATI et al., 2018). In product development activities, these tools create virtual models of the product, which enables an immersive simulation of the product design and its usage (GUO et al., 2018). These virtual models can detect flaws of product usage, with less need of physical prototypes, and also assist product manufacturing with information about component requirements in production processes (TAO et al., 2018b, 2018a). Lastly, collaborative robots with embedded motion sensing can interact with operators through gestures or speak, resulting in human-machine collaboration in manufacture. This way, manufacturing work is improved with the accuracy, reliability and efficiency of robots, without losing the flexibility of human work (DU et al., 2012; WANG; TÖRNGREN; ONORI, 2015).

Table 2: Support technologies

Technologies for smart supply chain	**References**
Digital platforms with suppliers	(ANGELES, 2009; PFOHL; YAHSI; KURNAZ, 2017; SIMCHI-LEVI; KAMINSKY; SIMCHI-LEVI, 2004)
Digital platforms with customers	
Digital platforms with other company units	
Technologies for smart working	**References**
Remote monitoring of production	(EL KADIRI et al., 2016; WANG et al., 2016b; ZHONG et al., 2017)
Remote operation of production	
Augmented reality for maintenance	(ELIA; GNONI; LANZILOTTO, 2016; SCURATI et al., 2018)
Virtual reality for workers training	(ELIA; GNONI; LANZILOTTO, 2016; GORECKY; KHAMIS; MURA, 2017)
Augmented and Virtual reality for NPD	(ELIA; GNONI; LANZILOTTO, 2016; TAO et al., 2018a)
Collaborative robots	(DU et al., 2012; WANG; TÖRNGREN; ONORI, 2015)

Considering that, as we explained above, both technologies – Smart Supply chain and Smart working – support the production in different dimensions under Industry 4.0, inside and outside the factory. Therefore, we expect that:

H3: Support technologies of the Industry 4.0 such as Smart Supply Chain technologies (H3a) and Smart Working Technologies (H3b) are strongly associated with the implementation levels of Smart Manufacturing technologies.

3.3.3 Base technologies of the Industry 4.0

The concept of smart manufacturing comprises several technologies for different applications, which in a most advanced stage of Industry 4.0 will allow factories capable to adapt themselves for production orders and changing conditions. In the past decades, some of these technologies – such as sensors, PLCs, ERP, MES and SCADA –have been individually applied in factories (JESCHKE et al., 2017). However, in this new industrial stage, these technologies will all be integrated with themselves, objects and services in an interconnected network, through cyber-physical systems (CPS) (ADOLPHS et al., 2015; SCHUH; ANDERI; GAUSEMEIER, 2017; WANG et al., 2016b).

CPS can manage complex integration of physical resources with virtual capabilities, creating a virtual copy of the whole factory, called as digital twin. In a virtual layer, this digital twin shows production status in real-time, promoting transparency of all processes inside factory (BRADLEY; HEHENBERGER, 2016; THOBEN; WIESNER; WUEST, 2017). The digital twin can be complemented with advanced analytics for predictive diagnosis of the factory, reaching autonomy capability (SCHUH; ANDERI; GAUSEMEIER, 2017). However, even though the development of an entire connected system with transparency, predictive analysis and autonomy capabilities requires further researches, the emergence of the so-called new ICT - Internet of Things (IoT), cloud computing, big data and analytics – will support the effective implementation of CPS (TAO et al., 2018b; THOBEN; WIESNER; WUEST, 2017; WANG et al., 2016b), as shown in Table 3.

IoT represents the integration of sensors and computing, automatically identifying things through wireless communication (ASHTON, 2009). Recent advancements in the internet successfully allowed the communication of several objects, achieving IoT concept. This was supported by the cost-reduction of sensor technology in the past years (BRETTEL et al., 2014; SCHUH; ANDERI; GAUSEMEIER, 2017), which enabled the sensing of any kind of object and its identification in a network (BOYES et al., 2018). The connectivity system based on the internet supports several applications in manufacturing and brings a plethora of improvement opportunities for factories, once previous communication systems employed so far have considerable capacity constraints, allowing only automation tasks with partial integration to the system (AHUETT-GARZA; KURFESS, 2018; JESCHKE et al., 2017; ZHONG et al., 2017).

Cloud computing technology enables an "on-demand network access to a shared pool of computing resources (MELL et al., 2009). This technology has the capacity to store data in an internet server provider and easily released this data for people with access to the server (YU; XU; LU, 2015). Cloud computing promotes transparency through the integration of systems, where information can be easily shared throughout different functions within company or between different companies (THOBEN; WIESNER; WUEST, 2017; YU; XU; LU, 2015). In addition, cloud computing can provide services that uses even huge amounts of data (Big data) stored at large scale (LIU, 2013; LU, 2017).

Big data is the gathered data from systems and objects, comprehended in different formats, from sensor readings in operations to sales history in business management (PORTER; HEPPELMANN, 2015). Together with analytics – e.g. data mining and machine learning, it is considered one of the most important drivers of the fourth industrial revolution and a key source of competitive advantage for the future (AHUETT-GARZA; KURFESS, 2018; PORTER; HEPPELMANN, 2015; TAO et al., 2018b). The main importance is due to the information it can generate. Big data is necessary to generate the digital twins of the factory and, subsequently, analytics enables advanced predictive capacity, identifying events that can affect production before it happens (SCHUH; ANDERI; GAUSEMEIER, 2017). The combination of big data with analytics can support the self-organization of the production lines and optimizes decision-making activities in every dimension of an industrial business (BABICEANU; SEKER, 2016; WAMBA et al., 2015; WANG et al., 2016b).

Table 3: Base technologies for Industry 4.0

Base technologies	References
Internet of Things (IoT)	(GILCHRIST, 2016; WANG et al., 2016b; ZHONG et al., 2017)
Cloud computing	
Big data	
Analytics	

The four technologies aforementioned – IoT, cloud computing, big data and analytics – have different capabilities, being considered base technologies for the final concept of Industry 4.0 - autonomous and flexible production systems. IoT holds the promise to solve communication issues among all objects and systems in a factory, while cloud computing provides easy access to information and services. Lastly, big data and analytics are considered key enablers to advanced applications of smart manufacturing. Thus, focusing on the central element of Industry 4.0, we formulate our fourth and last hypothesis:

H4: The more advanced the company is in smart manufacturing technologies, the stronger the support will be of base technologies.

3.4 Research method

3.4.1 Sampling

In order to test our hypotheses, we performed a cross-sectional survey in manufacturing companies. We obtained our sample from the Southern Brazil regional office of the Brazilian Machinery and Equipment Builders´ Association (ABIMAQ). This association was chosen due to its interest and alignment to the Industry 4.0 concept, being part of the strategic plan of development of the companies of this association. The sample is composed by 143 companies associated to the Southern ABIMAQ office. The questionnaire was addressed to the Chief Executive Officers or Operations Directors of the companies. Two follow-ups were sent each after two weeks from the last one. We obtained a total of 92 complete questionnaires for the variables studied in this paper, representing a response rate of 64.33%. This high response rate is due to the way the questionnaire was administrated, since the own Southern ABIMAQ office contacted all companies, shared the research in the association's industrial seminars, sent the questionnaires by e-mail and followed the collection process aiming to achieve a high level of representativity of the sample. Table 4 shows the composition of the sample regarding company's size, respondent's profile and target industrial sectors of this sample, considering that all companies are B2B and included in machinery and equipment.

Table 4: Demographic characteristics of the sample

Category	Description	(%)	Category	Description	(%)
Target industrial sectors	Agriculture	48%	**Company's size**	Small (<100 employees)	41%
	Biotechnology	1%			
	Chemicals	24%		Medium (100 - 500 employees)	37%
	Construction	10%			
	Energy	15%		Large (>500 employees)	22%
	Food products	29%			
	Leather and related products	3%	**Respondent's profile**	Managers or directors	78%
	Mining	21%		Supervisors	10%
	Furniture	10%			
	Pharmaceutical	10%		Analists	4%
	Pulp and paper	16%			
	Software and technology	17%		Other	8%
	Steelworks	18%			
	Transport	13%			
	Metal products (not machinery and equipment)	34%			
	Other manufacturing	24%			

3.4.2 Variables definition

Following the technological framework represented in Figure 1, we developed a questionnaire using the technologies of these three main dimensions (appliance, support and base technologies), which were described above in Tables 1, 2 and 3. The questionnaire assessed the level of implementation of these technologies in the manufacturing companies following a five-point Likert scale varying from 1 – Not implemented to 5- Advanced implementation. Thus, the highest degree (5 = Advanced implementation) shows an advanced maturity of this technology.

Since we aimed to classify companies regarding their implementation patterns of the Industry 4.0 concept, we also included in the questionnaire companies' information that may help us to better understand their profile. These characteristics were already presented in the demographic description shown in Table 4.

Before implementing the questionnaire, we refined the description of the technologies as well as its structure by a round of interviews with 15 scholars and seven practitioners representing this industrial sector. The scholars are researcher from technological institutes in Southern Brazil dedicated to develop innovative solutions based on IoT technologies. The industry representatives are companies' CEOs that compose the directory board from ABIMAQ. They help to align the questionnaire to the technical language of this industrial sector, aiming to reduce possible misunderstanding in the technologies described in the questionnaire.

3.4.3 Sample and method variance

We tested potential sample bias using Levene's test for equality of variances and t-test for the equality of means between early and late respondents. Aiming this, we grouped respondents into two main waves, the early respondents, i.e. those from the first e-mail (63 answers), and the late respondents, i.e. the remaining 29 answers. Following (ARMSTRONG; OVERTON, 1977), we concluded that there were no evidences for a significant difference compared to the population since the results of these tests indicated no differences in means and variation in the two groups.

Regarding the common method variance (PODSAKOFF et al., 2003), we randomized the technologies list order to avoid that the respondent may directly associate technologies of the list. Furthermore, we sent our questionnaire to key respondents (CEO and Operations Directors), as explained in the sampling section (4.1.), so that we could obtain a broader vision of the implementation level of the Industry 4.0 concepts in the companies. Finally, we calculated the Harman's single-factor test with an exploratory factor analysis to address common method bias, i.e. the variance due to the measurement method rather than to the measures they are assumed to represent (PODSAKOFF et al., 2003). This test with all variables resulted into a first factor that comprehended only 19% of the observed variance and that, therefore, there is no single factor accounting for the majority of the variance in the model. Nonetheless, to be completely sure of the absence of this potential problem, a multiple-respondent approach representing each company should be used, which was no possible in our survey, being a limitation of our study (GUIDE; KETOKIVI, 2015).

3.4.4 Data analysis

Considering the purpose of this paper, the first step was to identify companies with different maturity levels in the adoption of smart manufacturing technologies. At least two groups with distinct technological level were necessary to enable our hypotheses tests, in order to discover different patterns between these groups that can explain Industry 4.0 adoption. Therefore, we followed a two-step cluster analysis for the identification of distinct groups with similar technological characteristics in the sample, as previously done by other studies (MARODIN et al., 2016; MONTOYA et al., 2009). We clustered groups according to their similarity of adoption of smart manufacturing technologies, due to its relevance as the central element of Industry 4.0. Following Milligan and Cooper (1985), we firstly performed a hierarchical cluster analysis (HCA), which determines the adequate number of groups for sample division. HCA was performed using Ward`s method in the clustering process, with the Euclidean distance measure of similarity among respondents. The second stage considered the refinement of the cluster solution and the definition of variables that discriminated the clusters obtained. This was performed using a non-hierarchical K-means cluster algorithm (HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, 2009).

After obtaining the cluster compositions, we performed a demographic analysis of the cluster members. The aim of this analysis was to understand if the groups formed with cluster analysis presented different patterns of high implementation of the smart manufacturing technologies from the Industry 4.0 (H1). We also used the demographic analysis and independence tests to understand the relationship of these groups of companies allocated in the different clusters with levels of smart products development (H2), support technologies (H3a and 3b) and of base technologies (H4). In this case, we used the Pearson's Chi-squared standardized measure of association, which is used to reject the null hypothesis that there is no association between the variables. In a contingency table, Pearson's Chi-squared compares the frequencies of expected values of a variable with its actual values. A higher value of association means that for the category in analysis (column), the variables (row) have a different value than expected (ROSS, 2010). In our analysis, the rejection of the null hypothesis supports our formulated hypothesis, indicating a different pattern of technology adoption between the clustered groups. According to Hair et al. (2009), this measure is suitable for samples larger than 50 cases, with a minimum of five observations for each class. Therefore, for the associations resulting in less than five observations, we used the Fisher's exact test (CORTIMIGLIA; GHEZZI; FRANK, 2016).

3.5 Results

3.5.1 Results for the appliance technologies in the Industry 4.0

Figure 2 shows the dendrogram of the performed hierarchical cluster analysis using the smart manufacturing technologies (Table 1) as selection variables. The dendrogram represents the similarities between companies based on the profile of adoption of these smart manufacturing technologies. As shown in this dendrogram (Figure 1), the companies can be grouped into two or three main clusters for the adopted technologies. We choose to work with three groups, avoiding to select more refined groups since this would lead to some clusters with little representativeness due to the low number of companies.

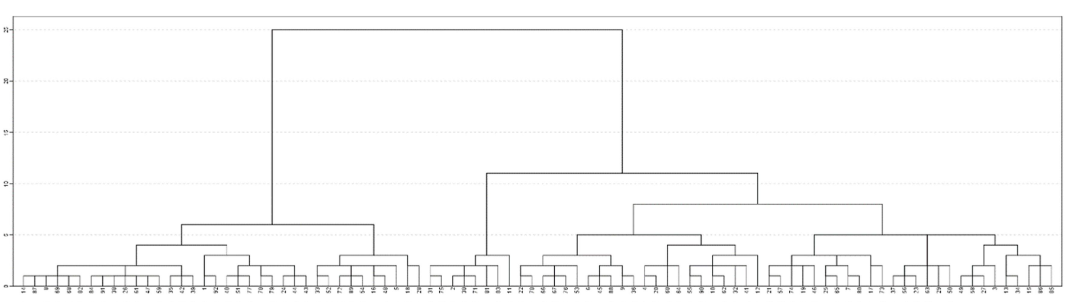

Figure 2 : Dendrogram for the selection of the number of clusters

These three clusters were used to perform the K-means analysis aiming to refine the selected cluster memberships. Table 5 shows the contribution of each of the smart manufacturing technologies for the definition of the clusters' composition. The means for maturity in adoption of smart manufacturing technologies are statistically different between the three groups for all technologies considered in our analysis except for flexible lines, evidenced by the results of the ANOVA F-value test. Considering the threshold value of the means equals three, which in our scale provided represents only a project of implementation, the technologies that presented a lower or equal mean value in the clusters express an average non-adoption, while mean values ≥ 3.0 represents its partial and ≥ 4.0 advanced implementation. Therefore, we defined these three groups as low adopters (Cluster 1), moderate adopters (Cluster 2) and advanced adopters (Cluster 3) of the Industry 4.0 core technologies. Regarding the size of the companies constituting each of these clusters, it is worth noticing that the more advanced the cluster is in terms of technology adoption, the larger the predominant size of the companies composing it.

The findings presented in the K-means results of Table 5 support H1, which defines that different patterns of Industry 4.0 can be defined based on the type of smart manufacturing technologies adopted by the manufacturing companies. These findings show that the adoption pattern is divided according to levels of implementation of all the technologies and based on different levels of adoption. In other words, one could expect that some companies cluster may show high implementation of one type of technologies while other companies clusters may show high implementation of other type of technologies, but this did not happen. What the results show is that companies are clustered in a progressive implementation of all the considered technologies, excepting flexible lines, which did not show statistical significance between groups. Therefore, the described smart manufacturing technologies are complementary and not substitutable while companies are growing in maturity, according to our findings. Additionally, Table 5 presents three levels of technologies independently of the level of adoptions according to the clusters. This can be seen in the classification presented with the grey scale. The first category, represented with dark grey color, is composed by those technologies with a mean ≥ 4.0, i.e. high to advanced level of implementation. The traditional set of technologies for vertical integration is the leading one in the smart manufacturing technologies: Sensors/PLCs + SCADA + MES + ERP systems. Then, it is followed by technologies for energy efficiency and traceability. The second category of technologies – highlighted with middle grey color – is composed by those technologies focused on virtualization of the factory and automation of the decision-making process. Finally, the less implemented – highlighted in light grey color – is represented by the less implemented technologies independently of the level of maturity of the clusters.

Table 5: K-means results for cluster variables

Smart manufacturing technologies (H1)	**Cluster Mean + S.D.**						
	Cluster 1 *Low adopters*		**Cluster 2** *Moderate adopters*		**Cluster 3** *Advanced adopters*		**ANOVA F-value**
Sensors, actuators and PLCs	2.36	*±1.22*	**3.55**	*±1.00*	**4.60**	*±0.63*	27.89***
Enterprise Resource Planning (ERP)	**3.20**	*±1.15*	**4.06**	*±1.00*	**4.53**	*±1.06*	10.80***
Manufacturing Execution System (MES)	2.14	*±0.90*	**3.39**	*±1.00*	**4.33**	*±0.72*	38.48***
Supervisory Control and Data Acquisition (SCADA)	2.32	*±0.98*	**3.21**	*±1.02*	**4.07**	*±1.10*	18.61***
Energy efficiency monitoring system	1.75	*±0.65*	2.15	*±0.76*	**4.07**	*±0.96*	54.72***
Energy efficiency improving system	1.77	*±0.60*	2.15	*±0.83*	**4.07**	*±0.96*	52.23***
Identification and traceability of final products	2.32	*±0.96*	**3.64**	*±1.19*	**4.00**	*±0.76*	23.12***
Identification and traceability of raw materials	2.18	*±0.97*	**3.52**	*±1.20*	**4.00**	*±0.65*	25.43***
Simulation of processes (digital manufacturing)	2.20	*±0.85*	2.73	*±1.13*	**4.00**	*±0.93*	19.22***
Machine-to-machine communication	1.80	*±0.73*	2.79	*±0.99*	**3.93**	*±0.70*	40.01***
Industrial robots	1.80	*±0.82*	2.94	*±1.30*	**3.80**	*±1.21*	23.00***
Artificial Intelligence for production	1.77	*±0.60*	2.70	*±0.85*	**3.40**	*±1.06*	28.79***
Virtual commissioning	1.73	*±0.66*	2.39	*±0.97*	**3.33**	*±1.29*	18.72***
Artificial Intelligence for predictive maintenance	1.68	*±0.74*	2.42	*±0.94*	**3.33**	*±1.23*	19.95***
Automatic nonconformities identification	1.95	*±0.61*	2.55	*±0.83*	**3.27**	*±1.10*	16.70***
Additive manufacturing	1.80	*±0.67*	2.48	*±1.18*	2.60	*±1.24*	6.39**
Flexible lines	2.00	*±0.89*	2.45	*±1.23*	2.53	*±1.36*	2.19
Number of companies	44		33		15		
Small size companies	63.6%		21.2%		6.7%		
Medium size companies	22.7%		54.5%		20.0%		
Large size companies	13.6%		24.2%		63.3%		

*** = p < 0.05; *** = p < 0.001*

In the second step, we associated the three smart manufacturing maturity-level clusters with the adoption of different types of solution for smart product and services, something part of the broader Industry 4.0 concept, as proposed in our hypothesis H2. These results are reported in Table 6 in which it can be seen that H2 is supported. The results show that Cluster 3, which is composed by companies with advance adoption of smart manufacturing, is also the one with high adoption of three types of the five capabilities for smart product: connectivity (73%), monitoring (67%) and control (67%). Thus, our findings show that there is a connection, at least at the advanced level of Industry 4.0, between the adoption of smart manufacturing and smart product technologies in the industrial sector of our sample. On the other hand, optimization and autonomy are capabilities less implemented at the advanced level (47% of the companies of this cluster did not adopted this level of technologies for products), although they show a growing number of companies adopting them when compared with the low or moderate adopters.

Table 6: Cluster demographic composition for the adoption of Smart products

Smart product technologies (H2)	**Adoption**	**Cluster 1** *Low adopters*	**Cluster 2** *Moderate adopters*	**Cluster 3** *Advanced adopters*	**Test**
Smart products with connectivity capability	Yes	14%	36%	73%	Fisher's test = 18.40***
	No	86%	64%	27%	
Smart products with monitoring capability	Yes	20%	45%	67%	Pearson's X^2 test = 1.84**
	No	80%	55%	33%	
Smart products with control capability	Yes	23%	39%	67%	Pearson's X^2 test = 9.66**
	No	77%	61%	33%	
Smart products with optimization capability	Yes	7%	18%	53%	Fisher's test = 3.86**
	No	93%	82%	47%	
Smart products with autonomy capability	Yes	7%	6%	53%	Fisher's test = 16.69***
	No	93%	94%	47%	
	Total count	**44**	**33**	**15**	

** p= 0.05; *** p = 0.001

3.5.2 Results for the support technologies in the Industry 4.0

After we defined and analyzed the clusters for the appliance or end technologies of the Industry 4.0, we proceed with the test of our hypotheses H3a and H3b for the association of support technologies (smart supply chain and smart working) to those set of companies with advanced implementation of the smart manufacturing technologies of the Industry 4.0. The results are presented in Table 7, showing that H3a and H3b are partially supported by our findings. Firstly, regarding smart supply chain technologies of the Industry 4.0, it is possible to see that the three types of platforms for integration with suppliers, customers and other units of the company present a predominantly low level of adoption. It is worth noticing that suppliers and customers, the horizontal integration concept of the Industry 4.0, is very low even in companies with advanced level of implementation of smart manufacturing. Only platforms for integration with other units showed a higher level of adoption (53%) among those advanced adopters of the smart manufacturing technologies.

Table 7: Cluster demographic composition of smart supply chain and smart working technologies

Support Technologies		**Adoption**	**Cluster 1** *Low adopters*	**Cluster 2** *Moderate adopters*	**Cluster 3** *Advanced adopters*	**Fisher's exact test**
Smart Supply Chain technologies (H3a)	Digital platforms with Suppliers	Yes	7%	9%	33%	6.38**
		No	93%	91%	67%	
	Digital platforms with customers	Yes	5%	9%	33%	7.81**
		No	95%	91%	67%	
	Digital platforms with other company units	Yes	9%	21%	53%	11.91**
		No	91%	79%	47%	
Smart Working technologies (H3b)	Remote monitoring of production	Yes	9%	39%	93%	37.17***
		No	91%	61%	7%	
	Collaborative robots	Yes	2%	9%	67%	28.30***
		No	98%	91%	33%	
	Remote operation of production	Yes	5%	3%	40%	12.95***
		No	95%	97%	60%	
	Augmented reality for maintenance	Yes	0%	6%	27%	10.24***
		No	100%	94%	73%	
	Virtual reality for workers training	Yes	0%	6%	27%	10.24***
		No	100%	94%	73%	
	Augmented and Virtual reality for NPD	Yes	2%	6%	33%	10.31***
		No	98%	94%	67%	
		Total count	**44**	**33**	**15**	

** p= 0.05; *** p = 0.001

Regarding the smart working technologies (Table 7), we also found partial support for our hypothesis H3b. In this case only the use of remote monitoring of production and the use of collaborative robots presented a relative high level of adoption (93% and 67% of the companies) among the advanced adopters of smart manufacturing technologies. Remote operation of production showed a slight higher level of adoption in Cluster 3 (40% of the companies) but it still predominant in this cluster the none adoption of this technology (60%). The less implemented technologies for smart working are those related to augmented reality and virtual reality, which are very low adopted among the different clusters.

Therefore, summarizing the support technologies of the Industry 4.0, our findings of Table 7 showed that smart working technologies are partially adopted among those companies with stronger implementation of smart manufacturing while smart supply chain technologies are those less implemented in all clusters, even when they are quite stronger in the Advanced adopters cluster.

3.5.3 Results for the base technologies of Industry 4.0

In the final step, we analyzed how the base technologies support the implementation of the smart manufacturing technologies of the Industry 4.0, according to our proposed hypothesis H4. In this case, our findings support H4 since for the four technologies considered, there is a slightly higher presence of companies adopting these technologies in the Cluster 3 which composes the advanced adopters of smart manufacturing. Comparing the three clusters, it is also possible to see that Cloud computing are those more adopted in all clusters, which indicates that it is the most accessible solution used by these companies. This can be stated also with the Internet of things and analytics are less adopted in Cluster 1 and 2 while Big Data is the last one implemented in these clusters. Anyway, Cluster 3 demonstrates that all these technologies are present in the advanced adopters, as proposed by our hypothesis H4.

Table 8: Cluster composition of base technologies

Base technologies (H4)	**Adoption**	**Cluster 1** *Low adopters*	**Cluster 2** *Moderate adopters*	**Cluster 3** *Advanced Adopters*	**Test**
Internet of Things	Yes	18%	39%	67%	Pearson's X^2 test = 12.51**
	No	82%	61%	33%	
Cloud	Yes	43%	58%	60%	Pearson's X^2 test = 2.13
	No	57%	42%	40%	
Big Data	Yes	9%	27%	60%	Fisher's test = 15.20***
	No	91%	73%	40%	
Analytics	Yes	18%	36%	60%	Pearson's X^2 test = 9.62**
	No	82%	64%	40%	
	Total count	**44**	**33**	**15**	

** p= 0.05; *** p = 0.001

3.6 Discussions

We summarized our findings in Figure 3, aiming to illustrate a holistic vision of our findings regarding the adoption patterns of the Industry 4.0 technologies. The framework summarizes the results presented in Tables 5 to 8. We divided the structure following our initial theoretical framework of Figure 1, which we expanded with the empirical findings. We also divided the implementation complexity based on the results from the three clusters, showing those more implemented (light grey color) to those less implemented (dark grey color) technologies. It is worth noticing that we are not proposed these stages as the ideal stages of implementation, but we show them as the current way industry is prioritizing the technologies adoption. This framework can be compared with other prior proposals from the literature, such as Schuh et al. (2017), Lee et al. (2015) and Lu and Weng (2018). The main difference between these models and the framework obtained from our findings is that they proposed ideal stages while ours present what is happening in an industrial sector based on empirical data. We also detail the technologies, while they focus mainly on capabilities required for the Industry 4.0. Moreover, our model is broader, since it considers not only the internal smart manufacturing technologies as the other models does, but we also integrate them with smart products capabilities and with support and base technologies. We use this framework to guide the discussion of our findings as follows.

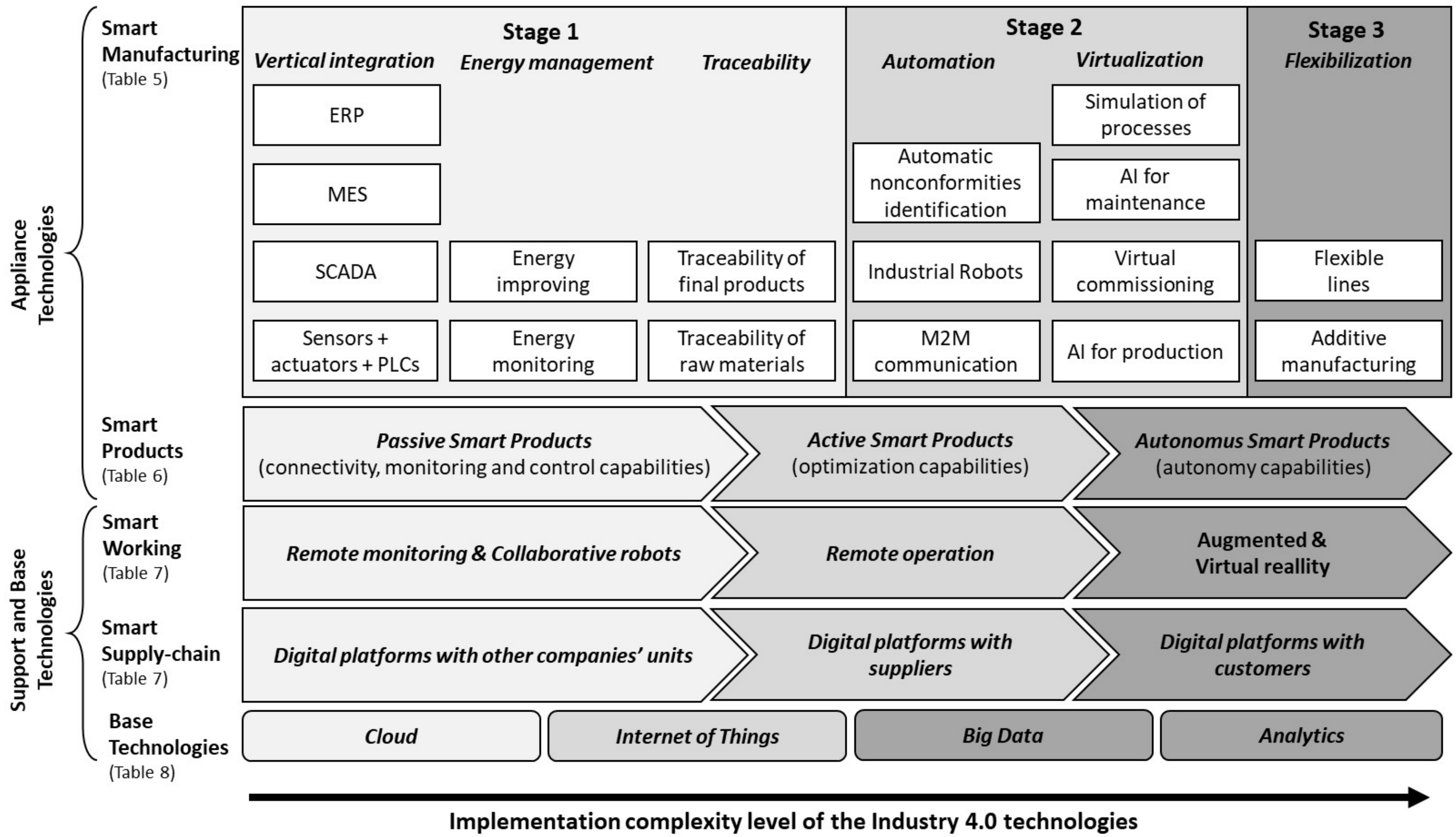

Figure 3: Framework summarizing the findings of the adoption patterns of the Industry 4.0

Our findings allowed us to understand the Industry 4.0 technology patterns, showing three different groups of adoption level of the smart manufacturing concepts and the relationship with smart product technologies as well as with the supporting smart supply chain and smart working technologies and the base technologies. These findings allow us to verified, based on empirical data evidence, some prior suggestions of the literature. One of them is that the maturity of the Industry 4.0 concepts dependent of the companies' size, as suggested by Kagermann et al., (2013) and Schuh et al. (2017). Our results (Table 5) show that the larger the company, the more the concentration of advanced adopters of this concept. This is aligned with the general innovation literature, which affirms that large companies are more prone to invest in process and product innovation, since it requires large amounts of investments in technological infrastructure, something not viable for small companies (FRANK et al., 2016). Moreover, these findings showed that advanced adopters are leading in all the technologies and not in some specific, which may indicate that the growing maturity in Industry 4.0 technologies implies in aggregating technological solutions as a 'Lego' instead of substituting one to another. This is represented in our framework of Figure 3 as the progressive adding of technologies in the growing maturity of the Industry 4.0. This evidence supported our hypothesis H1, even when it was surprising to us seeing a complete set of technologies advancing in maturity instead of different mix of solutions for each cluster.

Additionally, a surprising result from our findings regarding smart manufacturing adoption is that flexible lines is the only technology which was not strongly adopted in any of the three maturity clusters. Flexible line has been proposed as one of the Industry 4.0 concepts, which can be also supported by the use of additive manufacturing to produce different components and products in the same line (D'AVENI, 2015; WANG et al., 2016a; WELLER; KLEER; PILLER, 2015). However, previous studies in emergent countries also highlight productivity as one of the first industrial concerns instead of flexibility in Industry 4.0 (CNI, 2016), being the main concern of big factories focused on economies of scale. Since we studied an industrial sample focused on business-to-business solutions in which customization of the products might require more flexibility and adaptation of the plants instead of large-scale production, we were expecting different results and more implementation of flexible lines. Therefore, one of our concerns is that companies are just replicating an adoption pattern of the Industry 4.0 from other business context where productivity is the main interest. Other possibility is that companies see this as a very advanced level of implementation, being at the top of the maturity, as we show in the framework of Figure 3. Dalenogare et al. (2018) study at the industry level has also shown that flexible lines are not associated to the expected benefits of the Brazilian industry as a whole. Thus, the role of flexible lines in Industry 4.0 would require more investigation in future research.

Regarding the connection between smart manufacturing and smart products, which we tested in our hypothesis H2, the extant literature suggests that Industry 4.0 can foster the implementation of digital solutions for the end customer (ARDOLINO et al., 2018; KAMP; OCHOA; DIAZ, 2017; OPRESNIK; TAISCH, 2015), stimulating the offering of smart products and services (LERCH; GOTSCH, 2015) and triggering the digital product-service transformation of companies' business models (VENDRELL-HERRERO et al., 2017). We could evidence such a relationship in our results from Table 6, since those high adopters of the smart manufacturing concepts are the same with strong implementation of some of the smart product capabilities. In this sense, we reinforce prior works of Kamp et al. (2017) and Rymaszewska et al. (2017) that highlighted potential returns of the digital smart products and services for the internal manufacturing processes of the company, having both the potential of being interconnected. However, as we showed in our results, the companies of our sample are only implementing what we called as `passive` smart products that help to monitoring and control, while those more advanced that help to optimize and to provide autonomy to the machines are still low implemented in this industrial sector.

Regarding the support technologies, our results showed partial evidence to the hypotheses H3a and H3b which considered the association of these technologies with the smart manufacturing adoption. The literature has highlighted the supply chain integration as one of the advantages of the Industry 4.0 based on integrated platforms with suppliers (ANGELES, 2009; PFOHL; YAHSI; KURNAZ, 2017; SIMCHI-LEVI; KAMINSKY; SIMCHI-LEVI, 2004). Our results show that, at least in the industrial sector considered in our sample, supply chain integration is still behind even with the suppliers. The same limitation was founded in the technologies for smart working activities, where only remote monitoring of production and collaborative robots were prominent among the advanced adopters of the smart manufacturing technologies. In this case, augmented and virtual reality are still low implemented as previously reported also in other studies that consider them still emerging and initial technologies (ELIA; GNONI; LANZILOTTO, 2016). Therefore, we could state that these two are in fact support technologies that might grow only after a consolidation of the internal smart manufacturing of the Industry 4.0.

Regarding the base technologies some interesting and counterintuitive results were found. Firstly, one could expect that cloud computing may be dependent of the implementation of IoT solutions, since the equipment should be first connected to generate data stored in the cloud (WANG et al., 2016b). However, the fact that cloud computing is the first implemented technology may suggest that cloud computing is used not as a way to store real-time data from the equipment but as a simply data store remotely used. In this sense, cloud may represent only a remote storing of data, while the real-time data collection may be represented by the sequence of IoT + Big Data + Analytics, which are the following technologies in the implementation, according to our framework of Figure 3. As previously demonstrated by Dalenogare et al. (2018) at the industry-level, these are a set of technologies still very immature in traditional manufacturing sectors as the one considered in our sample, which could be also evidenced in the fact that the three clusters present a high number of companies not implementing these technologies.

3.7 Conclusions

In this paper, we aimed to identify different patterns of adoption of three technology layers of the Industry 4.0: base technologies, support technologies and appliance technologies, this last one subdivided into: smart manufacturing and smart products. Our results support our premise that smart manufacturing is the central role of Industry 4.0 and that it is connected with smart products, meaning that those companies with more implementation in smart manufacturing tend to focus also their effort in smart products. We also showed how the support and base technologies are used to complement smart manufacturing and products. According to our findings, the group of companies with more advanced level of implementation of the Industry 4.0 tend to adopt most of the technologies and not a specific set, when compared to other clusters with lower level of implementation. For the technologies adopted, a sequence of implementation level can be drawn, based on the general patterns of technologies adopted in the different industrial clusters studied. We summarized this in a framework, which is the main contribution of our findings, since it shows how Industry 4.0 technologies are implemented and interrelated.

3.7.1 Practical implications

Our results can contribute for companies seeking for technological upgrade, with insights about requirements for Industry 4.0 application technologies. Such results are important since there is still considerable uncertainty about Industry 4.0, regarding technology requirements and potential benefits, as previous researches have shown (CNI, 2016; DALENOGARE et al., 2018). Thus, managers can use our framework to focus not only on the appliance technologies, but also on those technologies that provide complementary and basic conditions for the Industry 4.0 implementation. Managers can also use our framework as a maturity implementation model to evolve in the Industry 4.0 concept. The framework shows levels of implementation of several technologies which we interpreted as related to complexity levels for the complete implementation of the Industry 4.0 concept.

3.7.2 Limitations and future research

This research has some limitations that open new avenues for future research. Firstly, our work considers a sample from a specific industrial sector which has its own characteristics. Therefore, one should be careful to accept our findings as a general pattern for the Industry 4.0. The comparison made with our prior works (e.g. DALENOGARE et al., 2018; LEE; BAGHERI; KAO, 2015; LU; WENG, 2018;SCHUH; ANDERI; GAUSEMEIER, 2017) makes us believe that our findings can be extended to other industrial fields. However, more empirical evidences are needed to validate this extending such kind of survey to other industries as well. Second, our study did not consider the effect that these technologies may have on industrial performance, which could be a very interesting issue for future research. The real benefit of the Industry 4.0 is still a concern for practitioners and such a study could be beneficial for this field. Dalenogare et al. (2018) have recently studied such an impact but only at the industry-level, and they called the attention to the need of firm-level analysis. We move our research a first step towards this direction, since we provided an empirical base for the understanding of how technologies are adopted and relate among them. From this point on, future research can advance by studying how these technologies impact on industrial performance at the firm level. Lastly, we demonstrated that large companies are more prepared for Industry 4.0, as expected. However, the higher maturity group also presented small size companies that successfully adopted smart manufacturing technologies. Future research could deep in this kind of companies to understand what factors support them to innovate, since the literature indicates many barriers for them when comparing to large companies. Some prior works have addressed this need (e.g. KAGERMANN; WAHLSTER; HELBIG, 2013, MÜLLER; BULIGA; VOIGT, 2018) and now, with our new findings the analysis could be systematized based on the study of the proposed technologies.

3.8 References

ADOLPHS, D. P. et al. Reference Architecture Model Industrie 4.0 (RAMI4.0). v. 0, n. July, p. 28, 2015.

AHUETT-GARZA, H.; KURFESS, T. A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing. **Manufacturing Letters**, v. 15, p. 60–63, 2018.

ANGELES, R. Anticipated IT infrastructure and supply chain integration capabilities for RFID and their associated deployment outcomes. **International Journal of Information Management**, v. 29, n. 3, p. 219–231, 2009.

ARDOLINO, M. et al. The role of digital technologies for the service transformation of industrial companies. **International Journal of Production Research**, v. 56, n. 6, p. 2116–2132, 2018.

ARMSTRONG, J. S.; OVERTON, T. S. Estimating Nonresponse Bias in Mail Surveys. **Journal of Marketing**, v. 14, n. 3, p. 396–402, 1977.

ASHTON, K. That "Internet of Things" Thing. **RFiD Journal**, p. 4986, 2009.

BABICEANU, R. F.; SEKER, R. Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. **Computers in Industry**, v. 81, p. 128–137, set. 2016.

BALOGUN, O. O.; POPPLEWELL, K. Towards the integration of flexible manufacturing system scheduling. **International Journal of Production Research**, v. 37, n. 15, p. 3399–3428, 1999.

BARRATT, M.; OKE, A. Antecedents of supply chain visibility in retail supply chains: a resource-based theory perspective. **Journal of Operations Management**, v. 25, n. 6, p. 1217–1233, 2007.

BOYES, H. et al. The industrial internet of things (IIoT): An analysis framework. **Computers in Industry**, v. 101, n. March, p. 1–12, 2018.

BRADLEY, D.; HEHENBERGER, P. **Mechatronic futures**. [s.l: s.n.].

BRETTEL, M. et al. How Virtualization , Decentralization and Network Building Change the Manufacturing Landscape : **International Journal of Mechanical, Industrial Science and Engineering**, v. 8, n. 1, p. 37–44, 2014.

CHIARELLO, F.; TRIVELLI, LEONELLO BONACCORSI, A.; FANTONI, G. Extracting and mapping industry 4.0 technologies using wikipedia. **Computers in Industry**, v. 100, p. 244–257, 2018.

CHIEN, C. F.; KUO, R. T. **Beyond make-or-buy: Cross-company short-term capacity backup in semiconductor industry ecosystem**. [s.l: s.n.]. v. 25

CHRISTOPHER, M. The agile supply chain: competing in volatile markets. **Industrial Marketing Management**, v. 29, n. 1, p. 37–44, 2000.

CNI - CONFEDERAÇÃO NACIONAL DA INDÚSTRIA. **Industry 4.0: a new challenge for Brazilian industry**. [s.l.] Available at: (https://bucket-gw-cni-static-cms-si.s3.amazonaws.com/media/filer_public/54/02/54021e9b-ed9e-4d87-a7e5-3b37399a9030/challenges_for_industry_40_in_brazil.pdf), 2016.

CORTIMIGLIA, M. N.; GHEZZI, A.; FRANK, A. G. Business Model Innovation and Strategy Making Nexus: Evidence from a Cross-Industry Mixed-Methods Study. **Ssrn**, 2016.

D'AVENI, R. The 3D printing revolution. **ICIS Chemical Business**, v. 284, n. 26, p. 8, 2015.

DALENOGARE, L. S. et al. The expected contribution of Industry 4.0 technologies for industrial performance. **International Journal of Production Economics**, v. 204, n. December 2017, p. 383–394, 2018.

DE SOUSA JABBOUR, A. et al. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. **Technological Forecasting and Social Change**, v. 132, p. 18–25, 2018.

DRATH, R.; HORCH, A. Industrie 4.0: Hit or hype? [Industry Forum]. **IEEE Industrial Electronics Magazine**, v. 8, n. 2, p. 56–58, 2014.

DU, G. et al. Markerless Kinect-based hand tracking for robot teleoperation. **International Journal of Advanced Robotic Systems**, v. 9, p. 1–10, 2012.

EL KADIRI, S. et al. Current trends on ICT technologies for enterprise information systems. **Computers in Industry**, v. 79, p. 14–33, 2016.

EL MARAGHY, H. A. Flexible and reconfigurable manufacturing systems paradigms. **Flexible Services and Manufacturing Journal**, v. 17, n. 4 SPECIAL ISSUE, p. 261–276, 2006.

ELIA, V.; GNONI, M. G.; LANZILOTTO, A. Evaluating the application of augmented reality devices in manufacturing from a process point of view: An AHP based model. **Expert Systems with Applications**, v. 63, p. 187–197, 2016.

FOGLIATTO, F. S.; DA SILVEIRA, G. J. C.; BORENSTEIN, D. The mass customization decade: An updated review of the literature. **International Journal of Production Economics**, v. 138, n. 1, p. 14–25, 2012.

FRANK, A. G. et al. The effect of innovation activities on innovation outputs in the Brazilian industry: Market-orientation vs. technology-acquisition strategies. **Research Policy**, v. 45, n. 3, p. 577–592, abr. 2016.

GAWER, A.; CUSUMANO, M. A. Industry platforms and ecosystem innovation. **Journal of Product Innovation Management**, v. 31, n. 3, p. 417–433, 2014.

GILCHRIST, A. **Industry 4.0: the industrial internet of things**. Berkeley: Apress, 2016.

GORECKY, D.; KHAMIS, M.; MURA, K. Introduction and establishment of virtual training in the factory of the future. **International Journal of Computer Integrated Manufacturing**, v. 30, n. 1, p. 182–190, 2017.

GUIDE, V. D. R.; KETOKIVI, M. Notes from the Editors: Redefining some methodological criteria for the journal. **Journal of Operations Management**, v. 37, p. v–viii, 2015.

GUO, Z. et al. Using virtual reality to support the product's maintainability design: Immersive maintainability verification and evaluation system. **Computers in Industry**, v. 101, p. 41–50, out. 2018.

HAIR, J.F., BLACK, W.C., BABIN, B.J., ANDERSON, R. E. **Multivariate data analysis: A global perspective**. [s.l.] Upper Saddle River: Prentice Hall, 2009.

JANAK, L.; HADAS, Z. Knowledge Acquisition and Cyber Sickness: a Comparison of Vr Devices in Virtual Tours. **MM Science Journal**, p. 665–669, 2015.

JESCHKE, S. et al. **Industrial Internet of Things and Cyber Manufacturing Systems**. [s.l.] Springer, 2017.

KAGERMANN, H.; WAHLSTER, W.; HELBIG, J. **Recommendations for implementing the strategic initiative INDUSTRIE 4.0Final report of the Industrie 4.0 WG**. [s.l: s.n.].

KAMP, B.; OCHOA, A.; DIAZ, J. Smart servitization within the context of industrial user–supplier relationships: contingencies according to a machine tool manufacturer. **International Journal on Interactive Design and Manufacturing**, v. 11, n. 3, p. 651–663, 2017.

KORTMANN, S.; PILLER, F. Open Business Models and Closed-Loop Value Chains. **California Management Review**, v. 58, n. 3, p. 88–109, 2016.

LEE, J.; BAGHERI, B.; KAO, H. A. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. **Manufacturing Letters**, v. 3, p. 18–23, 2015.

LERCH, C.; GOTSCH, M. Digitalized Product-Service Systems in Manufacturing Firms: A Case Study Analysis. **Research-Technology Management**, v. 58, n. 5, p. 45–52, 2015.

LIAO, Y. et al. Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. **International Journal of Production Research**, v. 55, n. 12, p. 3609–3629, jun. 2017.

LIN, H. W. et al. Design of a global decision support system for a manufacturing SME: towards participating in collaborative manufacturing. **International Journal of Production Economics**, v. 136, p. 1–12, 2012.

LIU, H. Big data drives cloud adoption in enterprise. **IEEE Internet Computing**, v. 17, n. 4, p. 68–71, 2013.

LU, H. P.; WENG, C. I. Smart manufacturing technology, market maturity analysis and technology roadmap in the computer and electronic product manufacturing industry. **Technological Forecasting and Social Change**, v. 133, n. January, p. 85–94, 2018.

LU, Y. Industry 4.0: A survey on technologies, applications and open research issues. **Journal of Industrial Information Integration**, v. 6, p. 1–10, 2017.

MARODIN, G. A. et al. Contextual factors and lean production implementation in the Brazilian automotive supply chain. **Supply Chain Management: An International Journal**, v. 21, n. 4, p. 417–432, jun. 2016.

MELL, P.; GRANCE, T.; OTHERS. The NIST definition of cloud computing. **National institute of standards and technology**, v. 53, n. 6, p. 50, 2009.

MILLIGAN, G. W.; COOPER, M. C. An examination of procedures for determining the number of clusters in a data set. **Psychometrika**, v. 50, n. 2, p. 159–179, 1985.

MONTOYA, M. M. et al. Can You Hear Me Now? Communication in Virtual Product Development Teams. **Journal of Product Innovation Management**, v. 26, n. 2, p. 139–155, 2009.

MORTENSEN, S. T.; MADSEN, O. A Virtual Commissioning Learning Platform. **Procedia Manufacturing**, v. 23, n. 2017, p. 93–98, 2018.

MÜLLER, J. M.; BULIGA, O.; VOIGT, K. I. Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. **Technological Forecasting and Social Change**, v. 132, n. September 2017, p. 2–17, 2018.

OPRESNIK, D.; TAISCH, M. The value of big data in servitization. **International Journal of Production Economics**, v. 165, p. 174–184, 2015.

PARK, Y.-R.; LEE, J.-H.; LEE, Y.-J. A Study on Job Satisfaction of Smart Work Worker and Smart Work Continued Usage. **Journal of Society for e-Business Studies**, v. 19, n. 3, 2014.

PFOHL, H.-C.; KÖHLER, H.; THOMAS, D. State of the art in supply chain risk management research: empirical and conceptual findings and a roadmap for the implementation in practice. **Logistics research**, v. 2, n. 1, p. 33–44, 2010.

PFOHL, H.-C.; YAHSI, B.; KURNAZ, T. Concept and Diffusion-Factors of Industry 4.0 in the Supply Chain. In: FREITAG, M.; KOTZAB, H.; PANNEK, J. (Eds.). . **Dynamics in Logistics: Proceedings of the 5th International Conference LDIC**. [s.l: s.n.]. p. 381–390.

PODSAKOFF, P. M. et al. Common method biases in behavioral research: a critical review of the literature and recommended remedies. **The Journal of applied psychology**, v. 88, n. 5, p. 879–903, 2003.

PORTER, M. E.; HEPPELMANN, J. E. How smart, connected products are transforming companies. **Harvard Business Review**, v. 2015, n. October, 2015.

PORTER, M.; HEPPELMANN, J. How smart, connected products are transforming competition. **Harvard Business Review**, v. 92, n. 11, p. 64–88, 2014.

RAGUSEO, E.; GASTALDI, L.; NEIROTTI, P. Smart work: Supporting employees' flexibility through ICT, HR practices and office layout. **Evidence-based HRM**, v. 4, n. 3, p. 240–256, 2016.

ROSS, S. M. **Introductory Statistics**. 3. ed. [s.l.] Elsevier, 2010.

RYMASZEWSKA, A.; HELO, P.; GUNASEKARAN, A. IoT powered servitization of manufacturing–an exploratory case study. **International Journal of Production Economics**, v. 192, p. 92–105, 2017.

SCHEER, A.-W. Whitepaper - Industry 4 . 0 : From vision to implementation. n. September, 2015.

SCHUH, G.; ANDERI, R.; GAUSEMEIER, J. **Industrie 4.0 maturity index. Managing the Digital Transformation of Companies (acatech STUDY)**. [s.l.] Available at: (http://www.acatech.de/fileadmin/user_upload/Baumstruktur_nach_Website/Acatech/root/de/Publikationen/Projektberichte/acatech_STUDIE_Maturity_Index_eng_WEB.pdf), 2017.

SCURATI, G. W. et al. Converting maintenance actions into standard symbols for Augmented Reality applications in Industry 4.0. **Computers in Industry**, v. 98, p. 68–79, 2018.

SIMCHI-LEVI, D.; KAMINSKY, P.; SIMCHI-LEVI, E. **Managing the supply chain: The definitive guide for the business profesional**. [s.l: s.n.].

STOCK, T. et al. Industry 4 . 0 as enabler for a sustainable development : A qualitative assessment of its ecological and social potential. **Process Safety and Environmental Protection**, v. 118, p. 254–267, 2018.

TAO, F. et al. Digital twin-driven product design, manufacturing and service with big data. **International Journal of Advanced Manufacturing Technology**, v. 94, n. 9–12, p. 3563–3576, 2018a.

TAO, F. et al. Data-driven smart manufacturing. **Journal of Manufacturing Systems**, n. January, 2018b.

TELUKDARIE, A. et al. Industry 4.0 implementation for multinationals. **Process Safety and Environmental Protection**, v. 118, p. 316–329, 2018.

THOBEN, K.-D.; WIESNER, S.; WUEST, T. "Industrie 4.0" and Smart Manufacturing – A Review of Research Issues and Application Examples. **International Journal of Automation Technology**, v. 11, n. 1, p. 4–16, 2017.

VENDRELL-HERRERO, F. et al. Servitization, digitization and supply chain interdependency. **Industrial Marketing Management**, v. 60, p. 69–81, 2017.

WAMBA, F. S. et al. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. **International Journal of Production Economics**, v. 165, p. 234–246, jul. 2015.

WANG, L.; TÖRNGREN, M.; ONORI, M. Current status and advancement of cyber-physical systems in manufacturing. **Journal of Manufacturing Systems**, v. 37, p. 517–527, 2015.

WANG, S. et al. Implementing Smart Factory of Industrie 4.0: An Outlook. **International Journal of Distributed Sensor Networks**, v. 2016, 2016a.

WANG, S. et al. Towards smart factory for industry 4.0: A self-organized multi-agent system with big data based feedback and coordination. **Computer Networks**, v. 101, p. 158–168, 2016b.

WELLER, C.; KLEER, R.; PILLER, F. T. Economic implications of 3D printing: Market structure models in light of additive manufacturing revisited. **International Journal of Production Economics**, v. 164, p. 43–56, jun. 2015.

YIN, Y.; STECKE, K. E.; LI, D. The evolution of production systems from Industry 2.0 through Industry 4.0. **International Journal of Production Research**, v. 56, n. 1–2, p. 848–861, 2018.

YU, C.; XU, X.; LU, Y. Computer-Integrated Manufacturing, Cyber-Physical Systems and Cloud Manufacturing - Concepts and relationships. **Manufacturing Letters**, v. 6, p. 5–9, 2015.

ZHONG, R. Y. et al. Intelligent Manufacturing in the Context of Industry 4.0: A Review. **Engineering**, v. 3, n. 5, p. 616–630, 2017.

ZHOU, J. Intelligent mannfacturing-main direction of " made in China 2025 ". p. 3969, 2017.

4 CONSIDERAÇÕES FINAIS

Este capítulo apresenta as conclusões da proposta da dissertação, apresentando as principais contribuições acadêmicas e práticas, assim como algumas sugestões para trabalhos futuros a partir dos resultados encontrados.

4.1 Conclusões

A Indústria 4.0 tornou-se um conceito de interesse em nível mundial, dadas as diferentes iniciativas promovidas por governos de vários países desenvolvidos e emergentes (LIAO et al., 2017). O amplo envolvimento de governos para difusão do conceito e para promover ações que viabilizam a sua implementação indica a magnitude da importância da Indústria 4.0 para a competividade industrial, atualmente. O interesse em nível governamental no desenvolvimento de fábricas inteligentes reforça a necessidade de maior compreensão do conceito, que ainda é caracterizado por incertezas quanto à correta adoção das tecnologias difundidas inclusive em países desenvolvidos (SCHEER, 2015). Portanto, tendo em vista a sua inovatividade, esta dissertação propôs a entender os benefícios esperados com o conceito da Indústria 4.0 na indústria brasileira, estudar quais tecnologias relacionadas ao conceito da Indústria 4.0 permitem tais benefícios e definir os padrões de adoção de tecnologias da Indústria 4.0 no contexto das empresas brasileiras.

Desta forma, o Artigo 1 analisou uma amostra com empresas de todos os setores industriais no Brasil, a partir de *survey* conduzida em escopo nacional pela Confederação Nacional da Indústria (CNI, 2016). A análise foi realizada considerando a adoção de tecnologias pelas empresas e os benefícios esperados com esta adoção. Embora um tema crescente, existe pouca literatura sobre o assunto, principalmente no contexto de países emergentes.

O Artigo 2 propôs hipóteses sobre a adoção de tecnologias digitais da Indústria 4.0 compreendidas em tecnologias de aplicação, tecnologias complementares e bases tecnológicas. Em cada classificação, diferentes elementos são relacionados com o elemento central da Indústria 4.0, considerado pela literatura como a manufatura avançada. A literatura aborda este tema, porém existem poucas evidências quantitativas sobre a tendência de adoção de tecnologias do conceito, visto a inovatividade do tema.

4.2 Contribuições acadêmicas

Esta dissertação traz importantes contribuições para um tema recente e com grandes lacunas na pesquisa acadêmica. O Artigo 1 demonstrou estatisticamente como as tecnologias da Indústria 4.0 estão sendo utilizadas no contexto de países emergentes, sob a perspectiva de diferentes dimensões da performance industrial. Nos resultados apresentados, foram identificadas as tecnologias com maior contribuição para performance operacional e para o desenvolvimento de novos produtos. Não foi evidenciada uma relação entre as tecnologias e a terceira dimensão de performance industrial em análise, relacionada à sustentabilidade. Esta falta de relação é justificada pela baixa priorização das empresas industriais brasileiras em melhorar o desempenho sustentável de suas operações, focando apenas em maior produtividade, conforme indicado na *survey* conduzida pela CNI (2016). Ainda, foram encontradas disparidades entre a percepção industrial e a literatura sobre os benefícios das tecnologias digitais do conceito, como a percepção negativa de big data analytics e manufatura aditiva para o desenvolvimento de novos produtos e para a performance operacional, respectivamente. Big data analytics é um tema crescente em publicações acadêmicas e relatórios de consultoria, sendo que autores apostam nesta tecnologia como uma determinante para a competitividade em diversos setores da economia (PORTER; HEPPELMANN, 2015; WAMBA et al., 2015; BABICEANU; SEEKER, 2016). A importância desta tecnologia é corroborada parcialmente no Artigo 2, no qual o grupo com maior adoção de tecnologias de manufatura avançada também apresentou maior adoção de big data analytics.

O Artigo 2 comprovou uma dependência do elemento central da Indústria 4.0, manufatura avançada, com outros elementos externos à fábrica e que transcendem a manufatura, como as tecnologias de integração da cadeia de suprimentos e tecnologias que visam aumentar a performance do trabalhador em atividades compreendidas nos diferentes estágios do ciclo de vida do produto. Também foi comprovada uma maior tendência de desenvolvimento de produtos inteligentes pelas empresas mais desenvolvidas no conceito de manufatura avançada. Por fim, considerando a alta complexidade do conceito da Indústria 4.0, foram encontradas evidências que as tecnologias consideradas como base do conceito são determinantes para a implementação de um sistema produtivo inteligente, com foco na manufatura avançada. Embora mais estudos sejam necessários para comprovar estas relações, a tendência de adoção das tecnologias 4.0 indica um caminho a ser seguido, em orientação similar à de *roadmaps* sugeridos para desenvolvimento da Indústria 4.0 (SCHUH et al., 2017; LEE et al., 2015; LU; WENG, 2018).

4.3 Contribuições práticas

Os resultados encontrados permitem contribuições práticas, principalmente para a gestão de operações industriais e também para o desenvolvimento de novos produtos. Conforme os resultados do Artigo 1, algumas tecnologias são destacadas conforme a orientação estratégica: diferenciação dos produtos ou redução de custos operacionais. Estes resultados podem contribuir para a perspectiva estratégica das empresas, priorizando investimentos em tecnologias conforme as dimensões de performance industrial consideradas no artigo. Ainda, a identificação de percepções negativas sobre tecnologias como big data analytics contribui para a diretriz das empresas às tecnologias digitais. Considerando a importância desta tecnologia destacada por diversos autores e os interesses governamentais em difundir as tecnologias do conceito, de forma a orientar o país à nova revolução industrial, o resultado encontrado serve como um ponto de atenção para este fim. Logo, este resultado é um importante indicador da condição do Brasil frente à Indústria 4.0, pois de modo geral, esta percepção negativa indica uma tendência de não adoção de uma tecnologia com crescente influência na performance industrial.

Os resultados do Artigo 2 também auxiliam as empresas na diretriz da Indústria 4.0. Ao analisar, nas empresas mais avançadas no conceito, o grau de maturidade nas tecnologias específicas para aplicação em fábricas inteligentes e também em outros elementos complementares. Estes resultados podem servir de exemplo para empresas que visam a atualização digital de suas fábricas, assim como os resultados referentes as bases tecnológicas requeridas para este fim.

4.4 Sugestões para trabalhos futuros

A partir dos resultados dessa dissertação, algumas contribuições podem orientar trabalhos futuros. Os resultados indicam que apesar dos diferentes benefícios com a adoção de tecnologias digitais, existe uma tendência de adoção destas tecnologias. Esta tendência deve ser analisada com maior profundidade quanto às limitações técnicas das tecnologias consideradas. Assim, é possível confirmar se algumas tecnologias podem ser implementadas em uma sequência diferente, conforme os objetivos estratégicos das empresas sem comprometer o *roadmap* para o desenvolvimento da Indústria 4.0 em todo sistema produtivo. Considerando o alto custo das tecnologias compreendidas pelo conceito como uma importante barreira para a adoção destas (CNI, 2016), torna-se importante estudar um *roadmap* mais flexível à Indústria 4.0, principalmente em países emergentes que possuem um parque industrial mais heterogêneo quanto a sua intensidade tecnológica do que países desenvolvidos. Ainda, objetivos estratégicos das empresas não foram considerados nas análises dos artigos desta dissertação, assim como outros fatores que podem impactar na adoção das tecnologias, como a existência de setores de pesquisa e desenvolvimento nas empresas, o capital humano nas organizações e a existência de métodos de gestão da produção (LEONARD-BARTON, 1992). Estes fatores são importantes para o desenvolvimento de diferenciação estratégica em um contexto organizacional, e a relação destes com a adoção das tecnologias da Indústria 4.0 deve ser entendida para a adaptação das empresas ao conceito.

4.5 Referências

BABICEANU, Radu F.; SEKER, Remzi. Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. **Computers in Industry**, v. 81, p. 128-137, 2016.

CNI - Confederação Nacional da Indústria. Industry 4.0: a new challenge for Brazilian industry, 2016. Disponível em: (https://bucket-gw-cni-static-cms-si.s3.amazonaws.com/media/filer_public/54/02/54021e9b-ed9e-4d87-a7e5-3b37399a9030/challenges_for_industry_40_in_brazil.pdf).

LEE, Jay; BAGHERI, Behrad; KAO, Hung-An. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. **Manufacturing Letters**, v. 3, p. 18-23, 2015.

LEONARD-BARTON, Dorothy. Core capabilities and core rigidities: A paradox in managing new product development. **Strategic management journal**, v. 13, n. S1, p. 111-125, 1992.

LIAO, Yongxin et al. Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. **International Journal of Production Research**, v. 55, n. 12, p. 3609-3629, 2017.

LU, Hsi-Peng; WENG, Chien-I. Smart manufacturing technology, market maturity analysis and technology roadmap in the computer and electronic product manufacturing industry. **Technological Forecasting and Social Change**, v. 133, p. 85-94, 2018.

PORTER, Michael E.; HEPPELMANN, James E. How smart, connected products are transforming companies. **Harvard Business Review**, v. 93, n. 10, p. 96-114, 2015.

SCHEER, A. W. Industry 4.0: from vision to implementation. **Whitepaper,[Online]**, n. 9, 2015.

SCHUH, Günther et al. Industrie 4.0 Maturity Index. **Managing the Digital Transformation of Companies. Munich: Herbert Utz**, 2017.

WAMBA, Samuel Fosso et al. How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. **International Journal of Production Economics**, v. 165, p. 234-246, 2015.