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Master of Science in Management Engineering

JOB PROFILING:
HOW ARTIFICIAL INTELLIGENCE SUPPORTS THE MANAGEMENT OF COMPLEXITY INDUCED BY PRODUCT VARIETY:
A FRAMEWORK BASED ON LITERATURE REVIEW

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Abstract

Firms and supply chains (SC) increasingly are forced to customise products and optimise processes since today's markets are, on average, more demanding in terms of both costs and customer satisfaction. Generally, when product variety (PV) increases not only improves sales performance, since products offered better fit customers' expectations, but also increases the complexity in SC processes management, rising operational costs. For that reason, accurate management of product diversity is a fundamental point for the brands' success, which is why it is going to be investigated in that project. Moreover, firms' managers apply strategies to mitigate or accommodate this complexity, avoiding the customer satisfaction and cost trade-off to remain competitive and survive. However, we were wondering if it is enough. Artificial Intelligence (AI) has emerged to stay. Digitalisation era, data availability, and the improvement in computing power have boomed AI's potential in improving systems, controlling processes, and tackling complexity. These strengths are suitable to help managers not only to tackle the complexity arising from PV but also to boost the supply chain performance (SCP).

1. Introduction

In the nowadays market context, global competition has led to a need for increased product diversification to satisfy more sophisticated customer demands and expectations, thus, creating complexity in the supply chain (SC) management. The more products a company has to manage, the more items it has to plan, the more data it has to collect and analyse. Thus, it appears the need to balance priorities among different SKUs to respond to greater product availability and SC emergencies is generated. At the same time, it implies managing a wide range of supplier relationships, a more complex inventory system, and more floating production plans. Therefore, the higher the number of SKUs of different product items a company has, the higher its complexity. For that reason, accurate management of product diversity is a fundamental point for the brands' success, which is why it is going to be investigated in that project.

Although variety management has become a researched topic in the industry for the past decade, and Artificial Intelligence (AI) applications into SC management are becoming more and more investigated, potential AI benefits in supporting PV complexity management have never been analysed before. Besides, even though there are strategies studied for years to improve and reduce the complexity of the SC, it has not been studied before which are the ones that help mitigate the variety of products. Moreover, since papers were more focused on defining a few relations and impacts rather than having a global vision of PV impact on all the SC, in this study, we will synthesise the SC impacts, divided into four main areas, to obtain an almost complete vision of PV impact on the overall SC.

To accomplish this goal, firstly, it is essential to understand how product variety (PV) influences supply chain performance (SCP) to succeed in managing the before-mentioned complexity. We will examine the impact on sales, transportation, manufacturing, and purchasing areas, analysing the effect on drivers impacting each area's performance. Secondly, we will explore the most common practices traditionally used by firms supporting the mitigation or accommodation of the complexity arising from product range proliferation by recognising the successful strategies in handling complexity. Some of the studied approaches may not have been analysed from this point of view before, since some are just used for the more efficient management of the SC, even though they may be related to the variety management. Finally, an attempt was made to investigate how AI can support the PV-induced complexity. In this part of the work, thanks to the previously studied advantages that AI brings to the different SC areas, we have discussed its consequent effect on PV management.

2. Research questions and contribution

Traditional trends towards rising product variety to satisfy increasingly sophisticated customer needs raise questions concerning the impact derived from this decision on companies' performance. Therefore, we seek to present research evidence on the traditionally examined effects of PV on supply chain complexity (SCC) and, subsequently, how it affects supply chain performance (SCP) by identifying how an increase of PV impacts sales, transportation, manufacturing, and procurement. Furthermore, we have examined those efficient approaches that companies have been applying to mitigate or accommodate the PV subsequent complexity since complexity derived from the PV increase could be managed efficiently by standardisation practices. Thus, the core research question specifically addresses which are the direct and indirect impacts of product proliferation in the different affected areas of a SC, as well as which are the traditionally used approaches proved to be effective.

Moreover, to add quality value to the research and go a step further, we additionally seek to provide the current and updated vision of PV impact, which is strongly influenced by the digitalisation era. Therefore, secondary research questions specifically discuss aspects related to the possible shift of the traditionally analysed effects of PV once the new technologies come into play. In our case, we will be focused on artificial intelligence (AI) technology, considered the king information technology of this decade. AI is a mature and consolidated technology in advanced processing information, whose main strengths are its versatility when tackling a wide breadth of challenges and its capacity to enhance value generation in core processes. For that reason, we have considered AI as the appropriate technology to be discussed concerning the PV management topic. Further explanation about the reasons that motivate us to focus on AI is explained in section 8.

Research questions investigated in this study are shown below:

Research question 1 (R1): *Which are the traditional implications of an increase in PV on companies' performance derived from an increase of complexity in the SC?*

Research question 2 (R2): *Which are the most effective practices that have been used traditionally by firms to accommodate or mitigate the negative impact of PV on SCC?*

Research question 3 (R3): *What is the role of Artificial Intelligence (AI) technology in changing the impact of increased PV in each of the affected areas? Can it even change the traditional positive or negative relationship?*

3. Methodology for data collection

A systematic literature review has been conducted to ensure replicability and completeness while reducing possible bias in the approach. Moreover, literature review has followed steps recommended by (vom Brocke, 2009). The main objective of this literature is to contextualise the thesis scope, by mapping and integrating articles outcomes and subsequently identifying methods and practises as well as shifts and trends. As well as (Gosling & Naim, 2009), we conducted the literature review in three distinctive steps:

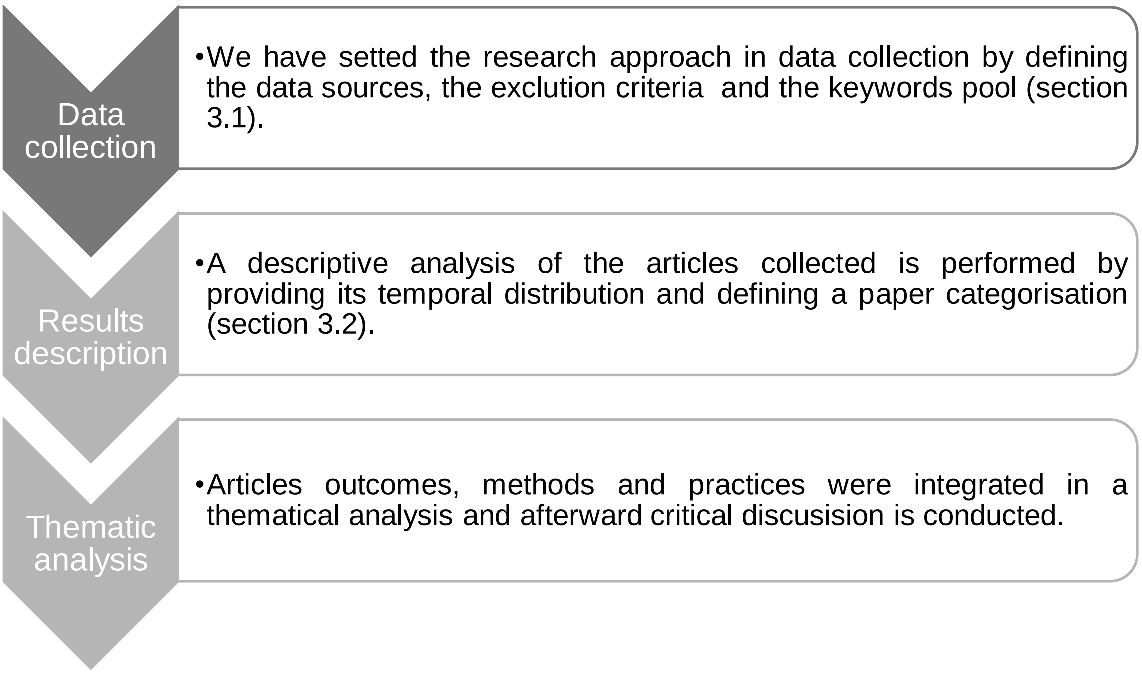

Figure 1. Research methodology. Source: Prepared by authors.

Note that the aforementioned systematic literature review was conducted for each of the main research topics. Firstly, complexity caused by product variety and strategies to mitigate them were studied and researched. Secondly, AI was analysed and afterwards contextualised to the PV topic in section 8.

3.1. Data collection

Data was collected through the Scopus database, whose reputation is indisputably established as one of the greater, more complete, more accurate, and more comprehensive databases (Youssra , Tarik , & Angappa , 2021). Besides, their content is recognised as high academic quality. However, secondary sources were examined in the snowball effect (forward search) if needed.

Firstly, a structured keyword searching was developed by identifying keywords strongly correlated with our research scope, also considering possible keywords synonyms to fulfil completeness in our review (view Table 1). The keywords selection process was performed by an initial brainstorming and a "*postmodum"* discussion whereby an additional keywords categorisation was conducted to better structure the study areas. Afterwards, a keyphrase density analysis (section 3.2.1) was conducted to corroborate the keywords selection. Secondly, a critical keywords combination analysis was accomplished to avoid missing necessary or relevant articles for our study scope. The resulting keywords pool is showed below.

Context	Keywords' pool
SCC	Supply chain; Complexity; Complexity drivers; Complexity indexes; Complexity metrics; Complexity measure; Complexity evaluation; Complexity management; Uncertainty; Volatility;
PV	Variety; Product variety; Product diversity; Variety management; Performance; Operational performance;
Strategies	Standardisation; Diversification; Commonality; Postponement; Customisation; Modularity; Portfolio; Differentiation; Strategy; Segmentation; Rationalization; SC integration; Information Technologies.
AI	Artificial Intelligence; Machine Learning; Natural Language Processing; Deep learning; Artificial Neural Networks;

Table 1. Keyword's pool categorised by analysed area

Finally, the search results were limited by following the exclusion criteria to limit the number of papers selected. Exclusion criteria:

1. Papers must be written in English language.
2. Duplicated articles obtained in previous searches were excluded.
3. Document type is restricted to journal articles (conference papers, short surveys, reviews, and notes were excluded).
4. Articles must be "Open access" (payments are not necessary to download it).
5. Non-aligned papers were excluded by title and abstract screening.

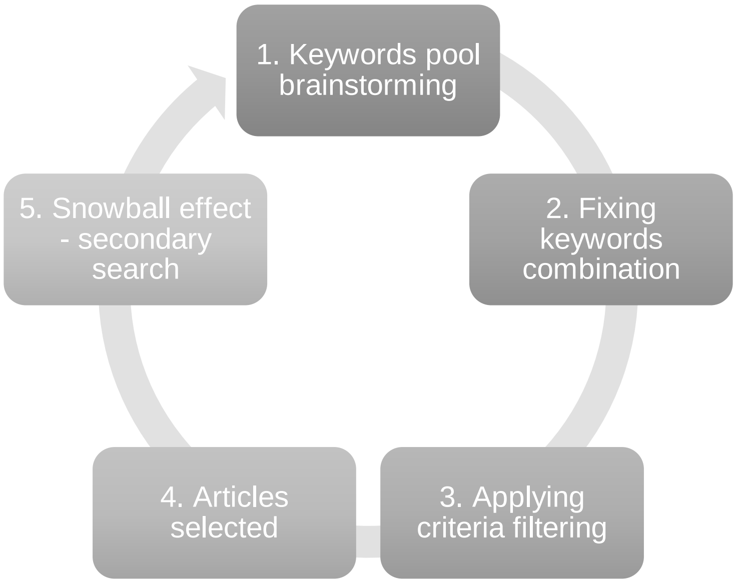

Figure 2. Literature review methodology diagram. Source: Prepared by authors.

It should be noted that it was not feasible to cover the complete wide range of papers available in the Scopus database. Probably, we may have missed some papers while conducting the literature research according to keyword choice, for example. However, the methodology followed tried to minimise misremembered as much as possible.

3.2. Descriptive analysis

In this section, firstly, we are going to identify research trends in the PV topic by downloading data from the Scopus database and analysing this data through the SciVal tool. Secondly, we will conduct a descriptive analysis of the papers previously selected in section 3.1, looking for interrelationships and alignments with general trends observed in section 3.2.1 while extracting outcomes from the papers' temporal distribution.

3.2.1. Topic trend analysis – SciVal

Firstly, we have conducted a preliminary analysis to verify the density of documents about "product variety" and "supply chain" generated through the SciVal software to evaluate if our selected keywords were adequate. SciVal is a web-based analytics solution that allows the research activities evaluation from several perspectives and publications records within the Scopus database, helping to develop, execute, and evaluate strategies based on reliable evidence.

Figure 3. Keyphrase density of PV topic. Source: SciVal tool.

On the one hand, traditional strategies to mitigate PV, identified also in keywords pool, are clearly reflected in the keyphrase density figure. Furthermore, we can observe that some of them are losing importance, such as postponement or component commonality while product modularity or SC integration are gaining weight. On the other hand, noted that keywords such as traceability, SC flexibility or customer integration are also shown in Figure 3, and denotes this tendence in tackling PV by SC more flexibles, with higher visibility and more customer oriented.

3.2.2. Research papers description

The existing literature can be divided between PV and AI topic. The first one involves how complexity induced by PV impacts the SC processes and which strategies are traditionally used by firms to mitigate it. On the other hand, the second topic answers how AI can impact SC processes, which are its strengths and weaknesses, and how AI can support SC and firms to tackle PV. Therefore, we have mainly summarised those papers division in the following table:

Authors	Source	Topic
(Alfaro & Corbett, 2003)	Production and Operations Management	PV
(Alptekinoğlu & Ramachandran, 2019)	Wiley Online Library	PV
(Balakrishnan, Chui, Hall, & Henke, 2020)	McKinsey Global Institute	AI
(Belhadi, Mani, Kamble, Rehman Khan, & Verma, 2021)	Annals of Operations Research	AI
(BENJAAFAR & KIM, 2004)	Annals of Operations Research	PV
(Bode & Wagner, 2015)	Journal of Operations Management	PV
(Bozarth, Warsing, Flynn, & Flynn, 2009)	Journal of Operations Management	PV
(Bughin, Chui, Henke, & Trench, 2017)	McKinsey Global Institute	AI
(Castka, 2020)	Sustainability	PV

Authors	Source	Topic
(Caux, David, & Pierreval, 2007)	International Journal of Production Research	PV
(Chan & Arikan, 2020)	International Journal of Production Research	PV
(Chand, Thakkar, & Ghosh, 2018)	Resource Policy	PV
(Chen, 2005)	Computers in Industry	PV
(Chopra, 2003)	Transportation Research Part E: Logistics and Transportation Review	PV
(Daaboul, Da Cunha, Bernard, & Laroche, 2011)	CIRP Annals	PV
(Dawes, LarsMeyer-Waardenb, & Driesener, 2014)	Journal of Business Research	PV
(de Groote & Yücesan, 2011)	Proceedings - Winter Simulation Conference	PV
(de Vos & Meijers, 2019)	Journal of Economic and Human Geography	PV
(Dubey, Rameshwar; Gunasekaran, Angappa; Childe, Stephen J.; Bryde, David J.; Giannakis, Mihalis; Foropon, Cyril; Roubaud, David; Hazen, Benjamin T., 2020)	International Journal of Production Economics	AI
(Dwivedi, 2021)	International Journal of Information Management	AI
(Enz, Lambert, & Schwieterman, 2019)	International Journal of Logistics Management	PV
(Flynn, Huo, & Zhao, 2010)	Journal of Operations Management	PV
(Forza & Salvador, 2002)	International Journal of Production Economics	PV
(Gosling & Naim, 2009)	International Journal of Production Economics	PV
(Granero, 2019)	Economics Letters	PV
(Hendriks, Singhal, & Stratman, 2006)	Journal of operations management	PV
(Howard & Squire, 2007)	International Journal of Operations & Production Management	PV
(Islam, Mahmud, & Pritom, 2019)	Neural Computing and Applications	PV
(Kar, Dwivedi, & Grover, 2020)	Annals of Operations Research	AI
(Kevilal, Prasanna Venkatesan, & Sanket, 2017)	Journal of Manufacturing Technology Management	PV
(Li, 2019)	International Journal of Production Research	PV
(Lyons, Um, & Sharifia, 2020)	International Journal of Production Economics	PV
(Malinowski, Karwan, & Sun, 2021)	International Journal of Production Economics	PV
(Mani, Kamble, Belhadi, Rehman Khan, & Verma, 2021)	Annals of Operations Research	AI
(Murphy, 2020)		PV
(Narasimhan & Talluri, 2009)	Journal of Operations Management	PV
(Olhager, 2010)	Computers in Industry	PV
(Pankaj & Jayaram, 2014)	Journal of Operations Management	PV
(Perona & Miragliotta, 2002)	International Journal of Production Economics	PV
(Piya, Shamsuzzoha, & Khadem, 2020)	International Journal of Logistics Research	PV
(Praveen, Farnaz, & Hatim, 2019)	Procedia Manufacturing	AI
(Priore, Ponte, & Rosillo, 2018)	International Journal of Production Research	AI
(Ren, Meng, Wang, Lu, & Yang, 2020)	Transactions on Neural Networks and Learning Systems	AI
(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021)	Expert Systems with Applications	AI
(Rizky Huddiniah & Mahendrawathi, 2019)	Operations and Supply Chain Management	PV
(Sanders & Wan, 2017)	International Journal of Production Economics	PV
(Sanders, Boone, Ganeshan, & Wood, 2019)	Journal of Business Logistics	AI

Authors	Source	Topic
(Santos, Sempaio, & Alliprandini, 2020)	Journal of Manufacturing Technology Management	PV
(Schulze-Horn, Hueren, Scheffler, & Schiele, 2020)	Applied Artificial Intelligence	AI
(Scuch & Rudolf, 2015)	International Conference on Industrial Technology	PV
(Serdarasan, 2013)	Computers & Industrial Engineering	PV
(Shou, Lee, Park, & Kang, 2016)	International Journal of Physical Distribution & Logistics Management	PV
(Siddhartha S.Syam, 2015)	Journal of Retailing and Consumer Services	PV
(Singh, Goyal, & Bedi, 2020)	Third International Conference on Intelligent Sustainable Systems	AI
(Stavrulaki & Davis, 2010)	International Journal of Logistics Management	PV
(Su, Lin, & Lee, 2010)	Journal of Intelligent Manufacturing	PV
(Thonemann & Bradley, 2002)	European Journal of Operational Research	PV
(Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021)	Journal of Business Research	AI
(Trattner, Hvan, Forza, & Lee Herbert-Hansen, 2019)	CIRP Journal of Manufacturing Science and Technology	PV
(Turner, Aitken, & Bozarth , 2018)	International Journal of Operations & Production Management	PV
(Um, Han, Grubic, & Ghalib, 2018)	International Journal of Productivity and Performance Management	PV
(Um J. , Lyons, Lam, & Dominguez-Pery, 2017)	International Journal of Production Economics	PV
(Vahid, Pejvak, Reza, & Ali, 2021)	Technological Forecasting and Social Change	AI
(van Hoek, Vos, & Commandeur, 1999)	Long Range Planning	PV
(Verstraete, Aghezzaf, & Desmet, 2020)	Computers & Industrial Engineering	AI
(vom Brocke, 2009)	European Conference on Information Systems	
(Wan, Evers, & Dresner, 2012)	Journal of Operations Management	PV
(Wang & Huang, 2020)	International Conference on New Energy Technology and Industrial Development	AI
(Wang Z. , 2016)	Cooperative Design, Visualization, and Engineering	PV
(Weng, Liu, & Xiao, 2019)	Industrial Management & Data Systems	AI
(Williams & Mahmoodi, 2019)		PV
(Wilson, Paschen, & Pitt, 2021)	Management of Environmental Quality	AI
(Youssra , Tarik , & Angappa , 2021)	Expert Systems with Applications	AI
(Zhoua, Awasthi, & Stal-Le Cardinal, 2021)	Computers in Industry	AI

Table 2. Summary of used papers pool divided into PV topic and AI topic.

Despite non-temporal limitations were fixed during the data collection phase, the temporal range on literature review comprises 19 years from 2002 to 2021, mainly weighed to the contemporary period, with a cumulative total percentage of 70% selected articles from 2015. The AI tendence showed in Figure 4 is strongly aligned with Figure 17, observing an increasing interest in AI from 2018 to now. Moreover, PV papers selected are constant until 2018 that sharply increase. Therefore, we can conclude that possible outcomes extract from PV and AI are strongly based on an updated content, enabling hypotheses relying on current SC contextualisation.

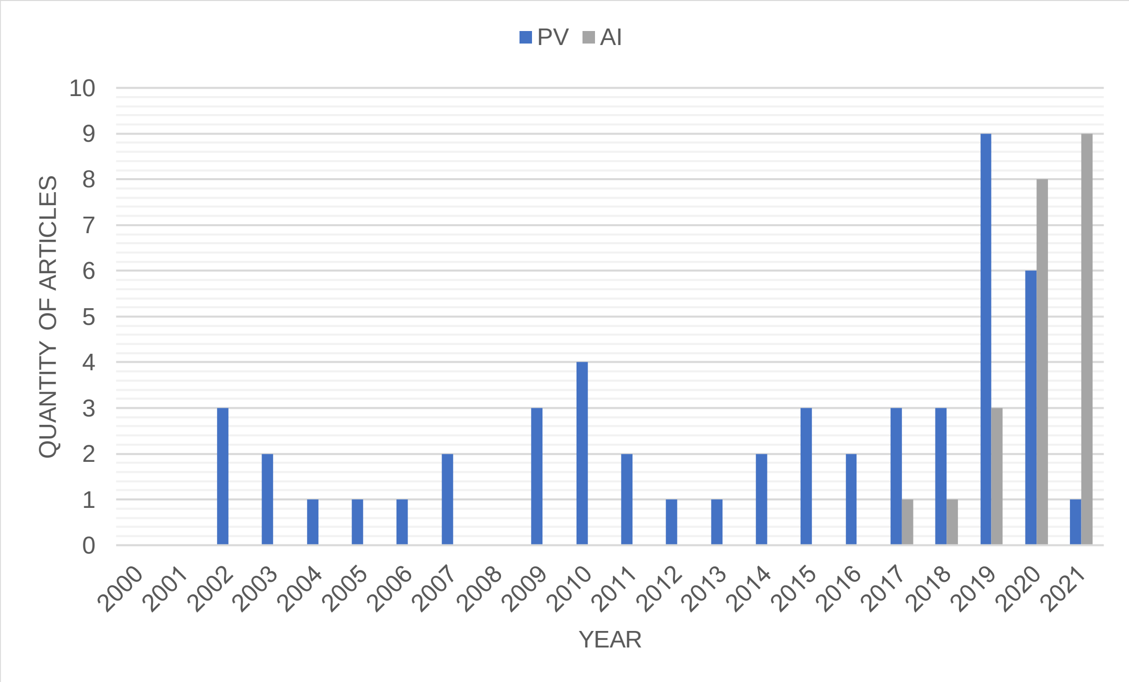

Figure 4. Temporal article publications distribution by scope of study. Source: Prepared by authors. Data from SciVal tool.

Furthermore, the distribution of published journals of the selected papers is presented in Figure 4. It shows that the literature review has been based on papers published in a wide variety of journals (31 in total) which are distributed almost equally, although two journals are standing out as being the most recurrent: *International Journal of Production Economics* and *Journal of Operations Management* (7 papers each).

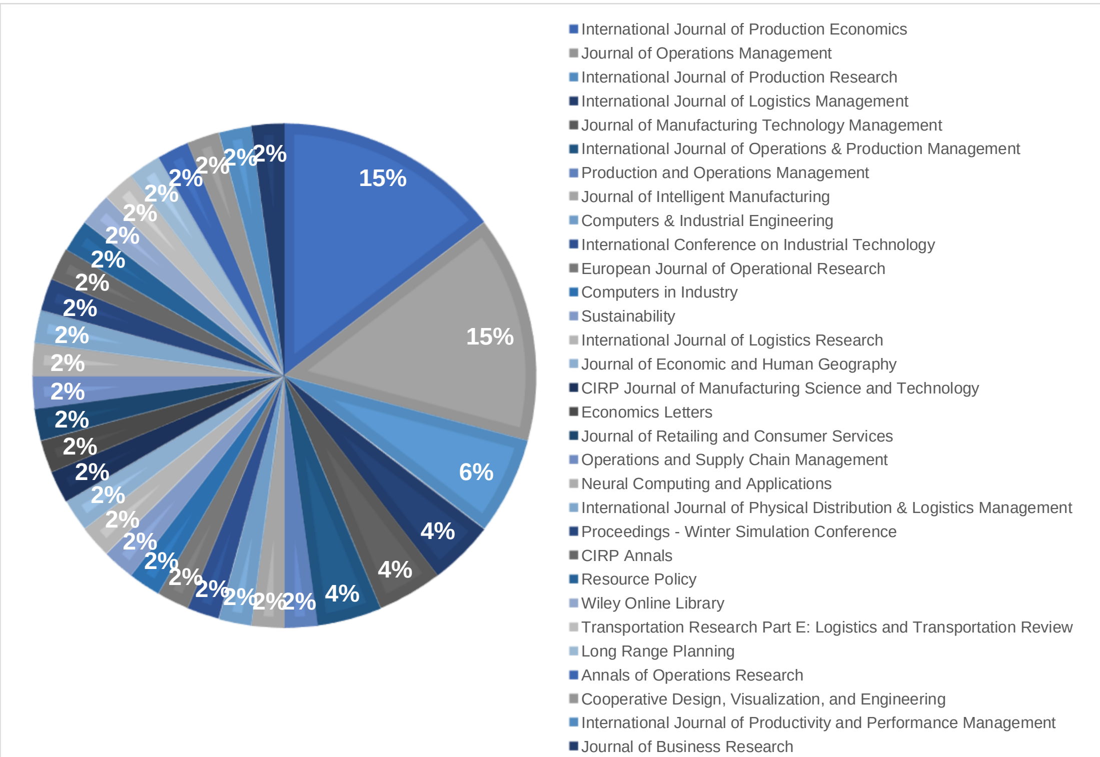

Figure 5. Journals distribution of selected papers sources. Source: Prepared by authors.

3.3. Literature review

The thematic analysis based on the selected articles' outcomes, methods, and practices, regarding the study pillars, is presented below with a subsequent discussion. The results structure is the following.

Firstly, an introduction into SC complexity is presented to contextualise the PV topic and examine the SC affected areas. Secondly, product variety complexity (PVC) implications are explored more in-depth, defining direct and indirect relationships between PV changes and subsequent SC processes performance. Thirdly, strategies traditionally used by firms to mitigate or accommodate PVC are studied. Finally, the potential support of AI technology in managing complexity induced by PV is investigated, and then the possible related impacts on the SC performance are discussed.

4. Supply chain complexity

A supply chain is a complex system where different entities, processes, and resources interact with each other. Current trends as product customisation, global supply base, and sustainability increased the SCC and, by extension, its uncertainties, and disruptions.

Therefore, when issues concerning complexity management arise, a fundamental question comes up: what is SCC? There is no simple answer since many researchers give distinct answers to this question. Some say that complexity measures the stability of connectivity between different suppliers (Kevilal, Prasanna Venkatesan, & Sanket, 2017). Others define SCC as a multi-faceted, multi-dimensional phenomenon that is driven by several sources (Piya, Shamsuzzoha, & Khadem, 2020). Nevertheless, complexity is not merely about managing high levels of information and materials flows, which requires a vast amount of labour and time-consuming resources, but also tackling self-emerging unpredictable and chaotic behaviours (Perona & Miragliotta, 2002) that arise from the non-linear interconnections between all activities, processes, and actors involved in the SC.

To stand out in today's competitive markets, where SCC increases with current business trends such as outsourcing or globalisation, organisational managers not only should monitor their supply network activities but also address complexities that come up at different levels of the SC. In general, with complexity comes uncertainty, and uncertainty leads to a negative impact on SC performance while complicates the decision-making processes. Thus, the ability to measure and control them will result in improving efficiency and effectiveness along with the SC. However, the success in managing the complexity of a system is not only given by the degree of its complexity, but also by the degree of control we have over the system, as shown in the figure below (Figure 6). Thus, systems with a high degree of control and a low level of complexity (quadrant 4) may have higher probability of success in tackling the complexities than systems with a lower degree of control and the same degree of complexity (quadrant 3). The strategies and actions applied at one complexity driver may have a positive or negative impact on another due to the SC non-linear behaviour. In practice, managers can apply this concept by tackling complexity drivers (CD) with a high degree of control to shift complexity instead of managing or mitigating those with a low control level.

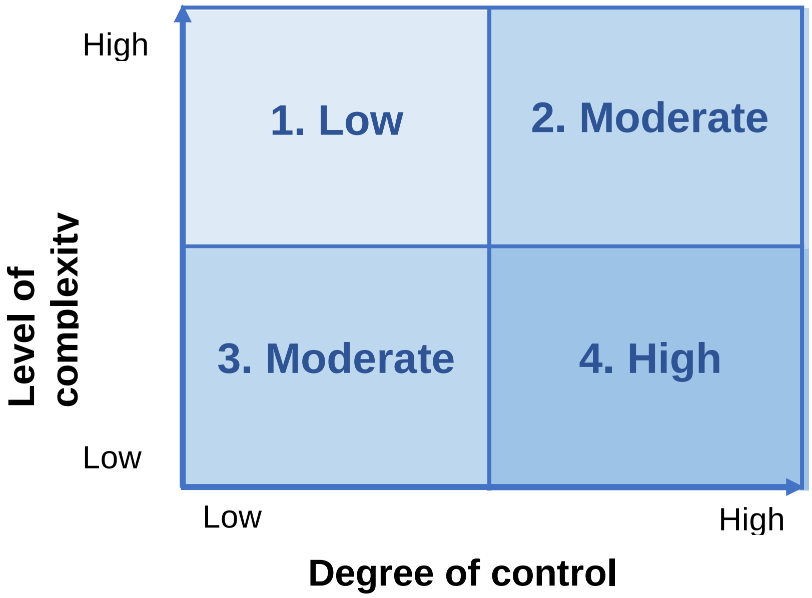

Figure 6. Probability of success with tackling complexities depending on level of complexity and degree of control dimensions. Source: Prepared by authors.

4.1. Complexity categorisation

SC inherent complexities can be categorised by multiple dimensions depending on the scope of the studies and researchers. Some authors were interested in SCC as a whole, whereas others were focused on specific segments or parts of the SC and its subsystems. In order to have a clear idea of how drivers can be structured, some of the categorisation approaches used in the articles reviewed are summarised and explained below:

A. Complexity categorisation based on its nature. Proposed by (Serdarasan, 2013), try to address CD at all levels of the SC while group them based on its stability:
   - Structural complexities (static complexity) refer to the structure of systems and subsystems involved in the SC. In other words, it concerns the quantity and variety of products, processes, and components defining the SC.
   - Operational complexities (dynamic complexity) refer to the interaction (operational behaviour) between the elements of a system and its environment (Bode & Wagner, 2015). It highlights the uncertainties of the processes in the SC and concern topics as time and randomness.

B. (Serdarasan, 2013) also proposed another approach of categorisation, adding a second dimension in the analysis, which CD are categorised based on their origin:
   - Internal CD is generated by characteristics, decisions, and components within the organisation such as product design. Those drivers are easily managed since are under the manager's scope of control.

- Supply or demand interface drivers are related to the existing interaction and cooperation with supply or demand base such as material and information flows between the focal company and its providers or customers. Interface drivers are somehow controllable due to the influence that the company could exert over the chain.
- External or environmental drivers are nearly out of the scope of the company and difficult to predict, such as governmental regulations, environmental factors, market trends, or technological disruptions.

C. Similar to the previous categorisation, (Chand, Thakkar, & Ghosh, 2018) also proposed classifying CD based on its location or origin, in that case, the drivers' cluster proposed is the following:
   - Upstream complexities refer to an unexpected triggering event that occurs in the supply network, inbound logistics, or sourcing environment which threatens the business operations of the focal firm. (Bode & Wagner, 2015) subdivide the supply base complexity into 3 main levels of this stage: vertical, horizontal, and spatial complexity.
   - Mid-stream refers to the internal complexities of the focal firm.
   - Downstream concerns to complexities that are related to the customer base, as could be number of customers, and PoS location.

D. (Scuch & Rudolf, 2015) adopted a point of view when evaluating the complexity in new projects development. CD categorisation was conducted by structuring the CD along factual coherences, such in this case:
   - Organisation is subdivided into company environment, company organisation, and project organisation.
   - Resources is subdivided into human resources, material resources, and financial resources.
   - Product is subdivided into product requirement, product program, and product architecture.
   - Technologies is subdivided into maturity of technologies, and diversity of technologies.

   In this approach, (Scuch & Rudolf, 2015) also defined a second dimension, by adding what they called "drivers characteristics". In this dimension is made a distinction between "endogenous vs exogenous", but also defines the level and time of influenceability.

Nevertheless, it is necessary to make an explicit distinction between which complexity is necessary and unnecessary (Serdarasan, 2013). On the one hand, necessary complexity provides a competitive advantage by increasing the market's willingness to pay while is required to cope with the business strategy, so it must be included by the supply chain activities (i.e., higher levels of customisation, global supply base). Thus, it is also known as strategic complexity (Turner, Aitken, & Bozarth , 2018). On the other hand, unnecessary complexity brings no benefits to the SC, however, involves additional costs, preventing the SC to obtain higher levels of performance (i.e., unreliable suppliers, excessive cycle times, or lead times). It is also known as dysfunctional complexities. In other words, complexities are considered necessary until marginal costs overcome marginal revenues.

Moreover, managers may face both strategic and dysfunctional complexities with different practices. Unnecessary complexities tend to be eliminated, reduced, or absorbed, whereas necessary complexity is usually managed or accommodated.

5. Complexity derived from product variety

The last-century mass production paradigm has shifted to more customer-order-driven production, based on the mass customisation paradigm due to the increasingly demanding customer expectations, defining product variety (PV) as a company's strategic complexity. Therefore, companies are focused on meeting customer preferences to improve their performance, looking for new customers while making them loyal. In this context, companies are pursuing diversification strategies by increasing PV in terms of design, colours, packaging, and accessories.

But how could PV be defined? (Fisher et al. (2002)) defined PV as the breadth of products that a firm offers at a given time. In the same vein, (Brun and Pero, 2012) determined that "PV is the number of different products a company offers to the consumer". However, too much product diversity may have contra-productive behaviours in business performance, as it is said "too much of a good thing". The increasing number of products affects the number of components and the interaction between its components to obtain a finished good, rising its management complexity, and consequently firm's internal complexity (Rizky Huddiniah & Mahendrawathi, 2019). Moreover, when customers face an overload of information, they tend to decide in a simple heuristic way that usually will not be optimal, and it will be translated into losing sales. (Daaboul, Da Cunha, Bernard, & Laroche, 2011) stated that PV should be minimised but not at the expense of customer satisfaction. For that reason, the impacts of the PV increase concerning the SC complexity generated, both positive and negative, will be specifically analysed below.

The PV is related to product complexity (PC). On this matter, (Bode & Wagner, 2015) defines product complexity as the number of components or raw materials required to make finished goods and the interrelationship between each component in the production process. (Trattner, Hvan, Forza, & Lee Herbert-Hansen, 2019) exposed that PC is considered as a multi-dimensional phenomenon which includes the number of components, the number of modules, the number of finished good variants in a portfolio, the number of interrelations between components, the commonality of products in an assortment, and the diversity of relations between components. Therefore, it is important to have the right balance between product variety to fulfil demand while maintaining the alignment of the SC.

Product variety management (PVM) aims to offer customised products while being cost-efficient behaviours. (Um J. , Lyons, Lam, & Dominguez-Pery, 2017) suggest the high levels of PV induce better customer satisfaction, firm performance, market share, and perceived brand image. However, too much PV negatively influences sales performance.

On the one hand, the internal PV is related to the variance linked to product creation within a firm or SC, which can be classified according to three dimensions (Um, Han, Grubic, & Ghalib, 2018): fundamental, intermediate, and peripheral. Firstly, the "fundamental" PV is related to the different product designs or models at the fabrication and design stage. The "intermediate" PV is related to several technical options dependent on core design at the assembly stage. Finally, the "peripheral" PV is associated with particular options and accessories independent of core design at the distribution and sales stage. On the other hand, external PV is associated with the availability of different distinguishable products offered by manufacturers in the marketplace.

The impact of variety management in each of the affected areas and drivers within the SC is qualitatively analysed below since the aim of the project presented is to qualify the impact of the complexity generated by the variety of products in the companies' performance. Note that, we have divided and categorised SC drivers into four main areas to simplify the analysis of the complexity induced by PV and its impact on the SCP (view Figure 7). Moreover, hypotheses are going to be extracted from each of the analysed areas to synthesise the impact of PV on different processes and the subsequent consequence on sales, manufacturing, transportation, and procurement performance.

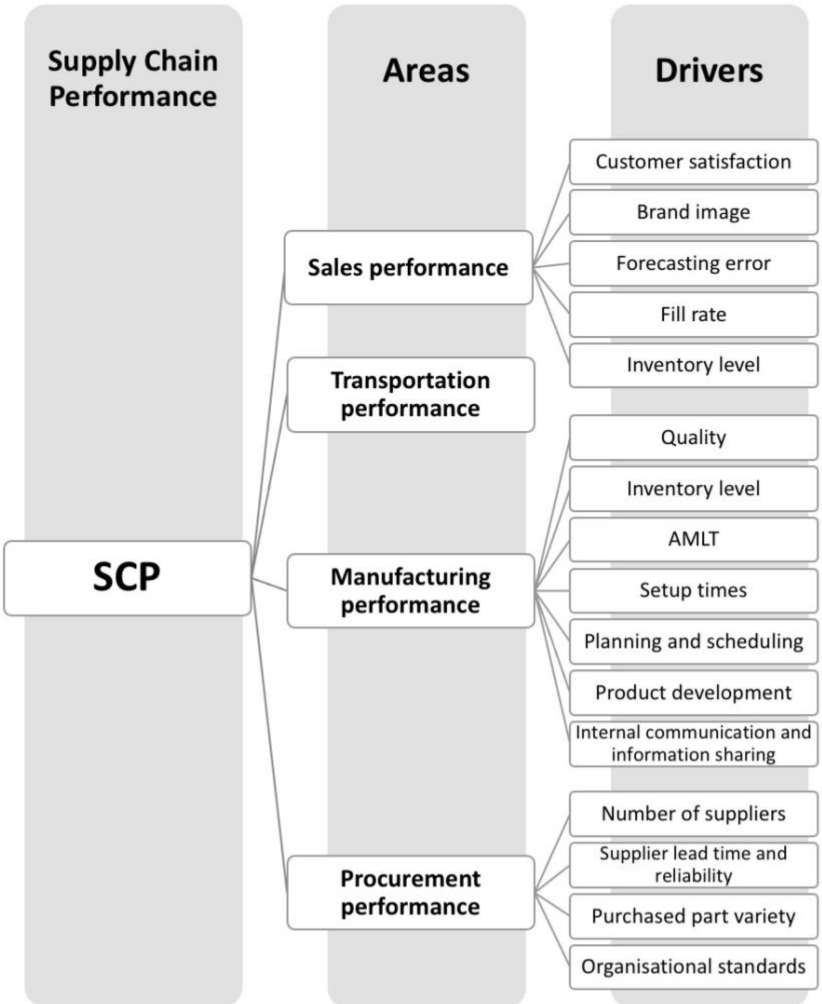

Figure 7. Categorisation tree of SCP drivers. Source: Prepared by authors.

An increase in PV scenario will be analysed since, to remain competitive, companies need to satisfy their customer needs by introducing new product varieties (Piya, Shamsuzzoha, & Khadem, 2020). With changing needs of the customers, firms may introduce more PV by improving the existing product portfolio or introducing a completely new product. Moreover, to achieve a competitive advantage over competitors, firms should closely follow competitor's actions to act accordingly. Thus, when competitors pretend to introduce new product varieties, firms should react by introducing new varieties to counter the negative effect of competitors' actions in the market.

- **Hypothesis 0A (H0A):** To satisfy increased customer needs, companies should increase their PV by improving the existing product portfolio or introducing a completely new product.
- **Hypothesis 0B (H0B):** To achieve a competitive advantage over competitors, companies should introduce new PV to counter the effect of competitor’s movement in the market.

5.1. Sales performance

At this first PV implication’s part, we are going to analyse how PV affects sales performance while understanding qualitatively the interrelation of each drivers affecting the sales performance, which are summarised in the figure below (Figure 8).

The arrows indicate influence relationship direction, and relationship shape information is shown between square brackets: (+) means a positive relationship (an increase of variable ‘a’ derives in an increase of variable ‘b’), whereas (-) means a negative one (an increase of variable ‘a’ derives in a decrease of variable ‘b’); (∩) means inverted U-shape influence whereas (∪) means U-shape influence. The previous description of arrows meaning will be also extrapolated and adopted in the following sections.

In short, if PV increases, the average fill rate decreases at a diminishing marginal rate as a result mainly of a decrease in demand forecasting accuracy. Hence, sales performance decrease when fill rate decline. Meanwhile, sales performance increases due to the positive influence of an increase in PV on customer satisfaction. Moreover, more PV leads to increased purchasing opportunities, which can move customers' purchases to other brands or variants, thus declining brand loyalty (Dawes, LarsMeyer-Waardenb, & Driesener, 2014). Therefore, the connection between PV level and the subsequent impact on sales performance is not trivial since more products do not always lead to increased sales when customer choices are more unpredictable (Alptekinoğlu & Ramachandran, 2019).

The more representatives affected drivers, which are summarised in the Figure 8, are going to be in-depth detailed in the following sections.

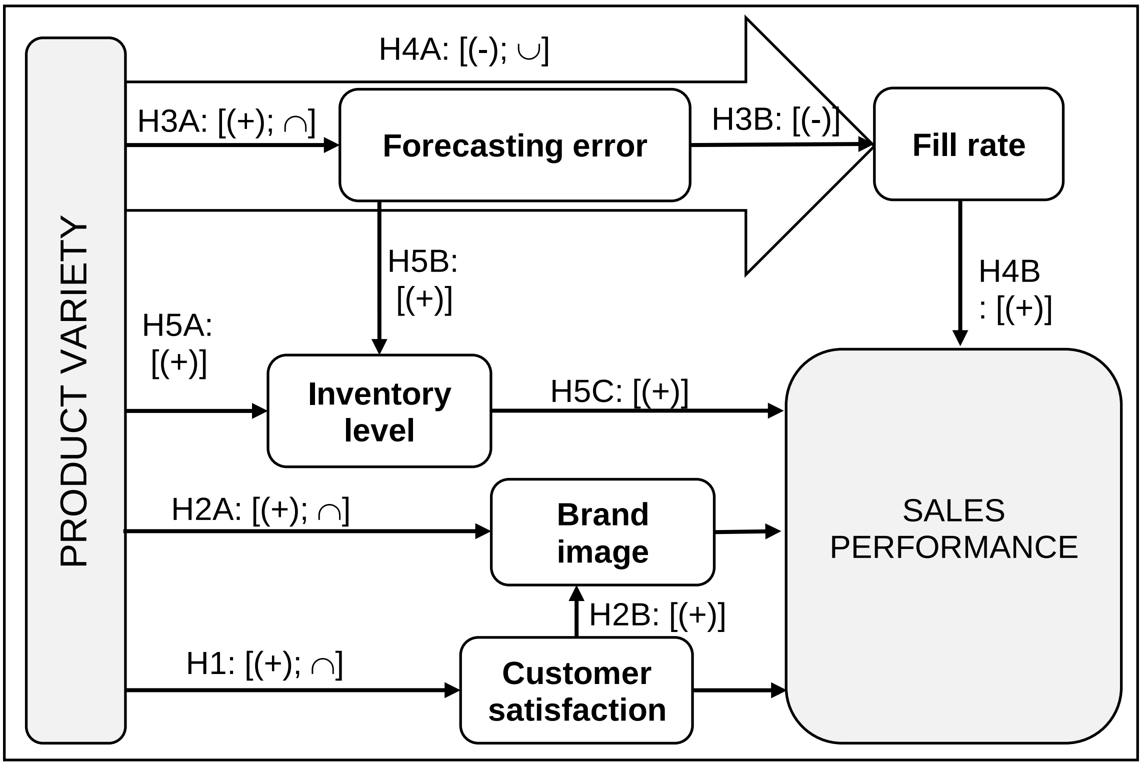

Figure 8. Influences diagram between drivers affecting sales performance. Source: Prepared by authors.

5.1.1. Customer satisfaction

Firstly, regarding customer satisfaction, (Santos, Sempaio, & Alliprandini, 2020) points out that PV can be used as an important lever for sales performance because of the greater possibility of the consumers finding a variant that matches their preferences. (Siddhartha S.Syam, 2015) points out that increasing the PV reduces the distance between what the consumer expects and what finds in the market, thus, boosting sales performance. However, over-diversity buying options could lead to customer confusion and abort the purchasing. Therefore, the overall customer satisfaction increases directly with increased PV at a diminishing marginal rate (H1-Figure 8).

- **Hypothesis 1 (H1):** Customer satisfaction increases with an increased PV at a diminishing marginal rate.

5.1.2. Brand image

(Um J. , Lyons, Lam, & Dominguez, 2017) points out that higher levels of PV induce a better-perceived brand image since offered products fit better customer expectations hence increase customer satisfaction. However, (Pankaj & Jayaram, 2014) rightly stated that too much product diversity should be perceived as a legitimacy deterioration by stakeholders and consequently, brand image will be negatively affected due to stakeholders could question the firm's ability to manage the border set of products efficiently.

- **Hypothesis 2A (H2A):** Brand image increases with an increased PV following an inverted U-shape.
- **Hypothesis 2B (H2B):** Increased customer satisfaction leads to a better perceived brand.

5.1.3. Forecasting error

High levels of PV make forecasting demand accurately and maintain a continuous supply more difficult, generating mismatches between product supply and demand, leading to product stockouts or inventories backlog (Wan, Evers, & Dresner, 2012). Moreover, biases induced due to managerial adjustments to statistical forecasting demand analysis are emphasised when tackling highly disaggregated SKUs. A large number of forecasts increase complexity and confusion and, by definition, non-optimal behaviours arise affected by those biases. Therefore, improper forecasting methods and distorted information flow at different points in the SC network can lead to wider fluctuations in the production, order delivery process and results in operational complexity (Piya, Shamsuzzoha, & Khadem, 2020). (Sanders & Wan, 2017) pointed out that PV increases forecast bias not only by SKU proliferation but also through added complexity of product interactions such as product substitution and cannibalisation on the demand side.

Contrarily, as PV increase also improves new product forecast accuracy due to more similarities with existing products could be found, as demand information from closely related existing products is relevant to the new forecast. Therefore, (Wan, Evers, & Dresner, 2012) concluded that negative effect from forecast inaccuracy to fill rate will be mitigated when PV increases.

- **Hypothesis 3A (H3A):** If PV increase, forecasting error increases at a diminishing marginal rate.
- **Hypothesis 3B (H3B):** Forecasting error negatively affects fill rate.

5.1.4. Fill rate

The fraction of customer demand which can be satisfied through immediate stock availability, without backorders or lost sales, is known as fill rate. It is impacted directly by changes in the product mix as it is stated by (Santos, Sempaio, & Alliprandini, 2020).

According to (Santos, Sempaio, & Alliprandini, 2020), a distribution centre's overall fill rate decreases with increased PV at a diminishing marginal rate (H4A-Figure 8). (Wan, Evers, & Dresner, 2012) justified this hypothesis (H4A-Figure 8) by pointing that the negative relationship mainly derives from the greater difficulties in forecasting demand, as PV increases. This relationship has a diminishing marginal rate due to more products implies more similarities, hence less effort in new product development forecasting.

- **Hypothesis 4A (H4A):** Overall fill rate decreases at a diminishing marginal rate when PV increases.

The consequence of variations on fill rate impacts sales performance since an increase in distributors' fill rate implies the achievement of retailer's demand, which is directly affecting positively at sales performance (H4B-Figure 8) (Santos, Sempaio, & Alliprandini, 2020). Therefore, a high fill rate indicates low levels of unmet demand, and consequently, an increase in sales due to the reduction of the product replacement possibilities.

- **Hypothesis 4B (H4B):** Increasing fill rate has a positive effect on sales performance.

5.1.5. Inventory level

To maintain fill rate level and sales performance in front of an uncertain market scope due to diversification strategy, companies need to increase their finished goods stocks. Therefore, increasing the number of products in a company portfolio leads to an increase in the number of different inventoried items (BENJAAFAR & KIM, 2004).

- **Hypothesis 5A (H5A):** Higher PV implies higher inventory level in retailers' point of view.
- **Hypothesis 5B (H5B):** Higher forecast inaccuracy implies higher inventory levels.

Inventory level in a distribution centre point of view implies a higher level of product available which can potentially increase sales performance in front of an unexpected increased demand scenario (Santos, Sempaio, & Alliprandini, 2020).

- **Hypothesis 5C (H5C):** Higher inventory level in retailers' point of view means higher sales in unexpected demand scenario increase.

5.2. Transportation performance

The role of transportation may reveal substantial support to manage the SC (Piya, Shamsuzzoha, & Khadem, 2020). Thus, inadequate and inefficient management of transportation leads to increased complexity that affects the productivity of the entire SC. An increased product diversification has an economic direct impact on transportation costs since low demand and consequently lower quantities for each particular component are needed, preventing companies to achieve economies of scale in transportation. Therefore, transportation costs increase due to the need to ship less-than-full truck loads, precluding the use of quantity discounts (Lyons, Um, & Sharifia, 2020).

- **Hypothesis 6 (H6):** Higher PV results in more SC partners and associated total transportation costs.

5.3. Manufacturing performance

The expectation when PV increase is that internal operations performances decrease, as a result of higher direct labour costs and materials cost (due to loss of bargaining power on suppliers and lower purchasing volumes), manufacturing overhead costs (such as materials handling, quality control, information systems, and facility utilisation), delivery times, and inventory levels (Lyons, Um, & Sharifia, 2020). Therefore, the more representatives affected drivers, which are summarised in the Figure 9, are going to be in-depth detailed in the following sections.

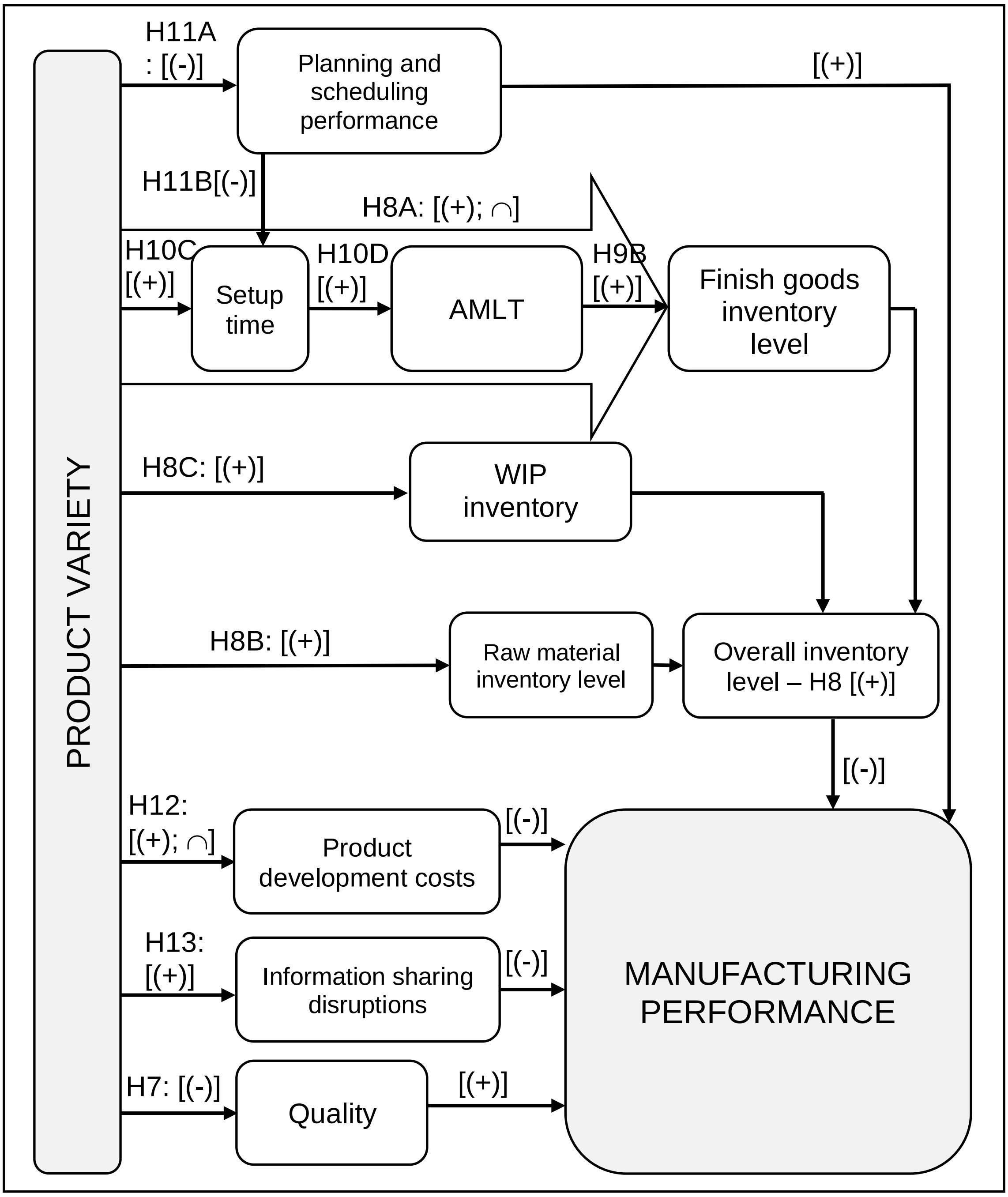

Figure 9. Influences diagram between drivers affecting manufacturing performance. Source: Prepared by authors.

As it is shown in Figure 9, planning and scheduling performance has a proportional relationship with manufacturing performance since improvements in operational processes synchronisation leads to more efficient performance. Moreover, increased quality implies better manufacturing performance since the process's effectiveness is improved. In contrast, overall inventory levels, product development, and information sharing disruptions have a negative effect on manufacturing performance. Firstly, higher inventory levels increase manufacturing costs due to increased storage costs, obsolescence, depreciation, and higher managerial complexity. Secondly, higher product development costs imply higher total operational costs, reducing manufacturing performance. Thirdly, increased information sharing disruptions lead to inefficient manufacturing performance since duplicate tasks, reworks, and delays are experienced.

In short, (Pankaj & Jayaram, 2014) determined that PV relationship with operational performance is mainly affected by the rise of operational costs while accommodating changes to engineering design, schedules, and bill of materials.

5.3.1. Quality

PV complicates the product quality control mainly due to the complexity derived from monitoring and controlling a higher number of components and the losing in the learning curve. Higher PV impacts on quality performance since heterogeneous operational routines require greater monitoring and control, and subsequently there is an increased likelihood of rejects (Pankaj & Jayaram, 2014). When product modularity is present, a fewer number of components needs to be monitored and controlled, leading to a lower likelihood of rejects.

- **Hypothesis 7 (H7):** More product diversity leads to higher likelihood of rejects.

(Granero, 2019) suggests that the average level of quality that is provided to consumers declines when there is an introduction of additional product varieties. Although the introduction of new brands can affect price competition inducing an excessive level of quality, on the other hand, when business stealing becomes dominant, firms end up choosing an insufficient level of quality.

5.3.2. Inventory level

PV not only has an impact focused on finished products inventories but also affects overall SC inventories such as raw materials inventory, or intermediate product buffers (WIP inventories). (Santos, Sempaio, & Alliprandini, 2020) concluded that the impact of PV on inventories is considered as non-proportional, since the distribution centres (DC) overall inventory level increase with increased PV at a diminishing marginal rate. In other words, more complexity implies more inventories in upstream and downstream management not only to face uncertainty but also due to variability management. (de Groote & Yücesan, 2011) has found that keeping total demand constant, the expected cost of inventories and backorders increase linearly with the number of products due to a loss of polling economies. Furthermore, intermediate and raw materials inventory levels can also increase due to the greater complexity generated by PV architectures. Finally, it was proved that total inventory cost increases linearly with the variety of products (Lyons, Um, & Sharifia, 2020).

- **Hypothesis 8A (H8A):** DC overall inventory level increase with increased PV at a diminishing marginal rate.
- **Hypothesis 8B (H8B):** Raw materials inventories increase with increased PV.
- **Hypothesis 8C (H8C):** WIP inventories increase with increased PV.
- **Hypothesis 8 (H8):** Total inventory carrying costs increase with increased PV.

5.3.3. Average manufacturing lead time

Average manufacturing lead time (AMLT) is considered as the time required from an order invoice, also considering its inherent time to manage flow invoice information, to serve the order. (Thonemann & Bradley, 2002) divided the lead time into three components: the time that the order waits in the batch buffer until the order arrived, the time the batch of orders waits in the process queue for the server to become available, and the service time for a batch of orders.

(Thonemann & Bradley, 2002) stated that expected AMLT is concave increasing in PV and increase at a rate that is asymptotically linear as it shown in Figure 10. Simplifying, more PV implies higher lead times. Moreover, higher lead times requires retailers to hold higher levels of inventories due to inventory models.

- **Hypothesis 9A (H9A):** AMLT increases at a diminishing marginal rate in PV.
- **Hypothesis 9B (H9B):** Overall inventory level increase with increased lead time due to inventory policies.

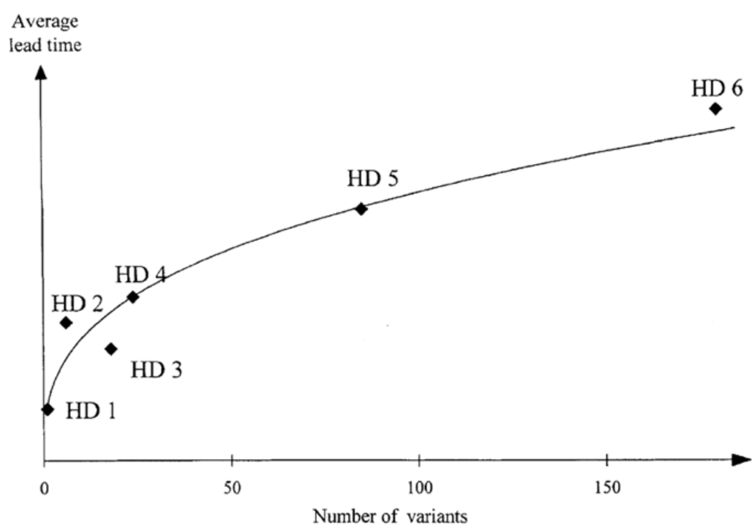

Figure 10. Average lead time and product variety by product line. Source: (Thonemann & Bradley, 2002)

Furthermore, (Thonemann & Bradley, 2002) stated that the effect of the batch size on the expected lead time is significant, particularly when PV is large. When capacity is not a constraint (utilisation rate < 1), the lead time linearly increases with the batch size.

- **Hypothesis 9C (H9C):** AMLT linearly increases with the batch size.

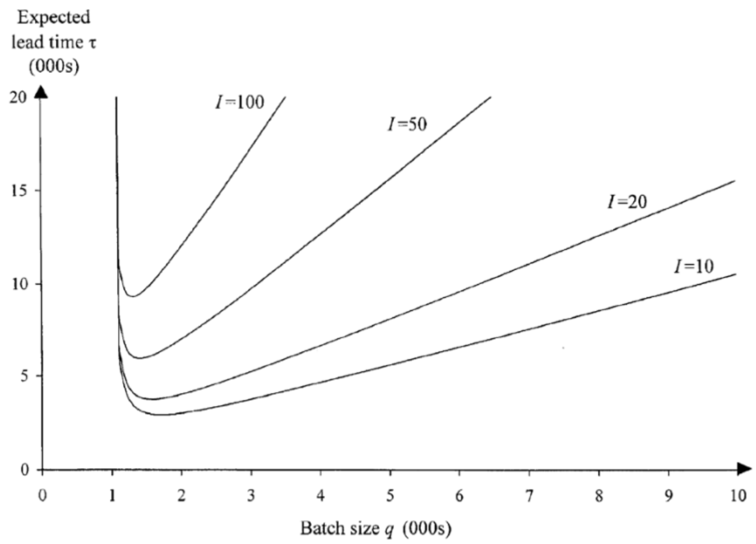

Figure 11: Expected lead time as a function of batch size. Source: (Thonemann & Bradley, 2002)

5.3.4. Set-up times

If PV increases, holding batch size constant, the waiting time in the batch buffer (to achieve the optimal batch level) increases because the order arrival rate to the production facility is reduced (Thonemann & Bradley, 2002). Therefore, managers may reduce the batch size to subsequently reduce the above-mentioned waiting time. However, if the batch size is reduced, the number of setups will be increased, thus increasing the utilisation rate.

- **Hypothesis 10 (H10A):** Smaller production batches increase the total setup time.

In this context of small-batch orders due to the high breadth of PV, setup times are crucial and have a significant effect on the overall manufacturing lead time (Thonemann & Bradley, 2002). There is a no-directly affectation in individual setup time. However, considering an absolute setup time of production, more product diversity induces smaller production batches and derives in more product changeovers and ultimately higher global setup time.

- **Hypothesis 10B (H10B):** Higher PV induces smaller production batches.
- **Hypothesis 10C (H10C):** Higher PV implies higher total setup time.

Furthermore, (Thonemann & Bradley, 2002) demonstrated that exists a positive linear influence between setup times and AMLT since a reduction in lead time due to a reduction in setup time depends only on the magnitude of the setup time reduction, independent of the current setup time, as it is showed in the Figure 12.

- **Hypothesis 10D (H10D):** AMLT increase linearly with increased setup time.

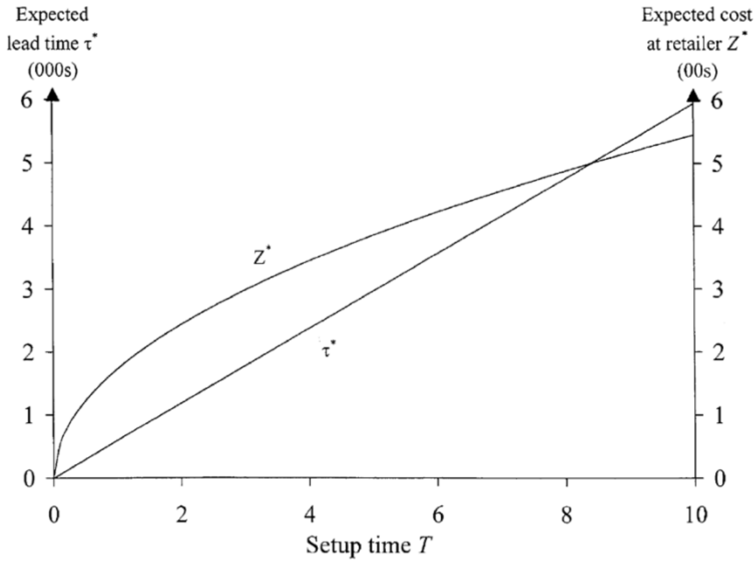

Figure 12. Expected lead time and cost at a retailer as a function of setup time. Source: (Thonemann & Bradley, 2002)

5.3.5. Manufacturing planning and scheduling

At the manufacturing planning level, increasing the number of products and parts, due to the higher finish good customisation, leads to an increase of the size and scope of the plant's manufacturing assignments hence deriving an increment of planning costs while making more challenging the decision-making associated (Lyons, Um, & Sharifia, 2020). Moreover, firms facing an unstable and uncertain master production schedule (MPS) leads to non-feasible production schedules due to the difficulty in effectively balancing the real demand necessities and production capacity (Bozarth, Warsing, Flynn, & Flynn, 2009). Additionally, inefficient planning and work scheduling leads to operational complexity, delivery delays, and increased production costs (Piya, Shamsuzzoha, & Khadem, 2020).

- **Hypothesis 11A (H11A):** Increasing PV implies an increase in complexity and costs of planning and scheduling.

- **Hypothesis 11B (H11B):** Setup time increase linearly with increased manufacturing planning and schedule inefficiencies.

5.3.6. Product development

Likewise the positive influence of PV in new product demand forecasting, product development takes advantage of similarities and synergies between new products and existing products. Moreover, higher PV scenarios require close cooperation between manufacturers, especially at early development stages (Shou, Lee, Park, & Kang, 2016). However, the combination of the growth in customised products with the budget constrains in terms of time and costs, makes more challenging for product developers to fulfil product launch schedules, leading to non-optimal solutions and biases' introduction.

- **Hypothesis 12 (H12):** A PV rise leads to a project development costs increase at a diminishing marginal rate.

5.3.7. Internal communication and information sharing

It can be intuitive that a high level of product variants gives rise to a wide scope of product and production information flows (Lyons, Um, & Sharifia, 2020). Therefore, one problem of companies that face a wide range of product attributes is the handling efficiency when managing a large amount of information due to all product variants offered or ordered. In simple words, more variety increases the probability of information disruptions as incorrect, incompatible, or lost data (Forza & Salvador, 2002).

- **Hypothesis 13 (H13):** Increasing PV derives in increasing the probability in information disruptions.

5.4. Procurement performance

In terms of procurement performance, PV influences drivers unequally and non-proportionally, being challenging to predict in advance the overall effect of PV on procurement. However, some conclusions and linkages are extrapolated thanks to the drivers' analysis provided in the following sections.

When increasing PV, purchased parts variety subsequently increase manly due to more PV leads to more parts required to customise final products. Consequently, affecting both bargaining power and synchronisation of the SC processes. Moreover, number of suppliers will increase due to the need to source more specialised parts and the emergence to reduce SC disruption risks. Finally, organisational standards increase since higher PV leads to the necessity to implement standards in products and processes to remain competitive.

In short, bargaining power is reduced since purchasing quantities are limited when purchasing an increased variety of parts. Subsequently, companies' profitability will decrease since raw material costs have a direct effect on finished goods margin. Synchronisation problems may also arise when tackling a vast number of suppliers due to the possibility to face information systems incompatibilities, consequently increasing the transaction and coordination costs. Besides, it can also arise when purchased part variety increase since it induces higher system complexity due to a rise in the number of information and materials flow to be managed. When global sourcing comes up to face PV impacts, firms should consider possible countereffects in the adoption of this sourcing strategy, such as reliability of suppliers, which may derive in manufacturing schedules adjustments leading to non-efficient processes and increasing buffering strategies to mitigate this risk.

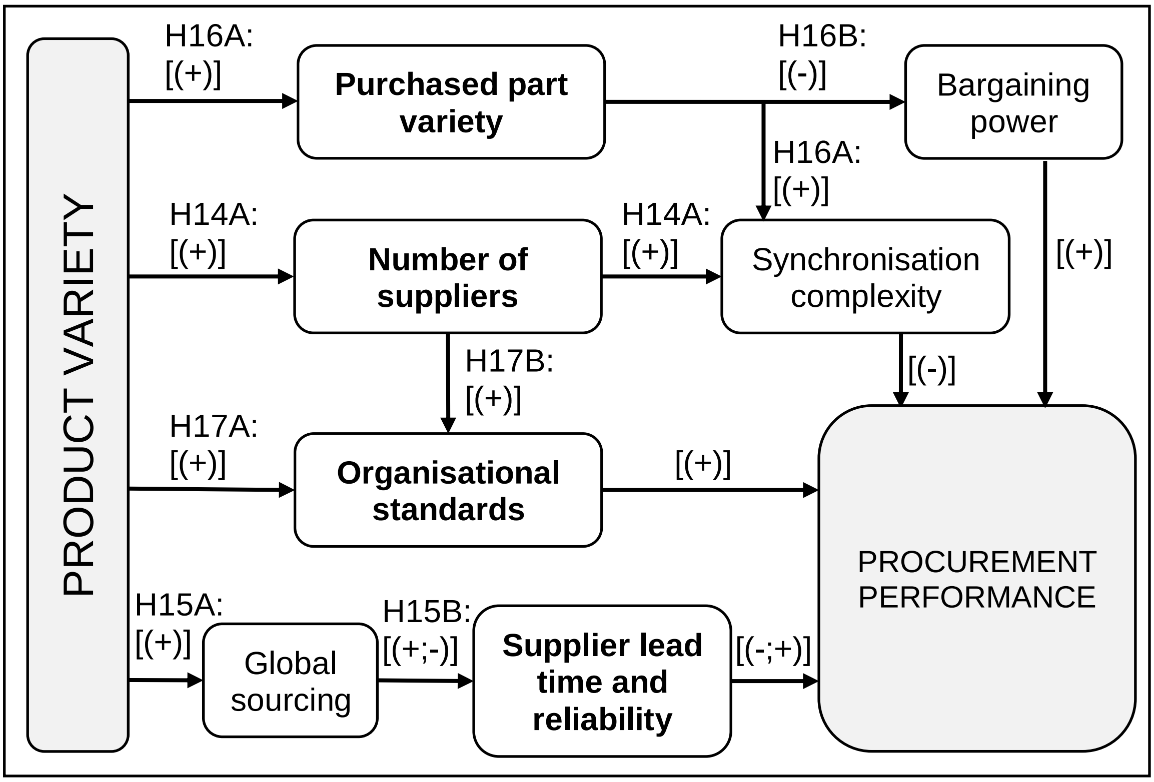

Figure 13. Influence diagram between drivers affecting procurement performance
Source: Prepared by authors.

5.4.1. Number of suppliers

An increase in the variety of products subsequently increases the number of parts needed, often increasing the number of suppliers. Therefore, increased PV leads to an increased number of suppliers, increasing difficulty for the company to have proper synchronisation of processes with all the partners (Piya, Shamsuzzoha, & Khadem, 2020). Additionally, the increased number of suppliers could lead to a higher possibility of having incompatible SC networks due to a mismatch of competencies or an incompatible Information Technology that could negatively affect the process synchronisation among partners.

To cope with network complexity associated with an increase in PV, higher levels of coordination and close and collaborative relationships are needed to achieve efficiency in the SC and reduce the increased transaction and coordination costs in exchanges between producers and their suppliers (Shou, Lee, Park, & Kang, 2016).

- **Hypothesis 14A (H14A):** Higher product diversity leads to more suppliers, increasing the level of complexity in terms of SC coordination and synchronisation.

Furthermore, when dealing with increased PV, higher SC disruption risks associated with the different technical specifications or lead times, increased complex schedules, and possible delays in deliveries are experienced. Consequently, usually dual or even multiple sourcing strategies, apart from buffering policy, are applied, increasing the SC complexity as a whole.

- **Hypothesis 14B (H14B):** Higher product diversity leads to higher SC disruption risks, applying multi-sourcing strategies to mitigate it.

5.4.2. Supplier lead time and reliability

Moreover, when firms face higher product diversity, increasing the total number of suppliers as aforementioned, it also increases the probability of globally managing suppliers, inducing longer physical SCs rather than domestic ones. Therefore, if firms are not cautious in selecting foreign suppliers, it can result in higher costs and difficulties in production schedule alignment (Piya, Shamsuzzoha, & Khadem, 2020).

- **Hypothesis 15A (H15A):** More PV leads to longer physical SC.

Increased distance between supplier locations from the parent company creates difficulty in monitoring and controlling suppliers, leading to longer and more uncertain lead times (LT). Besides, the global linkages potentially expose manufacturers to a wide range of complications such as import and export laws, fluctuations in currency, and cultural differences which may impact supplier's reliability.

- **Hypothesis 15B (H15B):** Global SCs induces longer and more uncertain LT.

Regardless of the source location, supplier's uncertain LT, will affect safety stocks (increase inventory level) and production planning horizons will increase (Bozarth, Warsing, Flynn, & Flynn, 2009). Besides, long or unreliable supplier lead times can force manufacturers to adopt planning and material management processes characterised by longer plan horizons and level of detail.

5.4.3. Purchased part variety

When companies follow customisation strategies, becomes challenging to offer more customised product without losing economies of scale. Therefore, concerning upstream impacts at the procurement level, more product and subsequently more part variety will induce a higher system complexity since a higher number of information and materials flows will be managed by firms (Bozarth, Warsing, Flynn, & Flynn, 2009). It is translated into higher costs in managing the upstream flows.

- **Hypothesis 16A (H16A):** Increased PV leads to an increase in purchased parts variety and higher system complexity.

Furthermore, the higher diversity of purchased parts is perceived as a decrease in the bargaining power due to reduced buying quantities, affecting direct raw materials costs. Additionally, reducing purchasing quantities could shift the supplier-firm relationship, leading to a supplier responsiveness loss while making it difficult to manage them efficiently (Piya, Shamsuzzoha, & Khadem, 2020).

- **Hypothesis 16B (H16B):** Increased parts variety induces a reduction in bargaining power and economies of scale.

5.4.4. Organisational standards

PV also generates complexities related to organisational standards (OS). It generates complexity due to the need to follow product standards based on the geographical regulations in the region in which they operate. To be competitive, company strives to achieve standards such as ISO, ASME for their products (Piya, Shamsuzzoha, & Khadem, 2020). Increased PV results in managing more logistics needs to maintain standards for all product varieties. However, it often generates a challenge since it is insufficient to acquire standards only by the parent organisation, but it is necessary to acquire them by the whole SC.

- **Hypothesis 17A (H17A):** More PV creates the necessity to implement standards for the products to remain competitive.

Moreover, it provokes complexity due to the different engineering standards followed by each of the multiple suppliers with whom the company is working. Different suppliers follow different standards which are based on the country or region of their operation, and it creates more complexity as the number of suppliers increase (Chand, Thakkar, & Ghosh, 2018).

- **Hypothesis 17B (H17B):** More suppliers induce higher complexity to align standards.

As a consequence of the increased complexity generated when increasing PV, which difficult the knowledge transfer across organisational boundaries, common organisational standards may arise. That refers to a set of rules, principles, and procedures that can enhance the transfer, merging, and creation of knowledge from multiple companies when interacting together. Therefore, the manufacturing company can achieve a level of integration that can reduce the negative impact of PV.

5.5. PV impacts summary

The outcomes of the PV impact on sales, transportation, manufacturing, and logistics performance, summarised in the hypothesis, are presented in Table 3. Moreover, the academic papers obtained from the literature review are classified in each area and sub-area analysed and presented in Table 3.

Area	Driver	Hypothesis related	Sources
Sales	**Customer satisfaction**	**H1:** Customer satisfaction increases with an increased PV at a diminishing marginal rate.	(Santos, Sempaio, & Alliprandini, 2020) (Siddhartha S.Syam, 2015) (Dawes, LarsMeyer-Waardenb, & Driesener, 2014). (Alptekinoğlu & Ramachandran, 2019)
	Brand image	**H2A:** Brand image increases with an increased PV following an inverted U-shape. **H2B:** Increased customer satisfaction leads to a better perceived brand.	(Um J. , Lyons, Lam, & Dominguez, 2017) (Pankaj & Jayaram, 2014)
	Forecasting error	**H3A:** If PV increase, forecasting error increases at a diminishing marginal rate. **H3B:** Forecasting error negatively affects fill rate.	(Wan, Evers, & Dresner, 2012) (Sanders & Wan, 2017) (Piya, Shamsuzzoha, & Khadem, 2020)
	Fill rate	**H4A:** Overall fill rate decreases at a diminishing marginal rate when PV increases. **H4B:** Increasing fill rate has a positive effect on sales performance.	(Santos, Sempaio, & Alliprandini, 2020) (Wan, Evers, & Dresner, 2012)
	Inventory level	**H5A:** Higher PV implies higher inventory level in retailers' point of view. **H5B:** Higher forecast inaccuracy implies higher inventory level. **H5C:** Higher inventory level in retailers' point of view means higher sales in unexpected demand scenario increase.	(BENJAAFAR & KIM, 2004) (Santos, Sempaio, & Alliprandini, 2020)
Transportation		**H6:** Higher PV results in more SC partners and associated total transportation costs.	(Piya, Shamsuzzoha, & Khadem, 2020) (Lyons, Um, & Sharifia, 2020)

Area	Driver	Hypothesis related	Sources
Manufacturing	**Quality**	**H7:** More product diversity leads to higher likelihood of rejects.	(Pankaj & Jayaram, 2014) (Granero, 2019)
	Inventory level	**H8A:** DC overall inventory level increase with increased PV at a diminishing marginal rate. **H8B:** Raw materials inventories increase with increased PV. **H8C:** WIP inventories increase with increased PV. **H8:** Total inventory carrying costs increase with increased PV.	(Santos, Sempaio, & Alliprandini, 2020) (de Groote & Yücesan, 2011) (Lyons, Um, & Sharifia, 2020)
	Average manufacturing lead time	**H9A:** AMLT increases at a diminishing marginal rate in PV. **H9B:** Overall inventory level increase with increased lead time due to inventory policies. **H9C:** AMLT linearly increases with the batch size.	(Thonemann & Bradley, 2002)
	Setup times	**H10A:** Smaller production batches increase the total setup time. **H10B:** Higher PV induces smaller production batches. **H10C:** Higher PV implies higher total setup time. **H10D:** AMLT increase linearly with increased set-up time.	(Thonemann & Bradley, 2002)
	Manufacturing planning and scheduling	**H11A:** Increasing PV implies an increase in complexity and costs of planning and scheduling. **H11B:** Setup time increase linearly with increased manufacturing planning and schedule inefficiencies.	(Lyons, Um, & Sharifia, 2020) (Bozarth, Warsing, Flynn, & Flynn, 2009) (Piya, Shamsuzzoha, & Khadem, 2020)
	Product development	**H12:** A PV rise leads to a project development costs increase at a diminishing marginal rate.	(Shou, Lee, Park, & Kang, 2016)
	Internal communication & information sharing	**H13:** Increasing PV derives in increasing the probability in information disruptions.	(Lyons, Um, & Sharifia, 2020) (Forza & Salvador, 2002)

Area	Driver	Hypothesis related	Sources
Procurement performance	Number of suppliers	**H14A**: Higher product diversity leads to more suppliers, increasing the level of complexity in terms of SC coordination and synchronisation. **H14B**: Higher product diversity leads to higher SC disruption risks, applying multi-sourcing strategies to mitigate it.	(Shou, Lee, Park, & Kang, 2016) (Piya, Shamsuzzoha, & Khadem, 2020)
	Supplier lead time and reliability	**H15A**: More PV leads to longer physical SCs. **H15B**: Global SC induces longer and more uncertain LT.	(Bozarth, Warsing, Flynn, & Flynn, 2009) (Piya, Shamsuzzoha, & Khadem, 2020)
	Purchased part variety	**H16A:** Increased PV leads to an increase in purchased parts variety and higher system complexity. **H16B:** Increased parts variety induces a reduction in bargaining power and economies of scale.	(Bozarth, Warsing, Flynn, & Flynn, 2009) (Piya, Shamsuzzoha, & Khadem, 2020)
	Organisational standards	**H17A:** More PV creates the necessity to implement standards for the products to remain competitive. **H17B:** More suppliers induce higher complexity to align standards.	(Piya, Shamsuzzoha, & Khadem, 2020) (Chand, Thakkar, & Ghosh, 2018)

Table 3. Summary of areas impacted by PV with hypothesis and references.

To satisfy increased customer needs, many companies are moving towards product customisation by increasing their PV (**H0**), introducing new products that require lower development costs (**H12**). Increasing PV affects the sales performance positively, despite the average fill rate will be decreased (**H2**) as a result mainly of a decrease in demand forecasting accuracy (**H4**), sales performance increases since products fit better with the customer expectations (**H1**), increasing brand image (**H3**). It also affects the manufacturing process, increasing the average manufacturing lead time (**H9**) and total setup time (**H10**). Additionally, it will increase both internal communication and information sharing (**H13**) and the likelihood of rejects (**H7**). Moreover, an increase in the variety of products increases the number of components required (**H16**), leading to a global rise in the inventory levels (**H8**) and an increase in the number of SC partners (**H14**). An increase in the number of suppliers will increase the possibility of having incompatible SC networks due to a mismatch of competencies. Such incompatibility will have an effect on process synchronisation among SC partners, causing an increased forecasting error (**H4**) which will affect all the activities at the shop-floor level, such as production planning and scheduling (**H11**), increased finished goods inventories (**H5**), or logistics and transportation (**H6**). Besides, increased PV will lead to an increase of organisational standards (**H17**) to meet global requirements, as well as it will induce higher supplier's lead time and reliability (**H15**).

6. Aligning supply chain strategy with product variety

Once analysed the impact of PV in the different areas within the SC, it is fundamental to understand if there is a connection between the strategies a company can pursue to obtain a successful SC performance. Therefore, the following section will analyse the alignment of SC strategies with the PV choice. First of all, it is presented a general framework of the strategies that an SC can adopt through the analysis of the SC gurus' contributions. Subsequently, we will develop a more in-depth analysis to connect the PV choice with the SC approach that fits better, inducing higher performances.

6.1. Hau-Lee model & uncertainty framework

SC management has emerged due to the shift of competition between company-vs-company to SC-vs-SC, where current trends are pushing firms to offer more product diversification while being cost-efficient to stay competitive in currents markets. Therefore, the added value is generated thanks to the strategies' alignment amongst tiers of a chain and not by the excellent performances of an individual.

In any case, focal firms' strategies may differ according to the market and supply network they are operating in since the statement one-size-fits-all loses weight in the current competitive marketplace due to the higher level of customisation required to satisfy an evolving demand.

The uncertainty framework proposed by Hau-Lee is both a simple and a formidable method to define the right SC strategy when characterising a product. This model joined the Fisher demand segmentation and the stability characteristics at the supplier level. Thus, the model segments strategies by differing between functional and innovative products and stable and evolving supply characteristics. According to Fisher the performance of an SC can be attributed to a match or mismatch between the type of product (i.e., innovative or functional) and the design of the SC. Thus, SC strategies can be divided into four groups which are Lean, Responsive, Risk-Heading, and Agile.

		Demand uncertainty	
		Low (Functional products)	**High (Innovative products)**
Supply uncertainty	**Low (Stable process)**	Lean Supply Chain	Responsive Supply Chain
	High (Evolving Process)	Risk hedging Supply Chain	Agile Supply Chain

Figure 14. Demand uncertainty vs Supply uncertainty SC classification. Source: Prepared by authors.

In the "Lean" Supply Chain the focus is on maximising efficiency in terms of total logistic costs by eliminating the non-value-adding activities, achieving economies of scale, controlling stocks and centralising management, maximising distribution and production capacity through optimisation, and automatising information sharing between clients and suppliers.

In the “Risk Hedging” Supply Chain the focus is oriented on risk management, both structural and abnormal (resilience), by applying backup strategies (stocks and backup suppliers), sharing resources inside the SC to share the risk of supply disruption, and using Information and Communication Technologies (ICT) as success enabler which allows owning real-time information on stocks and demand and the subsequent dynamic allocation of stocks and demand between partners who share the same warehouse stocks.

In the "Responsive" Supply Chain the focus is on reactivity and flexibility to cope with customers’ needs variety and variability by build-to-order and mass customisation approaches to satisfy the market-specific demand in which time-to-market has relevance importance.

Finally, in the "Agile" Supply Chain the focus is on satisfying flexibly market needs combining “risk hedging” strategies since stock and other capacity resources are shared between partners to face stockout and capacity interruption. Thus, "Agile" supply chains can face variable demand (outbound), minimising at the same time the risk of supply interruption (inbound).

6.2. Product variety strategic approach

Strategic approaches can be classified based on PV. On the one hand, SCs providing higher PV typically meet more unpredictable demand, shorter life cycles, closer customer relationships, and higher margins (Stavrulaki & Davis, 2010). On the other hand, SCs providing lower PV face more predictable demand, closer supplier relationship, and mass production (economies of scale). In the first case, the focus should be on SC agility, differentiation, and customer service. In the second case, it should be on cost efficiency and cost leadership. Thus, SC strategies are aligned with PV decisions, impacting business performance appropriately (Um, Han, Grubic, & Ghalib, 2018). According to (Um, Han, Grubic, & Ghalib, 2018), cost leadership strategy implies low price and low manufacturing unit cost while differentiation implies customer service, technology, and marketing differentiation.

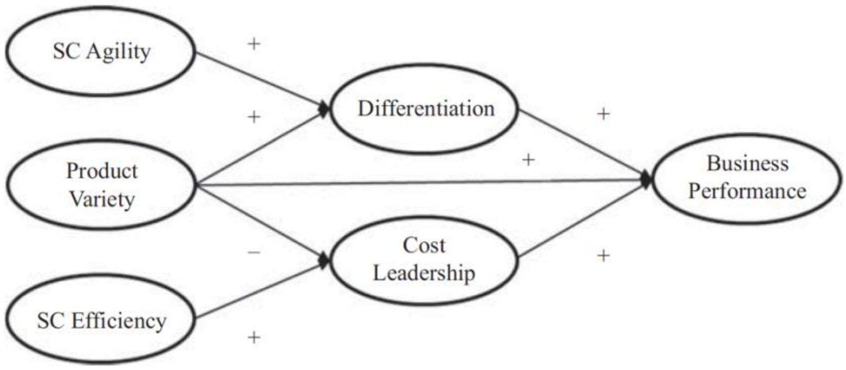

Figure 15. Strategic alignment model with variety in SC. Source: (Um, Han, Grubic, & Ghalib, 2018)

7. Strategies to minimise or accommodate product variety complexity

Current SCs are facing higher complexity arising from the increase of PV that, no doubt, somehow negatively affects SC processes performance. Therefore, applying the appropriate strategies is crucial if firms and SCs want to obtain the beneficial effects of product diversification. However, some authors claim that it is possible to increase variety without affecting the global SC performance. Therefore, the following section will analyse the trends that firms are following to manage the large breadth of product diversity more efficiently. Furthermore, companies managing a wide range of product portfolios require high flexibility levels to successfully satisfy customer demands. For that reason, agility is a fundamental characteristic for a company desiring to perform well.

SCC management aims to move away from the timeless trade-off between cost-efficient strategies and segmented marketplace due to product customisation (customer effectiveness) by improving both of them simultaneously thanks to smart-management of products and operations.

Efficiently managing variety implies making fundamental decisions to evaluate trade-offs, thus balancing the benefits and drawbacks of standardisation. For that reason, is crucial to align the corporate strategy and the level of standardisation of the product. Some of the most used approaches to efficiently manage the variety of products and the complexity of their SCs are shown below.

7.1. Postponement or delayed product differentiation

Customers' increased requirements in terms of diversity, quality, quick and reliable delivery, and competitive pricing dare to restructuration of SCs, which consider an appealing choice to delay the product differentiation point. The concept of postponement refers to the decision not to perform some activities in the SC until customer orders are received. That allows companies to defer the process in which products are transformed according to unique customer specifications, maintaining the products in an undifferentiated state as long as possible along the manufacturing process, which is called delayed product differentiation (van Hoek, Vos, & Commandeur, 1999). Consequently, it contributes to a company's competitiveness by simultaneously reducing cost levels while enhancing customer service. This approach permits firms to be more responsive because keeping products undifferentiated for as long as possible increases company flexibility in responding to customer demand variability.

The ability to design and produce customised parts with efficiency and speeds similar to mass production is called mass customisation. Under mass customisation, customised modules are chosen according to customer needs, each one produced by suppliers with customisation capabilities (Wang Z. , 2016). Besides, under postponement manufacturing, customised modules are divided into the standard production processes and customisation production processes by the differentiation point, called customer order decoupling point (COPD). To succeed, it is required to analyse which postponement strategies the customisation product family should possess to fulfil the diversified demands of customers.

Different postponement strategies are required depending on the internal organisational structure and the product specificity external demands. Therefore, postponement decisions should be aligned with the corporate strategy for a successful implementation of postponement, establishing the proper mix of customisation and standardisation along the SC.

Companies should assess the value of postponement integrating product design decisions and SC decisions. The different delayed differentiation approaches, which can be followed to implement a specific postponement strategy, are presented below.

7.1.1. Process restructuring

Process restructuring is a fundamental condition for delayed differentiation consisting of changing the current operation process sequence to modify it, delaying the time where the product is customised. Using the diversity of components and knowing the assembly line design, companies can redesign their production systems to postpone the moment of product differentiation. Moreover, process restructuring may also arise on a larger scale, not only in the manufacturing process but also in the entire SC.

According to (Gosling & Naim, 2009), six different SC structures can be defined to describe the range of possible operations: engineer-to-order (ETO), buy-to-order (BTO), make-to-order (MTO), assemble-to-order (ATO), make-to-stock (MTS), and ship-to-stock (STS). Thus, the difference between them relies on the location of the decoupling point, which can be placed at the design stage (ETO), before the manufacturing stage (MTO), before the assembly stage (ATO), after the assemble stage (MTS) (Olhager, 2010). Therefore, companies can redesign their processes by changing the structure of their SC to others with a decoupling point placed more closely to the customers.

7.1.2. Component commonality

Using standardised components until the products need to be differentiated and use them for different product models is one of the keys that enable delayed differentiation. It is an approach in which two or more diverse components used for unique finished products, are replaced by standardised parts that can perform the functions of those it replaces (Caux, David, & Pierreval, 2007).

Component commonality generally refers to a SC decision involving supplier selection and inventory policy, which has to be made considering conditions including different demand variabilities, component costs, inventory tracking cost, and inventory ordering costs.

Moreover, there are economic benefits associated with common components usage derived from the total cost of product proliferation reduction. The use of common components requires higher quantities of common parts, which can be utilised in several final products, thus reducing manufacturing costs due to economies of scale. Besides, with risk pooling, the usage of a common component reduces the inventory holding and shortage costs. On the contrary, lower quantities of distinctive parts are needed when a specific final product requires them (Su, Lin, & Lee, 2010). For example, make-to-order companies such as Dell hold inventories as common components and postpone product customisation, thus lowering the level of inventories carried (Chopra, 2003).

Major advantages of component commonality are risk-pooling and lead-time uncertainty reduction. By keeping undifferentiated inventories, the level of safety stock required to meet the service level is reduced, thus improving SC cost-effectiveness. Moreover, it reduces administrative and R&D costs, reducing the number of components to manage, and speeding up the new products market introduction, respectively.

7.1.3. Product design and product modularity

Product design is another path necessary to employ the postponement strategy. While postponement searches efficiency from a process design point of view, modularisation addresses it from a product point of view, and both main function is offering customisation while minimising the costs, delays and internal complexity (Daaboul, Da Cunha, Bernard, & Laroche, 2011). Product modularity is strictly linked with the usage of standard components and the redesign of the production system. By using modularity and commonality as design principles, simultaneously with functionality and performance, it is possible to manufacture products that have been designed from the very beginning to be as standardised as possible. Thus, changing product architecture can result in minimising complexity and associated costs in SC functions (Howard & Squire, 2007).

Subsequently, customisation is achieved by combining standard modules or joining together modular components formulating multiple product variants. Therefore, standardisation in product design includes both integrations of common components and optimisation of the manufacturing process design. However, the risk of excessive modularity and commonality, which is reported as cannibalisation, may damage customers' valuation of the product due to a lack of differentiation.

7.2. Process variety

(Lyons, Um, & Sharifia, 2020) exposed that process variety increases when PV increases mainly because the diverse breadth of products offered to customers may lead to increased variation in the production systems from machines, specialised labour, tools, and etcetera. (Lyons, Um, & Sharifia, 2020) defined process variety as “the diversity and complexity in the processes due to process alternatives for each product variant”.

How process variety affects SC areas was stated by (Daaboul, Da Cunha, Bernard, & Laroche, 2011) which determined that an increase of process variety also implies an increase of both customisation options and economies of scope and scale, while contrarily total order delay time decrease, as well as inventory level and set-up time.

7.3. Supply Chain segmentation

Segmentation in SC management emanates from heterogeneity in operational, tactical, and strategic requirements for serving heterogeneous products and customers (Chan & Arikan, 2020). The aim is to reasonably differentiate SCs through several segments and to implement targeted market strategies and product differentiation based on groups of customers that show similar buying behaviour. Thus, classifying SCs and acting differently on a group basis allows an increased level of standardisation and subsequent avoidance of managerial complexity incurred in fully customised SCs.

Segmentation is fundamental for firms dealing with a wide range of product portfolios since the similarity of different products can be used to segment them into groups. Thus, obtaining results sufficiently close to those obtained if they had been treated individually. However, it is fundamental to understand how to form the groups on which to base the decisions. On the one hand, segment the product portfolio on a small number of groups entails creating higher standardisation while reducing managerial complexity and benefits from potential cost synergy. On the other hand, segment the product portfolio on smaller group sizes occasions higher differentiation (Castka, 2020).

To tackle the aforementioned fundamental trade-off and obtain the maximum benefits from segmentation, results obtained having a smaller number of groups should balance against results obtained from the smaller group sizes. That is, the trade-off between cost synergy from pooling and gain from differentiation should be balanced.

To develop a satisfactory segmentation of SCs through network design, entities not only have to decide between product differentiation and customisation but also have to consider complex interactions among different parts of processes and options. Moreover, an in-depth understanding of business structure is needed since trade-offs stand out when companies plan to segment their SCs. Demand characteristics and geographic differences impact the decision of grouping products, determining whether to centralise manufacturing processes in one facility to obtain pooling benefits or to decentralise them, becoming more adaptative (Li, 2019).

7.4. SC rationalisation

One of the most widely used approaches to manage SC complexity is the so-called rationalisation which can be carried out, on the one hand, by the optimisation of the supplier portfolio and, on the other hand, by the optimisation of the number of SKUs in the company. However, the rationalisation process is a continuous process that has to be refined and optimised every certain period for even better performance in the future.

7.4.1. Supplier rationalisation

Traditionally, supplier rationalisation has been focused on choosing the right number of suppliers, with the right kind of performance, price, and reliability, to support an efficient sourcing strategy (Murphy, 2020). Therefore, the focus was on the supply base maximum reduction through an accurate evaluation which encouraged competition between suppliers. Subsequently, supplier competition imposed with this evaluation method forced suppliers to serve the company with better services, despite being fewer participants in the exchange. However, reducing the supplier portfolio to the maximum, difficulties in managing possible interruptions in the SC could arise, limiting the company's resilience and agility.

The main objectives of this process could be summarised in the maximisation of supplier performance and compliance while minimising risk exposure, the building of both resiliency and agility into the SC to protect business continuity and competitive performance, and, finally, the identification and take of advantage of savings opportunities as well as opportunities to collaborate, among others (Murphy, 2020).

7.4.2. SKU rationalisation

The higher the number of stock-keeping units (SKU) of different product items you have, the higher the SC complexity, thus affecting the service level for customers. Moreover, SKU proliferation may increase operating costs and lead to situations in which only a reduced percentage of products contribute to profitability (Enz, Lambert, & Schwieterman, 2019)

Therefore, a strategy for mitigating the negatives impact of managing such a wide variety of products is SKU rationalisation, consisting of finding the right balance between too many and too few. SKU rationalisation is the branch of research serving to optimise a business' portfolio of product supply or SKUs while analysing the subsequent effects of providing fewer or more supply (Malinowski, Karwan, & Sun, 2021).

Benefits associated with SKU rationalisation are broad, including the reduction in manufacturing, logistics, and inventory costs due to simplifications in each of the processes. However, reducing in excess the product portfolio has clear negative implications on the business' incoming demand, and therefore on sales. On the contrary, a higher number of SKUs means more customers, a wider market capture, a deeper market penetration, and increased competitive position, a tighter customer engagement, and a higher level of customer relevancy (Williams & Mahmoodi, 2019).

The decision lies in understanding which is the amount of variety that enhances revenues while counterbalancing operational inefficiencies. In other words, to find the equilibrium point in which the added value due to increased PV starts to be marginally negative. As aforementioned, PV is assumed to increase sales, enhancing market share, and leading customers to perceive the brand as being of higher quality. Contrarily, service levels fall due to increased complexity, and higher costs had to be assumed due to reduced economies of scale (Enz, Lambert, & Schwieterman, 2019). Additionally, some authors mention that reducing SKUs may be more cost effective than inventory optimisation, highlighting the villainous role of product proliferation on inventory levels (Alfaro & Corbett, 2003).

The digitalisation era opens a new horizon for the study and optimisation of the supplier portfolio, which not only includes financial savings but also other data that can be analysed thanks to the power of digital transformation. In the end, the priority remains on the result, but the current rationalisation prioritises both value creation and savings opportunities. It is an ongoing analytical process where vendor monitoring and governance implementation are necessary to maintain a rationalised portfolio.

7.5. SC integration

SC integration is another approach considered to be helpful in mitigating PV induced complexity along the SC (Shou, Lee, Park, & Kang, 2016). Increased PV complexity can be mitigated by integrating different actors along with the SC with efficient information sharing, adequate coordination, and key collaborations. Therefore, it can be anticipated and eliminated the subsequent uncertainty and SC risks derived from PV induced complexity (Narasimhan & Talluri, 2009).

Moreover, when integration with customers is achieved, manufacturers can enrich their customer demand information and market trends, thus enhancing product specifications details, as quality and quantity requirements (Flynn, Huo, & Zhao, 2010). Consequently, manufacturers' customer information knowledge is transmitted upstream to relevant suppliers improving SC transparency and visibility. Through supplier integration, the company ensure that their suppliers deliver raw materials in a timely and accurate manner, or otherwise, it enables the firm to react in front of a supply non-fulfilment scenario. Furthermore, it can acquire access to new technology or knowledge about components or materials for certain types of products which cannot be achieved in traditional market relationships, improving firm's innovation capabilities.

On the other hand, although it can previously seem evident to integrate actors in the SC, there are companies not pursuing this mindset. Therefore, applying collaborative approaches as the sharing of benefits and risks can be a way to increase the willingness of SC partners to exchange both relevant information and knowledge, thus coping with the adverse repercussions of PV complexity.

7.6. Information technologies (IT)

IT, to some extent, is closely related to SC integration and information sharing. In this context, IT leads firms to real-time information access and information sharing, which are needed to run and consolidate all business processes while helps companies' decision-making. Therefore, IT enables efficient and effective information exchange between SC partners, which drives SC to better performance by improving the information quality and consolidating collaboration and coordination. However, produce more PV may result to incompatible information technology between different firms' IT applications and SC partners due to the different IT solutions available in the market (Piya, Shamsuzzoha, & Khadem, 2020). Some case examples linked to how SCM adopts IT are listed below.

7.6.1. Radio frequency identification (RFID)

RFID is a technology concerning automatic object identification that consists of information transference between a smart-device, which can be passive or active, and a remote reader. Introduced for the first time by Wal-Mart in 2005, this technology enables intra- and inter-organisational communication regarding product identification, such as inventory management regarding intra-organisational processes, or adopted for inter-organisational processes when tracing & tracking an item status (Chen, 2005).

RFID tech not only has saved time and labour costs by, for example, reducing the time spent in PoS daily inventorying proved by Decathlon but also mitigates the complexity of managing products along with the SC.

7.6.2. Enterprise resource planning (ERP)

ERP software is an enterprise system used by companies to integrate and manage all processes required to run the business, such as planning, purchasing inventory, finance, marketing, or human resources. In other words, information integration is the key benefit (Hendriks, Singhal, & Stratman, 2006). On the one hand, ERP replaces complex manual interfaces between different companies' systems with standardised, cross-functional transaction automation, leading to lower order cycle time and cash-to-cash cycle time. On the other hand, ERP leads to data consistency along with the enterprise due to the information is centralised and updated in real-time. The combination of both standardised cross-functional transactions and centralised enterprise data enables managers to clearly view the performance of various enterprise parts, leading to more manageable firms' governance and resulting in better performance.

7.7. Strategies impacts summary

The outcomes of the strategies used to minimise or accommodate PV induced complexity, and the outcomes related, are presented in Table 4. Moreover, the academic papers obtained from the literature review are classified in each strategy analysed, and presented in Table 4.

Strategy	Outcome related	Sources
Postponement or delayed product differentiation (DPD)	Increase company's flexibility in responding to customer demand variability by: • Changing the current operations process sequence. • Using standardised components until the product differentiation point. • Using commonality and modularity as design product principles.	(van Hoek, Vos, & Commandeur, 1999) (Wang Z. , 2016) (Gosling & Naim, 2009) (Olhager, 2010) (Pankaj & Jayaram, 2014) (Chopra, 2003) (Caux, David, & Pierreval, 2007) (Su, Lin, & Lee, 2010) (Daaboul, Da Cunha, Bernard, & Laroche, 2011) (Howard & Squire, 2007)
Process variety	Increase both customisation options and economies of scope and scale.	(Lyons, Um, & Sharifia, 2020) (Daaboul, Da Cunha, Bernard, & Laroche, 2011)
SC segmentation	Increase the level of standardisation by segmenting the product portfolio into groups and subsequently avoid managerial complexity incurred in fully customised SC.	(Chan & Arikan, 2020) (Castka, 2020)
SC rationalisation	Reduce managerial complexity by finding the right balance between too many and too few. Firms can rationalise: • Supplier base. • SKU portfolio.	(Murphy, 2020) (Enz, Lambert, & Schwieterman, 2019) (Malinowski, Karwan, & Sun, 2021) (Williams & Mahmoodi, 2019) (Alfaro & Corbett, 2003)
SC integration	Anticipate and eliminate the subsequent uncertainty and SC risks derived from PV with efficient information sharing, adequate coordination, and key collaborations.	(Shou, Lee, Park, & Kang, 2016) (Narasimhan & Talluri, 2009) (Flynn, Huo, & Zhao, 2010)
Information technologies (IT)	Enables efficient and effective information exchange between SC partners while consolidating it with all business processes.	(Chen, 2005) (Hendriks, Singhal, & Stratman, 2006) (Priore, Ponte, & Rosillo, 2018)

Table 4. Summary of strategies able to minimise or accommodate PV induced complexity.

8. Artificial Intelligence introduction

In the digitalisation era, the ability to manage a vast amount of information is vital to compete and stand out in some markets. However, the AI's real potential when generating value in the chain resides in squeezing all the profits out of the data analysis. Therefore, AI solutions are widely adopted, by mostly high-tech and telecom companies, as an advanced technique to process information and leverage data available not only in firms but also along with the SC, by recognising a multitude of challenges that arise in SC operations and becoming an established versatile technology. Moreover, AI's capabilities have dramatically scaled up due to better and larger data sets availability, improved algorithms, and more powerful graphics processing units (GPUs), which leads to the achieving of new levels of mathematical computer power. This increase in speed and data availability has enabled fasters training and more reliable AI algorithms. In other words, more data while more computing power has boomed AI, triggering the AI era for business.

A recent McKinsey discussion paper showed that organisations seeing more EBIT contribution from AI experience better yearly growth than do other organisations (Balakrishnan, Chui, Hall, & Henke, 2020). Moreover, Michael Chui, McKinsey senior partner, highlights that the AI investment is still being appetitive for companies despite losing AI's hype phase in market speculations (Balakrishnan, Chui, Hall, & Henke, 2020). This fact highlights companies' tendency to use AI technology to enhance their product offering by focusing on revenue drivers rather than improving their capital efficiency by targeting labour costs savings. More in-depth on the topic, (Bughin, Chui, Henke, & Trench, 2017) showed a strong relationship between AI adopters with proactive strategies and significantly higher profits margins (Figure 16). In this vein, those companies who adopt proactively AI stand to gain significant competitive advantages not only benefits from economies of learning but also more productive SC practices, generating value to customers. We have already seen some examples where new entrants beat incumbents and take the lead thanks to AI adoption, as Uber has done in the taxi industry.

In short, AI is considered a mature and consolidated technology in advance processing information due to its versatility when tackling a wide breadth of challenges and enhancing value generation in core processes. For that reason, despite AI's impact to date is relatively small in many industries, its potential for disrupting and expand amongst other sectors that, for instance, were hesitant in the past is high.

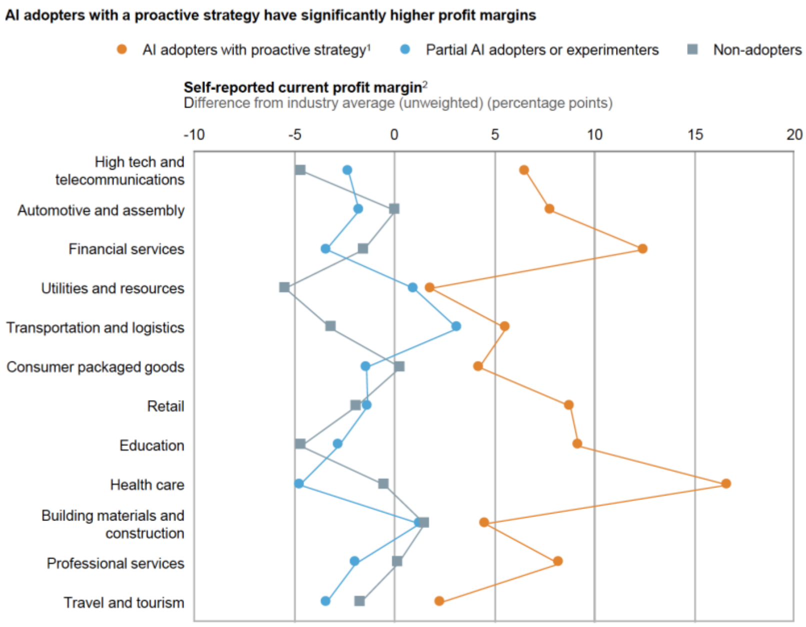

Figure 16. Profits margins depending on firms' level of AI adoption. Source: (Bughin, Chui, Henke, & Trench, 2017)

As reported below, we have developed a descriptive study about AI's scholarly interest trends by downloading and analysing data from SciVal. SciVal is a web-based analytics solution that permits researchers to evaluate research activities from a variety of perspectives and publications records within the Scopus database, thus helping researchers to develop, execute, and evaluate strategies based on reliable evidence. In our case, we have conducted a scholarly publications analysis based on keywords (1st tier: "supply chain" AND 2nd tier: "artificial intelligence").

As shown in Figure 17, the results obtained are aligned with the documents outcomes about AI, which conclude that the new advances in power computing and data availability have boomed the adoption of AI and interest of studies and papers from recent years.

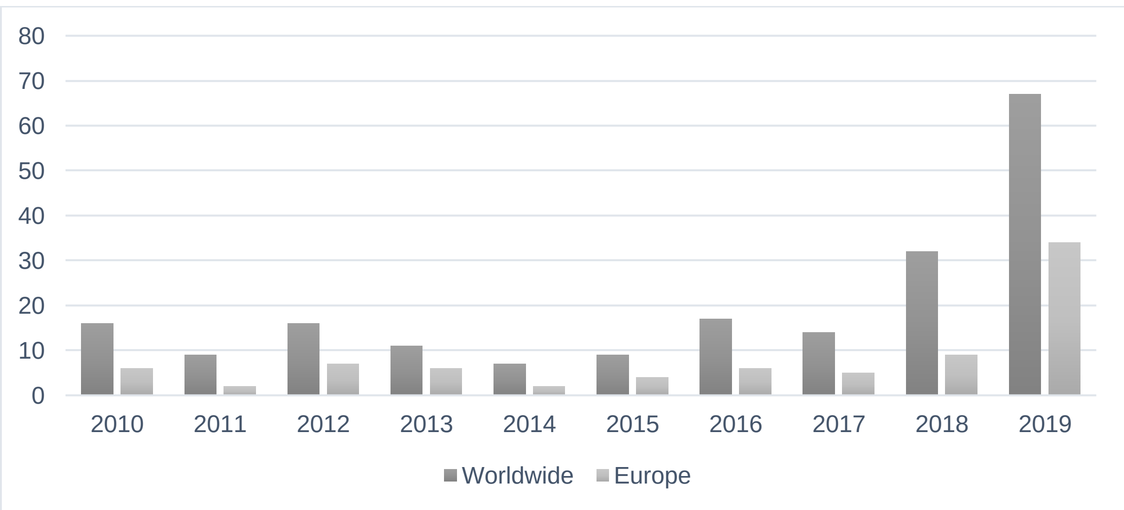

Figure 17. Documents related to AI and SC published per year. Source: Prepared by authors. Data from SciVal tool.

The outcomes and conclusions aforementioned convinced us to finally focus our thesis on how AI boosts complexity arising from PV management. Therefore, in this section, we will describe AI technology and its functionalities to figure out how it could support product variety-induced complexity and boost traditional strategies to mitigate them.

8.1. AI technology in SCM

AI technology enables systems to make resourceful decisions and execute tasks automatically without human intervention using computational abilities that mimic human intelligence, even amplifying it (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). (Kar, Dwivedi, & Grover, 2020) define AI as a pathbreaking analytic tool that enhances the SC performance (SCP) sphere since it facilitates presenting diverse solutions, providing prescriptive inputs in the decision-making process in the face of a complicated solution.

Besides, AI allows companies to implement predictive approaches to rapidly assess and more effectively minimise the risks of disruptive events that could occur throughout the SC since it also lets users recognise patterns in the SC. Therefore, companies exploit AI to gain insights into their intern business areas since AI can clearly and quickly identify relevant SC data to develop models that enable managers to understand better how each process works. AI's emergence in the SC context has caused a radical change in the organisation of work processes since any sector can benefit from the right integration of AI in its processes and become a more proactive, predictive, automated, and personalised sector (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). In short, AI lets companies constantly learn about areas that require improvement, identify factors that affect performance, and predict performance.

8.2. Success factors for AI adoption

It is well-known that AI can go beyond changing business processes to change the entire business models. Thus, entities that are hesitant in implementing AI take the risk of fell behind. For that reason, firms that decide to act must be accurate in the adoption process of AI, aligning AI transformation with the corporate strategy while designing reliable and precise AI outputs. The main factors that firms may consider when adopting AI are summarised in Figure 18.

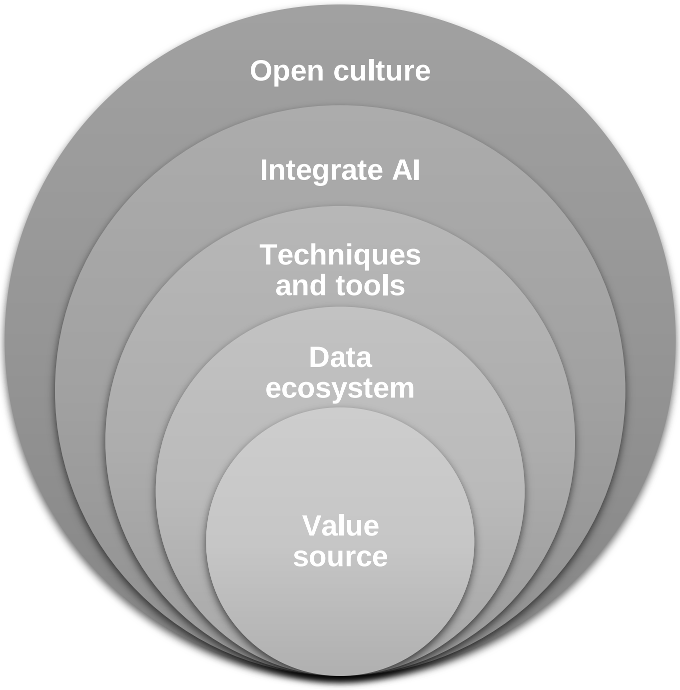

Figure 18. Main factors in successful AI transformations. Source: Prepared by authors.

Identify the value source

The first step firms should consider when are adopting AI is to identify a business case and connect it to firms' strategy and its core process and value chain. For that purpose, it is vital to have a deep AI know-how, acknowledging its strengths and limitations compared to conventional technological approaches, to identify the AI's capabilities in a real-world context. However, to ensure a focus on the most valuable use cases, AI initiatives may be assessed by both business and technical roles.

Build the data ecosystem

Availability of data is crucial for any AI project or initiative since AI algorithms require large data sets, especially at their training phase. In other words, without data, the AI engine cannot start. Therefore, firms need to know the data they have access to and what is relevant to business purposes.

Moreover, algorithms are susceptible to bias induced by data sets. For that reason, it is crucial to avoid them by training algorithms with comprehensive data sets.

Know what you need

To capture the AI potential, firms need to adapt and build internal capabilities finding the tools that fit with the purpose. Companies can acquire the know-how by setting a "build, operate and transfer" partnership with AI start-ups and leaders or, otherwise, implement existing solutions aligned to company-specific needs.

(Bughin, Chui, Henke, & Trench, 2017) mentioned that the "test and learn" approach helps to agile and rapidly validate business cases when implementing AI and afterwards scale those that succeed.

Integrate to squeeze AI potential

Companies' capabilities must be integrated with AI's insights to capture the benefits obtained in the business case. Thus, AI implementation also transforms what people do within the organisation, changing their workflows and roles. Therefore, firms should carefully consider how processes will be redesigned to incorporate AI into the firms' workflows, determining what AI automates and how humans would interact.

Adopt an open-culture and reskill the workforce

To adopt long-term AI initiatives, it is essential to implement an open organisational culture where trust between humans and machine is preconceived. Typically, adapting people in the use of AI is more complicated than the technical implementation phase. Therefore, it may require investments to accommodate workers' capabilities to understand how to use and exploit data-driven AI outcomes as the basis of decision-making.

Roger Burkhardt in the article (Balakrishnan, Chui, Hall, & Henke, 2020), exposed that algorithm explainability is a key enabler to pursue workers to trust AI predictions and avoid the lack of AI adoption.

8.3. AI techniques

AI has several fundamental components, as shown in Figure 19, but the most relevant ones are Machine Learning (ML) and the ability to process unstructured data as Natural Language Processing (NLP) (Wilson, Paschen, & Pitt, 2021).

ML includes computational procedures that enable AI to learn by itself, allowing AI to improve its performance without being explicitly programmed to do so. Therefore, it can analyse a higher amount of information and obtain structured results, increasing the cost-effectiveness of the whole process while unlocking knowledge that was unobtainable using earlier technologies (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021).

Although many ML techniques can be used for SC management, some are used more than others (Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021). The most prevalent and influential is Artificial Neural Networks (ANNs), an information-processing technique that can be used to find patterns, knowledge, or models from a non-structured and extensive amount of data. In SCM, applications of the ANN technology range from sales forecasting, pricing, and customer segmentation to production forecasting, supplier selection, demand management, and consumption forecasting. Furthermore, the outcomes of (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) research shows that the

AI technique for inventory management is easily identifiable, which is the ANN since it enhances the logistics workflow responsiveness. However, it remarks that almost every paper used a new AI technique, such as decision trees, intelligent agents, bio-inspired algorithms, and particle swarm intelligence.

The second key component of AI is its ability to process unstructured data, such as natural language or images. While one of the main applications of NLP is to extract topics that people are discussing from large amounts of text (Zhoua, Awasthi, & Stal-Le Cardinal, 2021), processing images, which is also called computer vision, enables computers to recognise patterns and extract meaning from pixels.

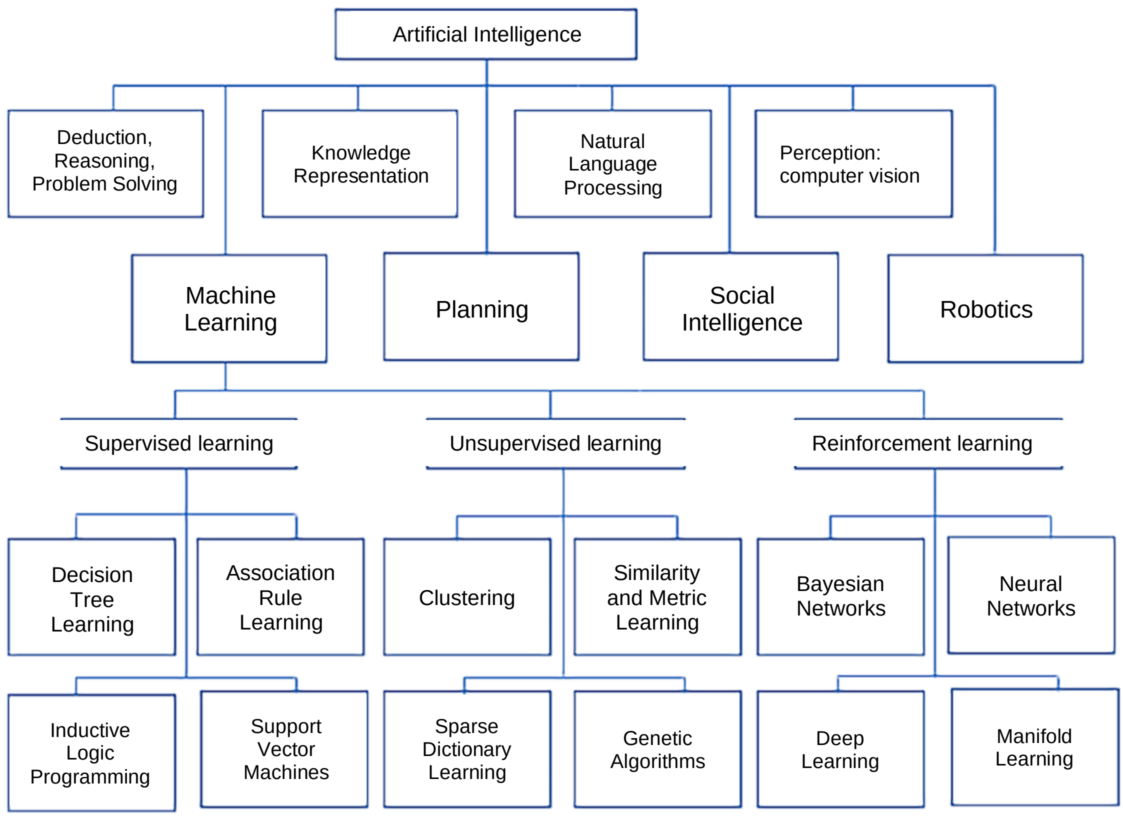

Figure 19. Artificial intelligence classification. Source: (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021).

9. AI applicated into PV discussion

AI has shown strong abilities in tackling multi-dimensional problems due to its high computing capacities while supporting decision-making activities to predict best-of scenarios accurately and reliably based on data learning. Furthermore, when Big Data comes up enhancing its potential in last years, AI has convinced firms to adopt AI technologies not only to automate processes, reducing the labour costs, and improving information exchange, but also enhancing core processes, giving firms a competitive advantage to stand out in such competitive markets of today. Therefore, we will link AI to the PV topic, investigating how it can support the management of complexity induced by PV in the previously analysed areas.

9.1. Sales performance

In general, AI provides Sales Managers with dynamic performance evaluations through AI-driven dashboards identifying upselling and cross-selling opportunities for the customers (Dwivedi, 2021). Based on customer attributes as demographics, location, or browsing history, products, offers, and prices can be personalised and "pushed" to the customer (Sanders, Boone, Ganeshan, & Wood, 2019). AI can go beyond what is expected, enhancing customer experience to new levels. It can personalise tips and suggestions, offer immediate assistance and automated customer service with virtual agents, and tailor products according to customer preferences.

Furthermore, AI predictive and forecasting capabilities, and the use of Big Data, can retain and develop new customer leads. Additionally, AI algorithms can contribute to productivity and provide sales process enhancement by eliminating non-productive activities.

Therefore, different areas affecting sales performance are going to be analysed more in-depth in the following sections.

9.1.1. Customer satisfaction

In the digitalisation era, it is possible to obtain data regarding the set of decisions a customer has experienced when buying a product or service, considering that individual customer buying behaviour is tracked (Sanders, Boone, Ganeshan, & Wood, 2019). With all this information AI can enhance campaign creation, planning, targeting, and evaluation since segmentation and targeting become easy through the data available. Hence, the past purchases, interests, and browsing behaviours can be used to create automated campaigns that can enhance the customers' purchase intention. Furthermore, AI can recognise the consumer's pattern about lifestyle decisions as music, favourite celebrity, and location to create unique content.

Therefore, AI helps brands that need to understand their customers and communicate with them on a personal and emotional level, boosting customer satisfaction (Dwivedi, 2021). Once firms understand their customers more accurately, AI can go further and deliver content in an optimised way, selecting the best times and days of the week to send an email campaign or post on social media, with the recommended frequency of the marketing messages, and the title they are more likely to engage with. Additionally, AI can select the content that fits better each user type to achieve an improved customer brand perception, avoiding the trade-offs between different customer personalities.

DISCUSSION 1: PV vs Customer satisfaction

Regarding the customer satisfaction, AI can support the product variety-induced complexity in three main ways, which will be analysed below.

Firstly, AI allows companies to segment the customers more accurately and precisely, leading to a definition of the different population targets according to the previously obtained segmentation. Thus, the PV level achieved balances the trade-offs between too much and too few, reaching an optimum solution that allows maximum customer satisfaction. Therefore, the PV quantity introduced is in equilibrium with the different customer expectations, enhancing the customer satisfaction and, consequently, brand loyalty. To this end, Support Vector Machines (SVM), also called Kernels machines, are the suitable data mining technique since it can cluster, classify, rank, or find correlations in a dataset.

- **Discussion 1A (D1A): AI supports to define the optimal level of PV according to customer expectations.**

Secondly, when firms decide to increase PV, consumers can see it unavoidably negative when they are only interested in certain portfolio products. Moreover, provide customers with a wide range of products can lead to customer confusion and abort the purchasing. Therefore, AI allows companies to provide customers with just the products they are interested in, mitigating the possible adverse effect of introducing too much PV. Thus, firms can provide the desired advertising content to the target, the so-called “natural fit”, and smartly automate aid actions based on best practises using ML algorithms. Consequently, customers perception of the brand is not damaged by introducing new products that may not interest them.

- **Discussion 1B (D1B): AI mitigates the hidden risk of customer confusion providing them with just the products they are interested in.**

Thirdly, AI allows firms to comprehend more accurately customer needs, adapting the PV level to the changing desires of the target segments, thanks to its potential to process and analyse real-time data. Besides, it permits firms to use feedbacks not only to recognise what customers currently desire but also to continuously understand the evolving trends, discovering new customers that they did not even know existed. Therefore, it becomes easier to identify whether to merge products or introduce more customised ones.

- **Discussion 1C (D1C): AI allows companies to adapt the PV level to the changing desires of the target segments.**

9.1.2. Brand image

Brand image is strongly linked with customer satisfaction since improvements in the alignment between customer expectations and what they find in the market magnifies the perceived brand value. Therefore, improved customer satisfaction due to AI adoption leads to higher perceived brand image, enhancing sales performance. It is useless to investigate the AI impacts on brand image considering that it is not directly affected by its potential benefits, but an indirect impact comes from the customer satisfaction improvement.

9.1.3. Forecasting error

The application of AI in demand forecasting is one of the most promising applications for optimising SC performance since it implies improved supplies, which lead to fewer product shortages, fewer overstocks, and less waste (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). Moreover, it can also improve planning, making it possible to optimise storage capacities or even reception and dispatch. Besides, AI can be used to understand opportunities as customer needs, attitudes, and preferences, considering their specific and increasingly real-time context (Dwivedi, 2021). The importance of improving sales forecast resides in its influence on several organisational levels, as it has previously mentioned. An inaccurate or lack of forecasting can lead to inadequate inventory and material flow management, loss of sales or excess of products, and customer dissatisfaction (Vahid, Pejvak, Reza, & Ali, 2021).

(Verstraete, Aghezzaf, & Desmet, 2020) argue that traditional statistical forecasting methods extrapolate historical trends and seasonal fluctuations to predict the future, being incapable of predicting environmental macroeconomic changes in the business that usually influence demand significantly. Consequently, firms either manually adjusted their statistical forecasts or relied on experts' judgmental forecasts. However, these approaches are biased, since humans are generally inefficient in making such adjustments, and the process is time-consuming. Therefore, (Vahid, Pejvak, Reza, & Ali, 2021) emphasises that even though historical sales forecasting techniques prevail in research, causal methods (AI-based) are proven to be more accurate and precise, especially when sales behaviour changes in an unstable pattern and there are unpredictable fluctuations in its trend. (Sanders, Boone, Ganeshan, & Wood, 2019) argues that near real-time tracking of inventory and customer buying patterns has made it possible to project sales (or estimate demand) more accurately than before, minimising wastes and anticipating sales trends so firms can offer more soon-to-be-popular items.

In short, the importance of embracing AI in SC demand forecasting demonstrated, on the one hand, the impact of improvements in that specific area and, on the other hand, the intrinsic benefits of the technology adoption. AI can autonomously select the optimal forecast algorithm whenever added new data to demand register; it continuously analyses and updates forecast planning criteria to improve forecast accuracy, ensuring an optimal SC performance; it can automatically detect erroneous demand history data points and substitutes a corrected value; it uses ML pattern recognition and NLP to recognise complex patterns and provide data insights; and finally, it uses ML to understand the forecast variability very rapidly.

DISCUSSION 2: PV vs Forecasting error

Regarding the forecasting error, AI can support the product variety-induced complexity in three principal ways, which will be analysed below.

Firstly, thanks to AI, the amount of PV does not affect the demand forecasting precision, and forecast accuracy remains high when introducing more products since it is a tool capable to evaluate hidden interactions and patterns that humans cannot perceive. Besides, AI helps reduce the time spent in forecasting demand, which increases when having more PV. More PV for AI technology does not imply extra time, so that more forecasts can be covered than before, reducing personnel costs since fewer workers are required to cover more SKUs because of AI's support.

- **Discussion 2A (D2A): Demand forecast accuracy remains high when increasing PV if AI technology is adopted.**

Secondly, AI helps to forecast demand by considering factors that humans cannot contemplate. As the PV increases, the complexity induced also increases due to the need to predict the demand for many products that can interact with each other and with competitors' ones. It is difficult for humans to accurately understand the interactions appearing between products on the demand side (substitutions, cannibalisations). Therefore, AI can recognise patterns of demand fluctuation by not only analysing the company portfolio evolution but also those of the market (interactions with competitors).

- **Discussion 2B (D2B): AI’s technology enables forecasts considering products interrelationship arising when PV increases.**

Thirdly, AI allows the forecasting of new products without historical data since forecasts are based traditionally on historical data and then adjusted by experts. When increasing the PV and consequently increases the degree of customisation, there is no historical data to base the forecast. Thus, demand for new products is often difficult to forecast. Therefore, AI helps make more accurate forecasts when products, with shorter product life cycles and a higher level of customisation for a specific target, do not have a historical register to base the predictions through AI-powered attribute-based modelling techniques. AI can better predict future product demands, creating new demand profiles by looking for similar products and finding synergies better than experts can do, and learning from previous product introductions to base the profile pattern and volumes.

- **Discussion 2C (D2C): when increasing PV, AI supports managers to predict forecast without historical register.**

9.1.4. Fill rate

Fill rate is strongly linked with the forecasting accuracy since product availability depends heavily on the inventory level based on demand forecasting. Therefore, improved forecasting error due to AI adoption leads to higher fill rates and lower lost sales. It is useless to investigate the AI impacts on fill rate considering that it is not directly affected by its potential benefits, but an indirect impact comes from the forecast and inventory improvement.

9.1.5. Inventory

When increasing PV, one of the most noticeable impacts is the effect on increased finished goods inventories, a primary source of cost which is necessary to meet demands by ensuring product availability and readiness at the right time (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). High levels of inventories are one of the biggest wastes present in SC, caused by errors in demand forecasting if compared with the actual demand, resulting in costs that could have been avoided (Praveen, Farnaz, & Hatim, 2019). Therefore, AI technology is one of the most effective ways for managing inventory since it can automatise the process.

On the one hand, an AI system can automatically track sales, storing the data that can monitor the inventory in real-time, avoiding overstocking or understocking. Moreover, AI algorithms can even generate reports automatically informing of a demand change avoiding the time spent estimating the stock.

On the other hand, the use of ML can assist with the rapid changes in customer demand (Praveen, Farnaz, & Hatim, 2019), minimising the supply vs. demand mismatch and the subsequent costs, thus increasing profit margins.

Artificial Neural Networks (ANN) modelling is the most adopted technique in inventory management thanks to its capability of handling data with high volatility more accurately, overcoming the weaknesses of traditional forecasting models (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). ANN Models can be applied to non-linear and complex problems and can make predictions by inferencing invisible relationships. The models are also a good predictor when high variability and non-constant-variance are present in the data sets. (Praveen, Farnaz, & Hatim, 2019) shows that by implementing an AI system that uses the ANN algorithm, the average accuracy increases by two to three percent, improving the overall performance and efficiency of the SC network. This model also enhances the forecasting analysis and gives a better prediction of future sales. For instance, the overall improved efficiency of the SC networks also results in various other benefits as the reduction in overall operational costs.

DISCUSSION 3: PV vs Inventory

Regarding the retailers' inventory, AI can support the product variety-induced complexity in two principal ways, which will be analysed below.

AI allows having less uncertainty on the demand side, giving rise to better forecasts even by increasing PV. Without AI, final product stocks increase with increasing PV since the uncertainty of future demand also increases. However, by adopting AI, more accuracy in demand predictions is achieved, which causes a reduction in safety stocks despite increasing the number of products, compared with those we had before adopting AI technology. It should be noted that even using AI, the stocks of the final product will increase with increasing PV, but to a lesser extent than without using AI.

- **Discussion 3A (D3A): AI allows firms to reduce the final goods stock when increasing PV, in comparison with the non-AI-adoption.**

Thanks to AI technology capabilities to process large quantities and complex information, sales forecasts are very close to reality. Therefore, by definition, it impacts all manufacturing activities since all planning can be improved and updated in the face of changes. When adopting AI technology, it is possible to monitor final product stock levels, as well as to have traceability of a greater quantity of PV in a more agile and precise way without misinformation problems. Thus, the greater visibility of stocks in real-time, as well as the most efficient and accurate flow of information, allows greater agility in the face of changes, thus reducing the levels of stock of the final product.

- **Discussion 3B (D3B): AI allows firms to trace a greater quantity of PV more agile and precise, reducing the levels of stock of the final product.**

9.2. Transportation performance

According to (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021), AI-based solutions can reduce transportation costs and increase the ability to efficiently meeting customer's demands. Firstly, on-time deliveries can be ensured with near-optimal solutions to routing problems (RP) since AI helps to solve complex RP faster. Secondly, it is improved the management of warehouse activities performed by robots, automated storage solutions, or operators can be assisted by handling equipment. Finally, AI can use real-time traffic data, robotics, computer vision, and autonomous vehicles, all of which can help build specific models to improve transportations. Therefore, transportation scheduling of vehicle and transportation nodes is an important factor to create a stable chained network by ensuring the highest amount of product distribution and lowest logistics cost (Islam, Mahmud, & Pritom, 2019).

Furthermore, AI can also allow firms to use reverse logistics systems efficiently, adding value during the collection, warehousing, and processing activities (Wilson, Paschen, & Pitt, 2021).

DISCUSSION 4: PV vs Transportation performance

Regarding the transportation performance, AI can support the product variety-induced complexity in two principal ways, which will be analysed below.

On the one hand, AI helps automate internal warehouse transportation since AI combined with the robot and automated warehouse solutions, with a certain degree of intelligence through AI-based software, enables firms to flexibly adapt warehouses to new environmental conditions and requirements even though PV increases.

- **Discussion 4A (D4A): AI enables firms to flexibly adapt warehouse internal transportation even though PV increase.**

On the other hand, AI systems allow the entire PV portfolio to be combined when generating routes that optimise transport, both in cost and time, by using Genetic Algorithm as a Heuristics AI tool. Thus, AI can find synergies that allow generating trucks with more than one product avoiding less-than-full truckloads, leading to use its full capacity. Besides, AI not only provides the optimal route but also reacts to unexpected real-time problems due to environmental conditions, adapting the initially proposed solution to a new one that minimises damage in delivery times.

- **Discussion 4B (D4B): AI systems allow firms to include the overall product portfolio when generating routes, optimising the transportation capacity when increasing PV.**

9.3. Manufacturing performance

AI can assist organisations in developing both operational and strategic situation consciousness to link that experience into actions increasingly quickly, efficiently, and effectively (Dwivedi, 2021). Therefore, using the data coming from operations, partners, and the SC, can help organisations understand the current status, predict and manage incidents and failures, and improve efficiency and reliability.

Sensors and connected applications can generate significant amounts of data about processes near real-time, allowing companies to design better methods and monitor and react to any changes quicker to increase quality and productivity (Sanders, Boone, Ganeshan, & Wood, 2019). AI allows companies to run their operations with higher productivity, lower cost, and better efficiency since it can improve and automate processes, reduce errors, limit product rework, and reduce material delivery time. Moreover, it can optimise preventive maintenance, improve production performance, reduce energy waste, and support training.

Therefore, different areas affecting manufacturing performance are going to be analysed more in-depth in the following sections.

9.3.1. Quality

Product quality analysis is an essential duty for industrial processes and an emerging issue of industrial intelligence. Historically, traditional inspections were mainly based on sampling inspection, conducted by offline physical measurement, leading to several additional economic costs and unexpected damages. Moreover, quality controls were often conducted by shop-floor operators, sometimes leading to controversial paradigms between productivity and quality indicators. Therefore, manufacturers are using smart cameras and the related AI-based software to support quality inspection not only to improve its speeds, latency, and costs but also to go beyond traditional human inspectors. Moreover, automated quality forecast implementation based on statistical analysis has been introduced to extract the hidden valuable information from the industrial data. Thus, manufacturing processes can be adjusted to enhance products' quality based on the data evaluation in real-time.

For this purpose, AI can provide companies with mechanisms to accurately predict the quality and provide warnings of defective products in industrial processes (Ren, Meng, Wang, Lu, & Yang, 2020), including several variables generated from the SC and time-variant machining processes. For example, a data-driven method based on a wide-deep-sequence (WDS) model is proposed by (Ren, Meng, Wang, Lu, & Yang, 2020) to present a reliable quality forecast for industrial processes with varying manufacturing data.

DISCUSSION 5: PV vs Quality

Quality inspection is one of the industrial activities that is evolving along with technological capabilities. Therefore, the emergence of AI empowers tested technologies such as machine vision to go a step further. Continuing with machine vision example, combining it with AI-based technologies, such as deep-learning or ANN, enables to continuously learn which product aspects or parameters are relevant to identify product quality, without the necessity to rely on rules designed by experts. This aspect gains importance when firms are tackling high PV levels, considering that the quality inspection requires a lot of different parameters, shifting and changing depending on the product analysed. Therefore, adopting a tool that can learn on its own, creating rules that set the combination of characteristics that define the product quality is a competitive advantage in a PV context.

- **Discussion 5 (D5): AI-based technology enables faster, less costly, and less complex quality inspections, when tackling high levels of PV.**

9.3.2. Inventory level

In today's competitive marketplace, determining the appropriate inventory policy is a key enable to success, because inventories mismatches induce unnecessary costs derived from stock-outs, holding too many inventories and unreliable production schedules. However, an inventory policy that fits in a time range could shift and become non-optimal due to volatile SC environments. In this context, AI technologies enables decision-makers to tackle inventory policy choice over the time, capturing the valuable variables that impact in company's performance and proposing the best policy option in a given time (Priore, Ponte, & Rosillo, 2018).

On the other hand, AI not only can support managers by presenting recommendations based on data-driven analysis but also act independently without human supervision. The AI capacity to act on its predictions in routines tasks enables managers to focus on more strategic decision-making. Therefore, in the inventory management context, AI can automatically order the number of raw materials required to fulfil production planning by analysing datasets while using the optimal inventory policy. It is translated in cost savings and wastes reductions.

Moreover, AI enables companies to exploit real-time data to control the different manufacturing critical inventories (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021), thus anticipating parts requirements and reducing material delivery time. It is translated into costs saving (Priore, Ponte, & Rosillo, 2018) by the optimisation and reduction of raw materials and WIP inventories.

DISCUSSION 6: PV vs Inventory level

Regarding the Inventory level, AI can support the product variety-induced complexity directly or indirectly improving other drivers, which will be analysed below.

PV induces uncertainty and complexity between processes synchronisation. In that case, WIP inventories will increase due to the inefficiencies arising from the improper processes synchronisation and buffering strategies to mitigate this uncertainty and complexity. As AI allows knowing all the manufacturing processes in real-time, it is possible to have only the necessary stock level in each intermediate process since synchronisation between different production stages is much more efficient, with more optimised sequences. In this vein, AI technologies support decision-makers generating data-driven recommendations to improve processes synchronisation and coordination, subsequently reducing WIP inventories aligned with the Just-in-Time (JIT) manufacturing strategy. Therefore, AI impacts indirectly on the manufacturers inventory level by improving the manufacturing planning and scheduling.

- **Discussion 6A (D6A): AI enables to reduce WIP inventories by improving synchronisation and coordination between production processes when the PV increases.**

On the other part, keeping stock parts at the right level, avoiding stock-outs that leads to production stops, becomes more difficult when companies are managing thousands of stock parts coming from hundreds of suppliers around the world. However, companies tend to be more digitalised, and AI technologies disruption provides real-time supplier data, improving transparency on the supplier side, leading to better inventory management and production synchronisation with suppliers' capabilities. Moreover, if PV increases then replenishment complexity rise, and subsequently raw material inventories increased to mitigate the risk to stockout. In this vein, AI-based technologies can automate and optimise the raw material replenishment routine tasks by not only assisting materials and production managers with recommending what materials to order and when, leading to waste reductions, but also enabling managers to focus on more strategic decision-making.

- **Discussion 6B (D6B): AI automate and optimise the raw material replenishment tasks when tackling high levels of PV.**

9.3.3. Average manufacturing lead time

In the current context of mass customisation and short delivery times is challenging to maintain decreasing lead times. For that reason, it is becoming the visible KPI at the corporate level at most companies.

AI enables manufacturers to optimise processes in real-time due to leveraging the growth in data collection since existing fault detection and classification tools can be inaccurate and cause expensive delays on the assembly line. Therefore, AI technologies not only identify processes inefficiencies but also prevent unnecessary production interruptions (Bughin, Chui, Henke, & Trench, 2017).

In this vein, machine learning could help operators in maintenance routines by implementing a predictive maintenance schedule analysing failure indicators in real-time, and predicting the failure and fixing a punctual maintenance intervention, which will afterwards minimise the impact of maintenance intervention in production capacity. Hence, lead times can be reduced by optimising maintenance interventions while avoiding non-predicted failures, subsequently increasing the utilisation rate of plants capacity. Moreover, Virtual Agents could deliver instructions and information on interactive personal-communications devices to reduce production errors at the shop-floor level and smooth the learning curve for new operators (George, Blackwell, & Rajan, 2019).

DISCUSSION 7: PV vs Average manufacturing lead time

Regarding the AMLT, AI can support the product variety-induced complexity directly or indirectly improving other drivers, which will be analysed below.

The average manufacturing lead time is affected mainly thanks to improvements that AI introduces in the reduction of the total changeover time, due to the better sequencing of production orders, and in the optimisation of production planning, due to computational improvements at the planning level. For this reason, the highest impact on the AMLT comes directly from the previously mentioned improvements, which indirectly impact the AMLT. These will be analysed below in the following sections, also investigating the existing relationship with PV.

- **Discussion 7A (D7A): AMLT is indirectly affected by AI improvements in setup times and planning and schedule when increasing PV.**

On the other hand, increasing PV inevitably generates complexity to manage the different manufacturing orders efficiently. One of the areas in which AI can support real-time management of breakdowns and even in the forecast of possible stops, thanks to the machine learning potential. Therefore, AI can give warnings so that interventions are managed more efficiently, considering the complexity of the production planning induced by increasing the PV so that AMLT can be reduced despite the complexity.

- **Discussion 7B (D7B): AI supports the management of interventions, reducing total AMLT even when increasing PV.**

9.3.4. Setup times

Define the optimal job sequence is often challenging for managers operating in large factories that manage a vast amount of WIP inventories. Therefore, defining an optimal sequence solution, minimising total setup time sequence while fulfilling customer delivery times requirements, is clearly beyond human capabilities that are limited to process and consider a few scenarios and possibilities. Therefore, AI helps the manager in decision-making in terms of jobs' sequencing, reducing setup times and maintaining delivery times at extraordinary fulfilment levels (George, Blackwell, & Rajan, 2019).

DISCUSSION 10: PV vs Setup times

Firms tackling high levels of PV may experiment an increase in total setup time, mainly because higher PV reduces the batch sizes, increases differences between batch parameters and subsequently increases the number of setups and its total time. Therefore, AI-based technologies not only can optimise the job sequence in a pull group, considering also more variables such as delivery time fulfilment, but also react in real-time to invoices and unexpected events, such as corrective maintenance or capacity losses. Optimal sequencing enables to minimise the total setup times, and especially when tackling high PV.

Discussion 8 (D8): AI can minimise total setup time by optimising the sequence of a pull group characterised by high levels of PV.

9.3.5. Manufacturing planning and scheduling

Most production planning and scheduling methods rely on lead times, and hence the efficiency of these methods is crucially affected by the accuracy of its prediction.

Furthermore, predict the lead time is often difficult to achieve due to customised products have several features influencing the manufacturing parameters. Predictions faults may lead to direct planning and scheduling unbalances, shifting capacities, and optimal sequences.

(Gyulai, Pfeiffer, & Gabor, 2018) concluded that AI-based prediction models can outperform traditional analytical ones, such as Linear Regression, in terms of reliability and accuracy. Consequently, AI becomes a suitable technology to enhance prediction reliability, boosting lead-time prediction, which is a key factor of successful planning and scheduling. Firms figure out this challenge through machine learning (ML), based on the products and processes data obtained from the manufacturing execution system (MES). Moreover, the production planning process can be automated thanks to AI's analytical capacity and its ability to correlate large volumes of data extremely quickly.

DISCUSSION 9: PV vs Manufacturing planning and scheduling

Regarding the Manufacturing planning and scheduling, AI can support the product variety-induced complexity in 3 principal ways, which will be analysed below. Moreover, improvements in planning and schedule directly affect the AMLT and setup time.

Production planning suffers when the quantity of products increases, increasing the complexity to determine most of the machines' capacity. However, AI allows the creation of production sequences that fully exploit the processes' utilisation rate while considering other indicators such as the order delivery time so that the planning process can be automated and optimised. Without AI, when increasing the number of products, it is complicated to manually make an optimal order assignment, which causes the loss of utilisation rate.

- **Discussion 9A (D9A): AI allows companies to really exploit the maximum utilisation rate of machines when increasing PV.**

Secondly, AI allows production orders to be planned in real-time considering the current machines' capacities, the real-status of the different WIPs, the status of raw materials, the planned preventive maintenance, the availability of complementary materials, among others. Therefore, planning acquires a greater capacity to adapt to changes such as corrective maintenance, breakdowns, lack of a component, problems in the stages correlated with each other. Thus, modifications can be made in the planning in a more agile way updating optimal process sequence in real-time, dynamically rescheduling production operations as new orders arrive and problems arise on the production floor. When PV increases, it is almost impossible to react to each entering new invoice or each arisen difficulty affecting the current schedule, becoming more complicated to plan and schedule the PV. In this vein, AI can make the difference, transforming the planning and schedule task into an agile and easy job that can be continuously optimised according to changes in the environment.

- **Discussion 9B (D9B): AI allows companies to react to each entering new invoice or each unexpected event in real-time, which are higher as PV increase.**

By increasing the complexity of processes derived from the rise in PV, the lead time increase induced by smaller production batches, increasing changeover times, subsequently increasing the time spend from the order invoice to the order delivery. As previously mentioned, AI allows improved synchronisation of processes since it can analyse real-time data, adapting the sequences in the face of changes, reducing the probability of increasing the lead time when unexpected events arise. Therefore, by reacting very quickly to unforeseen events, despite having a great variety of products, it is possible to minimise the AMLT due to better synchronisation and increased adaptability between processes.

- **Discussion 9C (D9C): AI adoption leads to a reduction in AMLT as PV increase, due to more complicated schedules.**

9.3.6. Product development

Engineers face innovation difficulties with the growth in customised products in fragmented markets while budget constraints limit the engineering teams' development time disposal and the number of iterations available to develop a product. Traditionally, product development was based on trial-and-error approach, sometimes involving customers at early stages and becoming high time and cost consuming. Moreover, product developers worked on companies' information legacy and marketing benchmarking of demand necessities and requirements. Developers often seeks reliability rather than best-of solutions, which are time consuming. Therefore, AI technologies can help engineers and developers to improve the agility of product development by eliminating the waste in the design process and possible biases, leading to more effective design processes by focusing only on added-value product capabilities while reducing the time required to solve design problems (Bughin, Chui, Henke, & Trench, 2017).

In short, AI is used by manufacturers not only to enhance the product design process to be manufactured but also making faster and better decision-making when tackling design trade-offs. This acceleration in innovation capacities stands to enable SC firms to create new profit streams faster and decrease costs in the process, thereby enhancing SC efficiency (Mani, Kamble, Belhadi, Rehman Khan, & Verma, 2021).

DISCUSSION 10: PV vs Product development

AI potential is based on optimising the product production process while offering more suitable products to customers' needs. In other words, AI can detect demand tendency and identify soon-to-be-popular products, more accurately and reliably than experts can do, while optimising the product production process. It will be translated into faster product development and better customer perception, leading to achieve levels of PV defined by firms, with no-time and cost limitations.

In short, this will result in higher speed to hit the market, lower product development costs (less trial-and-error iterations) and added value to final products, enhancing customers' expectations.

- **Discussion 10 (D10): AI will enable faster, cheaper, and more added value product development, fostering product proliferation.**

9.4. Procurement performance

Regarding the impacts in the different purchasing areas, no benefits have been found at this point in the AI adoption since AI can help manage the supply base but cannot improve the previously selected drivers. When PV increases, even with AI adoption, the drivers will not change their behaviour, increasing the number of suppliers, raising the supplier lead time and reliability, and extending the organisational standards. Note that supplier lead time could decrease if the selected supplier adopts AI, but not if the focal company implements it. Therefore, AI can improve procurement performance supporting selection and contract negotiation processes.

AI can assist companies' supplier selection process by training machines by decision-makers or using historical data to make predictions and recommendations. Therefore, the supplier evaluation and selection process, which constitutes a critical and complex multi-criteria decision-making procedure, can be more efficient. Thus, AI-based models, as ANN, have been broadly used since they can solve supplier selection problems with multiple constraints (quality, delivery, performance, service, price, warranties, reliability, and financial position) (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). They can predict outcomes based on past trends and can process information at high speed. Moreover, AI technology can leverage data to present an integrated picture of the spending, enabling firms to optimise and automatise contracts, achieving a smart sourcing (Sanders, Boone, Ganeshan, & Wood, 2019). As a result, administrative costs can be reduced due to faster and more reliable managers decision-making when selecting suppliers, and due to more automated selection process, delaying human intervention until core and strategic decisions (Bughin, Chui, Henke, & Trench, 2017).

In addition, SCs are becoming more transparent, and it is becoming easier to track the environmental, social, and economic performance of suppliers, improving risk management (Sanders, Boone, Ganeshan, & Wood, 2019). Therefore, AI makes it possible to process and correlate several data facilitating understanding and anticipating the impacts of external events since its resilient strategies commonly rely on fast decision-making based on potentially large and multidimensional data sources (Riahi, Saikouk, Gunasekaran, & Badraoui, 2021)**.** Hence, the advanced AI-powered capability to recognise SC variability can be used to develop a range of possible supply responses when running simulations within the expected range of supply possibilities. Besides, it helps organisations to improve their response to changes in the environment by, for example, re-learning business rules, making firms more adaptive (Dwivedi, 2021).

Finally, AI can help firms managing negotiations with suppliers, which is a complex task that requires deep knowledge of economics and consists of several interdependent phases combining various negotiation elements (auctions, exclusive offers, ...) (Schulze-Horn, Hueren, Scheffler, & Schiele, 2020). Moreover, individuals' rational decision-making is limited by their cognitive abilities, available information to solve decision problems, and the finite amount of time to reach decisions, making it difficult especially when purchasers are usually not specialised in this field. Therefore, individuals lead to achieving satisficing instead of optimising outcomes, whereas AI can predict suppliers' bidding strategies and support them in determining appropriate bid prices. AI might also support the execution of game-theoretic negotiation approaches.

DISCUSSION 11: PV vs Procurement performance

Regarding the Supply base management, AI can support the product variety-induced complexity in two principal ways, which will be analysed below.

On the one hand, AI can support an automatise the supplier search and selection process. When a company increases its PV, the product life cycles are shorter due to the constant adaptation to changing customer expectations. AI allows companies to automate and streamline the supplier search and selection process, adapting it to the specific requirements of new products when PV increases. It also allows companies to eliminate subjective criteria when selecting suppliers, avoiding possible decisions not based on data but personal perceptions and historical behaviours. Additionally, AI can identify new criteria analysing the performance of the current supply base to apply them to the search of new ones. Therefore, AI not only allows companies to manage the supplier selection process more agile, but it can also define new criteria and rules based on finding patterns and relationships between performance parameters of current suppliers. The concept where an expert establishes a series of bases to support the search criteria, such as delivery times or quality of delivery, disappears since AI, from learning with a lot of information, concludes its bases to define the provider that best fits the requirements.

- **Discussion 11A (D11A): AI can support the supply search and selection process, which is more frequent as PV increases.**

On the other hand, AI can support contract negotiation, which becomes more complex as PV increases. When the PV increases, the product specifications also increase, becoming more concrete and specific. Therefore, purchasers will not be informed enough to make a good negotiation considering parameters that are also changing. Hence, AI will support negotiations finding the optimal results for the company, considering multiple criteria in a very efficient way.

- **Discussion 11B (D11B): AI can support the contract negotiation process whose complexity increases induced by PV.**

9.5. AI impacts summary

The outcomes of the AI application helping to manage PV induced complexity, summarised in the hypothesis, are presented in Table 5. Moreover, the academic papers obtained from the literature review are classified in each area and sub-area analysed, and presented in Table 5.

Area	Sub-area	Hypothesis related	Sources
Sales	**Sales**		(Dwivedi, 2021) (Sanders, Boone, Ganeshan, & Wood, 2019)
	Customer satisfaction	**D1A:** AI supports to define the optimal level of PV according to customer expectations. **D1B:** AI mitigates the hidden risk of customer confusion providing them with just the products they are interested in. **D1C:** AI allows companies to adapt the PV level to the changing desires of the target segments.	(Sanders, Boone, Ganeshan, & Wood, 2019) (Dwivedi, 2021)
	Forecasting error	**D2A:** demand accuracy remains high when increasing PV if AI technology is adopted. **D2B:** AI's technology enables forecasts considering products interrelationship arising when PV increases. **D2C:** when increasing PV, AI supports managers to predict forecast without historical register.	(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) (Dwivedi, 2021) (Vahid, Pejvak, Reza, & Ali, 2021) (Verstraete, Aghezzaf, & Desmet, 2020) (Sanders, Boone, Ganeshan, & Wood, 2019)
	Inventory level	**D3A**: AI allows firms to reduce the final goods stock when increasing PV, in comparison with the non-AI-adoption. **D3B**: AI allows firms to trace a greater quantity of PV more agile and precise, reducing the levels of stock of the final product.	(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) (Praveen, Farnaz, & Hatim, 2019)
Transportation		**D4A:** AI enables firms to flexibly adapt warehouse internal transportation even though PV increase. **D4B:** AI systems allow firms to include the overall product portfolio when generating routes, optimising the transportation capacity when increasing PV.	(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) (Islam, Mahmud, & Pritom, 2019) (Wilson, Paschen, & Pitt, 2021)

Area	Sub-area	Hypothesis related	Sources
Manufacturing	**Manufacturing**		(Dwivedi, 2021) (Sanders, Boone, Ganeshan, & Wood, 2019)
	Quality	**D5**: AI-based technology enables faster, less costly and less complex quality inspections, when tackling high levels of PV.	(Ren, Meng, Wang, Lu, & Yang, 2020)
	Inventory level	**D6A**: AI enables to reduce WIP inventories by improving synchronisation and coordination between production processes, when the PV increases. **D6B**: AI automate and optimise the raw material replenishment tasks when tackling high levels of PV.	(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) (Priore, Ponte, & Rosillo, 2018)
	Average manufacturing lead time	**D7A**: AMLT is indirectly affected by AI improvements in setup times and planning and schedule when increasing PV. **D7B**: AI supports the management of interventions, reducing total AMLT even when increasing PV.	(Bughin, Chui, Henke, & Trench, 2017)
	Setup times	**D8**: AI can minimise total setup time by optimising the sequence of a pull group characterised by high levels of PV.	(George, Blackwell, & Rajan, 2019)
	Manufacturing planning and scheduling	**D9A**: AI allows companies to really exploit the maximum utilisation rate of machines when increasing PV. **D9B**: AI allows companies to react to each entering new invoice or each unexpected event in real-time, which are higher as PV increase. **D9C**: AI adoption leads to a reduction in AMLT as PV increase, due to more complicated schedules.	(Gyulai, Pfeiffer, & Gabor, 2018)
	Product development	**D10**: AI will enable faster, cheaper and more added value product development, fostering product proliferation.	(Bughin, Chui, Henke, & Trench, 2017) (Mani, Kamble, Belhadi, Rehman Khan, & Verma, 2021)

Area	Hypothesis related	Sources
Procurement	**D11A**: AI can support the supply search and selection process, which is more frequent as PV increases. **D11B**: AI can support the contract negotiation process whose complexity increases induced by PV.	(Riahi, Saikouk, Gunasekaran, & Badraoui, 2021) (Sanders, Boone, Ganeshan, & Wood, 2019) (Bughin, Chui, Henke, & Trench, 2017) (Dwivedi, 2021) (Schulze-Horn, Hueren, Scheffler, & Schiele, 2020)

Table 5. Summary of areas impacted by PV and consequences of AI adoption with discussion outcomes and references.

Once we investigated and understood how AI affects and influences the different areas and processes in the SC and analysed how it can help manage the complexity generated by PV, we have realised the potential of AI technology. AI not only improves results, reduces costs, or minimises waste but also transforms the entire SC, making it more agile, adaptable, flexible, and resilient against possible disruption risks since all processes in the SC can benefit from its potential. It has been possible to present the main ways in which AI supports the SC processes. Firstly, AI extracts value from the analysis of large databases that would be cost and time consuming without its adoption. Specifically, in the sales area, AI allows firms to understand in-depth customers' behaviours so that the products offered fit better their expectations. On the other hand, AI's demand forecasting capabilities go beyond human breadth comprehension, detecting patterns and finding insights by analysing large datasets and extracting deep and complete knowledge from the SC operations. Secondly, AI can solve complex optimisation problems, such as routing problems, process sequencing with multi-criteria restrictions, among others. Therefore, it can be achieved a near-optimal solution. Thirdly, AI allows companies to control SC processes due to real-time information usage supporting the decision-making. Specifically, it is used for inventory management as well as for the management of quality inspection processes. Finally, one of the most advanced advantages of AI is its capability to learn from data and adapt criteria based on environmental changes. Therefore, it is possible to not only automate processes but also delegate the decision-making reasoning, mainly due to the data-driven analysis and its self-learning capacity. Thus, AI constitutes an efficient means of imitating adaptivity through learning from the external environment, thereby making complex systems more organised, highly reconfigurable, and adaptive. For that reason, AI is highly extended in demand forecasting or manufacturing planning and scheduling, regarding that capability.

10. Limitations and future research questions

Although the framework was conducted following a methodological and scientific approach, it is unavoidable to induce biases, arising limitations during the different thesis stages that might be considered by scholars and practitioners evaluating the outcomes of this study.

Firstly, since our framework was based on a literature review, outcomes and findings may be limited and strongly linked to the keyword choice and combination. Thus, some conclusions may be overlooked because some papers have might be missed since it was not feasible to cover the complete range of databases. Moreover, to simplify the evaluation of the different SC performance drivers, we have divided the SC into four main areas that were studied independently. Therefore, relationships between drivers belonging to different areas were neglected, diminishing not only the analysis complexity but also the quality of results obtained. Consequently, AI techniques used to mitigate the PV-induced complexity were also limited to the researched areas, leaving space for others not mentioned in this study that can affect PV.

Future research question 1 (FRQ1): *Are there other areas or drivers within the SC that can be affected by PV? Are there other AI techniques that affect PV?*

Secondly, even though our outcomes were based on qualitative and quantitative papers, only qualitative outcomes were proposed by this study. Therefore, we may point out that a quantitative analysis of the qualitative results should be done, not only to corroborate the qualitative outcomes but also to enhance the value of those findings. Thus, future research is recommended to explore and design quantitative methods to get deeper insights into the hypothesised and discussed outcomes. For example, testing outcomes into real-industry cases analysing the influence grade of the study's relationships outcomes, or designing a survey oriented to the cross-functional industry experts to test and compare the conclusions with current experts' opinion.

Future research question 2 (FRQ2): *Which techniques and methodologies can be applied to test the qualitative results? Which are their results? Are they aligned with the qualitative conclusions?*

Thirdly, findings were based on a snapshot in range time, and unexpected events, such as COVID-19, can completely change the business model and business paradigms that might be neglected. For this reason, future research might consider COVID-19 impact on PV and AI.

Future research question 3 (FRQ3)*: How COVID-19 affected PV by changing mass customisation trend? Did it enhance PV, or otherwise soften PV?*

11. Conclusions

The literature review has highlighted the growing importance of SC variety management in an evolving market context in which competition is on the basis. Thus, firms' SCC is increasing due to increased product range proliferation. The purpose of this study was to investigate the effect of AI on SCC induced by PV. To this end, we have designed a framework based on a systematic literature review structured in three main steps; collect, describe, and analyse. We performed this review using 72 research articles from the Scopus database published between 2002 and 2021. Previous literature has typically examined the correlation between PV and SCC, and AI applications in SCM. However, potential AI benefits in managing PV complexity have never been analysed before.

The first proposition drawn from the literature review is the relation between PV and SCC, a popular topic in past research. We conclude that more PV induces higher complexity in managing processes, decreasing the four areas performance, except for sales, which apart from also experimenting more difficulties in the management, has a positive effect by fitting better customers' requirements, hence improving the sales. When PV increases, for example, higher materials are required to produce the different product variants. Or also, for example, higher complexity in sequencing batch orders, when managers are planning and scheduling the production, leads to higher total setup time, lower production capacity, higher lead time, and at the end, higher production costs.

A second proposition is that there are proved strategies to mitigate or accommodate the complexity arising from PV, enabling to increase PV to satisfy the increasing customer expectations without strongly affecting SC processes performance. Moreover, the "traditional" strategies adoption has become a must for firms attempting to remain competitive because they are forced to adopt more product customisation in response to today's market expectations. Therefore, selecting the proper PV mitigation strategies is a fundamental enabler to success and a condition required for a company that seeks to remain on the market.

AI is a pathbreaking analytic toolset that enhances the SCP due to its outstanding capabilities for analysing, optimising, controlling, and learning from data. Moreover, the increase in data availability and computer computation capacity have boomed the potential of AI, leading industries that hesitate in the past to adopt these technologies. For that reason, we have concluded that AI is the suitable technology to not only tackle the complexity induced by PV but also enhance SC processes performance, giving early AI adopters a competitive advantage. AI has demonstrated a formidable capacity to manage the adverse consequences of increased PV on companies' performance, not only mitigating it but also eliminating it. Therefore, companies adopting strategies to manage PV-induced complexity can remain competitive in markets, whereas companies adopting AI technology absolutely shine for their competitive advantage.

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