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In search of a suitable way to deploy Triple-A capabilities through assessment of AAA models' competitive advantage predictive capacity

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Abstract

Purpose – To determine how to best deploy the Triple-A supply chain (SC) capabilities (AAA-agility, adaptability and alignment) to improve competitive advantage (CA) by identifying the Triple-A SC model with the highest CA predictive capability.

Design/methodology/approach – Assessment of in-sample and out-of-sample predictive capacity of Triple-A-CA models (considering AAA as individual constructs) to find which has the highest CA predictive capacity. BIC, BIC-Akaike weights and PLSpredict are used in a multi-country, multi-informant, multi-sector 304 plant sample.

Findings – Greater direct relationship model (DRM) in-sample and out-of-sample CA predictive capacity suggests DRM's greater likelihood of achieving a higher CA predictive capacity than mediated relationship model (MRM). So, DRM can be considered a benchmark for research/practice and the Triple-A SC capabilities as independent levers of performance/CA.

Research limitations/implications – DRM emerges as a reference for analysing how to trigger the three Triple-A SC levers for better performance/CA predictive capacity. Therefore, MRM proposals should be compared to DRM to determine whether their performance is significantly better considering the study's aim.

Practical implications – Results with our sample justify how managers can suitably deploy the Triple-A SC capabilities to improve CA by implementing AAA as independent levers. Single capability deployment does not require levels to be reached in others.

Originality/value – First research considering Triple-A SC capability deployment to better improve performance/CA focusing on model's predictive capability (essential for decision-making), further highlighting the lack of theory and contrasted models for Lee's Triple-A framework.

Keywords Triple-A supply chain, AAA, Agility, Adaptability, Alignment, PLSpredict, BIC, Akaike weights, Competing model assessment, Performance, Competitive advantage

Paper type Research paper

1. Introduction

Supply chain (SC) adaptability, alignment and agility are dynamic capabilities that enable global SCs to respond to their changing business environments (Machuca *et al.*, 2021). These capabilities

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can be defined as follows (Marin-Garcia *et al.*, 2018): SC agility is the SC's ability to rapidly detect and respond to short-term changes in real demand and supply; SC adaptability is the SC's ability to adapt its strategies, products and/or technologies to structural market changes, and SC alignment is the SC's ability to share information, responsibilities, roles and incentives with SC members to synchronise and coordinate processes and activities. This set of dynamic capabilities was proposed by Lee as a conceptual framework called the Triple-A SC (Lee, 2004) and has become one of the most influential of all frameworks for SC practitioners and researchers (Mak and Shen, 2021). It argues that SCs should strive to improve by implementing the Triple-A capabilities rather than focusing exclusively on efficiency and cost improvements (Lee, 2004).

The main reasons for the relevance of this topic include the increasingly important role of SCs in the world economy and the significant investments in resources and efforts required in the design of global SCs and in the deployment and implementation of the Triple-A (also called AAA) SC capabilities to improve performance/competitive advantage (CA). These capabilities demand complex resources whose implementation in SCs might be difficult, expensive and hard to replicate (Whitten *et al.*, 2012). Therefore, they could generate a superior level of performance/CA. Together with the fact that firms have limited resources, their expensive implementation makes finding the most suitable way to deploy the Triple-A SC capabilities to improve CA particularly relevant rather than trivial (Machuca *et al.*, 2021).

However, neither the initial conceptual framework proposed by Lee (2004) nor his more recent article on the topic (Lee, 2021a) hypothesises about how the AAA-SC can be best related or deployed to obtain an "optimum" result, even though, as mentioned above, finding an answer to this is relevant not only for researchers but also for managers, who would then have a guide as to *how to adequately deploy the Triple-A SC capabilities in their SC design to better improve SC performance/CA*. Moreover, the lack of theory and a contrasted model for this conceptual framework has led to the appearance of different approaches to its development. Nevertheless, research results regarding the most suitable implementation of AAA capabilities for the relationship between the Triple-A SC capabilities and performance/CA or the possible linkages between the capabilities are still scarce and inconclusive (Dubey and Gunasekaran, 2016), which leaves a major research gap in the (still developing) Triple-A research area, where the topic continues to be considered under-researched (Machuca *et al.*, 2021). Resolving this issue is also relevant for practice as it will indicate a suitable way to implement AAA-SC to improve performance/CA.

To fill this gap, the present research focuses on identifying how to deploy the Triple-A SC capabilities to best improve SC performance/CA. This is done by focusing on models' predictive capability (as well as their practical relevance). This is important because a model's predictive capability is the most important condition for its relevance for decision-making and providing recommendations for business practice (Chin *et al.*, 2020; Shmueli *et al.*, 2016). This is another important gap filled by this research as, despite the relevance of the model's predictive capability, the previous literature on Triple-A SC has mostly focused on model fit. This is in line with the call regarding the interest in research studies "that use PLS-SEM and related methods to address the interplay between explanation and prediction in order to advance our understanding and knowledge of the LSCM field" (Cheah *et al.*, 2022).

For all the above reasons, *identifying the model (out of the models proposed in the literature) with the highest predictive capability that shows how to best deploy the Triple-A SC capabilities to improve CA should be considered an important original contribution*. This model should be a benchmark for researchers and managers. This leads to the following research question, which is the focus of the present research.

RQ1. Does a Triple-A SC capabilities–performance/CA relationship model with a higher predictive capability exist than the others proposed in the literature that could be considered a benchmark for deploying AAA-SC?

Regarding the RQ1, two main approaches to AAA-SC and performance/CA models have been found in the literature. Some works have modelled this relationship considering the Triple-A SC as an aggregate high-order construct (HOC) of the Triple-A SC capabilities directly related to performance/CA (e.g. Whitten *et al.*, 2012; Attia, 2015; Alfalla-Luque *et al.*, 2018; Machuca *et al.*, 2021). Other models consider Triple-A SC capabilities as individual constructs (IC) and have analysed their influence on performance/CA as such (e.g. Dubey and Gunasekaran, 2016; Alfalla-Luque *et al.*, 2018; Yang, 2021). This article's RQ1 determines that only the second group of models should be considered in this research, as the first modelling method (Triple-A SC as an HOC) does not allow the influence of each individual Triple-A SC capability on performance/CA or the relationships between the AAA-SC capabilities themselves to be analysed. Nevertheless, it must also be stated that there is no consensus regarding the second group as various models have been proposed to represent the mentioned relationships either directly (e.g. Alfalla-Luque *et al.*, 2018; Attia, 2016; Yang, 2021) or through mediation (e.g. Dubey and Gunasekaran, 2016; Dubey *et al.*, 2015).

Therefore, regarding the RQ1, it is relevant *to determine whether any of the models in the literature that propose different deployments of the Triple-A SC capabilities (directly or through mediation) predict performance/CA better than the others.* To date, there is no consensus on modelling the relationships between the AAA-SC capabilities and performance/CA (Dubey and Gunasekaran, 2016), and in addition, as previously stated, the previous research has not analysed which model provides the highest performance/CA predictive capability. So, further research is needed to fill this major gap. For this, we need to compare the Triple-A→performance/CA models proposed in the literature based on their predictive capability (and not their fit, although a good fit is a pre-condition for every model considered in this research). Comparing the existing models to identify the model that can serve as a benchmark to guide further research could be considered a (methodological) contribution to the topic field (especially if we consider that the topic is still in development) that facilitates theory development and entails important managerial implications.

Based on the above, we consider that this research provides original contributions that can facilitate the theoretical development of the Triple-A SC research topic. Specifically, the contribution of this paper for researchers is threefold. Firstly, original insights are offered about the model with the highest predictive capability in the relationships between the AAA-SC capabilities and performance/CA for theory development and progress on the Triple-A SC topic. Secondly, the result of the comparison of the different types of Triple-A SC–CA models proposed in the literature (with AAA-SC capabilities as IC) has led to a further contribution, as these models are ranked by performance/CA predictive capability, thus providing a guide for further research. Lastly, concerning the methodology, as far as we know, this is the first time that multiple PLS-related methods (BIC, BIC-Akaike weights and PLSPredict) have been used to complement each other in a single paper to assess CA predictive capability and reinforce the reliability of the conclusions, thus enhancing our knowledge on this matter and providing guidelines for predictive model selection in management areas. Furthermore, this research uses a wide multi-country, multi-informant, multi-sector database that offers a high guarantee of reliable results.

The findings also have clear implications for managers, who are provided with a guide for the effective design of their SC strategies to seek higher performance/CA in a highly competitive global context through the appropriate deployment of the AAA capabilities. Determining the key drivers and how they should be related can guide firms with limited resources that wish to find an appropriate way to achieve the most effective influence on performance/CA (Alfalla-Luque *et al.*, 2018). This is particularly relevant due to the significant investments in resources and effort required for the implementation of the Triple-A SC capabilities (Alfalla-Luque *et al.*, 2018).

The remainder of this paper is organised as follows. Section 2 analyses the theoretical background of this research. Section 3 describes the sample and the methodology used.

Section 4 reports the analysis of the data and the results. Lastly, Section 5 presents the most important conclusions and specifies the paper's contributions, implications for managers and academics, limitations and possible further research.

2. Theoretical background

2.1 Triple-A capabilities

The conceptual framework developed by Lee (2004) proposes the Triple-A SC capabilities as drivers for achieving a sustainable SC–CA and is gaining relevance in the current markets characterised by increasing uncertainty, turbulence, high competitive intensity and a complex SC (Garrido-Vega *et al.*, 2021). In line with the resource-based view (RBV) theory (Barney, 1991) and the dynamic capabilities view (DCV) (Teece *et al.*, 1997), the AAA-SC are dynamic capabilities that help companies gain SC competitiveness but demand complex resources whose implementation might be difficult, expensive and hard to replicate (Machuca *et al.*, 2021; Whitten *et al.*, 2012). As Lee (2021a) states, "the AAA concept is still applicable, and winning SCs should still be agile, adaptable, and aligned". In this line, the Covid-19 pandemic has revealed the increasing need to revive the AAA-SC capabilities to allow SCs to better respond to disruptions and disasters (Khan *et al.*, 2022). For this, firms should concentrate their efforts on evaluating the depth and strength of AAA capabilities so as to be better equipped for the threats provided by the external environment (Patrucco and Kähkönen, 2021). However, despite its importance, the Triple-A SC is still an under-researched field (Machuca *et al.*, 2021) that needs further development with new theoretical and empirical studies.

In the conceptual area, Lee (2004) neither developed nor validated scales for the Triple-A SC capabilities, and their definition and measures are scarce and diverse in the literature (Marin-García *et al.*, 2018). In addition, only a few studies have analysed the Triple-A SC framework and from different perspectives. Some works have proposed definitions and dimensions of the three As based on a conceptual view (e.g. Arana-Solares *et al.*, 2011), some empirical papers have developed scales (e.g. Whitten *et al.*, 2012; Dubey *et al.*, 2015) and a very small number of papers have focused on developing and validating a Triple-A SC measurement model (e.g. Marin-García *et al.*, 2018; Feizabadi *et al.*, 2019a). Consequently, although the replication of scales in different samples is suggested for constructing theory, a variety of scales have been used in previous research to measure the Triple-A SC capabilities.

2.2 Triple-A and performance: models in previous research

The key question in most of the scarce empirical research on the topic focuses on the relationship between the Triple-A SC and performance or CA, with the consideration of one or other of the two ways to model this relationship mentioned in Section 1. The first considers the Triple-A SC as a single HOC composed of all 3 As that influences performance/CA. The second considers the 3 As singly, as individual variables that influence performance/CA. The results of the research using HOC suggest that there is a positive relationship between the Triple-A SC and performance (Attia, 2015; Whitten *et al.*, 2012) or CA (Alfalla-Luque *et al.*, 2018; Machuca *et al.*, 2021), although the authors also agree on the need for further research. Specifically, Whitten *et al.* (2012) state that a Triple-A SC-based strategy has a positive influence on SC performance and that there is a mediated positive influence of SC performance on financial performance. Attia (2015) concludes that there is a positive relationship between Triple-A SC and SC performance, and between SC performance and organisational performance. Alfalla-Luque *et al.* (2018) state that the Triple-A SC has a positive and significant relationship with most CA components (cost-CA, delivery-CA, flexibility-CA and financial proxy-CA). Finally, an analysis by Machuca *et al.* (2021) of two separate samples of emerging and developed countries concludes that there is a significant positive relationship between the Triple-A SC and CA in both contexts.

In the second way to model the AAA-SC capabilities (IC), the conceptual framework established by Lee (2004) does not hypothesise about the possible influence of the individual Triple-A SC capabilities on performance/CA or how they can best be related to obtaining an "optimum or better result". Regarding their influence, most of the previous research supports a positive relationship between each of the individual As and performance/CA (Machuca *et al.*, 2021), although in some cases the results are not clearly conclusive for all the relationships (e.g. Alfalla-Luque *et al.*, 2018; Dubey and Gunasekaran, 2016; Dubey *et al.*, 2015). However, regarding obtaining an optimum result, the different models that have been theorised do not show conclusive results for the most suitable set of relationships between the three Triple-A SC capabilities and performance/CA or the linkages that might exist between the capabilities (Dubey and Gunasekaran, 2016), and this continues to be an important gap as it is a key question for researchers and managers. Therefore, as the first step in our research, a literature analysis is performed of the different models used, and these will be compared in a second step to determine whether any model has a greater predictive capability of performance/CA. Should this be the case, the "winner" will be considered the most appropriate model to best indicate how to deploy the Triple-A SC capabilities.

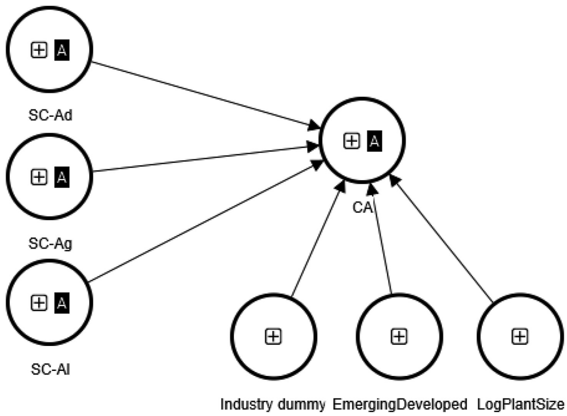
The above is related to resource orchestration theory (ROT), which is rooted in the RBV but overcomes its limitations in our research. While the RBV does not specify how to deploy the resources to create effects that could facilitate the development of CA (Sirmon *et al.*, 2011; Gruber *et al.*, 2010), ROT complements RBV by proposing that superior performance is provided by "a certain combination of resources, capabilities and managerial acumen" (Chadwick *et al.*, 2015), and that this unique combination allows differentiation in the marketplace (Ketchen *et al.*, 2014). In this line, managers should use the Triple-A framework to orchestrate the deployment of the AAA-SC to obtain sustainable CA. As already stated by some authors (Feizabadi *et al.*, 2019a, b; Gligor *et al.*, 2020), ROT is embodied in Lee's (2004) framework.

As previously stated, two main types of models have been found in the literature for the deployment of the AAA-SC capabilities: *direct relationship models (DRMs)* and *mediated relationship models (MRMs)* (Figure 1).

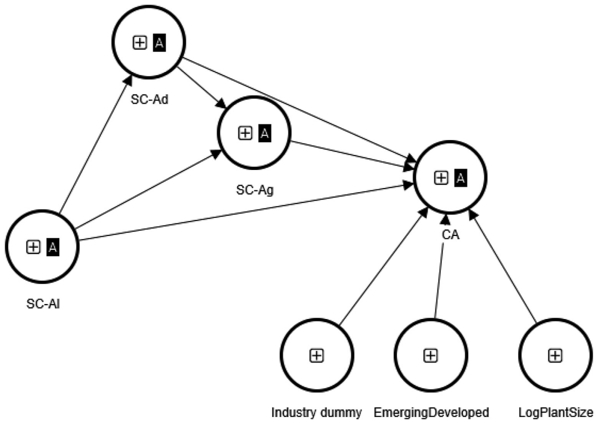
2.3 Triple-A and performance: direct relationship models

DRMs could be considered to be directly derived from seminal Lee's (2004) statement that "only SCs that are agile, adaptable and aligned provide companies with sustainable CA". They do not consider any mediating effect between the three As to achieve performance (Attia, 2016; Lussak, 2020; Yang, 2021; Khan *et al.*, 2022) or CA (Alfalla-Luque *et al.*, 2018; Sheel and Nath, 2019), which would imply that managers could develop each A independently as none has been established to leverage any other to improve performance/CA. This is in line with the conclusions of Machuca *et al.* (2021), who used a DRM for a wide sample of developed and emerging countries and confirmed that there are no significant differences in the importance of SC adaptability, SC agility and SC alignment as levers in the Triple-A SC–CA relationship as the effects of the three capabilities are summative.

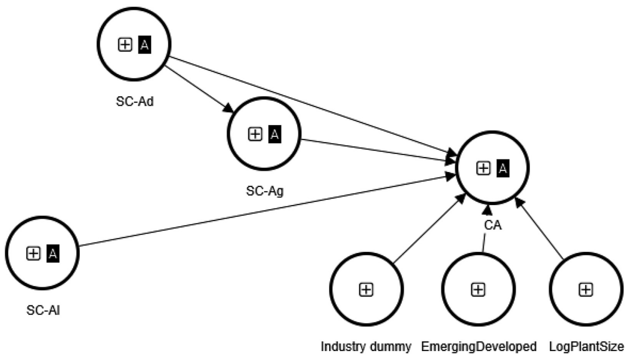
Most research using DRM finds that the Triple-A SC capabilities have a positive influence on performance/CA. For example, Attia (2016) confirms that each of the three capabilities has a significant influence on organisational performance in a sample of Egyptian manufacturing firms. The same result is obtained by Lussak (2020) for SC performance in the Indonesian service industry. Yang (2021) confirms a significant relationship between SC agility, adaptability and alignment and operational and relational performance improvements in a sample of USA manufacturing firms. Lastly, Alfalla-Luque *et al.* (2018) report similar results for most of their analyses of a sample of manufacturing firms in eight developed countries, with confirmation of significant positive relationships between SC agility and flexibility and financial CA; SC adaptability and cost, quality, delivery, flexibility and financial CA; SC alignment and cost, quality, delivery and financial CA. However, no positive relationship is confirmed between



Direct relationships model (DRM)



Mediated relationships model 1 (MRM1)



Mediated relationships model 2 (MRM2)

Figure 1.
Triple-A capability relationship models

SC agility and cost, quality or delivery CA, or between SC alignment and flexibility. A more recent analysis by Khan *et al.* (2022) of the effects of AAA-SC capabilities on post-covid disruption performance in a sample of Pakistani textile firms concludes that these are positively and significantly related to performance. It is interesting to note that the majority of DRM research focuses on the impact of the AAA capabilities on performance/CA without including any other variable as an antecedent of the former, as the primary issue to be solved is the relationship between AAA and performance/CA. Only two recent papers, Yang (2021) and Khan *et al.* (2022), each include one antecedent of the AAA in the Triple-A SC framework, specifically Knowledge Management Capability and Supply Chain Analytics, respectively.

2.4 Triple-A and performance: mediated relationship models

Regarding the other type of model, MRMs consider some relationships between the As. In this sense, Feizabadi *et al.*'s (2019a) literature review states that previous research has considered alignment constructs as antecedents to SC agility. It also states that "while no research has directly assessed alignment as an antecedent to adaptability, all of the consequences of adaptability are shared with alignment, suggesting alignment as an antecedent to adaptability". In our search for the Triple-A models considered in this research, two main MRM proposals have been found in line with this statement.

The first type is a mediated model (MRM1) that proposes a sequence in which SC alignment leads to SC adaptability, which further leads to SC agility and then, to performance, as well as saturated mediation, which considers all possible direct and indirect links with performance (Figure 1) (e.g. Dubey and Gunasekaran, 2016; Jermsittiparsert and Kampoomprasert, 2019). Marin-Garcia *et al.* (2018) state that in the first step of the sequence, incentive, information and process alignment between SC partners affords cooperation, communication and shared goals, and risks and rewards, which benefits the key dimensions of SC adaptability (e.g. organisational design and the use of technology in the SC, and medium- and long-term market knowledge). Consequently, alignment is considered to be an antecedent of adaptability. In the same line, Lee (2004) states that SC alignment implies that information and knowledge are exchanged freely along the SC to clearly establish roles, tasks and responsibilities, and equitably share risks and costs between all partners. This furthers knowledge about suppliers and markets and helps to identify the needs of end consumers, enabling the creation of flexible product designs and the determination of technology and product life cycles. This signifies that the alignment of upstream and downstream SC partners influences the capability of the SC to address long-term changes (adaptability), which indicates that it could be considered an enabler of SC adaptability. Therefore, it can be considered that SC adaptability is built upon the foundation of SC alignment and that the influence of SC alignment on performance could be mediated by SC adaptability.

The next step in the sequence means that an aligned and adaptable SC could favour the obtention of SC agility to recognise and respond to short-term changes through the achievement of variety and volume flexibility. SC agility responds to unanticipated changes in turbulent markets (Charles *et al.*, 2010; Abdallah *et al.*, 2021). For example, the creation of flexible product designs that make the SC more adaptable could generate a design based on postponement that facilitates SC agility (Lee, 2004). Consequently, the achievement of an agile SC could mediate the influence of SC adaptability on performance.

Regarding the complete MRM1 sequence, Dubey and Gunasekaran (2016) and Jermsittiparsert and Kampoomprasert (2019) propose an interpretive structural model for the context of humanitarian SC where SC alignment acts as the enabler at the beginning of the sequence, directly followed by SC adaptability, which is in turn followed by SC agility, which leads to performance at the top level. Dubey and Gunasekaran (2016) confirm positive relationships between SC alignment and SC adaptability, SC adaptability and SC agility, and SC alignment and SC agility. Regarding the relationship with SC performance, SC agility and adaptability are found to have positive significant relationships with SC performance but SC alignment is not. Jermsittiparsert and Kampoomprasert (2019) also confirm the proposed MRM1 sequence and, in their case, the three Triple-A SC capabilities are positively associated with SC performance.

The second type of mediated model (MRM2) found in our literature search proposes a direct relationship between the three As and performance/CA, and the mediation of SC agility between SC adaptability and performance/CA (Figure 1). The consideration of SC adaptability as an antecedent of SC agility has been analysed in the literature. In this sense, Sharma and Bhat (2014) suggest that adaptability is an enabler of an agile SC as, when it is present, the SC can adjust to long-term changes (e.g. demographic trends, political shifts, economic progress, etc.), enabling an agile SC that can react appropriately to short-term changes. Swafford *et al.* (2006) also confirmed SC adaptability as an antecedent that positively impacts SC agility. In the same line, Eckstein *et al.* (2015) state that adaptive capabilities provide a structural basis that acts as an enabler for developing agile capabilities, in the sense that the ability to adapt the SC design to market structural changes and develop new supply bases and markets (adaptability) enables the SC to develop agile capabilities that allow a quick reaction to short-term changes in supply or demand.

Following the MRM2 model, the agile capabilities created on the basis of adaptable capabilities could translate into improved performance. In this sense, the Eckstein *et al.* (2015) analysis of the relationships between SC adaptability and SC agility and performance concludes that both have positive effects on cost and operational performance and that there is a partial mediating role of SC agility on the links between SC adaptability and both cost and operational performance. Following Eckstein *et al.* (2015), Aslam *et al.* (2018) confirm that SC agility significantly mediates the relationship between SC adaptability and performance (SC efficiency and SC responsiveness).

Apart from including the mediated influence of SC agility between SC adaptability and performance, the MRM2 model also includes the direct effect of SC alignment on performance. Regarding this effect, Gligor *et al.* (2020) state that SC alignment may in itself be sufficient to obtain strong firm performance without the need for the mediation of the other As.

Lastly, Dubey *et al.* (2015) analyse humanitarian SC in India with the MRM2 model and conclude a positive direct relationship between the three As and human and logistics performance, except for the relationship between SC adaptability and human performance. They also show that SC agility fully mediates the relationship between SC adaptability and human performance and, partially, logistics performance.

At this point, it is worth commenting that the initial models proposed in the literature are "*direct relationship models (DRMs)*" (by an HOC or IC), which seem to be more in line with Lee's (2004) proposal since these models are summative, i.e. an increase in the level of any of the As results in higher performance/CA. The "*mediated relationship models (MRMs)*" that later emerged as modifications of DRMs are more complex and impose constraints on practical deployment. Nevertheless, in contrast with DRMs, no justification is given for MRM frameworks (Dubey and Gunasekaran, 2016; Jermsittiparsert and Kampoomprasert, 2019; Aslam *et al.*, 2018), which would have been desirable. In our opinion, more complex models, which are less parsimonious, would be justified if they afforded a higher predictive capacity, at the very least. This implies that it is sensible to take DRM as the "reference" model against which MRMs should be compared when the latter's predictive capacity is analysed.

2.5 Triple-A models' competitive advantage predictive capacity

In summary, three main types of models have been proposed in the previous research (DRM, MRM1, MRM2). All have been validated and most find a positive effect of AAA capabilities on performance/CA. However, the question to be answered to respond to our RQ1 is: Which, if any, of these models has the highest predictive capability to predict CA? In response to the RQ1, this paper analyses the three mentioned models' predictive capability of CA. As previously stated, although all three models appear to confirm a positive relationship between the 3 As and CA in general terms, the adoption of one or another would have different implications for the design of the Triple-A SC and the appropriate deployment of each of the As for better CA. Therefore, it is important to determine whether any of these models can be considered more suitable from the point of view of its predictive capability as this would generate major implications for research and practice. To achieve this objective, a set of assessment techniques is used to measure the various aspects of the predictive capability of the models under study (see Methodology section).

3. Methodology

3.1 Sample and data collection

This research uses a dataset taken from the High-Performance Manufacturing (HPM) research project database (4th round). A random sample of plants (with ≥100 employees) was taken from 14 different country master lists that included a selection of plants in the machinery, electronics and automotive components industries. The mentioned sectors were selected because they face intense global competition in different environments and have a large number of plants in every country (Garrido-Vega *et al.*, 2015; Morita *et al.*, 2018). They are also present in global networks and share practices relevant to this research. In this sense, other researchers have also used these sectors either separately (e.g. Droge *et al.*, 2004; Ortega *et al.*, 2012) or jointly (Danese *et al.*, 2019; Morita *et al.*, 2018). The global selection of countries improves the generalisability of the results, which is more restricted when the sample is obtained at a national or regional level.

Local research teams contacted the plants and assisted respondents with completing the questionnaire. Initially, personal approaches were made to the plant CEOs, and HPM researchers subsequently visited the plants to explain the purpose of the project. To drive up involvement, plant managers were offered detailed copies of the survey results in return for their plant's participation. The survey report was based on HPM data and included plant assessments based on the OM practices that they had implemented and the performance that they had achieved compared to the average scores of national and international competitors in their industries. An approx. 65% response rate ensured that non-response bias was limited. Each of the 12 questionnaires in this research was tailored to the expertise of the focal informant. In particular, the contact person in each plant (see sample procedure above) distributed the questionnaires containing the questions related to this study to two SC managers and the plant manager, so there were multiple respondents per question (Danese *et al.*, 2019). Also, responses for dependent and independent variables were given by different people. For more information, see Marin-Garcia *et al.* (2018), Danese *et al.* (2019), Machuca *et al.* (2021).

The HPM fourth-round questionnaire was reviewed and updated from previous HPM rounds. A panel of experts reviewed the items to guarantee content validity and, lastly, it was piloted in several plants (see, for example, Schroeder and Flynn, 2001; Flynn *et al.*, 1995; Machuca *et al.*, 2021). Questionnaires have been reviewed over the HPM project's various rounds. The items and scales had previously been used and validated in several OM studies, and new scales were duly validated with prescriptive reliability, validity and internal consistency analyses (Ahmad and Schroeder, 2002; Flynn *et al.*, 1995; Marin-Garcia *et al.*, 2018; Sakakibara *et al.*, 1997). Ambiguous or complex items were avoided in the design phase. Items were piloted to check for their clarity and readability and a different choice of scale anchors was used with items in the same scale included in different parts of the questionnaire (items were not grouped by scale but randomly listed to prevent item proximity from triggering any response patterns) so as to avoid any priming effects in the questionnaires (Marin-Garcia *et al.*, 2018). During the data collection phase, informant confidentiality was ensured, no information was included about what the items were attempting to measure before the respondent viewed the items, and two people in each function were asked to respond to each of the questionnaires (Danese *et al.*, 2019). All these aspects reduced the risk of common method bias (Podsakoff *et al.*, 2003; Schwarz *et al.*, 2017). In addition, after data collection, Harman's Single-Factor test (Chin *et al.*, 2013; Schwarz *et al.*, 2017) was run. We analysed the correlation matrix using a principal component with varimax rotation. Robust valid results were obtained, indicating the presence of eight distinct factors with eigenvalues above 1, rather than a single factor, which would have pointed to common method bias. Further details about the HPM Round 4 questionnaires can be found in several previous papers (Flynn *et al.*, 1995; Schroeder and Flynn, 2001; Danese *et al.*, 2019; Beraldin *et al.*, 2022; Machuca *et al.*, 2021).

Each local HPM team was responsible for managing plant responses, checking that the questionnaires had been completed in full, and recontacting respondents if any answers were missing. Researchers also supported respondents during data collection. The HPM core team merged and cleaned up the responses received, and checked for any inconsistencies or outliers. When outliers were detected (for example, regarding plant size or plant age), the local HPM team contacted the respondents and updated the data when required. The fully cleaned-up HPM dataset consisted of 330 plant responses. In our case, all the data from the Israeli plants were removed as only 4 of their 26 plants responded to any of the Triple-A or CA items. So, we considered the total useable sample for our research to comprise 304 responses from 14 developed (169 plants) and emerging (135 plants) countries (Austria, Brazil, China Finland, Germany, Italy, Japan, South Korea, Spain, Sweden, Taiwan, UK, USA, Vietnam) in three sectors (electronics (101 plants), machinery (118 plants) and automotive components (85 plants).

Based on previous studies in the field of OM and Triple-A SC, the expected R^2 for the exogenous construct (CA) should be in the range of 0.1–0.3. Using G-Power 3.1, a pre-calculation was done of the minimum sample size required for the lowest forecasted value of R^2 (translated to f2 effect size) with Alpha 5% and Power 80% (Marin-Garcia and Alfalla-Luque, 2019). The minimum sample required was 103, which is much lower than the sample used in this research (304). A post hoc power check with $R^2 = 0.153$ (the lowest value in our analysis) shows a result of 0.99 power.

SPSS (IBM Corp. 2013) MVA was used to analyse missing completely at random (MCAR) and showed that the missing values of these 304 responses were MCAR (Little's MCAR test: Chi-Square = 1125.694, DF = 1093, Sig. = 0.240). As over 10% of values were missing in (only) two (of 30) variables, multiple imputations with 5 sets (Schafer and Olsen, 1998; Sarstedt and Mooi, 2019; Marin-Garcia, 2020) was used following the SPSS Multiple Imputation procedure, with the random seed set at a fixed value (SET RNG = MT MTINDEX = 2,000,000). After the multiple imputation procedure, 304 valid responses were deemed available for use in the analysis.

3.2 Measurement instrument

A 5-point Likert scale (1–strongly disagree, 3–neither agree nor disagree, 5–strongly agree) was used to measure the items for SC agility (SC-Ag), SC adaptability (SC-Ad) and SC alignment (SC–Al) (Marin-Garcia *et al.*, 2018) (see Annex [1] for details).

The SC agility, SC adaptability and SC alignment constructs were operationalised as lower-order formative composites. Items were selected that were mutually complementary and composite constructs were estimated as Mode A (correlation weights) to prevent any unexpected sign changes or any diminished weights due to collinearity or moderate positive correlation among the indicators (Becker *et al.*, 2013; Felipe *et al.*, 2019; Marin-Garcia *et al.*, 2018; Rigdon, 2016).

As the present study specifically focuses on CA in the OM area, only operational measures were targeted. To enable the modelling of the interrelationships of the Operational CA components, the operational CA was modelled as a lower-order reflective composite with 5 items. A 5-point Likert scale (1–poor, 3–average, 5–much better) was used to measure CA items according to respondents' perceptions of their plant's performance compared to their competitors, which allowed to obtain a measure of managers' perceived CA (see Annex).

The control variables used in this research follow the work by Machuca *et al.* (2021), which is supported by previous studies that analyse the relationships between SC practices and CA or performance (Aslam *et al.*, 2018; Dubey *et al.*, 2019; Dubey and Gunasekaran, 2016; Gligor *et al.*, 2015; Hult *et al.*, 2018). Specifically: (1) plant size (log10), as larger firms may be able to use scale economies to improve their competitive position by implementing specific SC practices (Dubey *et al.*, 2019; Gligor *et al.*, 2015; Machuca *et al.*, 2021); (2) industry, as some industries may have a more uncertain context than others (e.g. different stability of customer preferences or product features) (Dubey *et al.*, 2019; Machuca *et al.*, 2021); (3) country context; studies of developed/emerging countries consider that divergent aspects might exist with companies in different country groups presenting different behaviours in SCs due to workforce, culture, infrastructure or some other contextual factor (Machuca *et al.*, 2021). This is in line with control variables used in previous research that analyses the relationships between SC practices and CA or performance.

3.3 Analysis method

All the analyses have been repeated for the five datasets generated by the multiple imputation method, informed, when required, by the overall estimate for multiple imputation results obtained with the Schafer and Olsen (1998) procedure (Marin-Garcia, 2020).

The models under analysis have been estimated by Partial Least Squares (PLS) (Hair *et al.*, 2019a, 2022; Hair and Sarstedt, 2019; Henseler *et al.*, 2016; Marin-Garcia and Alfalla-Luque, 2019; Sarstedt *et al.*, 2016) using SmartPLS v3.2.8 (Ringle *et al.*, 2015). The primary advantage of PLS-SEM for this research is that predictive capacity can be analysed. The measurement model was tested for all the models, although due to length restrictions detailed results are only reported for the DRM model (other results are available from the corresponding author by email on request).

The three types of models were compared in three stages. The first stage was confirmation that they comply with the updated established guidelines to assess the measurement model and structural model and that they possess sufficient predictive validity (Cepeda-Carrion *et al.*, 2019; Hair *et al.*, 2019b; Henseler *et al.*, 2015; Ringle *et al.*, 2020; Becker *et al.*, 2023; Ciavolino *et al.*, 2022). For Bootstrapping, we ran 5,000 samples. A mediation analysis was run for the mediated models (MRM1 and MRM2) following the guidelines established for when PLS is used as the estimation method (Hair *et al.*, 2022). This is fully in line with the procedure used to check mediation in other papers (Schroeder *et al.*, 2011; Bortolotti *et al.*, 2015; Bolivar *et al.*, 2022). The direct and indirect paths were compared. Additionally, to test the strength of the mediation, we used the ratio of the indirect-to-total effect (VAF). Although it is not clear that fit measures should be used in PLS studies (Hair *et al.*, 2019a), we acknowledge the usefulness of model fit measures in other modelling contexts and this is why, using the current guidelines (Henseler *et al.*, 2014; Cho *et al.*, 2020; Hwang *et al.*, 2020), we have reported SRMR results. The number of repetitions was 10 for the PLSpredict procedure with 10 folds. If any model had not got through this stage, it would have been omitted from the subsequent analysis, but this was not the case.

The second stage was a two-phase comparison of the models' *in-sample predictive capacity*. Firstly, the Bayesian Information Criterion (BIC) was used for model selection (Danks *et al.*, 2020; Sarstedt and Danks, 2022; Shmueli *et al.*, 2019). BIC can be used to compare models when the aim is to identify one that balances prediction and explanation in a set of potentially reasonable models (Shmueli *et al.*, 2019). Secondly, as BIC cannot be used to compare the magnitude of any differences, the analyses were completed with a calculation of the Akaike weights based on the BIC data (Sharma *et al.*, 2021; Danks *et al.*, 2020). This gives a more complete end result as the Akaike weights, which can be interpreted as conditional probabilities, enable to observe whether any differences found between the BIC values in the compared models are large or small.

Lastly, the third stage was a comparison of the models' *out-of-sample predictive capacity*. The PLSpredict algorithm was used to measure how accurate the models' predictions are and to assess the predictive capacity of the PLS path models for the indicators using the prediction-error summary statistics (Shmueli *et al.*, 2016; Marin-Garcia and Alfalla-Luque, 2019; Sarstedt *et al.*, 2019). A situation with competing models arises when researchers are faced with alternative explanations (different model relationships) that are all plausible according to the theoretical frameworks published in the previous research. PLSpredict allows the empirical comparison of competing models with the same endogenous dependent variable (Shmueli *et al.*, 2019). MAE (mean absolute error) and RMSE (root mean square error) are particularly suitable when the aim is to select the best predictive model (the model which minimises RMSE or MAE) from a set of competing models (Sharma *et al.*, 2019). MAE is the average absolute difference between the predictions and the actual observations, with all individual differences having equal weight. RMSE squares the errors before averaging and, therefore, assigns a greater weight to larger errors. This means that when the distribution of prediction errors is highly non-symmetric or presents a departure from a normal distribution (as is the case in this research – see Appendix A in the supplementary material [1]), RMSE may produce an overly pessimistic picture of the model's predictive power. Therefore, MAE is the preferred option in our case as it is less sensitive to extreme values (Hair *et al.*, 2022). As a result, the best model selection criteria that will be used in the third stage are: (1) the number of CA indicators with least MAE in each type of model and (2) the sum of MAE for the 5 CA indicators to determine which model presents the lowest value.

4. Results

The descriptive statistics for the DRM model are given in Appendix B in the supplementary material and are very similar to those obtained for the MRM1 and MRM2 models (tables for the latter are available from the authors on request).

The mean Latent Variable Scores for the constructs are in the mid-to-high part of the scales (approaching 4 on a range of 1–5). No ceiling effect can be observed (the maximum value is practically 5 on all the scales), although a ground effect can be observed in constructs SC-Ad (around a value of 2) and SC–Al (just under a value of 3)), whereas the minimum value for SC-Ag is close to the accepted minimum value on the scale used.

Correlations between the Triple-A and CA constructs are moderately low (values of approx. 0.3), while those of the different Triple-A constructs are moderate (approx. 0.5).

The outcomes of the DRM measurement model are shown in Appendix C in the supplementary material. Those corresponding to the other models differ only slightly and are available from the authors on request.

Regarding the measurement model validity of the Triple-A constructs, indicator collinearity is low and most of the indicator weights are statistically significant and relevant. Only 4 DRM items (out of 30) have weights that are not significant: Adapt33, Agil11, and Agil12 (loading factors below 0.5), and Align33 (loading factor above 0.5). These indicators were retained to ensure the comparability of DRM, MRM1 and MRM2 in terms of their measurement models. Regarding the other types of models, all MRM1 indicators have significant weights, as do MRM2 indicators except for Align33 (but in this case, loading is above 0.5).

With respect to the CA reflective construct, the loadings are above 0.7 in all the model types. The internal consistency values (Cronbach's alpha; rho_A; composite reliability) and AVE also present adequate values for the usual cut-offs in management research. Regarding the structural model, the SC-Ad and SC–Al paths to CA are significant for p-value<0.05), as is the SC-Ag path for p-value <0.10 in all types of models. No control variable is significant at a standard 5% p-value cut-off.

SMRM calculations show a good model fit for DRM, MRM1 and MRM2 (see supplementary material, Appendix E). However, model fit measures such as SRMR, for example, should be used with caution (Hair *et al.*, 2019b; Rigdon *et al.*, 2017). Regarding mediation, for MRM1, we found all the direct paths (except the paths from the controls to CA) to be significant at the 5% or 10% level (see supplementary material, Appendix F). The same applies to the indirect paths (except for SC–Al → SC-Ag → CA), total indirect effects and total effects. This validates the structure of MRM1. We find that SC-Ad mediates the relationship between SC–Al and SC-Ag (complementary mediation) and that SC-Ad mediates the relationship between SC–Al and CA (complementary mediation). However, SC-Ag does not act as a mediator between SC–Al and CA (the indirect effect has a p-value of 0.133). In contrast, MRM2 is not clearly supported by path analysis. Direct effects for SC-Ad and SC–Al to CA are significant at the 5% level and SC-Ag to CA are just within the cut-off value at the 10% level. This is also the case for the indirect path SC-Ad → SC-Ag → CA. We found that SC-Ag may act as a mediator between SC-Ad and CA and that the mediation relationship would be complementary (both the direct and the indirect paths are positive but not clearly different from zero). In both models, the indirect effect from SC-Ad to CA represents 25–30% of the total effect. In MRM1, the indirect effects from SC–Al to CA represent 60% of the total effects.

4.1 Predictive capacity

In all cases, *predictive capability* was assessed with PLSpredict before comparing the three models. It should be noted that if a model type is identified as having low predictive power, it does not need to be included in the predictive model's comparison with BIC, Akaike weights or any further analysis based on PLSpredict results.

The descriptive statistics for the prediction errors in the three model types (DRM, MRM1 and MRM2) present a mean close to zero, a standard deviation of slightly under 1, and moderate *kurtosis* and *skewnes*s values (none above 0.80 in absolute values in any of the datasets). However, observation of the distribution graphs for the *PLS manifest variable prediction errors* shows a departure from a normal distribution (see supplementary material, Appendix A). Also, multimodal graphs with four defined peaks usually appear in all the datasets.

To classify the predictive performance of each model, we follow the guidelines of (Shmueli *et al.*, 2019) and benchmark each CA indicator, in each model (DRM, MRM1 and MRM2) against (1) an indicator average benchmark and (2) a linear regression model (LM). Appendix D in the supplementary material reports the PLSpredict results for the three models across all imputed datasets. We find that PLS outperforms the naïve indicator average in all models. In contrast, the models perform slightly differently when benchmarked against LM. Overall, the three types of models present adequate predictive power and so can be included in the subsequent comparative analyses.

4.2 Comparison of models' in-sample predictive capacity

Table 1 gives the results of R^2, BIC and Akaike weights for the three types of models. The R^2 and BIC data clearly show that DRM is the type of model with the highest explanatory capacity and the lowest errors in all the datasets. The Akaike weights, which identify a model's proportional gain over the other models, confirm this result, as the DRM model presents the highest value. DRM is, therefore, the type of model with the best *in-sample predictive capacity*.

4.3 Comparison of models' out-of-sample predictive capacity

Following the selection criteria commented on in Section 3, firstly we focus on the *indicator level*. The MAE results for all the datasets (first 25 data rows in Table 2) show that DRM has: (1) a lower prediction error than MRM1 in 4 (out of 5) CA indicators (GLOBLX03, GLOBLX04, GLOBLX05, GLOBLX08), and (2) a lower prediction error than MRM2 in 3 (out of 5) CA indicators (GLOBLX03, GLOBLX05, GLOBLX06).

Next, for the measure of the *sum prediction error of the 5 CA indicators (construct level),* the sum of the errors of all the CA indicators has been calculated for each of the 5 datasets separately and then the joint sum of the errors for all 5 indicators. DRM can be observed to surpass (last 6 data rows in Table 2) the other two types of models in each of the datasets and also the overall sum of the errors for all 5 datasets.

In line with the above, the obtained results can be stated to indicate a better *out-of-sample prediction* for DRM than for MRM1 and MRM2.

5. Discussion and conclusions

Proposed in 2004 by Lee, the AAA-SC capabilities continue to be essential for SC competitiveness (Cohen and Kouvelis, 2021) and a key to competing profitably in a dynamic global environment (Sodhi and Tang, 2021). For nearly two decades, the Triple-A SC framework has influenced SC curricula, research and practice worldwide (Erhun *et al.*, 2021) and it has become one of the most influential SC concepts (Mak and Shen, 2021). The impact of the Covid-19 pandemic on SCs has further highlighted the need for their restructuring and for implementing the competencies required to enable them to compete effectively when faced with unprecedented disruptive events (Khan *et al.*, 2022). In this sense, in line with the RBV and the DCV, the Triple-A (dynamic) capabilities enable firms to sustain superior performance in dynamic environments (Sheel and Nath, 2019; Alfalla-Luque *et al.*, 2018; Aslam *et al.*, 2018; Yang, 2021). For this, the AAA-SC capabilities must be revamped and continue to be dynamic in uncertain environments since they are developed to address changing customer requirements and structural changes in economies and markets (Yang, 2021).

Most of the literature supports the existence of a positive relationship between the Triple-A SC capabilities and performance/CA and that the co-existence of the former improves the result (e.g. Alfalla-Luque *et al.*, 2018; Attia, 2015; Machuca *et al.*, 2021; Whitten *et al.*, 2012).

	R^2 CA MI1	MI2	MI3	MI4	MI5
DRM	0.159	0.175	0.173	0.176	0.165
MRM1	0.153	0.165	0.166	0.165	0.158
MRM2	0.155	0.168	0.166	0.167	0.159

	BIC MI1	MI2	MI3	MI4	MI5	BIC Akaike weights MI1 %	MI2 %	MI3 %	MI4 %	MI5 %
DRM	−13.80	−19.53	−18.74	−19.88	−15.96	58.28	70.54	65.10	76.05	64.34
MRM1	−11.42	−15.65	−16.02	−15.95	−13.16	17.73	10.14	16.71	10.66	15.87
MRM2	−12.02	−16.94	−16.19	−16.39	−13.60	23.93	19.32	18.19	13.28	19.77

Table 1. Summary of R^2, BIC (Bayesian information criteria) and BIC Akaike weights

Dataset	Indicator	DRM	MRM1	MRM2	DRM-MRM1	DRM-MRM2
MI1	GLOBLX03	0.583	0.653	0.656	−0.070	−0.073
MI1	GLOBLX04	0.643	0.660	0.607	−0.017	0.035
MI1	GLOBLX05	0.608	0.623	0.646	−0.015	−0.038
MI1	GLOBLX06	0.654	0.582	0.681	0.072	−0.027
MI1	GLOBLX08	0.680	0.688	0.581	−0.008	0.100
MI2	GLOBLX03	0.596	0.641	0.636	−0.044	−0.040
MI2	GLOBLX04	0.625	0.644	0.599	−0.018	0.026
MI2	GLOBLX05	0.597	0.616	0.627	−0.018	−0.030
MI2	GLOBLX06	0.633	0.593	0.681	0.039	−0.049
MI2	GLOBLX08	0.681	0.693	0.593	−0.012	0.088
MI3	GLOBLX03	0.589	0.655	0.643	−0.066	−0.054
MI3	GLOBLX04	0.642	0.649	0.586	−0.007	0.056
MI3	GLOBLX05	0.582	0.602	0.642	−0.020	−0.060
MI3	GLOBLX06	0.642	0.589	0.665	0.053	−0.022
MI3	GLOBLX08	0.664	0.682	0.586	−0.018	0.078
MI4	GLOBLX03	0.589	0.656	0.655	−0.067	−0.065
MI4	GLOBLX04	0.642	0.666	0.613	−0.024	0.029
MI4	GLOBLX05	0.610	0.628	0.648	−0.017	−0.038
MI4	GLOBLX06	0.654	0.587	0.677	0.067	−0.023
MI4	GLOBLX08	0.678	0.692	0.587	−0.014	0.091
MI5	GLOBLX03	0.581	0.653	0.658	−0.072	−0.077
MI5	GLOBLX04	0.640	0.666	0.603	−0.026	0.036
MI5	GLOBLX05	0.599	0.621	0.642	−0.022	−0.043
MI5	GLOBLX06	0.658	0.582	0.680	0.075	−0.023
MI5	GLOBLX08	0.682	0.692	0.577	−0.010	0.105
MI1	Sum error all indicators	3.168	3.205	3.170	−0.037	−0.002
MI2	Sum error all indicators	3.132	3.186	3.137	−0.054	−0.005
MI3	Sum error all indicators	3.119	3.178	3.121	−0.059	−0.002
MI4	Sum error all indicators	3.174	3.229	3.180	−0.055	−0.006
MI5	Sum error all indicators	3.160	3.213	3.161	−0.054	−0.002
Sum error all datasets	Sum error all indicators	15.752	16.011	15.769	−0.258	−0.017

Table 2. Comparative model out-of-sample predictive power (MAE)

So, in line with the DCV, AAA-SC implementation is expected to improve performance/CA. However, no consensus exists around the modelling of the AAA-SC relationship (Dubey and Gunasekaran, 2016) despite the importance of identifying *how to best deploy the Triple-A SC capabilities to improve SC performance/CA* for research and practice, which was identified as a major gap in Section 1. This justifies the object of the present research, which is to fill this gap. For this, we have to determine whether, among all the models in the literature, any exists that proposes a Triple-A capability implementation sequence with a predictive capability to predict performance/CA that is higher than the others, and which could, therefore, be taken as a reference model for research and practice. This is a novel and original contribution as, despite its importance, the previous research has not analysed this matter.

To achieve this aim, in line with ROT, this study focuses only on Triple-A SC models that consider SC capabilities as IC, as only these allow an analysis of the individual relationships of Triple-A SC capabilities and performance/CA and the linkages between the Triple-A SC capabilities themselves. The analysis of the previous literature does not show a Triple-A SC framework with a single consensual proposal that could be tested in different samples. Some researchers have hypothesised with DRM models, which show a direct relationship between each of the Triple-A SC capabilities and performance/CA (e.g. Attia, 2016; Yang, 2021; Alfalla-Luque *et al.*, 2018). As stated in Section 1, this is more in line with Lee's (2004) proposal.

However, other authors have proposed mediated models (MRM1 and MRM2) that establish mediation via some of the capabilities (e.g. Dubey and Gunasekaran, 2016; Dubey *et al.*, 2015), but they do not assess whether their proposed sequence could be considered more suitable than DRM for improving performance/CA. Therefore, a comparison of these models is necessary to ascertain which has the highest performance/CA predictive capability, if any.

The first step of the analysis of the three types of models (Figure 1), direct (DRM) and mediated (MRM1 and MRM2) requires verifying whether they all meet the requirements to be good measurement models for the analysed sample. The results show that they all do. Thus, all three models satisfy the essential condition to be considered valid, as in every case the indicators of the constructs are relevant, reliability is adequate and, in general, the direct and indirect paths are significant.

Once the three measurement models have been validated, the second step is to compare their *in-sample predictive capability*. This was done using R^2, BIC and Akaike weights. DRM was consistently proven to have the highest predictive capability, followed by MRM2 and, lastly, MRM1, which leads to the conclusion that DRMs are the most advantageous models as far as in-sample prediction of performance/CA is concerned. It is interesting to remember that R^2 values alone are not recommended for assessing the adequacy of theoretical models as they may tend to generate overfit and not differentiate the relationships from the noise inherent in any dataset (Chin *et al.*, 2020). This is why it is useful to use BIC and Akaike weights, which have a lesser tendency to suffer from overfit. The corresponding results indicate that the DRM model produces fewer prediction errors in data used to estimate model parameters and maximises the likelihood of coincidence with the underlying data.

As the results of the in-sample prediction measures are not clearly generalisable to other data samples, the third step is the measurement of *out-of-sample predictive capability*. For this, PLSPredict was used, which entails a trade-off between explanation and prediction to prevent overfit (Chin *et al.*, 2020). All three models were shown to achieve adequate Q2 predict values for all the CA indicators. The results obtained from the comparison of the three models reveal better *out-of-sample prediction* for DRM than for MRM1 and MRM2. This means that, although all three models perform better in prediction than the simple mean of data or a linear regression model, DRM gives a lower prediction error than the competing models (MRM1 and MRM2). In other words, DRM have a greater predictive capability of performance indicators and so can be considered more generalisable beyond the current sample to estimate PLS path models.

In the context of the proposed models and our sample, the control variables (plant size, industry and country context) do not have a sufficiently relevant influence to explain the variation in performance. In relation to the plant size and industry control variables, several papers have found no differences between the manufacturing and service sectors (e.g. Martinez-Sanchez and Lahoz-Leo, 2018; Liu *et al.*, 2013) or plant/firm sizes (Mandal, 2016; Liu *et al.*, 2013). In the same line, the previous research has not confirmed the influence of the country context (usually developed vs developing countries) in the relationship between Triple-A SC and performance/CA (Machuca *et al.*, 2021).

The above results show that although Triple-A research with MRM has added more relationships to the original DRM models, the information provided by our results shows that the inclusion of complexity in the DRM model does not seem to have been successful in improving both the in-sample and out-of-sample information. The use of PLSpredict has enabled research on Triple-A to reduce the uncertainty around model choice by comparing the different alternative models and identifying DRM as the model with the highest predictive power. On the managerial side, where the focus is on finding generalisable approaches/models that could be useful for business or produce predictive power (Ruddock, 2017), the use of PLSpredict has allowed us to choose the model with the lowest generalisation error, which enables managers to make decisions that will be more likely to work in other settings (Chin *et al.*, 2020).

Summarising, DRM has frequently been used in previous Triple-A SC research (e.g. Alfalla-Luque *et al.*, 2018; Attia, 2016; Lussak, 2020; Sheel and Nath, 2019; Yang, 2021) and demonstrates a greater predictive capability (both in-sample and out-of-sample) for predicting performance/CA than MRM1 and MRM2. In other words, *the probability of obtaining a higher performance/CA predictive capacity is greater with DRM than with MRM1 and MRM2*, which means that it can be considered a benchmark model for research and practice when the specific goal is to obtain the highest performance/CA predictive capability possible. In addition, it must be stated that mediated models are also less parsimonious than DRMs and their use adds to the complexity of Triple-A capability deployment for managers. Greater complexity might be acceptable if they also had a higher predictive capability, but this is not supported by the results.

The choice of DRM as the benchmark model implies that the AAA-SC capabilities can be considered independent levers for achieving CA. As shown below and in the following section, this has important managerial implications. It means that, unlike in the case of MRM models, no specific AAA capability deployment sequence needs to be followed when seeking better performance/CA. It is worth highlighting at this point that the AAA-SC capabilities focus on different SC aspects that can be developed independently and could complement each other. In this sense, SC alignment, adaptability and agility connote long-, medium- and short-term perspectives, respectively (Tang and Tomlin, 2008). Each Triple-A capability has a role to play in company strategy and all are needed, especially nowadays as whatever the strategy a company adopts, the Triple-A will always be affected by the competitive environment (Garrido-Vega *et al.*, 2021). The three capabilities consider the different planning levels to focus the whole SC on serving the end customer and achieving CA. In addition, in the current uncertain and complex environment, companies increase the value that they offer customers by raising their levels of SC agility, adaptability and alignment to contend with higher competitive intensity (Garrido-Vega *et al.*, 2021). Doing this could also help to mitigate or reduce the risks to SCs (Tang and Tomlin, 2008) that derive from unexpected situations such as the Covid-19 pandemic.

Proposing DRM, in other words, a simultaneous AAA deployment instead of a specific sequence (MRM1 or MRM2) when seeking to obtain a higher value of predictive performance/CA, implies that: (1) DRM is summative, which means that the sooner all the AAA are implemented and reach high values, the higher the CA that will be obtained; (2) the absence of any of the AAA at any given moment results in an unfavourable competitive position. This is in line with Khan *et al.* (2022), who state that the SC's ability to outperform the competition in sensitive times depends on its members' ability to simultaneously deploy the AAA. In this context, simultaneously does not indicate that a firm needs to develop all AAA abilities at the same point in time and with the same intensity (which is not in line with the business practices), but it implies that the firms need to possess or establish all the AAA capabilities in every competitive situation. This matter is better clarified in the subsection Implications for managers.

It is also worth stating that fit is the only criterion of analysis used in the previous research and that our work goes further by using predictive capability, which is indispensable due to its relevance for decision-making and providing recommendations for business practice (Chin *et al.*, 2020; Shmueli *et al.*, 2016). Therefore, the explicit implications proposed in this research add originality and value for researchers and managers.

Lastly, we would stress that the dependent variables in the analysed models are operational measures. This means that different results might be obtained in other research contexts more focused on other aspects such as financial or sustainability measures, for example, and in some of these cases, MRMs might have a better predictive capacity.

6. Implications, limitations and further research

6.1 Implications for research

The analysis developed in this study has some relevant implications for researchers. Firstly, the different Triple-A SC models proposed in the literature have been jointly analysed and compared in the same sample for the very first time. The results obtained identify DRM as the model with the highest performance/CA (in-sample and out-of-sample) predictive capability and so it can be considered a reference model for future research to analyse and identify how to trigger the Triple-A SC levers (agility, adaptability, alignment) when the main objective is to improve performance/CA. As such, when the use of a mediated model is proposed in research, it would be appropriate to compare this with the direct model (DRM) to determine whether the results of the mediated model are significantly better for the specific aim of the study in question. Secondly, given BIC, Akaike weights and PLSPredict all identify DRM as the best option for performance/CA predictive capability, when the sole purpose of a study is to determine the effect of the Triple-A SC on CA (i.e. without determining how to deploy the AAA-SC capabilities), it would make sense to group their effects in a HOC. This would produce a more parsimonious model to identify the contribution made by Triple-A to CA. This research framework has been used in some previous papers (e.g. Alfalla-Luque *et al.*, 2018; Attia, 2015; Machuca *et al.*, 2021; Whitten *et al.*, 2012). With respect to the methodology, as far as we know, this is the first time that PLSPredict has been used to compare Triple-A SC models, and also the first time that BIC, BIC Akaike weights and PLSPredict have been used in the same paper as complementary methods to assess the models' CA in-sample and out-of-sample predictive capacity. This represents progress in the use of these techniques to enhance our knowledge and provide guidelines for predictive model selection not only in operations and SC management but also in other management areas. Finally, it can be stated that this research represents an advance in the consideration of the RBV, DCV and ROT as important theories for understanding the role of AAA-SC capabilities as key factors in CA in the Triple-A SC framework.

6.2 Implications for managers

This paper also has relevant implications for managers, to whom having a clearer understanding of the most suitable way to deploy the Triple-A SC capabilities offers an opportunity to improve CA (Lee, 2004). Correctly developing a Triple-A SC is even more critical in the current uncertainty environment as it minimises the effects of SC interruptions on material and information flows (Khan *et al.*, 2022). In this context, the limited business resources and significant investments needed to properly implement the AAA capabilities (Machuca *et al.*, 2021) make our findings especially relevant. In line with ROT, company resources must be orchestrated for any potential advantage to be obtained (Chirico *et al.*, 2011) and, in this sense, this research proposes a suitable way for managers to deploy the Triple-A SC capabilities with the greatest likelihood of obtaining higher performance/CA.

As DRM is identified as the best option to obtain a higher performance/CA predictive capability, AAAs can be considered independent levers and, as a result, could be triggered separately given their additive nature. Therefore, CA could be improved with any of the capabilities without the need to reach prior levels in the other two. It should be possible to take long-, medium- and short-term decisions to improve performance/CA without the need to follow a specific sequence, as is suggested should be done when using mediated models (MRM). Implementing the AAA capabilities independently seems to be more effective with DRM than following a pre-established sequence. Nevertheless, it should be borne in mind that the greatest potential is achieved when all three capabilities are deployed, as other authors (e.g. Lee, 2004; Khan *et al.*, 2022) have also stated. In addition, this implementation is less complex as DRMs are more parsimonious than MRMs. Therefore, based on the business aims and considering that each A capability has a distinct impact on the various performance measures (Alfalla-Luque *et al.*, 2018), managers can decide whether it is more expedient to start with one specific A or with all three in unison.

Furthermore, the current highly uncertain context demands that managers need to be conscious of the growing importance of correctly implementing the AAA capabilities, as SCs have to be more agile, adaptable and aligned than before (Lee, 2021a). SCs need to respond to growing uncertainties and disruptions by enhancing SC agility in order to survive and be competitive This can be done by rapidly identifying uncertainties and responding with a quick and flexible design (Lee, 2021a). Managers also need to stay abreast of medium- and long-term market changes by adapting their SC processes and structure to market changes and introducing new technologies based on the detection of technological cycles (Alfalla-Luque *et al.*, 2018). Finally, higher SC alignment is needed in terms of incentive alignment (defining the roles, tasks and responsibilities of SC partners), information alignment (sharing risks, costs and benefits equitably) and process alignment (sharing knowledge and important and correct information for planning, control and decision-making) (Marin-Garcia *et al.*, 2018). It is also important to state that alignment should no longer be focused only on the partnership between sellers and buyers along the SC, as an expanded view is needed that considers stakeholders' ecosystems, which include multiple interdependent SCs and new actors with an interest in environmental and social issues, such as local governments, NGOs and communities (Lee, 2021). Lastly, regarding this last point, managers must also take note of the growing importance of social aspects in SC design, which Lee (2021b) calls "SC with a conscience" and envisages the extension of the SC view to the SC ecosystem view (Sodhi and Tang, 2021).

6.3 Limitations

There are some limitations to the present study that can be used as the basis for further research. Firstly, the data used correspond to only three industries (electronics, machinery and automotive components) and a developing/developed country sample, so, the results have to be interpreted in the context of these sectors and areas. Nonetheless, the control variables are seen to have little influence on the results, which could be regarded as a sign of robustness. Be that as it may, it would be interesting to extend the study to an analysis of other samples from different sectors and country contexts (Al Humdan *et al.*, 2020). Moreover, as this sample has analysed the CA predictive capacity of Triple-A SC models, further research could also explore this issue for the case of performance.

Another limitation is also found in most studies in this area: the use of cross-sectional analysis, which does not allow to observe change and reactions to change in practice. Further research using a longitudinal study would allow to observe the way that the variables evolve and, thus, to analyse the evolution of the levels of the variables and their relationships with CA. It would then be possible to confirm whether Triple-A SCs have sustainable CAs (Lee (2004)). Hopefully, the database of the next round of the HPM project will allow this research.

6.4 Further research

New empirical research is also encouraged to replicate the analysis developed here with other samples to observe whether the conclusion that DRM is the model with the highest predictive capability of performance/CA is generalisable. If confirmed, the role of the DRM model would be strengthened both as a reference point in the Triple-A SC research framework and as a guide for managers to implement each of the AAA-SC capabilities independently and in no specific order.

It should be noted that recent research addresses the analysis of the levels of each Triple-A SC capability required or sufficient to achieve certain levels of CA (e.g. Gligor *et al.*, 2020;

Feizabadi *et al.*, 2021). This could be considered a promising research stream to complement the present study's findings, as the fact that each of the As on its own could lead to an improvement in CA does not preclude the possible existence of a joint effect that enables synergy to be obtained when all the 3 As are achieved. Future research should shed some light on this issue, not only with the use of different samples but also using different analytical methods.

One last comment is related to statistical tools for the assessment of out-of-sample predictive capacity. While we have chosen to use the well-established PLSpredict method (Shmueli *et al.*, 2016, 2019), this could be complemented by the use of promising tools such as CVPAT (Chin *et al.*, 2020; Liengaard *et al.*, 2021; Sharma *et al.*, 2022). This will be the subject of further research on this topic, as subtle differences in the generation of the PLS-SEM predictions can be important for models' predictive performance (Danks, 2021).

Note

1. Annex and supplementary material (Appendixes) cited in the text have been put in additional material downloadable from https://doi.org/10.5281/zenodo.7486519

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