



# Judgmental adjustments through supply integration for strategic partnerships in food chains<sup>☆</sup>

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## ABSTRACT

Despite significant attention to strategic partnerships among members of supply chains, there has been limited research in food supply chains where such partnerships can provide a competitive advantage through forecasting practices of time-sensitive food items in volatile business environments. The current paper aims to close this gap by examining manufacturers' strategic partnerships with retailers, with a special emphasis on information sharing, integration, and collaborative forecasting of time-sensitive products in food supply chains. Through Partial Least Square (PLS) analysis of survey data collected from 105 food manufacturers in Europe and North America, this research reveals the importance of strategic partnerships for satisfaction from forecasts generated for perishable, seasonal, promotional and newly-launched products in the food industry. Group forecasting and manufacturers' external integration with retailers are found to be significant for strategic partnerships. In addition, our findings show that manufacturers' internal integration is positively associated with group forecasting, external integration and judgmental adjustments. Our findings also reveal that information sharing with retailers facilitates consensus forecasts in group forecasting. These results provide unique insights to researchers and practitioners of human judgment in supply chain forecasting towards enhancing strategic partnerships in food supply chains.

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## 1. Introduction

The Food Supply Chain (FSC) distinguishes itself from other supply chains due to its complicated, dynamic and fragile profile, where the quality and availability of products are critical and the primary goal is to “guarantee the provision of safe and healthy products that are fully traceable from farm to fork” ([7], p.2). FSC relies on foundations of quality, forecasting, logistics and Information Technology (IT), and depends heavily on partnerships among manufacturers and retailers. Also, the shelf life of products and price variability emerge as significant concerns [2], while information sharing between partners are vital for forecasts due to the heterogeneous structure of FSC [122], in addition to the supportive role of IT for the integration of partners [19].

This necessitates chain members' strategic integration, that is “the degree to which a manufacturer strategically collaborates with supply chain partners and collaboratively manages intra- and inter-

organizational processes, in order to achieve effective and efficient flows of products and services, information, money and decisions, to provide maximum value to customers” ([34], p.58). Past literature revealed the benefits of strategic partnerships, where partners can improve not only market share, customer service, average selling price and return on assets [70], but also product development and rapid response to changes [69]. Process innovation, efficient logistics management and transaction, and reduced response times are among the additional benefits of strategic partnerships [50]. However, manufacturers and retailers face considerable barriers in their efforts to foresee the demand for perishable, seasonal, promotional and newly-launched products in such partnerships [27,66].

The short shelf life of perishable and seasonal products necessitates substantial care and effort in managing their freshness and shelf availability; calling for promising forecasts and responsive operational practices [2,25]. Insufficient demand management during sales promotions causes sales variability, excessive/deficient stocks and deteriorated customer service [81]. Correctly using contextual information through judgmental adjustments is also important when it comes to improving forecasting accuracy during

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promotions and special events [27,30,106]. In particular, forecasting demand for newly-launched products is a challenge due to demand variability [115]. Additionally, lack of trust and commitment between partners [104], manufacturers' long lead-times and poor internal operations [46,93] and inadequate information transfer in partnerships [120] are some of the reasons that obstruct accurate forecasts in strategic partnerships. Sun and Debo [97] also stress the difficulty of establishing strategic partnerships in turbulent markets and fragile environments, which are typical in food supply chains (FSCs).

It has been suggested that the behavioral aspects of manufacturers' decision making [59] to build trust in and commitment to retailers need further attention for enhanced operations across food chains [27,46,93]. Even though extant research has examined strategic partnerships [1,95,116], scant attention has been paid to the role of forecasting and supply decisions of manufacturers in partnerships [27]. Such decisions become even more acute for accurate demand forecasting of time-sensitive products [81,115]. Therefore, extending previous work, this research explores strategic partnerships from manufacturers' standpoint through their supply integration and forecasting practices with retailers. The end goal is to address the key gap in strategic partnerships where both parties are satisfied with the forecasts of time-sensitive products [95,116].

To address the above gap, this research specifically asks: *To what extent can coordination, collaboration and effective information sharing in multi-tier operations help improve human judgment and satisfaction in forecasting and decision making in strategic partnerships?* Accordingly, this paper focuses on manufacturers' strategic partnerships with retailers to help generate accurate forecasts for time-sensitive products in the FSC. For this, manufacturers' intra- and inter-organizational practices are examined empirically using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method based on survey data from 105 food manufacturers in North America and Europe, all of which collaborate with retailers through seasonal, perishable, promotional and newly-launched products in different regions. The rest of this paper is organized as follows. Section 2 provides an overview of the literature, formulates a set of hypotheses and proposes a conceptual framework. The research methodology is developed in Section 3. The analysis of the conceptual model and findings are presented in Section 4. Discussions and managerial implications are provided in Section 5, followed by conclusions and future research opportunities in Section 6.

## 2. Literature review and hypotheses

In developing the hypotheses and the conceptual framework, we review the extant literature at the intersection of collaborative forecasting and strategic partnerships in food chains. In doing so, we make use of the systematic literature review by Eksoz et al. [27] who review the extant literature in the field of collaborative forecasting in the food chains. We supplement their literature findings by extending the scope and time frame of the search to account for recent papers in the area of strategic partnerships in food chains.

### 2.1. Strategic partnerships

The attributes of successful partnerships involve high levels of trust, commitment, coordination, and interdependence [68]. Compared to operational partnerships, which are short-lived and aim for supply chain efficiency, building strategic partnerships necessitates organizational compatibility and top management visions from partners. Strategic partnerships are long-term relationships that focus on strategic goals aimed at delivering value to customers and profitability to partners [66]. A strategic partnership is

“a relationship formed between two independent entities in supply chains to achieve specific objectives and benefits” ([60], p.420), and provides competitive advantage and increased financial performance to partners [83,95]. In partnerships, agreeing on a shared vision, and a joint business plan, enables partners to further benefit from such alliances [17,62]. Whilst partners build co-operative relations, it is imperative for them to identify strategic priorities that are combined in a joint business plan [13]. These issues are further supported by Whipple and Russell [108] noting the critical role of collaborative approaches in the context of joint planning between manufacturers and retailers stressing, inter alia, their inputs towards Collaborative Planning, Forecasting and Replenishment.

Having accurate forecasts for products traded between partners is one of the factors that strengthens strategic partnerships [70]. However, manufacturers' limited competence in generating sales forecasts [46,93] and partners' different forecasting approaches regarding aggregation levels [32], along with poor adjustments and communications of forecasts [75,99] may hinder such partnerships [27]. Accordingly, we argue that the existence of a joint business plan, as well as trust and commitment by partners in generating accurate forecasts, are key antecedents of strategic partnerships as partners should not only share their forecasts and decisions, but should also show commitment to and trust in each other [42,51,103]. These strategic partnerships between firms will generate many positive outcomes including increased responsiveness, product availability assurance, optimized inventory and associated costs, and increased revenues and earnings (see [62]). Likewise, many past studies have shown that these strategic partnerships will also result in high satisfaction for the supply chain members involved (see [45]).

Extending the above arguments focusing on the forecasting point of view (and on forecast satisfaction), the literature supports the criterion of accuracy as the representative of forecast efficiency. Nevertheless, several organizations in practice add value to additional factors such as customer service, ease of use, interpretation and inventory turns [61,67,117]. In this sense, to be able to generalize the reliability of the research findings from the practitioners' point of view, we argue that satisfaction from forecasts is an important outcome of strategic partnerships. The latter argument presents a unique dimension as, to our knowledge, there is a scarcity of relevant research. We propose to examine the forecast satisfaction of manufacturers based on the forecasts of perishable, seasonal, promotional and newly-launched products. These forecasts are estimated during strategic partnerships with retailers, and represent the consensus forecasts of partners. Accordingly, forecast satisfaction is posited as the primary outcome of strategic partnerships for manufacturers and retailers, and is hypothesized as follow:

**H1.** Strategic partnerships positively influence forecast satisfaction.

### 2.2. Judgmental adjustments and group forecasting

Forecasters typically incorporate their judgment into final forecasts in various ways. For instance, they may ignore statistical forecasts altogether and use their expertise and information to base predictions purely on judgment, or they may make judgmental adjustments to statistical forecasts once they become available (*a posteriori incorporation*) [57,82,106]. Justified based on perceived informational asymmetries and incorporation of expertise, such judgmental adjustments are extremely common across a wide range of domains [57] including supply chain forecasting [31,86]. In the FSC, forecast adjustments appear to be used to diffuse multiple forecasts by different departments of manufacturers, which can potentially cause internal conflicts [46] and harm part-

nerships with retailers [47]. In addition, accuracy of judgmentally adjusted predictions appears to depend on multiple factors including the contextual information available to forecasters. Contextual information is “information, other than the time series and general experience, which helps in the explanation, interpretation and anticipation of time series behavior” ([106], p.97). It is argued that judgmental adjustments can potentially enhance forecast accuracy if they incorporate contextual information that are not already captured by statistical models, such as the influence of promotions or special events [40].

Building on this argument, relevant empirical findings reveal that negative (deflated) and large (wide-range) adjustments are more effective than positive (inflated) and small (narrow-range) adjustments when demand arrives instantaneously in a short period such as during promotions [31,99]. Kremer et al. [54] show the overreaction of forecasters to forecast errors in stable environments whilst underreacting to errors in unstable environments. Önkal et al. [75] demonstrate the impact of advice and types of information on the direction of adjustments and forecasters' confidence. Fildes and Goodwin [30] report that companies from various industries largely adjust statistical results by 33.7% for a number of reasons including promotions, price changes, and demand on special days. In essence, these outcomes underline the importance of judgmental adjustments in partnerships, but highlight the lack of attention given to the role of adjustments to decisions made in supply chains [74,98].

On the other hand, group forecasting is common practice in many organizations and can improve judgmental adjustments. Judgmental forecasts given by groups appear to attain a higher level of accuracy than individual predictions, mainly due to the negation of informational asymmetries through efficient group processes [72,73]. Group forecasting meetings are held to estimate demand forecasts and to identify/resolve exceptions over the item-level forecasts [48]. Subsequently, partners generate order forecasts and re-identify/resolve exceptions for consensus over a single order forecast. During these meetings, critical decisions are made in generating/adjusting forecasts, and evaluating the impact of seasonality, promotions, and/or external factors based on pre-established procedures, all of which are highlighted in a joint business plan [48]. Manufacturers' forecasts involve production plans and lead-times, while retailers' forecasts consider inventory levels that cause problems reaching a consensus forecast in meetings [93]; such disagreements may damage partners' relations. Christopher and Jüttner [13] extend this further by illustrating the role of joint forecasting in relation to supply chain partnerships and Power [79] advocates the urgent need for new, innovative approaches in relation to conventional forecasting which will be able to deal with dynamic supply chains. Our argument is that group forecasting could be a viable approach to consider in relation to FSCs, which are very dynamic and complex and subsequently, the next hypothesis is formulated as follows:

**H2.** Group forecasting positively influences strategic partnerships.

### 2.3. Supply integration

Partners' different expectations hamper their partnerships and worsen forecasts [6,29]. For instance, manufacturers aim at enhancing profitability by presenting their products on retailers' shelves with minimum expense, while retailers' goals are to purchase products with minimum cost, achieve high inventory turnover, and to increase profit per square foot in stores [21]. In partnerships, collaborating based on strategic objectives, mutual planning, and problem solving efforts are essential, but not enough. Successful partnerships also require partners' tight integration during information sharing and forecasting processes [66].

Therefore, partners need to show interdependence between one another [24], whilst their top management need to share the same vision in order to invest in the partnership [58]. To cope with demand variability and long lead-times, partners should have reciprocal willingness and be flexible in complex supply chains [103]. In addition, responsiveness against instant demand changes also needs to increase when partners integrate their chains [18] and the latter integration can be extremely important considering the large business and environmental uncertainty that firms (including food firms) now operate within (see [112]). Overall, this integration can be a catalyst for major supply chain improvements including enhanced operational and business performance for the supply chain partners involved (see [34]). This is further validated in the fast-moving consumer goods sector by Gimenez and Ventura [37] noting the pivotal role of external integration and collaboration between supply chain firms towards improved performance in logistics operations. Based on these findings, the following hypothesis is formulated:

**H3.** External integration positively influences strategic partnerships.

Manufacturers' impediments in managing interdepartmental relations cause inefficient use of demand/forecast data and loss of information [93]. Multiple and inconsistent forecasts that are generated based on departmental objectives worsen the forecast accuracy. These forecasts do not only exacerbate internal conflicts [32,46], but also prevent consensus with retailers [47]. Williams et al. [109] argue that organizations' internal integration is strongly related to their responsiveness in supply chains, with responsiveness here representing their flexibility to respond to demand changes in dynamic markets. According to Schoenherr and Swink [89], externally integrated, interdepartmental relations of partners moderately improve their delivery performance and flexibility. However, internally improving integration requires partners to adopt a common culture by synchronizing internal practices as an extension to external operations [32]. Likewise, Zhao et al. [119] analyzed Chinese manufacturing firms and highlighted that it is important for firms to achieve internal integration capabilities before embarking on external integration. In the food industry, Gimenez [38] also finds supporting evidence for the previous argument and stresses that companies should aim to achieve collaboration within their internal functions first before planning an external integration. These issues are of major importance in the FSC, where sustaining the quality and freshness of perishable and/or seasonal products calls for partners to integrate both internally and externally [105] whilst many authors stress the urgent need for further research in this research domain (see for example [102]); hence, the following hypothesis is formulated:

**H4a.** Internal integration positively influences external integration.

Generating consensus forecasts regarding retailers' orders, and managing timely replenishment operations depend largely on manufacturers' forecasts which are generated by their departments [48]. Overall, retailers' orders rely on both manufacturers' and retailers' forecasts. This gives rise to the importance of manufacturers' interdepartmental relations and forecasting activities. Failure to generate consensus forecasts in a timely manner by partners can cause delays in delivery and diminishes shelf availability. This will in turn reduce retailers' satisfaction and harm their partnerships with manufacturers [53,92]. Won et al. [111] expand on the above issues and note the key role of internal integration for firms as well as having access to inventory information during various processes. Furthermore, Power [79] provides a wider and holistic perspective for key and relevant issues such as the need for an integration between core processes via communication, the need to consider a

strategic view of supply chain issues and the need to factor in implementation challenges related to inter and intra-organizational supply chain aspects. Power [79] highlights the interdependence of these three issues which should inform and support each other. We follow this view by adopting a wider perspective by examining the influential role of internal integration in relation to intra-organizational challenges, in this case, group forecasting. Therefore, the next hypothesis is formulated as follows:

**H4b.** Internal integration positively influences group forecasting.

For better consensus forecasts with retailers, manufacturers' departments need to agree on a single and reliable forecast [57]. In addition to manufacturers' multiple forecasts, forecasters' lack of confidence in sales forecasts is likely to reduce forecast accuracy [46]. In the FSC, adjusting forecasts seems to be a solution to fix the effect of manufacturers' multiple forecasts. According to Sanders and Manrodt [84], 57.3% of companies use judgment-based forecasting methods for a range of reasons including their forecast accuracy, ease of use and cost advantages, besides difficulty of procuring information for quantitative methods. Fildes and Goodwin [30] note that promotions, price changes, and special days appear to be the leading reasons for applying judgmental adjustments. These issues are prevalent in FSCs considering their very competitive nature. Therefore, food companies try to differentiate their offerings and, subsequently, they focus on providing value- and cost-oriented propositions to their customers [7]. Internal integration within these company operations will be fundamental to support these company strategies (see also [38]). Not surprisingly, these company strategies could vary and could be adopted frequently as companies factor in competitors' propositions and they are driven by the dynamic, continuously changing and cut-throat nature of that sector. Finally, forecasts are less frequently adjusted when they come from a well-known source and are based on sound explanations and assumptions [39]. Based on the above arguments, the following hypothesis is formulated:

**H4c.** Internal integration positively influences judgmental adjustments.

#### 2.4. Information sharing

Manufacturers' sales forecasts that are shared with retailers may not include modifications made to manage production capacity, inventory, and delivery operations [17]. This may cause disagreements during group forecasting meetings [32] due to contrasting views on aggregating order forecasts at different levels [48,122]. Such disagreements give rise to inaccurate forecasts, delays in replenishment operations and absence of products on shelves [46,93]. However, partners' proper sharing of sales forecasts is most likely to result in higher forecast performance. Trappero et al. [101], for instance, show reduced forecast error (6–8% based on MdAPE and MAPE respectively) with weekly information sharing between a UK grocery retailer and manufacturer.

Moreover, sharing order forecasts and production plans before meetings will allow retailers to clearly understand what purpose forecasts serve when used by manufacturers [56,121]. In addition to contextual information [31,55,99], historical and recent information are requisite for better forecasts, in order to reduce demand variability and associated costs [85,93]. Arshinder et al. [5] demonstrate how supply chain coordination is improved when demand, inventory, production scheduling, and capacity related data are shared. Similarly Zhao et al. [118] also note major cost savings emanating from information sharing between partners during forecasting. Byrne and Heavey [11] support this notion and illustrate that potential gains from this collaboration and information sharing are possible for all supply chain members involved. Overall, nu-

merous studies have demonstrated the link between information sharing and forecasting and based on these findings, we hypothesize that:

**H5.** Information sharing positively influences group forecasting.

Fig. 1 unifies the aforementioned hypotheses in a conceptual framework.

The current study uses this conceptual framework and focuses on FSCs. The food industry has witnessed an ascending trend in Europe with regard to conscious consumption and demand for fresh products [2]. Collaborations appear to be easier in North America compared to Europe due to both retailers' and manufacturers' willingness to collaborate in strategic partnerships [94] and forecasts. Partners in the European FSC appear to face difficulties in building such partnerships [93]. According to ECR Europe [26], the major differences between European and North American supply chains are not limited to geography and cultural habits, but also encompass other challenges related to the marketplace, promotions and technology. This emphasizes the importance of academic research in the FSCs of Europe and North America in order to close the gap between theory and practice.

### 3. Research methodology

We used a survey tool to collect data from food manufacturers located in Europe and North America. A 5-point Likert scale was used based on the guidelines of Flynn et al. [35]. The survey items are presented in Appendix A: Supplementary Material.

To ensure the validity of the outcome resulting from the survey tool, we conducted in-depth interviews with a supply chain manager of a leading UK-based food manufacturer. The company operates in several European countries, and owns more than ten brands along with a vast number of product groups in the industry. Offering a range of well-known food brands (including perishable, seasonal, promotional and newly-launched products) helped the company build strategic partnerships with several retailers in the UK and Europe. Before the interview, three pilot-tests with researchers from the fields of forecasting, operations management and supply chain were conducted to ensure the clarity and quality of the interview questions (as suggested by [91]). This approach is similar to previous studies that have used interviews to improve the validity of the survey tool. Vlachos and Bourlakis [104], for instance, interviewed key decision makers in the Greek food sector as a preceding step to testing their survey questionnaire. Similarly, when Zhou and Benton Jr [120] wanted to analyze the information sharing and supply chain practices of manufacturers in the USA, they conducted in-depth interviews to validate their survey questionnaire. From the forecasting arena, McCarthy Byrne et al. [63] employed in-depth interviews alongside reviewing the literature to examine the motivation of sales people in the forecasting process.

In total, 5277 surveys were emailed via Qualtrics to respondents who were identified from LinkedIn, Bloomberg, Financial Analysis Made Easy (FAME) and Osiris online databases. Our personal contacts with managers from food manufacturing companies were also included in the survey sample. Specific criteria were considered to achieve a representative sample [110] including: (i) region, (ii) industry, (iii) products, and (iv) managerial level of candidate respondents. Reminder emails were sent to non-respondents after a month via Qualtrics. The data collection was continued for three months and then stopped because at this point the rate of incoming responses per week approached almost zero. During this period, 105 usable responses were received, yielding a 3.06% response rate, as is typical in such surveys [16,87,110]. To ensure the sufficiency of the sample, the statistical power analysis was conducted that showed 0.80 statistical power can be achieved by a minimum

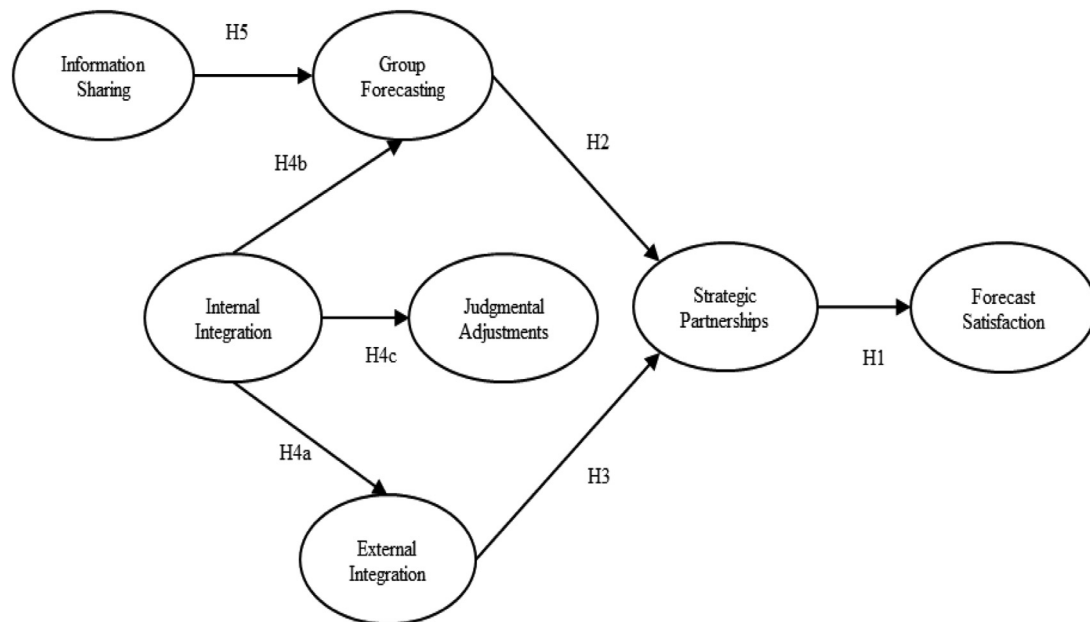


Fig. 1. Conceptual framework of strategic partnerships.

of 102 responses that is recommended for PLS-SEM by Peng and Lai [76].

Notwithstanding its limitations, we believe that the findings from this work can still provide valuable insights, as there are similar studies based on low response rate and sample size (please see, e.g., Melewar et al. [64] and Melewar and Saunders [65]). To ensure that the characteristics of the data are accurate enough to represent the target population [87], this research employed the probability of stratified sampling technique to select the sampling frame [9]. We also compared the sample size and response rate of this research with previous studies to ensure the comparability of statistical power [87,110]. For instance, when Zhou and Benton Jr [120] surveyed manufacturers in North America to evaluate their supply chain and information sharing practices, the authors delivered only 745 surveys and obtained an 18 percent response rate with 125 usable samples. This sample size did not prevent the study from offering contributions to the literature.

Participating managers and their companies represented a diverse geographical spread, as discussed below. Early and late responses were compared by using a *t*-test, and were based on companies' region, annual sales volume, number of employees, and number of years in operation in order to evaluate late response bias [4]. The *t*-test results are shown in Appendix B: Supplementary Material and indicated that there are no significant differences between early and late responses ( $p < 0.05$ ).

### 3.1. Descriptive statistics

The respondents of the survey are largely composed of "Supply Chain/Logistics Managers" (25.7%) and "Forecaster/Forecast Analyst/Forecast Manager" (22.9%), followed by "Marketing/Sales Managers" (16.2%), "Production Managers" (8.6%), "Finance Managers" (1%), and "Others" (25.7%). The last category includes chief executives, operations and managing directors, heads of supply chain and forecasting, and general managers. Therefore, it can be claimed that reliable information was collected with sufficient level of seniority among the respondents [78].

48.6% of manufacturers were in operation for more than 50 years. Manufacturers from southern Europe (25.7%), UK & Ireland (24.8%) and North America (21.9%) have a major presence in

the sample. The majority of participants worked in medium- and large-sized companies with more than 100 employees. More than 80% reported annual sales volume of more than £20 million (see Table 1). 55.2% of manufacturers always provide perishable products to retailers. Other product categories commanding significant presence in this sample include seasonal, promotional, and newly-launched products (see Table 2).

## 4. Findings

PLS-SEM technique was used for data analysis. To ensure that our research has adequate sample size, we run a statistical power analysis, which showed the requisite of minimum 102 responses to achieve 0.80 statistical power, according to Peng and Lai [76]. Given the complexity of the model and relatively small sample size, the PLS-SEM technique seems to be appropriate for data analysis while the other option was Structural Equation Modeling (SEM), which is "a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon" ([10], p.3).

Validating the usage of PLS-SEM, it is a statistical analysis technique that "focuses on explanation of variance (prediction of constructs) rather than covariance (explanation of relationships between items)" ([43], p.775). In other words, while SEM puts emphasis on the confirmation of causalities between constructs, PLS-SEM is rather exploratory and clarifies overall variances in a conceptual model [76]. There are an abundance of studies which employed the confirmation oriented SEM technique (e.g. He et al. [44], Ramanathan and Muyliderman [81] and Ramanathan and Gunasekaran [80]) while others relied upon the exploratory technique of PLS-SEM (e.g. Braunscheidel and Suresh [8], Perols et al. [77], Oh et al. [71] and Sawhney [88]).

Tables 1 and 2 summarize the descriptive details of manufacturers and major product-group of manufacturers while Table 3 shows the constructs and the items used to measure them, as well as the weights and loadings of items that are calculated by the Smart PLS software.

We initially analyzed the measurement model to evaluate relations between constructs and their observed variables. Then, we addressed the model fit of the conceptual model. Finally, the rela-

**Table 1**  
Descriptive details of manufacturers.

Number of years in operation	Frequency	Percentage
Less than 5 years	6	5.70
5 to 10 years	7	6.70
11 to 20 years	16	15.20
21 to 50 years	25	23.80
More than 50 years	51	48.60
<b>Total:</b>	<b>105</b>	<b>100</b>
<b>Region of Manufacturers</b>	<b>Frequency</b>	<b>Percentage</b>
<b>UK &amp; Ireland</b>	26	24.80
<b>North America</b> (USA and Canada)	23	21.90
<b>Eastern Europe</b> (Belarus, Bulgaria, Czech Republic, Hungary, Moldova, Poland, Romania, Russian Federation, Slovakia, Ukraine)	10	9.50
<b>Northern Europe</b> (Denmark, Faroe Islands and Greenland, Estonia, Finland, Iceland, Latvia, Lithuania, Norway, Sweden)	9	8.60
<b>Southern Europe</b> (Albania, Andorra, Bosnia and Herzegovina, Croatia, Cyprus, Greece, Italy, Rep of Macedonia, Malta, Montenegro, Portugal, San Marino, Serbia, Slovenia, Spain, Turkey)	27	25.70
<b>Western/Central Europe</b> (Austria, Belgium, France, Germany, Liechtenstein, Luxembourg, Monaco, Netherlands, Switzerland)	10	9.50
<b>Total:</b>	<b>105</b>	<b>100</b>
<b>Number of employees</b>	<b>Frequency</b>	<b>Percentage</b>
Under 20 employees	12	11.40
20 to 99 employees	15	14.30
100 to 999 employees	33	31.40
1000 to 4999 employees	19	18.10
5000 to 9999 employees	6	5.70
10,000 employees and over	20	19.00
<b>Total:</b>	<b>105</b>	<b>100</b>
<b>Annual sales volume</b>	<b>Frequency</b>	<b>Percentage</b>
Under (£20 - \$30 - €23) million	19	18.10
(£20 - \$30 - €23) to (£99.9 - \$150.9 - €115.9) million	22	21.00
(£100 - \$151 - €116) to (£499.9 - \$755.9 - €578.9) million	23	21.90
(£500 - \$756 - €579) to (£999.9 - \$1511.9 - €1157.9) million	7	6.70
(£1 - \$1.1512 - €1.158) to (£4.99 - \$7.49 - €5.79) billion	16	15.20
(£5 - \$7.5 - €5.8) billion and over	18	17.10
<b>Total:</b>	<b>105</b>	<b>100</b>

**Table 2**  
Major product-groups of manufacturers.

Product-groups	Frequency level of product-groups that food manufacturers provide to retailers					
	Always	Usually	Occasionally	Rarely	Never	Total (Percentage)
<b>Perishable products</b>	55.20	8.60	8.60	8.60	19.00	100
<b>Seasonal products</b>	16.20	15.20	38.10	17.10	13.30	100
<b>Promotional products</b>	23.80	17.10	41.90	12.40	4.80	100
<b>Newly-launched products</b>	25.70	21.00	37.10	14.30	1.90	100

tionships of constructs in the PLS-SEM were analyzed to verify the significance of the hypotheses [12].

4.1. Measurement model for reflective constructs

There are two different types of constructs that can be used when developing a conceptual model, which are reflective and formative constructs. While reflective constructs determine observed variables, formative constructs, in contrast, are determined by observed formative variables [76]. In other words, “for formative measurement models, the direction of causality flows from the measures to the construct, and it flows from the construct to the measures for reflective measurement models” ([49], p.203). In this research, the constructs developed measure the observed variables, and causality flows from construct to the variables, therefore the measurement model has been developed for reflective constructs.

The reliability coefficient and the composite reliability measures were used to analyze the construct reliability of the measurement model. Whilst the lower bound criterion for Cronbach’s  $\alpha$  is 0.70 [43], Table 4 shows that the  $\alpha$  value of all reflective constructs is greater than 0.70. Regarding the composite reliability, it evaluates whether or not observed variables commonly measure the relevant construct or not, and it does not consider equally weighted measures that make the  $\alpha$  value a lower bound criterion for reliability

[8]. The literature suggests a threshold of 0.70 [12], in accordance, the composite reliability of all constructs in our model is above 0.70, verifying the internal consistency of the model.

The construct validity of the model was analyzed through content validity, convergent validity and discriminant validity checks [8]. Convergent validity shows how well the observed items converge or load together as the representative of relevant constructs. It was measured via Average Variance Extracted (AVE), which should be greater than 0.50 [12]. As shown in Table 4, the AVE values of each reflective construct meet the threshold value, indicating that the scale of this research has sufficient reliability.

Content validity determines how well observed variables represent the main aspect of the relevant constructs [41]. The reflective items of the survey emerged from the literature review. Four academics and four practitioners from the food industry then examined the scales of the questionnaire to ensure its structure, readability, ambiguity and completeness [20]. Academics focused on observed variables to ensure that they theoretically represent the related constructs. Practitioners, on the other hand, guaranteed the perception of constructs and associated variables in practice. Validating the rigor of the survey by academics and practitioners independently further strengthened the structure of the survey [3,76]. Hence, this approach justifies the content validity of reflective constructs in the model.

**Table 3**  
Observed latent variables.

Codes	Constructs and items	Item weights	Item loadings
<b>FSat</b>	<b>Forecast satisfaction</b>		
FSat_1	Forecast satisfaction from perishable products	0.285	<b>0.719</b>
FSat_2	Forecast satisfaction from seasonal products	0.323	<b>0.821</b>
FSat_3	Forecast satisfaction from promotional products	0.334	<b>0.862</b>
FSat_4	Forecast satisfaction from newly-launched products	0.313	<b>0.768</b>
<b>SP</b>	<b>Strategic partnerships</b>		
SP_1	Accurate forecasts	0.283	<b>0.795</b>
SP_2	Trust	0.318	<b>0.847</b>
SP_3	Commitment	0.305	<b>0.851</b>
SP_4	Joint Business Plan	0.303	<b>0.804</b>
<b>EI</b>	<b>External integration</b>		
EI_1	Level of being dedicated to find solutions to overcome supply chain complexities	0.243	<b>0.838</b>
EI_2	Level of sharing responsibility for joint improvements	0.270	<b>0.848</b>
EI_3	Level of interdependence	0.281	<b>0.885</b>
EI_4	Level of flexibility	0.200	<b>0.748</b>
EI_5	Level of same vision of top management	0.234	<b>0.712</b>
<b>II</b>	<b>Internal integration</b>		
II_1	Level of delivery effort	0.300	<b>0.736</b>
II_2	Level of inventory management	0.340	<b>0.801</b>
II_3	Level of technological infrastructure for timely internal information sharing	0.276	<b>0.825</b>
II_4	Level of recording information sources	0.337	<b>0.822</b>
<b>IS</b>	<b>Information sharing</b>		
IS_1	Sharing of order forecasts	0.349	<b>0.802</b>
IS_2	Sharing of inventory levels	0.286	<b>0.772</b>
IS_3	Sharing of recent information	0.270	<b>0.719</b>
IS_4	Sharing of production plan	0.201	<b>0.747</b>
IS_5	Share of production scheduling	0.200	<b>0.763</b>
<b>JA</b>	<b>Judgmental adjustments</b>		
JA_1	Perishable products	0.239	<b>0.757</b>
JA_2	Seasonal products	0.305	<b>0.772</b>
JA_3	Promotional products	0.407	<b>0.860</b>
JA_4	Newly-launched products	0.288	<b>0.804</b>
<b>GF</b>	<b>Group forecasting</b>		
GF_1	Level of continuous meetings	0.238	<b>0.794</b>
GF_2	Level of decision-making procedures	0.253	<b>0.864</b>
GF_3	Level of hierarchy	0.222	<b>0.850</b>
GF_4	Level of constructive discussions	0.226	<b>0.892</b>
GF_5	Level of effective usage of information for consensus forecasts	0.236	<b>0.848</b>

**Table 4**  
Results of reliability analysis.

Latent variables/constructs	Cronbach's $\alpha$	Composite reliability	Average variance extracted (AVE)
External integration	0.866	0.904	0.655
Group forecasting	0.904	0.929	0.723
Internal integration	0.808	0.874	0.635
Information sharing	0.824	0.873	0.58
Judgmental adjustments	0.814	0.876	0.639
Strategic partnerships	0.843	0.895	0.681
Forecast satisfaction	0.803	0.872	0.631
Threshold values	Cronbach's $\alpha \geq 0.7$ ; Composite reliability $\geq 0.7$ ; AVE $\geq 0.5$		

In terms of discriminant validity, it helps clarifying dissimilarities among a set of items, representing different constructs. Table 5 shows that the square root of AVE for all reflective constructs is greater than the correlation between the scores of constructs in relation to its appropriate row and column values.

#### 4.2. Model fit

Tenenhaus et al. [100] recommended the Goodness-of-Fit (GoF) criterion to assess the model fit in PLS-SEM. GoF evaluates the quality of the measurement model over the average communality (AVE) and of the structural model over the average of  $R^2$ . As shown in Table 6, the GoF value of the conceptual model is 0.443 and it is above the threshold value of 0.36 indicating that the conceptual model performs well based on the GoF criterion [77]. The explained variance ( $R^2$ ), which is the level of the construct's

explained variance, is expected to be greater than 0.10 [28]. The values of 0.67, 0.33 and 0.19 indicate a substantial, moderate and weak variance and explaining the endogenous constructs [12,76]. As shown in Table 6,  $R^2$  values of all constructs are over the threshold value and support a satisfactory combined predictability for the model.

The effect size of independent variables ( $f^2$ ) shows the particular impact of exogenous variables based on increased  $R^2$  values that remain unexplained on an endogenous construct [76]. The effect size of an independent variable ( $f^2$ ) is measured based on the change of  $R^2$  values when it is eliminated from the conceptual model [15]. As shown in Table 7, forecast satisfaction has large effect size by strategic partnerships and all predictor variables for strategic partnerships have small effect size, while the endogenous construct of judgmental adjustment has small effect size by internal integration. Whilst external integration (a pre-

**Table 5**  
Results of discriminant validity check.

	External integration	Group forecasting	Internal integration	Information sharing	Judgmental adjustments	Strategic partnerships	Forecast satisfaction
External integration	<b>0.809</b>						
Group forecasting	0.44	<b>0.851</b>					
Internal integration	0.546	0.445	<b>0.797</b>				
Information sharing	0.418	0.513	0.332	<b>0.762</b>			
Judgmental adjustments	0.085	-0.012	0.207	-0.013	<b>0.800</b>		
Strategic partnerships	0.750	0.511	0.493	0.443	0.058	<b>0.825</b>	
Forecast satisfaction	0.265	0.278	0.357	0.338	0.248	0.514	<b>0.794</b>

**Table 6**  
Variance explained, communality and redundancy.

Latent variables/constructs	Variance explained (R <sup>2</sup> )		Communality	Redundancy
	Values	Size		
External integration	0.424	Moderate	0.655	0.174
Group forecasting	0.343	Moderate	0.723	0.129
Internal integration	0.164	Weak	0.635	0.029
Information sharing	0.422	Moderate	0.58	0.219
Judgmental adjustments	0.142	Weak	0.639	0.026
Strategic partnerships	0.603	Moderate	0.681	0.376
Forecast satisfaction	0.264	Weak	0.631	0.166
<b>(GoF): 0.443</b>	<b>R<sup>2</sup> = 0.67 ≥ Substantial, 0.33 ≥ Moderate, 0.19 ≥ Weak [12,76]</b>			

Note: Variance explained (R<sup>2</sup>) is measured for only endogenous constructs.

**Table 7**  
Effect size of independent variables (f<sup>2</sup>).

Effect size (f <sup>2</sup> ) over variance explained (R <sup>2</sup> )				
Predictor constructs	R <sup>2</sup> included	R <sup>2</sup> excluded	f <sup>2</sup>	Size
Strategic partnerships → Forecast satisfaction	0.264	0	0.360	Large
Group forecasting → Strategic partnerships	0.604	0.567	0.093	Small
External integration → Strategic partnerships	0.604	0.296	0.775	Small
Internal integration → External integration	0.425	0.319	0.183	Medium
Internal integration → Group forecasting	0.348	0.264	0.129	Small
Internal integration → Judgmental adjustments	0.043	0	0.045	Small
Information sharing → Group forecasting	0.348	0.2	0.228	Medium

f<sup>2</sup> = (R<sup>2</sup> included - R<sup>2</sup> excluded) / (1 - R<sup>2</sup> included).  
Effect size f<sup>2</sup>: 0.35 ≥ Large; 0.15 ≥ Medium; 0.02 ≥ Small.

dictor) has medium effect size, the endogenous variable group forecasting has small and medium effect size with internal integration and information sharing, respectively. Overall, f<sup>2</sup> of all endogenous constructs are greater than the lower bound 0.02 in the model. This result indicates that all independent variables of the conceptual model have the minimum required effect size for associated dependent variables, supporting the standard procedure regarding the effect size of independent variables (f<sup>2</sup>).

The Stone-Geisser test (Q<sup>2</sup>) was implemented as an additional assessment criterion for model fit when measured in relation to reflective endogenous constructs [36]. Q<sup>2</sup> is measured via a blindfolding procedure in which a part of the data matrix is omitted for once and the model is reevaluated to predict the omitted part of the conceptual model [23]. Q<sup>2</sup> values below 0.00 indicate a lack of predictive relevance in the conceptual model while values above 0.35, 0.15 and 0.02 exhibit a large, medium and small predictive relevance of the respective endogenous variables [52]. According to Chin [12], values for omission distance in blindfolding (referring to number of data points in the data matrix are skipped before omitting one data point [96]) can be from 5 to 10; however, higher values were preferred in similar studies (e.g. G: 30 in [23]). Therefore, the blindfolding procedure was estimated for both omission distances at 10 and 30 to reveal whether there are potential differences in terms of predictive relevance.

Table 8 shows that Q<sup>2</sup> values are greater than zero, which means that there is a good predictive relevance for both endogenous constructs (via cross-validated redundancy) and observed variables (via cross-validated communality). It is worthwhile to stress that strategic partnerships and forecast satisfaction have large cross-validated redundancy, which implies the strong predictive relevance of these variables. As a result, the outcomes of the blindfolding procedure indicate that the model fits well. Each endogenous variable has reliable predictive relevance in constituting the conceptual model, validating the Stone-Geisser test (Q<sup>2</sup>).

Finally, we estimated the effect size of endogenous variables (q<sup>2</sup>) by using the predictive values of Q<sup>2</sup>. Accordingly, R<sup>2</sup> values were used to evaluate the similar effect size (f<sup>2</sup>) [15]. The values of 0.35, 0.15 and 0.02 represent large, medium and small effect size (q<sup>2</sup>) respectively [52]. The effect size (q<sup>2</sup>) of each exogenous construct to endogenous construct is evaluated based on two different values. The first value of “Q<sup>2</sup> included” is obtained when the conceptual model is complete and includes all exogenous constructs. Another value of “Q<sup>2</sup> excluded” is found when the relevant exogenous construct is dropped from the model. By using these two different Q<sup>2</sup> values, the effect size (q<sup>2</sup>) for each exogenous construct to endogenous construct is estimated. The effect size (q<sup>2</sup>) represents the impact of endogenous variables in the model, thus the value of Q<sup>2</sup> which was found based on the analysis of cross-validated redundancy should be used [52]. The results of effect size (q<sup>2</sup>), es-



**Table 8**  
Outcomes of blindfolding procedure.

Reflective endogenous constructs	Cross-validated redundancy				Cross-validated communality			
	Omission distance (G)				Omission distance (G)			
	Q <sup>2</sup> (G: 10)	Size (G: 10)	Q <sup>2</sup> (G: 30)	Size (G:30)	Q <sup>2</sup> (G:10)	Size (G: 10)	Q <sup>2</sup> (G:30)	Size (G:30)
External integration	0.273	Medium	0.269	Medium	0.554	Large	0.538	Large
Group forecasting	0.244	Medium	0.25	Medium	0.607	Large	0.723	Large
Internal integration	0.08	Small	0.082	Small	0.344	Medium	0.339	Medium
Information sharing	0.211	Medium	0.21	Medium	0.333	Medium	0.327	Medium
Judgmental adjustments	0.023	Small	0.024	Small	0.544	Large	0.543	Large
Strategic partnerships	0.385	Large	0.389	Large	0.458	Large	0.449	Large
Forecast satisfaction	0.459	Large	0.451	Large	0.156	Medium	0.159	Medium

Predictive relevance  $Q^2 = 0.35 \geq$  Large (L),  $0.15 \geq$  Medium (M),  $0.02 \geq$  Small (S).

**Table 9**  
Effect size of endogenous variables ( $q^2$ ).

Effect size ( $q^2$ ) over predictive relevance ( $Q^2$ )					
Omission distance	Predictor constructs	Q <sup>2</sup> included	Q <sup>2</sup> excluded	$q^2$	Effect size
G: 10	<b>Strategic partnerships → Forecast satisfaction</b>	0.156	0	0.185	Medium
G:30		0.159	0	0.189	Medium
G:10	<b>Group forecasting → Strategic partnerships</b>	0.385	0.367	0.029	Small
G:30		0.389	0.368	0.033	Small
G:10	<b>External integration → Strategic partnerships</b>	0.385	0.179	0.333	Medium
G:30		0.389	0.179	0.343	Medium
G:10	<b>Internal integration → External integration</b>	0.273	0.204	0.094	Small
G:30		0.269	0.201	0.092	Small
G:10	<b>Internal integration → Group forecasting</b>	0.244	0.188	0.074	Small
G:30		0.241	0.187	0.071	Small
G:10	<b>Internal integration → Judgmental adjustments</b>	0.023	0	0.023	Small
G:30		0.024	0	0.024	Small
G:10	<b>Information sharing → Group forecasting</b>	0.244	0.135	0.145	Small
G:30		0.241	0.132	0.143	Small

$q^2 = (Q^2 \text{ included} - Q^2 \text{ excluded}) / (1 - Q^2 \text{ included})$ .

Effect size  $q^2 = 0.35 \geq$  Large;  $0.15 \geq$  Medium;  $0.02 \geq$  Small.

timated based on the values of predictive relevance ( $Q^2$ ), are presented in Table 9.

The results of  $q^2$  show sufficient effect size for each exogenous construct on the relative endogenous constructs with regard to the changes of predictive relevance ( $Q^2$ ). The effect size of forecast satisfaction by strategic partnerships is medium. Whilst the effect size of strategic partnerships by group forecasting is small, it has medium level of effect size by external integration. The rest of endogenous variables have small effect size in producing the predictive relevance ( $Q^2$ ). Overall, the results show that the effect size ( $q^2$ ) for each endogenous construct exceeds the lower bound, and the conceptual model has sufficient effect size for endogenous constructs over the predictive relevance ( $Q^2$ ), validating the effect size of endogenous variables ( $q^2$ ).

#### 4.3. Findings of the structural model

Through the Bootstrap analysis in the Smart PLS software, we evaluated the statistical significance of hypothetical relationships by resampling 5000 times based on 105 usable responses [14]. The results of bootstrapping analysis for the structural model are presented in Fig. 2. In addition to addressing the significance of relationships between constructs, we also reported the size of path coefficients, where the larger path coefficients indicate greater impact between related constructs. Accordingly, reliability of each construct is ensured [52].

Regarding the first hypothesis, since the size of path coefficient from strategic partnerships to forecast satisfaction was substantially large, this outcome demands the attention of practitioners by underpinning the reliability of strategic partnerships to be satisfied from forecasts for related product-groups in partnerships. Fol-

lowing this, the standardized path coefficient from strategic partnerships to forecast satisfaction was significant (Path C: 0.5141;  $p < 0.001$ ), supporting H1. The implication here is that despite that the satisfaction factor is subjective and likely to differ based upon the objectives of companies and/or forecasters, development of strategic partnerships has a strong and direct impact on the satisfaction of manufacturers when they forecast the time-sensitive and/or short-life product-groups.

The standardized path coefficient from group forecasting to strategic partnerships is not very high, but it is statistically significant (0.223;  $p < 0.05$ ), supporting H2. Following this, partners' external integration not only has robust standardized path coefficient, but it also has a significantly positive impact on strategic partnerships (0.651;  $p < 0.001$ ), supporting H3. These results confirm that although both group forecasting and external integration positively influence the development of strategic partnerships, efforts made by partners in integrating externally seems more important than their efforts in group forecasting meetings.

Manufacturers' internal integration positively influences their external integration with retailers (0.368;  $p < 0.05$ ), supporting H4a. Manufacturers' internal integration is also statistically significant as a predictor of group forecasting (0.308;  $p < 0.001$ ), supporting H4b. Internal integration is not only significant for external integration and group forecasting conducted with retailers, but also for judgmental adjustments (0.206;  $p < 0.005$ ), supporting H4c. It seems reasonable to call practitioners' attention to the importance of internal operations, which are very important not only for successful external operations, but also for group forecasting with retailers and judgmental adjustments.

Our research also explored that whilst more than 80% of manufacturers trade with retailers across all product-groups, 35.29%

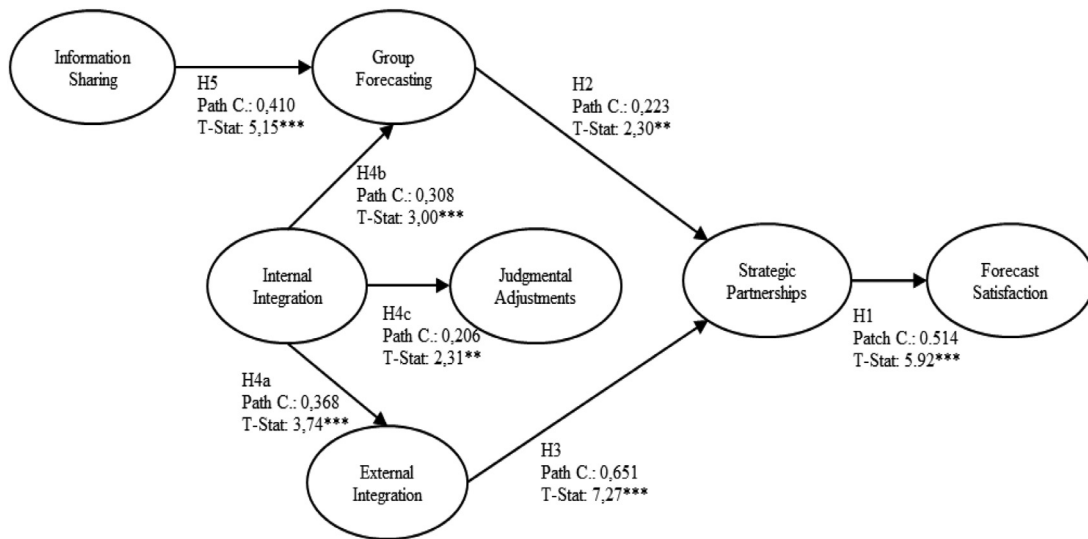


Fig. 2. Results of bootstrapping analysis for the structural model.

Table 10  
Decisions of manufacturers made for adjustments.

Judgmental Adjustments	Wide-range deflated	Narrow-range deflated	Not adjusted at all	Narrow-range inflated	Wide-range inflated	Sum	% of manufacturers trading related products
Perishable products	16 18.82%	30 35.29%	26 30.59%	10 11.76%	3 3.53%	85	80.95%
Seasonal products	18 19.78%	37 40.66%	27 29.67%	6 6.59%	3 3.30%	91	86.67%
Promotional products	20 20.00%	40 40.00%	28 28.00%	10 10.00%	2 2.00%	100	95.24%
Newly-launched products	28 27.18%	35 33.98%	25 24.27%	11 10.68%	4 3.88%	103	98.10%

narrow-range deflate forecasts for perishable products, followed by 30.59% who do not adjust at all. Likewise, seasonal and promotional products' forecasts are narrow-range deflated by 40.66% and 40% respectively, while 29.67% and 28% directly refer to statistical forecasts for the related products, respectively. While 33.98% of participants narrowly deflate the forecasts of newly-launched products, 27.18% of manufacturers prefer wide-range deflate forecasts (Table 10). Our results confirm those found in past studies [31,99] relating to adjustments for promotions in which the performance of negative (deflated) and large (wide-range) adjustments is better compared with positive (inflated) and small (narrow-range) adjustments. Our research extends these findings to perishable, seasonal and newly-launched products, particularly in the food industry.

The standardized path coefficient from information sharing to group forecasting is significant (0.410;  $p < 0.001$ ), supporting H5. This finding shows the importance of information sharing in partners' meetings with a view to reaching a consensus on a single forecast. Accordingly, it can be interpreted that manufacturers' information sharing with retailers will underpin their group forecasting meetings, and ease the generation of single consensus forecasts. The results of our hypothesis testing are presented in Table 11.

### 5. Discussions and managerial implications

This research offers insights into strategic partnerships, human judgment and forecast satisfaction between manufacturers and retailers of time-sensitive and/or short shelf-life product-groups in the FSC by developing and empirically testing a new conceptual framework. To accomplish this, we analyzed the behavioral aspects of manufacturers' decision-making [59] through supply integration, information sharing, group forecasting with retailers, and adjustments to inter-organizational forecasts.

#### 5.1. Strategic partnerships

Manufacturers and retailers can develop strategic partnerships if they demonstrate trust and commitment, and agree to a joint business plan, which, in turn, supports the generation of accurate forecasts for time-sensitive products in the FSC. Knowing the strong impact of trust on long-term partnerships and that of commitment on collaborations [114], partners' behavioral intentions of building trust and commitment were established as two significant indicators of strategic partnerships by this research. Harmonizing corporate objectives in a joint business plan [17] will also lead partners to achieve objectives collaboratively. From a forecasting standpoint, the generation of accurate forecasts is another important attribute of strategic partnerships, where the forecast accuracy plays an important role in supporting partnerships and collaboration when dealing with time-sensitive products in the FSC [27].

From the forecasting point of view, although forecast accuracy seems to be an efficient performance criterion, companies in practice go beyond that indicator and seek satisfaction from forecasts over several parameters, such as customer service, ease of use, interpretation and inventory turns [61,67,117]. Therefore, the unique forecasting approach of this research is to explore the significance of strategic partnerships for satisfaction from forecasts generated for perishable, seasonal, promotional and newly-launched products in the FSC.

This research also demonstrates the significant impact of group forecasting on strategic partnerships. Subsequently, this reveals that an increase in constructive discussions, and the effective use of information for consensus forecasts in meetings, leads to improved formation of strategic partnerships between partners in the FSC. Since partners need to focus on the development of single order forecast in meetings through discussions concerning seasonality, promotions and external factors [48], their decision-making

**Table 11**  
Results of hypothesis testing.

Codes	From	To	Significant at	
			0.001 level	0.05 level
H1	Strategic partnerships	→ Forecast satisfaction	***	
H2	Group forecasting	→ Strategic partnerships		**
H3	External integration	→ Strategic partnerships	***	
H4a	Internal integration	→ External integration	***	
H4b	Internal integration	→ Group forecasting	***	
H4c	Internal integration	→ Judgmental adjustments		**
H5	Information sharing	→ Group forecasting	***	

Significant at 0.001 level: \*\*\*; at 0.05 level: \*\*; at 0.1 level: \*.

process will be eased due to pre-established procedures developed in their joint business plan [90]. Knowing that group forecasts are more successful than individual forecasts [72,73], partners' relationships are likely to be strengthened due to increased accuracy, and a renewed faith in pursuing promising partnerships.

External integration is another strong predictor of strategic partnerships. This finding suggests that manufacturers' behavioral willingness to be flexible, to solve supply complexities, and to share responsibilities with retailers facilitates the development of strategic partnerships whilst adopting similar vision in the partnership. Our findings expand the findings of Schoenherr and Swink [89] from operational-level to strategic level, who conveyed the positive impact of external integration on delivery and flexibility performance, based on samples collected from 27 industries. Our results also expand the findings of Droge et al. [22] and Wong et al. [113], who demonstrated the significance of external integration on product innovation in the automotive industry. We contribute to this literature by investigating these issues from product-level to partnership-level in the food industry.

### 5.2. Judgmental adjustments

Judgmental adjustments involve the direction and size of adjustments [57] made on the statistical forecasts of seasonal, perishable, promotional and newly-launched product-groups in the FSC. Past literature not only emphasized the pragmatic features of adjustments [106], but also its necessity for minimizing multiple forecasts of manufacturers [27,46] for better relationships with retailers [47]. In this vein, this research not only explores the significant impact of internal integration on adjustments, but also reveals that manufacturers mostly deflate forecasts to broader product-groups. This finding supports and extends the findings of previous work by closing the gap regarding the role of adjustments in supply chains [31,98]. The implication for practitioners is that the outcomes of operational activities, such as delivery efforts and inventory levels, need to be actively incorporated into their judgment-based forecasting decisions. This will, in turn, ease inter-departmental agreement on a single forecast for manufacturers. Also, acknowledging the significant impact of information sharing on group forecasting, manufacturers' sharing of these adjusted order forecasts with retailers will most likely facilitate consensus forecasts in group forecasting as well.

### 5.3. Supply integration

Manufacturers' internal practices influence their integration with retailers in the FSC. Subsequently, manufacturers should improve their delivery performance, manage inventory levels effectively and invest in IT for timely internal information exchange among departments, with regular recording of information. These efforts will help overcome supply chain complexities, and pursue joint improvement with underpinning loyalty and flexibility be-

tween partners, where top management teams follow the same vision in collaborations. Some studies addressed internal integration through flexibility performance [89] and responsiveness in the supply chain [109], while some revealed its impact on both supplier and customer integration based on manufacturing data collected from China [119]. Our findings accordingly generalize the role of internal integration on partners' external practices in Europe and North America.

Further, revealing the importance of internal integration on group forecasting is an important contribution of this research, which links manufacturers' integration practices to forecasting meetings with retailers. Practitioners can make use of this result for more constructive discussions, effective usage of information, and more sustainable forecasting decisions for time-sensitive products in meetings. In doing so, they will be able to generate timely consensus forecasts and to preserve shelf availability in stores.

### 5.4. Information sharing

Information sharing is essential to achieve better results in group forecasting. Difficulties to agree on the same set of forecasts are apparent between manufacturers and retailers in meetings [32,33]. This is due to retailers being ill-informed regarding manufacturers' forecast modifications, which are designed to manage production capacity, inventory and delivery operations [17]. Our findings advise practitioners to not only share order forecasts, but also inventory levels, production plans and schedules of related products, as recent information is likely to affect sales. Examples of such information include environment-related information, weather, products, and forecasters' past experiences. By doing so, manufacturers will be able to settle delay problems in replenishment operations and preserve product availability on shelves [46,93]. Further, they will strengthen communication and transparency with retailers and will achieve a better understanding via updated forecasts [121].

## 6. Conclusion and future research opportunities

In this research, we address the forecasting aspects of manufacturers' strategic decision-making [59] through group forecasting, judgmental adjustments, information sharing and supply integration practices with retailers. Focusing on the question "to what extent can coordination and collaboration and effective information sharing in multi-tier operations help improve human judgement and satisfaction in forecasting and decision making in strategic partnerships?", this paper offers a new conceptual framework for the implementation of strategic collaborations on forecasting perishable, seasonal, promotional and newly-launched products. Secondly, it highlights the impact of group forecasting and external integration on strategic partnerships. Thirdly, our findings reveal the significant impact of internal operations, not only on external integration and on group forecasting meetings, but also on judgmental

adjustments. Finally, our analysis indicates that information sharing with retailers has a significant impact on the decisions made in group forecasting meetings with retailers, where sharing judgmentally adjusted order forecasts across partners has a mediating effect on group forecasting.

The contribution of this research should be considered in light of a few limitations. Firstly, the findings rely on survey data, and it is essential to further expand such work using multi-methods. Complementary methodologies would be essential to test the conceptual framework of strategic partnerships between manufacturers and retailers. Secondly, current work emphasized manufacturers' perspectives; a promising extension would be to replicate these studies with retailers to compare their views and to examine the role of power and information sharing in strategic partnerships.

Thirdly, the focus of this research is on perishable, seasonal, promotional and newly-launched products traded in the food industry. However, the potential differences in forecasting processes for each of these product-groups have been outside the scope of this research. Examining differential processes and methods used for such products will inform both practitioners and researchers towards enhancing strategic partnerships in FSCs. Fourthly, narrowing down our research to specific products limits our ability to generalize findings to different products and different industries (such as apparel, consumer goods, fast-moving consumer goods, and the pharmaceutical industry). Replicating similar work across different products in different industries can be expected to provide valuable insights for practitioners. Finally, the results of this study illustrate the partnership practices of manufacturers based in Europe and North America. Future research specifically profiling particular countries or regions (e.g. North/South Asia, Middle East and/or North Africa) and exploring region-based differences from the manufacturers' decision perspectives would be useful to further expand our understanding of behavioral factors critical for improving Operations Research practice [107].

### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.omega.2018.11.007](https://doi.org/10.1016/j.omega.2018.11.007).

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