JOURNAL OF INTERNATIONAL CRISIS AND RISK COMMUNICATION RESEARCH
ISSN: 2576-0017
2024, VOL 7, NO S6

Impact of Strategic Alliance Management and Absorptive Capacity on Business Performance

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ABSTRACT

The objective of this work was to determine the impact of knowledge, absorption, capacity and strategic alliance management on business performance. Through a quantitative study developed from structural equation modeling and a higher order model performed by the repeated indicators method and the two-station approximation, the analysis was carried out in the dairy sector from the perspective of dynamic capabilities. It was possible to detect that knowledge absorption capacity and strategic alliance management positively impact business performance, which is related to the creative function of dynamic capabilities from the identification, reconfiguration and use of opportunities to achieve competitive advantage.

KEYWORDS: Dynamic capabilities, adsorptive capacitive, alliance management, structural equation modeling, business performance.

1. Introduction

In today's dynamic business environment, the ability of organizations to absorb external knowledge and manage strategic alliances has become a crucial factor for company performance. This article examines the impact between knowledge absorptive capacity (ABS), strategic alliance management (GAE) and its impact on business performance (PERF) from the perspective of dynamic capabilities (DC).

The existing literature suggests that ABS operates as an interactive reciprocity process, generating benefits cemented by interactions between key allies. Various studies have pointed out that the proper management of these relationships and collaborative processes, both with external partners and with internal members of the organization, can result in obtaining significant income. This research delves into the synergy between ABS, GAE, and PERF, postulating that the effective interaction between these variables can lead to tangible improvements in business performance.

According to the Ministry of Agriculture (2022), the demand for differentiated dairy products has increased, but supply remains limited. In Europe, 45% of consumption corresponds to processed dairy products, in Colombia it is only 8%. The industrial dairy sector continues to be less productive than in developed countries (DANE, 2021). The government has proposed to increase its indicators of (R+D+i) and promote the technology transfer of the dairy industry, in order to increase productivity and competitiveness in a horizon of two decades. This sector faces multiple challenges, such as low levels of association, poor product diversification, technological backwardness, limited productivity and high production costs. These elements demand the design of strategies to consolidate both the market inside and outside the country (Minagricultura, 2022; CONPES, 2017).

It is argued that, in the face of market opportunities, companies reconfigure their capabilities, adjusting alliance management and their ABS to optimize their management, their products, their processes, their market strategies and in general promote the obtaining of competitive advantages. The balance between potential absorptive capacity (CAP), realized absorptive capacity (CAR), and adequate GAE, allows organizations to forecast demand, achieving performance that ensures long-term survival.

2. Theoretical Framework

Fundamentals of dynamic capabilities

DCs make it easier for organizations to adapt and capitalize on opportunities in changing business environments. According to Teece (2007), these capabilities are manifested through the ability of organizations to detect, take advantage of, and reconfigure resources, which allows them to maintain their competitive advantage in a dynamic global market. The micro-foundations of these capabilities include unique skills, processes, decision rules, and organizational structures that enable companies not only to adapt, but also to shape the business environment through continuous innovation. These capabilities relate directly to PERF, as companies with robust dynamic capabilities are able to improve their performance by responding effectively to emerging market and technology opportunities.

The DC management mechanism is developed by the permanent confluence and harmonization of all the capacities of the organizations, on the one hand, internally, it is supported by process planning, process information capabilities and automation capabilities, and on the other hand, externally, it is supported by alliances between key partners. networked computer cooperation and interaction with suppliers (Arafa & Elmaraghy, 2011).

Knowledge Absorption Capacity

ABS, understood as a dynamic capacity, allows companies to generate value through the development of key skills for the acquisition, assimilation, transformation and exploitation of external knowledge, which has a direct impact on business performance (Camisón & Forés, 2010; Forés & Camisón, 2008). These processes are essential to integrate external knowledge and leverage it to improve competitiveness and PERF.

ABS is key for organizations to improve their performance by integrating new insights into their operations. Bouguerra et al. (2022) highlight that ABS is broken down into two main dimensions: CAP, which involves acquiring and assimilating external knowledge, and CAR, which refers to transforming and exploiting this knowledge to generate innovations and performance improvements. In addition, companies that can effectively integrate these two dimensions can generate superior performance in dynamic environments.

Strategic Alliance Management

Cross-organizational routines and strategic alliances have a significant impact on business performance. According to Zollo, Reuer, and Singh (2002), these routines, which are consistent patterns of interaction between partner firms, are refined over time by accumulating experiences from previous collaborations. This helps to optimize coordination, problem-solving and decision-making, which has a positive effect on the performance of both the alliances and the participating companies.

In the same vein, Cadrazco, Santamaría, and Pertuz (2021) mention that GAE facilitates technology transfer, innovation, and the optimization of the competitive position of companies. They play a crucial role in improving business performance, as they allow organizations to access new resources and capabilities that would otherwise be difficult to obtain.

In the current context, strategic alliances are essential for companies to absorb knowledge and assimilate new technologies. He et al. (2020) point out that digital transformation has redefined strategic alliances, focusing them more on innovation and the use of disruptive technologies. This allows companies to not only stay competitive, but also expand their technological capabilities.

Siachou et al. (2021) argue that the strategic interdependence between partners in an alliance facilitates access to knowledge that organizations cannot generate internally, which is essential for their digital transformation. These collaborations enhance companies' ability to integrate new technologies and optimize their performance in a competitive environment.

Incidence between absorptive capacity, management of strategic alliances and performance

Strategic alliance management (GAE) capability is understood as a dynamic capability that allows a company to deliberately create, expand, or modify its resource base by integrating those of its strategic partners. Specifically, it refers to the ability to transform and expand internal resources by incorporating the assets of its allies into the alliance (Helfat et al., 2007).

On the other hand, some researchers argue that the proximity of technologically advanced industries contributes significantly to the cooperation required to use cutting-edge, rapidly evolving technology. Investing in specific infrastructure within manufacturing factories contributes to strengthening business cooperation and interactions, which, in turn, boosts business performance (Enright, 1995; Dyer, 1996). These actions can be interpreted as an expression of the GAE).

In addition, research indicates that productive improvements in supply occur when allies are prepared to make targeted transformations and acquire distinctive advances (Asanuma, 1989; Dyer, 1996). This approach suggests that manufacturing initiatives that integrate specialized advances generally gain competitive advantages by outperforming those that resist doing so. Thus, idiosyncratic relationships between organizations turn out to be the source of relational utilities and competitive differentiation.

This approach underscores that an organization's essential resources may be rooted in routines and processes shared with other companies. The "alliance explosion" over the past decade reveals that the relevant unit of analysis is often expanded to include networks or pairs of firms (Smith, Carroll, & Ashford, 1995). Studies that specifically examine collaboration between firms to generate economic benefits emphasize the benefits of learning, the reduction of transaction costs, or the integration of resources (Hamel, 1991; Dyer, 1996; Teece, 1986).

Organizations develop their GAE for a variety of reasons, such as learning new skills (Baum et al., 2000) or accessibility to additional skills (Dyer & Singh, 1998). In addition, entrepreneurs who enter into multiple partnerships often seek to minimize uncertainty and optimize risk, while increasing their profits by investing in additional resources. Collaboration with a variety of alliances can provide a more complete view of business capabilities and performance than operating in isolation or with few partners (George, Zahra, & Wheatley, 2001).

Flatten et al. (2011) highlights that absorption capacity, understood as a company's ability to identify, assimilate and exploit external knowledge, is enhanced through strategic alliances. These alliances allow companies to access new knowledge that, when effectively integrated, improves organizational performance, especially in the case of small and medium-sized enterprises (SMEs).

Strategic alliances and knowledge absorption capacity are key elements that directly influence organizational performance. Kustiningsih, Tjahjadi, and Soewarno (2022) argue that companies that establish strategic alliances have greater opportunities to access and apply external knowledge, which enhances their absorption capacity. This capability not only enhances their innovative capacity, but also their PERF, allowing technological companies to better take advantage of the competitive environment.

A key aspect provided by the study by Kustiningsih et al. (2022) is the importance of absorptive capacity as a mediator between strategic alliances and organizational performance, highlighting that this capacity not only improves internal efficiency, but also allows companies to integrate external innovations more quickly. This is especially relevant in micro, small and medium-sized technology companies, where the ability to adapt and take advantage of emerging technologies becomes a crucial competitive advantage in highly dynamic global markets.

The study by Rajan, Dhir, and Sushil (2023) highlights that previous experience in alliances and absorptive capacity are key factors in improving the productivity and performance of strategic alliances in the industry. Their work underscores that knowledge transfer and interorganizational learning improve firms' ability to internalize that knowledge and apply new innovations, resulting in greater competitive advantage. Based on the above, the following hypotheses are formulated:

H1: The absorption of knowledge has a positive impact on business performance.

H2: The management of strategic alliances has a positive impact on business performance.

3. Methodology

The construct illustrated in the work is a 2nd and 3rd order training model, elaborated from the application of repeated indicators in a two-station approximation. The model has multiple variables, in these situations, the use of models with structural equations based on variance (VB-SEM) and partial least squares fitting estimation is recommended (HAIR et al., 2012). The positive incidence of GAE in PERF and ABS in PERF was hypothetically proposed from the researchers' perspective.

The research was carried out using a quantitative approach, with a non-experimental cross-sectional and field design, with the aim of testing the relationships. The study, based on the positivist paradigm, allowed validating causal relationships between knowledge absorption, GAE and business performance respectively.

The constructs analyzed were evaluated through VL, which were operationalized through a seven-point Likert-type questionnaire in a sample of 75 companies in the dairy sector. The sample size was based on the suggestions of Cohen (1988) and Erdfelder et al. (2009), considering a significance level of 5% ($\alpha = 0.05$), a statistical power of 80% ($1-\beta = 0.80$) and a median effect size ($f^2 = 0.15$). In addition, the ability of the PLS-SEM method to handle small samples was highlighted (Cohen, 1992; Hair et al., 2021; Ringle et al., 2022). For the analysis of the data, structural equation modeling was used using the partial least squares method, implemented through the $SmartPLS_4$ software (Ringle, Sarstedt, & Straub, 2022).

4. Results

The results of the work associated with the ABS_GAE_PERF model are presented below. In the first instance, the quality characteristics of the data were verified. The loads of the observed variables (VO) were obtained, in addition to the model quality indicators, as shown below.

In the first stage, using the repeated indicators approach, the VL scores for the lower-order LOC constructs were obtained, which, in the second stage, served as manifest variables in the HOC higher-order measurement model. See Figure 1.

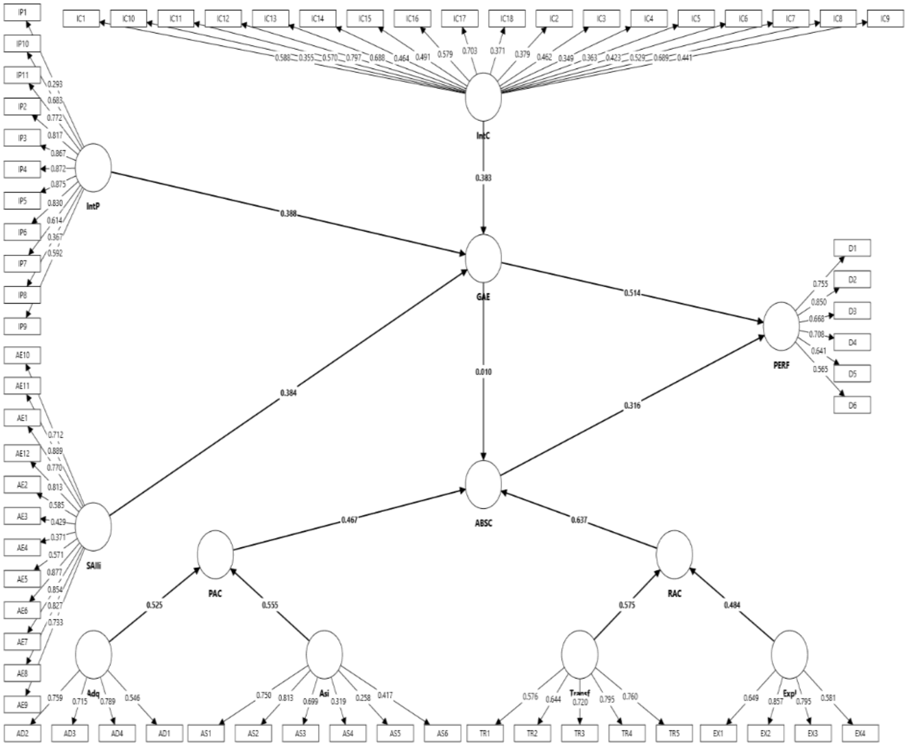


Figure 1. Knowledge Absorption Model, Management of Strategic Alliances and Business Performance ABS_GAE_PERF

Coding: ABS knowledge absorption capacity, PAC potential absorption capacity, RAC realized absorption capacity, AD acquisition, AS assimilation, TR transformation, EX exploitation. GAE strategic alliance management, SAlli strategic alliances, IntP integration with suppliers, IntC integration with customers, PERF business performance.

Source: Own elaboration

In the figure above, it can be seen that the higher order "construct" (HOC) made up of ABS_GAE_PERF is embedded in the nomological arrangement in such a way that it makes it possible for other VLs, such as those above, to express some of their variations, which generally results in significant path links.

Figure 2 shows the loads of the measurement model, and several loads were separated from the model, in contrast to the original design illustrated above.

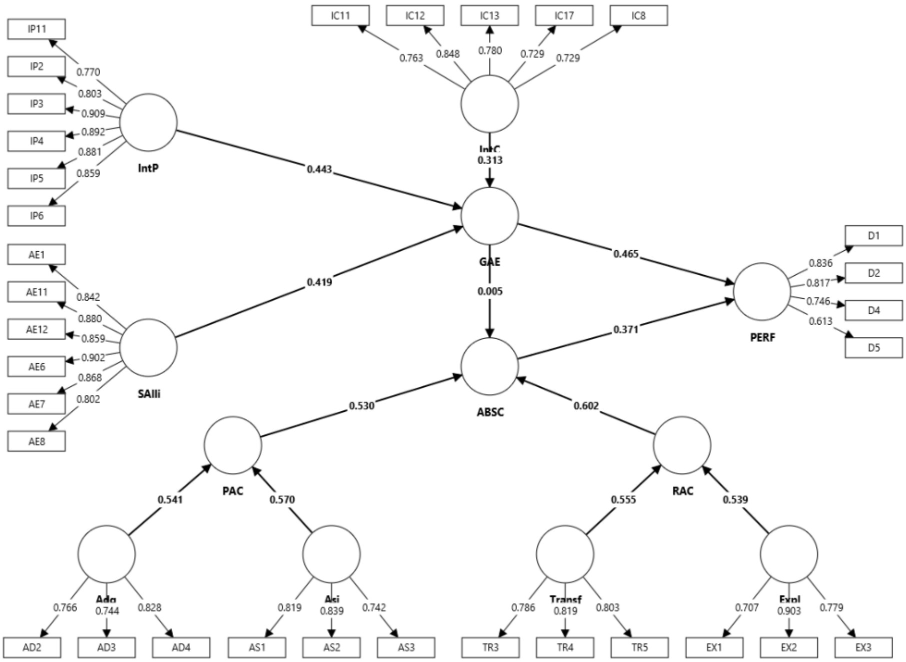


Figure 2. Refined Model of Knowledge Absorption, Management of Strategic Alliances and Business Performance ABS_GAE_PERF

Source: Own elaboration

The first quality criteria are then observed in the report, where a general verification of the quality of the adjusted model is obtained, Table 1.

Table 1 - Reliability and Construct Validity. Model: Absorption, Strategic Alliance Management and ABS_GAE_PERF Performance

OK2024	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Adq	0.678	0.684	0.823	0.609
Asi	0.719	0.724	0.843	0.641
Expl	0.713	0.739	0.841	0.641
GAE	0.936	0.940	0.944	0.499
IntC	0.829	0.835	0.880	0.595
IntP	0.925	0.931	0.941	0.729
PAC	0.802	0.807	0.859	0.505
PERF	0.757	0.817	0.842	0.575
RAC	0.824	0.831	0.873	0.536
SAlli	0.929	0.934	0.944	0.738
Transf	0.724	0.727	0.844	0.644

Source: Own elaboration

From then on, the necessary verifications are carried out to evaluate the suitability of the model. This process is carried out in two phases: initially, the measurement model is examined, and once the relevant adjustments have been made, the structural or road model is evaluated (Hair et al., 2021).

Convergent Validity

The first thing to observe is the convergent validity, through the mean extracted variance (AVE), in that order the Fornell and Larcker criterion was used (Jorg Henseler et al., 2009). The AVE represents the proportion of variance in the variables that is explained by each construct or latent variable (VL) within its respective group of variables. In other words, it reflects the degree to which variables are positively correlated with their corresponding constructs. An AVE value greater than 0.50 indicates that the model has an acceptable level of convergent validity, suggesting that the variables are sufficiently related to its construct (Fornell & Larcker, 1981).

Table 1 reveals that GAE has a mean extracted variance (AVE) of 0.499, which is slightly below the recommended threshold of 0.5. In this case, it would be necessary to eliminate the observed variables that are negatively affecting the AVE. However, most of the constructs mentioned in the table have adequate values in their factor loads. It should be noted that the external loads must exceed 0.708, since its square (0.708^2) corresponds to an AVE of 0.50 (Hair et al., 2021).

Generally, weights between 0.40 and 0.70 should be used for elimination only if their removal improves compound reliability or mean variance extracted (AVE). Indicators with loads below 0.40 should always be deleted (Hair et al., 2011). In summary, by maintaining the model variables, acceptable values were reached for all the AVE, exceeding 0.50, except for a slightly lower value (GAE with 0.499). Other external loads were not eliminated, as their exclusion did not significantly improve the reliability of the construct or other indicators such as Cronbach's alpha, composite reliability or AVE.

Cronbach's Alpha Internal Consistency and Composite Reliability

The second phase, after ensuring convergent validity, involves reviewing three key indicators: a) internal consistency (Cronbach's alpha), b) composite reliability (CC) and c) Dillon-Goldstein rho. Traditionally, Cronbach's alpha is used, based on correlations between variables, although CC is more suitable for modeling partial least squares structural equations (PLS-SEM), as it weights variables according to their reliability, while Cronbach's alpha can be influenced by the number of variables in each construct. Both indicators are used to assess the reliability of the responses. A Cronbach's alpha greater than 0.60 or 0.70 is adequate in exploratory studies, and a WC between 0.70 and 0.90 is considered satisfactory (Hair et al., 2021). According to Table 1, both Cronbach's alpha and composite reliability are adequate in all constructs, except for the construct "acquisition", which has values slightly lower than 0.70 (AC of 0.678 and CC of 0.684).

Discriminant Validity

The third phase consists of evaluating discriminant validity, which indicates that the constructs or VLs are independent of each other (Hair et al., 2021). This aspect is used using the criterion of Fornell and Larcker (1981). This method compares the square roots of the extracted mean variance (AVE) values with the Pearson correlations between the constructs. For discriminant validity to be fulfilled, the square roots of the AVE must be greater than the correlations between the constructs.

Table 2 - Discriminant validity. Criterion of (Fornell & Larcker, 1981).

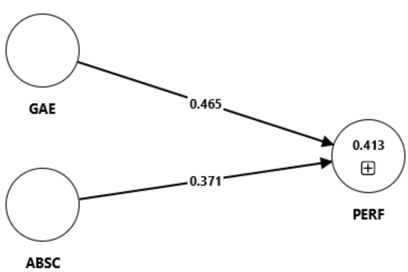
	Adq	Asi	Expl	IntC	IntP	PAC	PERF	RAC	SAlli	Transf
Adq	0.780									
Asi	0.618	0.801								
Expl	0.434	0.409	0.800							
IntC	0.046	0.200	0.239	0.771						
IntP	0.044	0.202	0.249	0.765	0.854					
PAC	0.894	0.905	0.469	0.139	0.139	0.710				
PERF	0.201	0.310	0.482	0.434	0.335	0.287	0.758			
RAC	0.526	0.477	0.911	0.226	0.147	0.558	0.488	0.732		
SAlli	-0.060	0.167	0.078	0.500	0.504	0.064	0.580	0.055	0.859	
Transf	0.522	0.458	0.672	0.180	0.029	0.544	0.414	0.917	0.030	0.803

Source: Own elaboration

The analysis in Table 2 indicates that, in most cases, the square roots of the extracted mean variances (AVEs) exceed the correlations between the VLs, with the exception of some values, suggesting that the model could be improved. However, since AVEs are generally larger than correlations, the model can be maintained without making additional changes. With the discriminant validity confirmed, the adjustments of the measurement model in phase 1 are concluded. This is followed by phase 2, focused on the analysis of the structural model, using the VL scores obtained in the previous phase (Hair et al., 2021).

Once this process is completed, the scores obtained are integrated into the database and a new project is designed that includes only the VLs for phase two. This new database is imported and a model that works exclusively with VL is developed, see figure 3 (Hair et al., 2021).

Figure 3. Structural Model ABS_GAE_PERF (VL only).



Source: Own elaboration

Figure 3 indicates that the model explains 41.3% of the total variance in the PERF, with a value of $R^2 = 0.413$. The relationship between ABS and PERF was significant, with a coefficient of 0.465. Similarly, the relationship between GAE and PERF was significant, with a coefficient of 0.371, as shown in Figure 3 and Table 3.

Table 3. Significance of the direct effect of ABS→PERF and GAE -> PERF

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ABS -> PERF	0.371	0.368	0.102	3.643	0.000
GAE -> PERF	0.465	0.468	0.085	5.443	0.000

Source: Own elaboration

Table 3 shows that the direct effect of ABS→PERF, as well as the GAE -> PERF effect were significant, with P-value values < 0.001.

Table 4 summarizes the results found, showing that ABS has a positive impact on PERF and GAE has a positive impact on PERF H1 and H2.

Table 4 Table of results ABS_GAE_PERF

	Original sample (O)	Conclusion
ABS -> PERF	0.371	Positive impact
GAE -> PERF	0.465	Positive impact
P < 0.001 *** P< 0.001***		

Source: Own elaboration

5. Discussion

Taking as a reference the literature presented and the findings of this study, the analysis shows that ABS capacity has a significant and positive impact on PERF, with a coefficient of 0.371 and a p-value < 0.001, which supports the hypothesis that this dynamic capacity contributes directly to the improvement of organizational performance. This finding is consistent with previous studies (Camisón & Forés, 2010; Bouguerra et al., 2022), who state that the ability to absorb, transform, and exploit external knowledge is essential for the development of innovations and continuous improvement. In this line, the ABS component allows companies to adapt and respond to market changes, facilitating the implementation of innovations that favor competitive advantage.

The management of strategic alliances shows a positive and significant relationship with business performance (coefficient 0.465, p-value < 0.001), which corroborates the second hypothesis raised. This result is consistent with research by Zollo, Reuer and Singh (2002) and Dyer & Singh (1998), who underline the importance of partnerships to optimize resources, share risks and promote knowledge transfer. It is observed that the integration of suppliers and customers strengthens the organizational capacity to implement innovations, a critical condition in sectors with high technological variability.

The literature has indicated that absorptive capacity and the management of strategic alliances are interdependent and mutually reinforcing (Flatten et al., 2011; Kustiningsih et al., 2022). In this study, the coexistence of both capabilities in the structural model shows that, when companies effectively integrate external knowledge through their alliances, they optimize their organizational performance. The results underpin this dynamic, suggesting that, in a business environment characterized by globalization and technological innovation, companies must not only establish strategic alliances, but also enhance their capacity to assimilate and apply the knowledge derived from these collaborations.

6. Conclusions

The present study confirms that both ABS and strategic alliance management are determining factors to improve PERF. It is concluded that:

The ability to absorb knowledge has a significant and positive influence on PERF, suggesting that firms that invest in the acquisition, assimilation, transformation, and exploitation of external knowledge achieve a superior competitive advantage. These findings are consistent with previous literature that underscores the importance of this capability as a crucial dynamic in highly competitive business environments (Camisón & Forés, 2010; Bouguerra et al., 2022).

The management of strategic alliances is also shown to be a key factor in organizational performance, since it facilitates the transfer of resources and knowledge that are difficult to obtain internally. This result reaffirms the role of alliances as a strategic tool for innovation and access to new technological opportunities (Zollo et al., 2002; Cadrazco et al., 2021).

On a practical level, companies looking to improve their performance should focus on strengthening their ABS and fostering strategic alliances that allow them to access external resources. The ability to integrate these strategies will be critical to maintaining competitiveness in dynamic global markets.

Detecting opportunities depends a lot on the ability to acquire, assimilate, transform and exploit knowledge and information vital to PERF. This happens due to strategic alliances, integration with suppliers and integration with customers, among other possible sources, including allies. Reconfiguring assets to streamline company operations and improve business performance in the case of the dairy sector, often occurs based on ABS and alliance management.

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