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Impact of Organizational Culture Values on Organizational Agility

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Abstract: To remain competitive within the current, uncertain business scenario, it is vital for firms to develop capabilities that lead them to adapt and offer quick responses to market changes. Under the dynamic capabilities view of the firm, this paper proposes a model that presents an exhaustive analysis of two relevant research gaps: (i) the underlying relationships that determine the impact exerted by each of the four organizational culture typologies, comprised in Cameron and Quinn's Competing Values Framework on organizational agility and, (ii) the contingency effect exerted by a key environmental factor, the industry's technology intensity. An empirical study is performed to test the relationships proposed, using data collected from 172 Spain-based companies. To examine the contingency effect of technology intensity, the sample is divided into two subsamples, high and medium tech companies. This work uses partial least squares path-modeling, a variance-based structural equations modeling technique, in order to test and validate the research model and hypotheses posited. In addition, thorough analyses are carried out to assess the predictive performance of our model.

Keywords: organizational culture; organizational agility; competing values framework; technology intensity; partial least squares

1. Introduction

Nowadays, firms must face extremely turbulent environments whose main characteristics are high levels of uncertainty, complexity and dynamism. If firms aim to survive in such volatile environments, they must develop capabilities to detect environmental changes early and to offer accurate responses to them, gaining new business opportunities and competitive advantages to exploit. In this context, the concept of organizational agility (OA) appears as one of the key issues that are attracting the attention of researchers and practitioners [1].

OA has been defined as an organization's capability to sense environmental changes and to respond efficiently and effectively to them [2]. Assuming the dynamic capabilities view (DCV) as the theoretical framework [3], OA is a critical dynamic capability that influences firms' competitive actions and therefore it becomes a significant antecedent of their performance [4]. In this vein, this paper approaches OA as a dynamic capability that organizations can deliberately use to reach and sustain competitive advantages [5] and to survive crises and changing environments [6].

Following Vinodh [7] in the current business scenario, OA needs to be coupled with sustainability. OA is a paradigm that enables firms to survive within the current hypercompetitive and dynamic business environment. Simultaneously, companies are nowadays incrementally required to become more respectful towards the environment. Concretely, fostering sustainability implies seeking the minimization of the firm's environmental impact. Thus, numerous firms have turned to the design and development of eco-friendly products and services and the deployment of more eco-efficient processes [8]. Therefore, sustainability also stands out as a central concept for organizational survival. This implies that in the current scenario, OA and sustainability are both considered as performance indicators for modern firms [7]. Moreover, several studies have recently posited that OA exerts a positive impact on corporate sustainability [9,10].

OA has been approached from a wide variety of academic disciplines since the mid-1990s, the information systems (IS) field being the one that has been most developed. This field has mainly addressed the influence of IS and their related capabilities (ISC) in the achievement of high levels of OA in firms [4,11].

The focus on the technological aspects that may affect the OA level in an organization has led to some relevant organizational and contextual factors [12] and their influence on OA being forgotten. This fact has been identified as an important research gap: technology is only one piece of a complex puzzle, where other relevant aspects might play an important role in developing the mechanisms that allow firms to become agile through a more inclusive social-technical approach [13]. One of the most commonly ignored variables that may affect OA is organizational culture (OC) [2]. The previous literature has developed few attempts to study the effects of OC on OA, people and organizations' characteristics are understudied dimensions if they are compared with technological and operational factors [12].

The purpose of this paper is hence to go deeper into the study of the antecedents of OA by approaching another relevant gap, the influence that might be exerted by diverse cultural values in achieving a higher level of OA. Following Cameron and Quinn's [14] four major cultural typologies (Hierarchy, Market, Clan and Adhocracy Cultures), this paper builds up a model that posits these four cultural values as drivers of a firms' OA levels. This theoretical model will not only serve for explanatory purposes but will also be a predictive model. This fact is a significant novelty in the OA literature.

Moreover, researchers tend to focus on internal organizational mechanisms to improve OA, while they ignore the external aspects of organizations [15]. The impact of cultural values and principles in the OA level is influenced by a complex set of factors that includes not only internal but environmental factors [11]. This paper proposes that the impact of the different types of OC values on OA may be moderated by one of these environmental variables, the technology intensity of the industry. This factor has traditionally been considered as one of the primary contingent variables in terms of organizational conditions [16]. Technology intensity at industry level can moderate the impact that OC values have on different organizational attributes that are linked to OA, such as adaptability to change, knowledge-based work and decentralization of authority, among others.

This work means to answer the following research questions:

RQ1: Could the presence of certain OC values become an antecedent of OA?

RQ2: Are the aforementioned relationships contingent on the technology intensity level of the industry?

RQ3: Are the four OC values able to generate accurate predictions of OA?

This paper carries out an empirical study to test the research hypotheses and the predictive performance of the research model. Sectors classified as innovative are the population selected for this study, as these industries can be considered as the most suitable, due to their hypercompetitive markets that require a flexible and quick response from organizations. This selection represents a population of 2360 firms. An off-line survey is the data collection instrument, the outcome being 172 usable surveys (a 7.3% response rate). The sample is split into two different groups (the high-tech and the medium-tech companies) to assess the contingency effect of the technology intensity of the industry.

The study proceeds as follows. The next section presents the theoretical background together with the research model and hypotheses. The third section gives a description of the research methodology. The fourth section presents the results of the different data analyses carried out. Finally, the fifth section brings together the discussion and implications.

This paper will bring new contributions to prior literature, as the results will shed light on the question of how firms can gain agility. As this remains unclear, new insights and lines of research are brought to the academic community as well as important implications for practitioners and executives, enabling a more effective management of companies' resources and capabilities, in order to prepare them to survive and succeed in such hypercompetitive environments.

2. Literature Review and Research Hypotheses

2.1. The Competing Values Framework

This paper uses OC taxonomies following the Competing Values Framework (CVF) theorized by Cameron and Quinn [14]. The 'competing values framework' is among the most recognized and widely applied frameworks within organizational culture research. The search for this term leads to 1,900,000 results in Google Scholar. This same search yields a total of 1630 document results within the Scopus database. Hence, CVF has served as a guideline and source of theoretical inspiration and managerial insights for many scholars and practitioners [17].

The CVF model comprises two dimensions. One dimension opposes an emphasis on flexibility, adaptability and dynamism to an emphasis on stability, order and control, while the second dimension confronts an internal orientation with a focus on integration, collaboration and unity, with an external orientation with a focus on differentiation, competition and rivalry. These dimensions, combined jointly against each other, lead to the identification of four distinctive culture types (i.e., clan culture, market culture, adhocracy culture and hierarchy culture) that involve particular and idiosyncratic characteristics. A brief conceptual delimitation of the four cultural archetypes is given below (Figure 1).

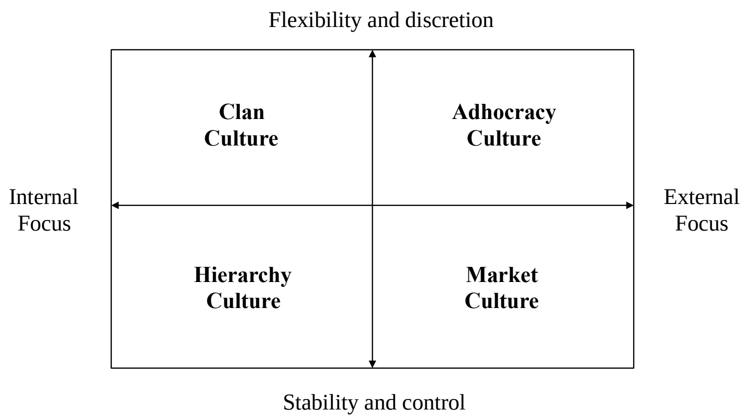

Figure 1. The Competing Values Framework.

Clan culture is often categorized with the following features: family-oriented, trustworthiness, closeness, empowerment and community [14]. This culture type is primarily oriented to its human capital, emphasizes individuals' level of wellbeing and fosters a positive working atmosphere over optimizing financial ratios and market goals [18]. Clan organizations combine a lower concern for structure and control and a greater focus on flexibility. Hence, instead of strict rules and procedures, the firm's members are driven through vision, shared goals, outputs and outcomes.

Market culture is recognized as being clearly concerned with a goal (or objective) accomplishment culture type. Hence, the predominant corporate values inherent to this culture are productivity, effectiveness, competitiveness and results optimization. These organizations normally stress gaining prestige, status and profitability and their main purpose is to end in transactions (i.e., exchanges, sales, contracts), with other parties, in the hope of achieving competitive advantages [19]. In market organizations, both internal and external transactions (exchanges of value) are viewed in market terms. In effective market organizations, value flows between their different members and stakeholders, with minimal cost and delay.

Adhocracy culture is regularly labelled as original, dynamic, entrepreneurial, innovative, risk-taking, prepared for changes, aggressive and flexible [20]. Firms possessing this culture type often pursue success while focusing on innovation development, sustained in the development of innovative products, services and processes. Therefore, this is the most innovation-oriented culture, whose main target deals with fostering adaptability, flexibility and creativity, in order to face uncertainty, ambiguity and information overload [21].

Finally, Hierarchy culture is normally described as extremely bureaucratic, rule-driven, by-the-book and top-down directed [22]. This archetype traditionally embraces an approach that highlights structure and control that emanates from a strict chain of command, as in Max Weber's original theory of bureaucracy. This culture stresses the minimization of ambiguity levels and the promotion of an intense sense of security, certainty, predictability, effectiveness, stability, formalization and standardization. This culture type endorses a long-lasting concern for order and control mechanisms, embodied in an explicit and very precise range of norms, rules, instructions and procedures. In summation, this culture is mainly focused on efficiency and internal control.

2.2. Organizational Agility

The notion of organizational agility (OA), as proposed by Sherehiy et al. [23], is rooted in two previously developed, related concepts (i.e., organizational adaptability, a reactive facet and organizational flexibility, a proactive facet). Concretely, OA encompasses companies' capability of sensing environmental changes and responding readily to them, by reconfiguring their set of resources, business processes and strategies [24]. In addition, Sambamurthy et al. [4] postulate that three interrelated dimensions shape OA: (i) customer agility, which involves leveraging customers' opinions to gain enhanced market intelligence; (ii) partnering agility, which comprises absorbing knowledge from the distinct business partners to enhance the firm's response to market requests; and, (iii) operational agility, which entails quick process redesign to exploit dynamic environmental and market conditions [25]. Consequently, following the inclusive approach proposed by previous works, such as that by Charbonnier-Voirin [26], this paper conceptualizes OA as the organization's deliberate response capability, aimed at enabling more efficient behavior, within highly turbulent and complex environments. This behavior not only involves reacting rapidly to change but also the firm's capability to anticipate and seize opportunities, especially through innovation and learning.

2.3. Linking OC Typologies to OA

In the words of Cameron and Quinn [14] (p. 1) "No organization in the twenty-first century would boast about its constancy, sameness or status quo compared to ten years ago. [. . .] The frightening uncertainty that traditionally accompanied major organizational change has been superseded by the frightening uncertainty now associated with staying the same." These authors point out in their seminal work 'Diagnosing and changing organizational culture based on the competing values framework,' that most organizations frequently fail in their attempt to manage change effectively, due to their inability to implement cultural change accurately. The CVF has been effectively applied to distinct key aspects of organizational performance (i.e., total quality management, human resource management roles and cultural change, among others) [14]. Hence, the application of the CVF might also stand as a powerful tool to analyze the influence of OC on OA.

The linkages between OC and diverse forms of OA have been suggested, to a certain extent but until now there has been a scarcity of empirical works aimed at providing explanatory or predictive evidence for these relationships [12]. This paper posits that the four OC typologies shaping the CVF involve idiosyncratic features and particularities that might exert different effects on OA. Moreover, it is intended to explore which cultures actually exert a stronger influence on the endogenous construct.

Organizations' awareness and struggle toward the development and wellbeing of their human capital, distinctive of clan culture, may be a good predictor of OA, since it may contribute to strengthening collaboration ties and the dissemination of knowledge [27]. Precisely, a key feature of agile companies is their ability to continuously manage the creation, adaptation, distribution and application of knowledge, throughout the organization [6], clan culture being a relevant breeding ground for these activities. Furthermore, clan culture is characterized by flat hierarchies based on autonomous individuals and teams, with leaders acting as facilitators, mentors and supporters [28], which may also enhance the OA level. However, its clear emphasis on individual issues might also hinder the implementation of new IS developments, which entail a certain degree of formalization and standardized procedures [29]. Nevertheless, the flexible organizational structure that supports the clan culture, in conjunction with open communication and employee commitment can overcome this limitation. A positive relationship between the clan culture and the OA level in an organization is therefore hypothesized (Figure 2):

Hypothesis 1 (H1). *Clan culture is positively related to OA.*

Market culture may lead to positive outcomes for OA. Its external focus and commitment toward predicting, understanding and reacting to market needs, trends and competitive changes may enable access to an extensive set of valuable external knowledge. Moreover, the market culture would maximize what Worley and Lawyer [30] call the "surface area," typical of agile organizations: the external orientation encourages the continuous contact of employees with regulators, suppliers, customers and any other key stakeholders. This fact will provide the firm with valuable information for the decision making and will prepare it for properly sensing and responding to unexpected environmental changes [30]. Besides, market culture decisively supports the managerial processes of strategic planning, directing and objective setting. Such a clear emphasis on uncertainty reduction might also enable OA. This is in line with previous works that argue that elements, such as strict deadlines and team effectiveness, reflect values inherent to market culture [31]. Moreover, OA often benefits from a business context that stresses values linked to productivity and goals attainment. Thus, it is hypothesized that market culture will positively influence on OA (Figure 2):

Hypothesis 2 (H2). *Market culture is positively related to OA.*

Due to its values, the adhocracy culture represents the most suitable cultural type to lead an organization in its way to becoming agile. Agile organizations work on potential alternative futures and they must be able to design and implement innovative responses to those foreseen scenarios, in a timely manner and with ease [32]. Therefore, given the tremendously uncertain, changing and complex business context where firms compete nowadays, an adhocratic culture that proactively emphasizes change, adaptability and innovativeness may be an effective driver of OA. In this line, Iivari and Iivari [31] (p. 513) argue that "enterprise agility is usually associated with adaptability and flexibility, i.e., an organizations' ability to adjust in response to changes in the environment, implying external focus and change." Indeed, change is the foundation of OA, which is defined as the capability that enables the firm to continuously reconfigure its resources to create responses to emerging futures, in the form of new products, services or business models [33]. Thus, as adhocracy cultures understand change as a positive phenomenon and a real source of opportunities, it is hypothesized that this culture type is positively related to OA (Figure 2):

Hypothesis 3 (H3). *Adhocracy culture is positively related to OA.*

Finally, hierarchy culture, in short, is viewed as a culture type that is primarily focused on efficiency and internal control. Likewise, this culture is internally focused and consequently, stresses preserving a stagnant and rigid hierarchical structure over seeking market opportunities. Moreover, an evident and unambiguous outcome of this culture is the methodical gathering and dissemination of extremely accurate, highly detailed, punctual, quantified, reliable and objective data [34]. The hierarchy culture hinders knowledge management, as it is strongly formalized and dependent on operating procedures, rules and regulations, as standard guides for decision making [35]. This excess of standardization in the hierarchy culture may lead to efficiency but it is just the opposite to the idea of agility. Managers used to working in a perfect bureaucratic system will find it difficult to adapt to a challenging market competition that demands continuous reconfiguration to meet environmental requirements [12]. In brief, this typology appears to be quite the opposite to what an agile organization should be, to sense and respond to continuous environmental changes. Hence, it is hypothesized that the hierarchy culture leads to lower levels of OA in organizations (Figure 2):

Hypothesis 4 (H4). *Hierarchy culture is negatively related to OA.*

2.4. The Contingent Effect of the Technology Intensity of the Industry

From the Dynamic Capabilities View (DCV) approach, OA has been identified as a dynamic capability by researchers [4,36]. The DCV is an extension of the Barney's [37] and Peteraf's [38] resource-based view (RBV) of the firm, in response to highly dynamic environments. A dynamic capability can be defined as the firm's ability to integrate, build and reconfigure internal and external competences, to address rapidly changing environments [3].

A traditional RBV approach tends to focus on the internal mechanism of organizations but dynamic capabilities are influenced by external environmental factors [15]. In this vein, the greater the uncertainty and the dynamism in the business environment, the more critical strong dynamic capabilities become for the firm's growth [39]. Therefore, the effectiveness of dynamic capabilities in companies is context dependent, although limited information is available on the joint effect of the internal and external mechanisms of organizations [15].

This paper has considered OC to be an antecedent of OA but the acceptance of agile values and principles can also be strongly influenced by environmental factors [11]. Considering technology intensity as one of the most relevant contingent variables in terms of organizational conditions [16], it is proposed as one of these external variables that may moderate the effects between OC in the firm and the OA level.

Technology intensity at industrial level refers to cross-sectional differences in the innovation potential of industries, which are derived from investments in knowledge and creative activities and its use in new applications [40]. In practice, this means that intensive technology industries invest a relatively high proportion of output in internal R&D [41]. Prior literature [42–44] operationalizes the environmental technological intensity following the OECD's technology-based classification of industries [45]. The OECD proposes to distinguish four technology groups (high, medium-high, medium-low and low-technology industries), according to two indicators of technology intensity, R&D expenditure divided by value added and R&D expenditure divided by production. The INE's (Spanish National Statistical Institute) classification of industries by their technological intensity, which adapts the OECD's to the Spanish economy, is used in this paper. Attention is focused on two different industry groups: high-tech and medium-tech industries. It can be assumed that these industries show rather different organizational characteristics derived from different sectorial and environmental features, such as accelerating and complex technologies, operational dynamics, continuous innovation, etc. [46]. Therefore, it is interesting to test whether this fact has any impact on the culture type that is most effective in order to improve OA.

Technology-intense industries are dynamic environments in which companies must be highly flexible and quick to implement changes [47]. High technology environments will require knowledge intensity and sophistication from firms, pushing them to adopt alternative organizational designs and new management techniques. Technologically driven industries need to be more creative and innovative than any others, if they want to survive [48]. The value of these companies lies increasingly in the creation and sharing of knowledge, rather than in any other type of assets or resources. Thus, the presumption can be made that OC values that improve the OA level in an organization will find more favorable conditions in this type of environmental context to exert its positive influence.

Moreover, high-tech industries demand highly educated skilled workers [46], contrary to medium and low-tech industries, which usually have a higher labor intensity and employ less human capital [49]. These facts lead to the consideration that in a high-tech context people are more self-motivated/directed and enjoy the autonomy and freedom of decision making and assuming responsibilities [46]. Thus, these environmental conditions will positively affect the agility values that could be involved in any of the four different OC typologies, as has been explained above (Section 2.3). Under such conditions, the agility values will be widely spread and smoothly assumed by the organization. Therefore, high technology intensity will enhance the OC values that are linked to a superior OA level, in a stronger manner than in a medium or low-tech context.

Furthermore, technology intensity has previously been noted as a moderator in the relationships between diverse organizational variables. Prior research has demonstrated that technology intensity moderates the impact on a firm's performance of cooperation and strategic renewal activities [42], foreign corporate-ownership [50], quality capabilities [51], or employment flexibility [52].

With this theoretical support, it is proposed that the technology intensity of the industry will positively moderate the relationship between culture typology and OA.

Hence, the following hypothesis is posited (Figure 2):

Hypothesis 5 (H5). *The technology intensity level of the industry positively moderates the link between OC and OA.*

Hypothesis 5a (H5a). *The technology intensity level of the industry positively moderates the link between clan culture and OA.*

Hypothesis 5b (H5b). *The technology intensity level of the industry positively moderates the link between market culture and OA.*

Hypothesis 5c (H5c). *The technology intensity level of the industry positively moderates the link between adhocracy culture and OA.*

Hypothesis 5d (H5d). *The technology intensity level of the industry positively moderates the link between hierarchy culture and OA.*

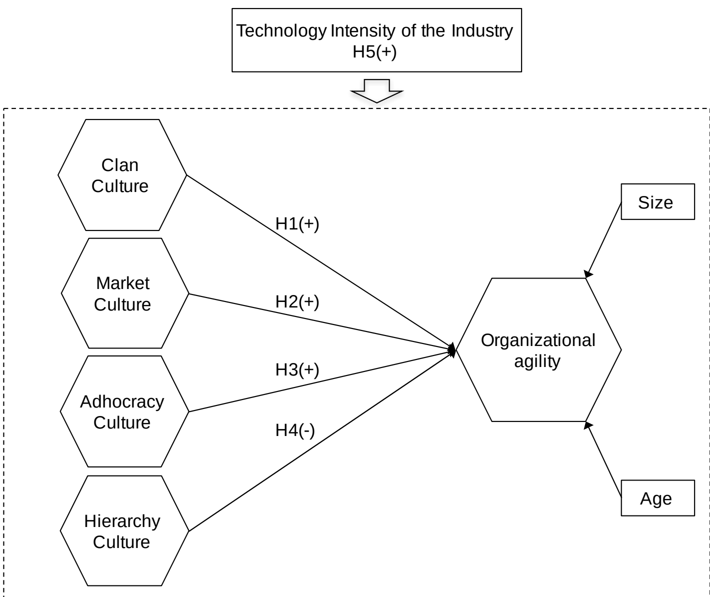

Figure 2. Research model and hypotheses.

3. Methods

3.1. Sample and Data Collection

Innovative sectors shape the population for this research. Both scholars and practitioners catalogue these industries as hypercompetitive, requiring a flexible and quick response from firms. This sector was chosen on the basis of the taxonomy developed by the Spanish National Institute of Statistics [53], which distinguishes between high and medium-high technology industries. This selection yields a population of 2360 companies. The data collection instrument consists of an off-line survey. Since the level of analysis is the organization, the survey respondents are senior managers. After one mailing effort, 189 questionnaires were initially received. Once those observations that did not satisfy the criteria suggested by Hair et al. [54] to handle missing data were removed, 172 valid surveys (a 7.3% response rate) were selected. This lower-than expected response rate might be explained by the fact that respondents (mostly executive managers) might possibly be overwhelmed by surveys. Nonetheless, this lower than expected response rate is not a severe source of bias, as we examined the generalizability through two different non-response bias tests. We assessed the potential non-response bias by means of a series of *t*-tests that compared early (responses to the initial mailing) with late (responses to the follow-up mailing) respondents, in terms of all the key constructs. Responding firms were compared with those that did not respond in terms of size and performance. No significant differences were found between these two groups, thus suggesting that non-response bias is not a serious concern. Finally, considering a statistical power of 0.8 at an alpha level of 0.05, our sample (n = 172) permits detecting an effect size (f^2) up to 0.036 [55], a figure very close to 0.02, a small influence according to Cohen [56].

The firms involved belong largely to the following industries: computer systems design (26.7%); machinery manufacturing (18%), chemical (17.4%); transportation equipment manufacturing sectors (8.1%); electrical equipment (7.6%); and, computer and electronic products (7%). Consistent with the European Union classification, 23.8% of the firms participating are large enterprises, more than 250 employees. Concerning the respondents' area of specialization, 23.8% of the respondents belong to the R&D department, followed by the marketing department (20.9%), general management (14%) and the engineering department (9.3%). Regarding the respondents' gender, 66% are male, whereas women represent 34%.

To analyze the industry contingency effect, the sample is split into two subsamples: (i) the high-tech; and, (ii) the medium-tech companies, following the classification established by the Spanish National Institute of Statistics [53] mentioned above. Results from the split are: 88 high-tech firms (51%) and 84 medium-tech firms (49%).

3.2. Measures

The variables included in our study have been modeled as composites. These variables can be described as design constructs or artifacts that consist of more elementary components, such as dimensions or facts. In this manner, composites are formed as linear combinations of their respective indicators or dimensions [57]. Consequently, dropping an indicator (or dimension) usually alters the meaning of the composite [58], since they represent different facets, whilst high correlations are common among indicators and dimensions but not required [59]. To measure the OC variables, this study adapts the OC Assessment Instrument proposed by Cameron and Quinn [19], which is based on the Competing Values Framework and encompasses six items that measure each of the four culture typologies as unidimensional constructs. Besides, following Sambamurthy et al. [4], OA is measured as a multidimensional composite shaped by three dimensions: customer agility, partnering agility and operational agility and a total of eleven items. This work adapts the scales proposed by Lu and Ramamurthy [60] for customer and operational agility and from Yang and Liu [61], Bradley, Pratt, Byrd, Outlay and Wynn [62] and Tallon and Pinsonneault [63] for partnering agility. All the constructs are measured through a seven-point Likert scale, with the exception of the control variables. In this case, using archival data from the SABI NEO database (Sistema de Análisis de Balances Ibéricos), size was measured as the number of employees and age as the number of years since its founding.

3.3. Data Analysis

Partial Least Squares (PLS), a variance-based structural equation modeling approach [64], was the technique chosen to test the research model. This decision is firstly based on the characteristics of the constructs included in our research model. These are composites. Therefore, as theoretical contributions [57,65] and empirical simulation studies [66,67] have demonstrated, the use of PLS is suitable when a composite measurement model is supported. In this case, the PLS path modeling estimates are consistent [68] and there is no bias [67]. Secondly, following Chin [69]. PLS is used because component scores are used in a subsequent analysis for modeling a multidimensional construct applying the two-stage approach [70]. Lastly, this study is mainly oriented to identifying key driver cultural constructs in order to predict a company's OA level [71].

The four culture variables have been modeled as composites and estimated in Mode B (regression weights). Given the original instrument used, an additive operation in order to generate scores by each type of culture and where the existence of correlated items or internal consistency was not presupposed, it was decided to apply Mode B as the estimation method for the culture variables. On the other hand, Mode A was selected for the OA variable, both at the dimension and the second-order construct level. Mode A used correlation weights, which is advisable for the estimation of standardized regression coefficients in small to medium samples and when the indicators are correlated [66]. Finally, SmartPLS 3.2.7 software was used [72].

3.4. Common Method Bias

Common method bias (CMB) refers to the difference between the trait score and measured score that is attributed to the use of a common method to take more than one measurement of the same or different traits [73]. Therefore, CMB could imply a threat in social science research given that bias may affect findings, due to systematic errors [74]. Consequently, it has been attempted to prevent CMB during the research design phase by applying the procedural remedies proposed by Podsakoff, MacKenzie and Podsakoff [75]. In addition, a statistical technique was used to detect a potential CMB situation. This was a full collinearity test based on variance inflation factors (VIFs) [76]. The guidelines followed were those described by Kock and Lynn [77], who proposed such a test in order to assess both vertical and lateral collinearity. Kock [76] indicates that when a VIF achieves a value greater than 3.3, there would be an indication of pathological collinearity. This would warn that a model may be contaminated by CMB. The present model, with a maximum VIF of 2.11 (Table 1), may be considered free of CMB.

Table 1. Full collinearity VIFs.

Variables	Clan Culture	Adhocracy Culture	Market Culture	Hierarchy Culture	Organizational Agility	Age	Size
VIF	2.01	2.11	1.44	1.70	1.83	1.15	1.16

4. Results

4.1. Measurement Model

When the measurement model is assessed, composites estimated in Mode A and Mode B are distinguished. Consequently, the OA construct which has been estimated in Mode A is evaluated. Since this multidimensional construct is an artifact (design construct), it is expected that the indicators (or dimensions) of the composites will be correlated [59]. This means that traditional measures of internal consistency, reliability and validity can be applied [58]. Both indicators and dimensions generally have loadings above 0.7. Consequently, the individual item reliability is considered satisfactory (Table 2). Additionally, both dimensions and the high order construct, achieve composite reliability (CR) figures greater than 0.7 (Table 2). This means that these variables meet the CR requirement. The average variance extracted (AVE) is used to evaluate the convergent validity. All the constructs and dimensions satisfy this criterion since their AVEs exceed the 0.5 level (Table 2). Finally, it can be observed that the OA construct attains discriminant validity. This is achieved by applying the Fornell-Larcker criterion [78] (Table 3). This means that this multidimensional construct differs from the other constructs.

On the other hand, the four cultural variables have been estimated in Mode B. Therefore, these composites are assessed on two levels, at the construct (discriminant validity) and at the indicator level (multicollinearity and weight assessment). Urbach and Ahlemann [79] propose an easy way to assess discriminant validity using inter-construct correlations. If correlations between the composites and all other constructs are less than 0.7, then the constructs differ sufficiently from one another. This is the case here (Table 2). On the other hand, at the indicator level, the analysis is started by testing potential multicollinearity between items [64]. Petter, Straub and Rai [80] indicate that a variance inflation factor (VIF) statistic, greater than 3.3, signals a high multicollinearity. Here, the maximum VIF value for indicators came to 2.6, below this threshold. Next, the magnitude and significance of the weights were checked (Table 2). Weights provide information about how each indicator contributes to the respective composite [81]. Hence, they allow indicators to be ranked according to their contribution. Also, a significance level of at least 0.05 suggests that a measure is relevant for the construction of the composite construct [64].

Table 2. Measurement model results.

Construct/*Dimension*/Indicator	**Weight**	**Loading**	**CR**	**AVE**
Clan culture (Composite, Mode B)			n.a.	n.a.
The organization is a very personal place. It is like an extended family. People seem to share personal information.	−0.099	0.205		
The leadership in the organization is generally considered to exemplify mentoring, facilitating or nurturing.	0.181	0.662		
The management style in the organization is characterized by teamwork, consensus and participation.	0.252	0.814		
The glue that holds the organization together is loyalty and mutual trust. Commitment to this organization runs high.	0.144	0.726		
The organization emphasizes human development. Greater trust, openness and participation persist.	0.091	0.796		
The organization defines success on the basis of the development of human resources, teamwork, employee commitment and concern for people.	0.560 *	0.926		
Adhocracy culture (Composite, Mode B)			n.a.	n.a.
The organization is a very dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.	0.479 *	0.860		
The leadership in the organization is generally considered to exemplify entrepreneurship, innovation or risk taking.	0.236	0.787		
The management style in the organization is characterized by individual risk taking, innovation, freedom and uniqueness.	−0.237	0.527		
The glue that holds the organization together is commitment to innovation and development. There is an emphasis on being cutting edge.	0.172	0.804		
The organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued.	0.327 *	0.774		
The organization defines success on the basis of having the most unique or newest products. It is a product leader and innovator.	0.204	0.671		

Table 2. *Cont.*

Construct/*Dimension*/Indicator	Weight	Loading	CR	AVE
Market culture (Composite, Mode B)			n.a.	n.a.
The organization is very results-oriented. A major concern is with getting the job done. People are very competitive and achievement-oriented.	0.532 *	0.750		
The leadership in the organization is generally considered to exemplify a no−nonsense, aggressive, results-oriented focus.	−0.082	0.455		
The management style in the organization is characterized by hard-driving competitiveness, high demands and achievement.	−0.304	0.444		
The glue that holds the organization together is the emphasis on achievement and goal accomplishment.	0.711 *	0.867		
The organization emphasizes competitive actions and achievements. Hitting stretch targets and winning in the marketplace are dominant.	−0.072	0.503		
The organization defines success on the basis of winning in the marketplace and outpacing the competition. Competitive market leadership is key.	0.310	0.622		
Hierarchy culture (Composite, Mode B)			n.a.	n.a.
The organization is a very controlled and structured place. Formal procedures generally govern what people do.	−0.296 *	0.251		
The leadership in the organization is generally considered to exemplify coordination, organization or smooth-running efficiency.	0.634 *	0.849		
The management style in the organization is characterized by security of employment, conformity, predictability and stability in relationships.	0.018	0.421		
The glue that holds the organization together is formal rules and policies. Maintaining a smooth-running organization is important.	0.261	0.649		
The organization emphasizes permanence and stability. Efficiency, control and smooth operations are important.	−0.009	0.498		
The organization defines success on the basis of efficiency. Dependable delivery, smooth scheduling and low-cost production are critical.	0.468 *	0.776		
Organizational agility (Multidimensional construct, Mode A) Relative to our competitors . . .			**0.922**	**0.797**
Operational agility (Composite, Mode A)	***0.337 ****	***0.869***	***0.911***	***0.773***
We fulfill demands for rapid-response, special requests of our customers whenever such demands arise. Our customers have confidence in our ability.	0.356 *	0.859		
We can quickly scale up or scale down our production/service levels to support fluctuations in demand from the market.	0.364 *	0.885		
Whenever there is a disruption in supply from our suppliers we can quickly make necessary alternative arrangements and internal adjustments.	0.416 *	0.894		
Customer agility (Composite, Mode A)	***0.420 ****	***0.951***	***0.912***	***0.776***
We are quick to make and implement appropriate decisions in the face of market/customer changes.	0.353 *	0.857		
We constantly look for ways to reinvent/reengineer our organization to better serve our market place.	0.401 *	0.904		
We treat market-related changes and apparent chaos as opportunities to capitalize quickly.	0.380 *	0.881		
Partnering agility (Composite, Mode A)	***0.360 ****	***0.856***	***0.884***	***0.610***
We collect detailed information about our suppliers and service providers.	0.303 *	0.856		
We are able to exploit the resources and capabilities of suppliers to enhance the quality and quantity of products and services.	0.293 *	0.888		
We work with external suppliers to create high-value products and services.	0.254 *	0.832		
We are able to manage relationships with outsourcing partners.	0.270 *	0.761		
We can switch suppliers to avail ourselves of lower costs, better quality or improved delivery times.	0.125 *	0.510		

Notes: CR: Composite reliability. AVE: Average variance extracted. n.a.: non-applicable. *: significant at $p < 0.05$ (2 tails).

Table 3. Measurement model. Discriminant validity.

	Clan Culture	Adhocracy Culture	Market Culture	Hierarchy Culture	Organizational Agility	Age	Size
Clan culture	**n.a.**						
Adhocracy culture	0.670	**n.a.**					
Market culture	0.410	0.468	**n.a.**				
Hierarchy culture	0.582	0.489	0.462	**n.a.**			
Organizational agility	0.575	0.610	0.440	0.563	**0.893**		
Age	0.145	0.126	0.216	0.134	0.143	**n.a.**	
Size	0.170	0.163	0.221	0.130	0.131	0.327	**n.a.**

Note: Diagonal elements (bold) are the square root of the variance shared between the constructs and their measures (AVE). Off-diagonal elements are the correlations between constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements. n.a.: Non-applicable.

4.2. Structural Model

Table 4 shows the explained variance (R^2) in the OA variable and the direct effects included in our research model. Bootstrapping (5000 samples) provides t-values and confidence intervals that enable the assessment of the relationships' statistical significance [64]. Thus, two of the hypothesized relationships (H1 and H2) are supported, whereas H4 (-) is not supported as there is a significant relationship but with an opposite sign, regarding the sign postulated. Finally, market culture (H3) has a non-significant effect on the endogenous variable. In this vein, market culture shows an extremely low f^2 value, under the minimum level of 0.02. Moreover, the control variables show negligible (see magnitude and f^2 values) and non-significant effects on OA (Table 4).

Furthermore, the coefficient of determination (R^2) is examined to assess the predictive power (in-sample prediction) for OA as the endogenous construct [69] (Table 4). Hence, OA achieves an explained variance of 0.485, which surpasses the moderate level (0.33) set up by Chin [81]. The model has also been evaluated by analyzing the cross-validated redundancy index (Q^2) for the dependent variable. A Q^2 greater than 0 implies that the model shows predictive relevance. In our case, the structural model obtained satisfactory predictive relevance for OA (Table 4).

Finally, we have carried out a multi-group analysis [82] in order to test the potential moderating influence of the industry's technology intensity on the relationships included in our research model. Accordingly, the sample was split into two groups, high and medium technology firms. As a first step, the three-step procedure to analyze the measurement invariance of composite models was applied (MICOM) [58]. Establishing the measurement invariance of composites will allow it to be ensured that the effect of the industry's technology intensity is restricted to the path coefficients of the structural model and not to the parameters of the measurement model. As Table 5 describes, the full measurement invariance of both groups was achieved for all the variables. Then, the permutation-based procedure developed by Chin and Dibbern [83] was applied, which represents a non-parametric approach to conduct multi-group analyses. As Table 6 illustrates, no significant differences were detected in the direct effects considered, although different results were obtained in both groups. Consequently, neither of the moderating hypotheses is supported.

Table 4. Effects on the endogenous variable.

	Direct Effect	*p*-Value	*t*-Value	CI	Support	Explained Variance	f^2
Organizational agility (R^2 = 0.485/Q^2 = 0.340)							
H1(+): Clan culture	0.162	0.018	2.099	[0.052; 0.307]	Yes	9.3%	0.023
H2(+): Adhocracy culture	0.327	0	4.609	[0.209; 0.444]	Yes	20.0%	0.104
H3(+): Market culture	0.096	0.083	1.383	[−0.005; 0.229]	No	4.2%	0.012
H4(-): Hierarchy culture	0.263	0.001	3.175	[0.122; 0.393]	No	14.8%	0.080
Control variables							
Age	0.027	0.663	0.436	[−0.097; 0.144]	No		0.001
Size	−0.014	0.783	0.275	[−0.110; 0.087]	No		0.000

Notes: CI: Percentile confidence interval. Bootstrapping based on n = 5000 subsamples. Hypothesized effects are assessed by applying a one-tailed test for a t Student distribution (CI 90%). Effects from control variables are assessed by applying a two-tailed test (CI 95%).

Table 5. Results of the measurement invariance of composite models (MICOM) procedure.

	Step 1	Step 2			Step 3a				Step 3b				
	Compositional Invariance				Equal Variances				Equal Means				
Construct	**Configural Invariance**	**Original Correlation**	**5%**	**Partial Measurement Invariance Established**	**Variance—Original Difference (HT-MT)**	**2.5%**	**97.5%**	**Equal**	**Mean—Original Difference (HT-MT)**	**2.5%**	**97.5%**	**Equal**	**Full Measurement Invariance Established**
CC	Yes	0.959	0.747	Yes	0.072	−0.444	0.470	Yes	−0.090	−0.297	0.296	Yes	Yes
AC	Yes	0.862	0.759	Yes	0.165	−0.405	0.414	Yes	−0.022	−0.304	0.295	Yes	Yes
MC	Yes	0.632	0.456	Yes	0.118	−0.414	0.418	Yes	−0.131	−0.294	0.298	Yes	Yes
HC	Yes	0.819	0.662	Yes	0.044	−0.454	0.462	Yes	−0.047	−0.302	0.303	Yes	Yes
OA	Yes	0.999	0.998	Yes	0.242	−0.502	0.508	Yes	−0.290	−0.306	0.313	Yes	Yes
Age	Yes	1	1	Yes	-0.436	−0.740	0.757	Yes	−0.415	−0.295	0.296	Yes	Yes
Size	Yes	1	1	Yes	1.262	−2.499	2.498	Yes	0.102	−0.292	0.274	Yes	Yes

Notes: CC: clan culture; AC: adhocracy culture; MC: market culture; HC: Hierarchy culture; OA: organizational agility. HT: high technology subsample; MT: medium technology subsample.

Table 6. Direct effects for high and medium technologies subsamples. Multi-group analysis based on permutation test.

Direct Effects on Endogenous Variable	**HT**			**MT**			**Permutation**	**Significant**
	R^2	**Direct Effect**	**p-Value**	**R^2**	**Direct Effect**	**p-Value**	**p-Value**	
OA	**R^2 = 0.541**			**R^2 = 0.523**			**0.803**	**No**
Clan culture		0.094	0.181		0.281	0.005	0.111	No
Adhocracy culture		0.356	0.000		0.305	0.004	0.363	No
Market culture		0.015	0.443		0.171	0.081	0.136	No
Hierarchy culture		0.389	0.001		0.161	0.065	0.096	No
Control variables								
Age		0.054	0.521		−0.080	0.384	0.336	No
Size		−0.024	0.780		−0.029	0.608	0.972	No

Notes: OA: organizational agility. HT: high technology subsample; MT: medium technology subsample. Bootstrapping based on n = 5000 subsamples. Sig.: Significant. Multi-group test based on 5000 permutations. One-tailed test for group comparisons for hypothesized effects. Two-tailed test for group comparisons for effects from control variables and R^2.

4.3. Assessment of the Predictive Validity Using Holdout Samples

The predictive power of a model is a model's ability to generate accurate predictions of new interpretable observations, temporal or cross-sectional [84]. Predictive validity indicates that a given set of measures of a particular construct can predict a given outcome variable [85]. Predictive validity (out-of-sample prediction) was evaluated using cross-validation with holdout samples. Specifically, this study applies the approach suggested by Shmueli et al. [86], where using the current PLS predict algorithm in the SmartPLS software version 3.2.7. [72], *k*-fold cross-validated prediction errors and prediction error summaries statistics were obtained, such as the root mean squared error (RMSE) and the mean absolute error (MAE), to assess the predictive performance of their PLS path model for the indicators and the constructs. On the basis of these statistics, the two new benchmarks developed by the SmartPLS team were used in order to assess the predictive performance of a specific PLS path model [87]:

(1) The Q^2 value, which compares the prediction errors of the PLS path model against simple mean predictions. If the Q^2 value is positive, the prediction error of the PLS-SEM results is smaller than the prediction error of simply using the mean values. Accordingly, the PLS-SEM model offers an appropriate predictive performance. This is the case here at three levels (Table 7), at the construct (i.e., OA), at the dimension (operational, customer and partnering variables) and at the indicator levels.

(2) The linear regression model (LM) approach regresses all exogenous indicators on each endogenous indicator to generate predictions. In comparison with the LM outcomes, the PLS-SEM results should have a lower prediction error (e.g., in terms of RMSE or MAE) and greater Q^2 values, than the LM. This would mean a theoretically established path model improves (or at least does not worsen) the predictive performance of the available indicator data. Once again, this is the scenario for our model. The RMSE and MAE values for the PLS model are lower than for the LM. In addition, the Q^2 values for the indicators of the PLS model are larger than those generated for the LM model (Table 7).

Table 7. PLS predict assessment.

Construct Prediction Summary									
	Q^2								
OA	0.334								
Dimension Prediction Summary									
	Q^2								
OpA	0.086								
CA	0.339								
PA	0.162								
Indicator Prediction Summary									
	PLS			LM			PLS−LM		
	RMSE	MAE	Q^2	RMSE	MAE	Q^2	RMSE	MAE	Q^2
OpA_1	1.149	0.903	0.133	1.219	0.974	0.023	−0.07	−0.071	0.11
OpA_2	1.16	0.917	0.14	1.238	0.942	0.02	−0.078	−0.025	0.12
OpA_3	1.141	0.897	0.208	1.245	0.967	0.057	−0.104	−0.07	0.151
CA_1	1.187	0.927	0.228	1.261	0.997	0.128	−0.074	−0.07	0.1
CA_2	1.175	0.937	0.331	1.271	0.999	0.217	−0.096	−0.062	0.114
CA_3	1.094	0.864	0.305	1.171	0.914	0.204	−0.077	−0.05	0.101
PA_1	1.355	1.106	0.228	1.465	1.162	0.098	−0.11	−0.056	0.13
PA_2	1.248	1.015	0.206	1.336	1.084	0.089	−0.088	−0.069	0.117
PA_3	1.373	1.092	0.146	1.5	1.191	−0.02	−0.127	−0.099	0.166
PA_4	1.255	1.011	0.184	1.389	1.12	−0.001	−0.134	−0.109	0.185
PA_5	1.59	1.302	0.014	1.713	1.359	−0.145	−0.123	−0.057	0.159

Notes: OA: Organizational agility; OpA: Operational agility; CA: Customer agility; PA: Partnering agility. RMSE: Root mean squared error. MAE: Mean absolute error. PLS: Partial least squares path model; LM: Linear regression model.

Next, with the invaluable help of the research team led by Galit Shmuelit at the National Tsing Hua University (Taiwan), it was attempted to assess the predictive validity of our model focusing on the "overfit" issue. Is the model fit too specifically to training data or will the model perform comparably with new data? In order to offer a response, in-sample versus out-of-sample predictions were compared to actual composite scores. With this aim in mind, the following steps were followed [88]:

(1) The actual composite scores for organizational agility (OA) were estimated for all cases, by estimating the model on the whole sample (n = 172).
(2) In-sample predictions for OA composite scores were calculated using a k-fold (k = 10) cross-validation procedure. The in-sample RMSE was than calculated by comparing each case's in-sample predicted OA score, versus its actual OA score.
(3) Out-of-sample predictions for OA composite scores were obtained using a k-fold cross-validation procedure (where k = 10). The out-of-sample RMSE was then calculated by comparing each case's out-of-sample predicted OA score, versus its actual OA score.

Using this procedure, the following metrics were given for the composite OA: In-sample RMSE: 0.708; Out-of-sample RMSE: 0.795. Given that the composite scores are normalized and have mean 0 and variance 1, RMSE can be interpreted in the sense of a standard deviation. The difference between in-sample and out-of-sample RMSE of 0.09 is less than a tenth of a standard deviation. Since the difference in RMSE is not substantial, overfit is not a problem for this study. The density plots of the in-sample and out-of-sample residuals are provided in Figure 3.

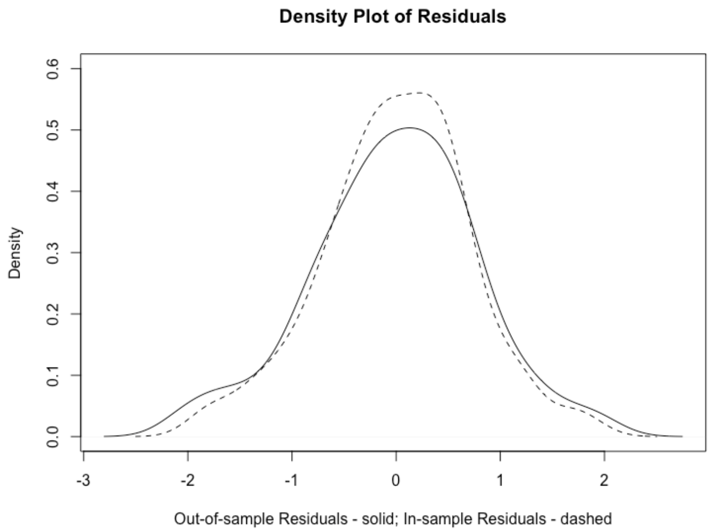

Figure 3. Density plots of the in-sample and out-of-sample residuals.

Consequently, as a result of the different analyses shown above, this work finds enough evidence that supports the predictive validity (out-of-sample prediction) of our research model, in order to predict values for new cases of OA. Therefore, the four cultural values together with the controls can predict the OA in additional samples that are separate from the dataset used to test the theoretical research model [89]. As a result, this predictive validity offers an additional support for the research model tested in this work.

5. Discussion

Quick technological updates, increased risks and challenges due to globalization, environmental awareness and an amplified desire for customization, are some of the features intrinsic to the business setting that most companies have to face these days [90]. To remain successful within such a context, OA may bring firms a competitive advantage that should be sustained through maintaining a good reputation for innovation, excellence and sustainability [12]. In this way, agile organizations combine their business processes and human capital with advanced technology, to satisfy clients' demands for customized, excellent and more sustainable products and services in a rather short time frame [91].

It can therefore be assumed that OA facilitates the firm's adaptation and quick response and is currently related to business success. In fact, OA has turned out to be more an imperative for organizational subsistence than a choice in itself [1]. Nevertheless, the academic sphere is asking for a more exhaustive assessment of this phenomenon. According to Chan et al. [92], due to the high complexity underlying the OA concept, its main drivers or antecedent variables require a much deeper research and supplementary empirical evidence. In this vein, our findings enable a richer understanding of the underlying effects that the distinct CVF OC typologies exert on OA.

An important finding deals with the positive effect found between adhocracy culture and OA. This is in line with prior related studies that have labelled agile organizations as highly adaptive and flexible. Actually, Sherehiy et al. [23] describe OA as a firm's ability to adjust and respond to changes in the environment, entailing a prevalence of external focus and change. This finding also fits with prior studies' empirical support of the adhocracy culture being an important precondition for innovation success [28]. The adhocracy culture, due to its lack of bureaucratization and complexity, enables the organization to be flexible and to rapidly reconfigure resources and processes. This fact provides a strong success basis for companies operating in dynamic environments.

This paper has also supported the clan culture's positive relationship with OA, though it is not as strong as that of the adhocratic type. An explanation of this result can be found in the clan's deep focus on internal aspects (loyalty, teamwork, shared goals and values) that would lead to relaxing the vigilance of environmental dynamics. However, this clan culture gathers together management practices and values that are intrinsically linked to what an agile organization must be: managers who enable self-organizing teams, different ways of coordinating work (dynamic linking), continuous improvement, radical transparency and communication awareness [93].

On the other hand, contrary to expectations, this study did not find a negative link between hierarchy culture and OA but a positive significant effect. This finding was certainly unexpected and suggests that certain features inherent to hierarchy culture lead to more agile organizations. We believe that this is an interesting finding, since it denotes that although adaptability and flexibility are fundamental features that shape agile organizations, these firms may also benefit from a certain degree of stability, control and order, especially in a scenario of crisis and uncertainty, such as that in which the empirical study was conducted. Precisely, in a time of crisis, an upper-level decision provides a faster response to any threat or critical situation than a lower-level decision, which would require too much time [1]. In this sense, some of the characteristic values that shape hierarchy culture are in line with some of the requirements that customers and stakeholders are demanding from firms within the environment described above. On occasions, in these circumstances, a company has performed better than its industry competitors over a sustained period of time on the basis of a strong culture focused on keeping their customers satisfied, while remaining efficient and controlling their costs [94]. Consequently, the presence of a solid and developed array of formalized structures and procedures, along with precise coordination mechanisms, may also become critical aspects when attempting to boost OA in such circumstances. Accordingly, certain aspects inherent to the attainment of OA will benefit from a certain degree of formalization, standardization and stability, typical of this cultural typology. Nevertheless, it must not be forgotten that although hierarchy culture may lead to short-term success, it may also hinder an organization's long-term capability to change, adapt, or innovate [94].

No evidence was found for the positive effect of the market culture on OA, contrary to what had been hypothesized. A priori, its external focus on markets and customers' needs could lead to improvement of the company's capability to capture external information and leverage it in order to offer agile responses and seize emerging opportunities. Yet, its emphasis on control and stability rather than flexibility would limit this effect. This result is in line with previous studies that have empirically tested that market culture has no significant effect on innovation [95].

Moreover, the results have confirmed none of the environmental contingency hypotheses related to the technology intensity of the industry, in the CVF typologies—OA relationship. Although there are slight differences between the two industries considered (high-tech and medium-tech), the effect is not statistically significant. This fact may indicate that the impact of the internal organizational factors regarding culture on OA is sound. Every effort that the organization makes to promote cultural values which enhance OA will be effective, regardless of the R&D intensity of the sector. To prepare the organization internally and the people who integrate it to better face environmental challenges, become key points in organizational strategy. It is clear that "change is much easier if a culture exists that embraces change" [31] (p. 26). Another reason that could sustain this result is that, currently, differences between the two groups (high tech and medium tech industries) are not so significant, as new technology developments have narrowed the gap between them. As the ODCE's scale shows four different groups (high, medium-high, medium-low and low), results could have differed if the sample had been selected according to more technologically separate groups (high and medium-high versus medium-low and low).

Finally, the model has shown a predictive power for the sample used in the study. In addition, enough evidence was found that supports the predictive validity (out-of-sample) of our model. The model of four cultural typologies is an adequate predictor of OA. This means that our model provides much more information than noise [89]. Therefore, those four cultural types are able to accurately predict the OA variable in new interpretable observations, both in a temporal and cross-sectional manner. As a result, the satisfactory level of predictive power achieved helps to support the research model proposed [85].

6. Conclusions

In brief, this work is among the scant empirical studies that aim to clarify the links between OC typologies and OA. Hence, a theoretical model was developed which combines Cameron and Quinn's [14] CVF of OC typologies with literature on OA. Our results stress the positive influence that adhocracy, clan and hierarchy culture exert on OA. These findings provide some support for the conceptual premise that the four cultural typologies are just ideal categories, meaning that a company is rather unlikely to, in isolation, reflect one single typology [96,97]. Indeed, the CVF theorists suggest a reasonable equilibrium between reverse focuses, although certain cultural aspects may be predominant. Agile methods illustrate this need for a reasonable balance between different but complementary cultural approaches, successful firms usually concentrate on a diversified mix of values and cultures [19].

These findings may help managers to understand the importance of adapting their firms' corporate culture to the aspiration of becoming more effective and agile organizations. Therefore, although we are aware of the significance of contextual factors [98] and accept that the promotion of an ideal culture typology that could be endorsed and effective in a particular context is certainly utopian, our findings advocate that certain foundations intrinsic to adhocracy and hierarchy culture are actual drivers of OA. Consequently, we praise those managers who aim to improve their companies' level of agility to combine the empowerment and knowledge sharing inclination, intrinsic to adhocracy culture, with the rigorous formalization and coordination mechanisms that characterize hierarchy culture.

The generalizability of these results is subject to certain limitations. For instance, we acknowledge that we only relied on managers' perceptions and failed to collect data from other groups within the company. Hence, we are unable to check the possible presence of different subcultures. Second, this paper only contemplates companies operating within a single geographical context (Spain). Therefore, extrapolating these results to different contexts must be approached with some caution. Third, this is a cross-sectional study that only analyzes the relationships at a static moment and fourth, the moderation effects of technology intensity need to be assessed from different industry groupings that will reflect more diverse technological contexts.

In conclusion, contemporary, non-peaceful and uncertain business contexts, are increasingly leading companies to face huge challenges, not only to remain successful but also to subsist. In these settings, scholars and managers are starting to internalize the central role of OA. Nevertheless, further research should be undertaken to investigate the main drivers or antecedents of OA and much needs to be explored with regard to the concrete actions and internal mechanisms underlying agility.

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