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Identificación de las capacidades de innovación de las empresas de Tecnologías de la Información y Comunicación en el contexto de un país emergente*

Identifying The Innovation Capabilities of Information and Communication Technologies Companies in the Context of an Emerging Country

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Resumen: En años recientes, la sociedad y la economía han experimentado cambios significativos que han requerido que las organizaciones se reinventen y se adapten a nuevas metodologías y procesos, lo cual se logra a través de la innovación. A pesar de los avances en tecnologías de información y comunicación (TIC), las empresas de este sector no siempre reconocen la necesidad de incorporar la innovación en áreas más allá del desarrollo y la infraestructura de las TIC. Este estudio se enfoca en evaluar las capacidades de innovación de

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empresas medianas que ofrecen Servicio de Gestión de Tecnología de la Información (ITSM) en el sector de las TIC en Medellín, Colombia, mediante un modelo de ecuaciones estructurales. Los resultados señalan que solo siete de las 42 variables del modelo obtuvieron resultados inferiores al umbral normal. Estas siete variables incluyen la evaluación de la marca corporativa, el desarrollo sostenible y la capacidad de improvisación. El sector de TIC se encuentra en constante innovación debido a su enfoque en el desarrollo y provisión de servicios relacionados con la tecnología y la Industria 4.0. El modelo propuesto puede contribuir a la evaluación de dichas capacidades y alcanzar ese objetivo.
Palabras clave: Sector TIC; modelado de ecuaciones estructurales; Industria 4.0; capacidades de innovación, país emergente.

Abstract: In recent years, the rapidly changing landscape of society and the economy has compelled organizations to adapt and innovate. Information and communication technologies (ICTs) have seen significant advancements in hardware and software. However, many companies within the ICT sector often overlook the need to infuse innovation into areas beyond ICT development and infrastructure. This study evaluates the innovation capabilities of medium-sized enterprises providing Information Technology Service Management (ITSM) in Medellín, Colombia. Utilizing a structural equation model, the study examined causal variables related to competitiveness and innovation capacity. Of the 42 variables considered, seven, including corporate branding evaluation, sustainable development, and improvisation capability, showed results below the normal threshold. The ICT sector, focused on the development and provision of technological and Industry 4.0-related services, continuously evolves. This model contributes to assessing and achieving that objective.
Keywords: ICT sector; structural equation modelling; industry 4.0; innovation capabilities, emerging country.

1. INTRODUCTION

Information and communications technologies have been an essential part in the development of society and the economy in recent years (Zambrano, 2020). This has been more evident since the beginning of the COVID-19 pandemic (Kitukutha et al., 2021) because society needed to adapt to a different daily life and carry out different regular activities through information and communications technologies (Zimmerling & Chen, 2021). As a result, the demand for this type of services has increased worldwide. However, society was not ready for this, and change and adaptation had to be immediate (Kwon et al., 2021). In 2016, according to The World Bank (2018)the global digital economy was worth usd 11.5 trillion, i.e., 15.5% of the world's gdp. This figure is expected to reach 25% in less than a decade. In Colombia, there are approximately 4,016 firms performed telecommunications and software development activities in 2014 (MINTIC et al., 2015). Most of these companies are located in the central region of the country (García Pineda & Macías Urrego, 2021), of these regions, Antioquia concentrates a large part of these companies, with most of them (80%) headquartered in the city of Medellín (SENA et al., 2015).

Therefore, ICT organizations have become essential service and product providers because they are responsible for the activities, development, and tools that facilitate the operation of other organizations in economic and social sectors (Zimmerling & Chen, 2021). Consequently, ICT organizations should constantly keep up to date and pay attention to different demands they should meet and changes they should make in order to adapt, innovate, be competitive in the market (Adeosun & Shittu, 2021; Essmann & Preez, 2010), and, therefore, avoid obsolescence (Hari et al., 2014). This, given the importance of small and medium-sized companies in developing countries, mainly those that offer ICT services, which is why the development of innovation capacities is vital for the sector and the country's sustainability (Adeosun & Shittu, 2021). To innovate, these companies should establish the competencies, abilities, and knowledge they have to develop their innovation capabilities. The foregoing, both with the intention of being competitive in the market, as well as being able to establish agile strategies that allow them to adapt to future changes quickly (Bhāle, 2020).

Hence, ICT organizations should clearly identify their innovation capabilities and utilize them to gain dynamic competitive advantage (Barrales et al., 2015; Tang & Chi, 2011), the foregoing through different frameworks, recommendations or establishment of strategies that also allow them to adequately evaluate their innovation capacity in order to establish strategies for an adequate obtaining and use of financing resources for innovation (Giménez, 2020). They can also take advantage of the knowledge that all the actors that collaborate with them possess and acquire (Boscherini et al., 2003; Gutierrez et al., 2018) and then generate different strategies to create and produce value-added services (Ferrer, 2007).

In addition, to make use of the different resources and prevalence that have been given to the ICT sector due to its growth in an emerging economy such as Colombia, where different companies are based on the innovations, activities and strategies implemented by large ICT companies from First World countries (Adeosun & Shittu, 2021; Fan et al., 2019). However, these organizations do not always manage to obtain innovative results, although their nature is technology-based and their products are related to ICT, sometimes they do not manage to establish strategies that allow them to innovate in their services or in their processes since they do not know the best methods, strategies and even the elements with which they can acquire capacity for innovation and dynamism. On the other hand, being medium-sized companies, they do not always have the resources to be able to innovate, nor do they have the economic, political or social support (Palma & Guzmán, 2023).

This paper aims to evaluate the innovation capabilities of medium-sized enterprises that provide Information Technology Service Management (ITSM) in the ICT sector in Medellín using causal variables of competitiveness and structural evaluation modeling (SEM). This given that, as stated by Adeosun & Shittu, 2021; Bhāle, 2020; Giménez (2021; 2020; 2020), although innovation capacities have been widely studied even in the ICT sector, there is still a gap in the literature for the study of them in this sector in countries with emerging economies. A structural equation model was designed based on the constituent variables of innovation capabilities

(ICs) proposed by Yam et al. (2004a) and causal variables of ICs obtained from a literature review. In addition, a survey was administered to a group of companies that provide ITSM in Medellín.

The document initially presents a context of theoretical capabilities on technology innovations and industry 4.0, detailing the variables related to the research topic. the methodology is presented, where the method used to obtain the data and the sample is concisely indicated, then the methodology used for the development of the model of structural structures is presented. Then, the results are presented and finally the conclusions.

2. Literature Review

2.1 Technological innovation capabilities

Innovation has been defined by Schumpeter as the main promoter of capitalist development and one of the main drivers of the profits obtained by companies (Freeman & Soete, 1997). In addition, innovation is one of the greatest generators of knowledge, as well as competitive advantage (Arredondo et al., 2016). In order to obtain innovative results, organizations should have the competencies, abilities, and capabilities required to innovate. These capabilities have been defined by different authors. According to (Burgelman et al., 2008), technological innovation capabilities (TICs) are a group of characteristics of an organization that facilitate the generation of technological innovation strategies. Yam et al. (2004b, p. 1124) defined these capabilities as "a comprehensive set of characteristics of an organization that facilitates and supports its technological innovation strategies". Osorio et al. (2014) defined them as abilities developed by organizations based on their daily activities that enable them to acquire the capability to innovate.

However, for TICs to properly work and guide an organization's innovation strategy, its activities and resources should be adequately articulated and work together; more specifically, its special resources, e.g., technology, product, process, knowledge, experience, and organization (Guan & Ma, 2003). In this regard, organizations dedicated to ICT should make greater efforts to conserve resources focused on knowledge (Gutierrez et al., 2018). This refers to the brain drain that widely affects countries in emerging economies (Adeosun & Shittu, 2021). This should allow organizations to coordinate their innovation strategy with their technological strategy and research and development (R&D) activities (Yam et al., 2004a).

Different authors have proposed groups of capabilities that compose innovation capability. Yam et al. (2004b) listed seven: learning capability, R&D capability, resources allocation capability, manufacturing capability, marketing capability, organizing capability, and strategic capability. In turn, Wang, Lu, and Chen (2008) referred to five constituent capabilities: R&D capabilities, innovation decision capabilities, marketing capabilities, manufacturing capabilities, and capital capabilities. Finally, (Robledo et al., 2010), based on the study by Yam et al. (2004b), proposed seven capabilities: strategic direction, R&D, manufacturing, marketing, organizational learning, resource management, and networking. Said capabilities are defined according to what was proposed by Yam et al. (2004b), as follows:

- Learning capability: understanding and applying knowledge in the organization.
- R&D capability: the ability to integrate the R&D strategy with the implementation of projects and the innovation management portfolio.
- Resources allocation capability: the ability to properly devote resources to activities aimed at innovation.
- Manufacturing capability: the ability to transform the results obtained from R&D activities into services and products that respond to the market needs and innovate at the same time.
- Marketing capability: an organizations' ability to offer its products and services according to the needs of the environment and innovation acceptance.
- Organizing capability: the ability to maintain harmony in the organization.
- Strategic capability: the ability to identify strengths, weaknesses, opportunities, and threats according to the objectives of the organization and adjust them to its strategic implementation plans.

Among them, R&D capability is the one that generates innovative results through research and the implementation of different activities. The resources allocation capability facilitates the allocation of strategically oriented capital and resources to projects aimed at innovation (Yam et al., 2004a).

2.2. Industry 4.0

The technological advances witnessed by mankind have marked different eras for the industry and the economy, and an increasingly faster progress has seen the rise and fall of different technologies—from steam-powered machines to the birth of the internet, Wi-Fi technology, and Bluetooth. The introduction of important technologies for the global economy has brought along industrial revolutions—from the first industrial revolution to what is currently known as the Fourth Industrial Revolution or Industry 4.0. "The term "Industry 4.0" was first coined by the German government in 2013 as a strategic plan by Industry Science Research Alliance in partnership with Acatech" (Ellahi et al., 2019).

The objective of Industry 4.0 is that new technologies are developed by organizations in the ICT sector because the latter advances hand in hand with the digital economy. Two of the most important components for the development of this industry are electronics and informatics. They facilitate the progress and implementation of activities in different economic sectors because the industries understand that it is increasingly necessary to implement innovative models, embedded systems, manufacture automatization, and artificial intelligence (Gutarra & Valente, 2018, p. 756) in order to improve organizational performance and productivity.

In addition, Industry 4.0 is considered a new industrial stage in which the integration of horizontal and vertical manufacturing processes and product connectivity can help companies achieve a better industrial performance (Dalenogare et al., 2018). According to Ghobakhloo (2020), different elements compose Industry 4.0, and they should be acknowledged and utilized by organizations for them to perceive the benefit that this industry provides in order to be sustainable. Said elements are the following:

- Business model novelty and innovation
- Carbon/harmful gas emission reduction
- Corporate profitability improvement
- Economic development
- Energy and resource sustainability
- Environmental responsibility development
- Human resource development
- Increased production efficiency and productivity
- Job creation
- Manufacturing cost reduction
- Manufacturing agility and flexibility
- Production modularity
- Product personalization
- Risk and safety management
- Supply chain digitization and integration
- Social welfare enhancement

In addition, due to the emergence of Industry 4.0 and the COVID-19 pandemic, the digitization of different sectors has been more noticeable, the use of smart devices has become more frequent, and more digital platforms and environments have been implemented to improve productivity, efficiency, and sustainability (Balogun et al., 2020). In order for organizations in the sector to address the previously described aspects, they should correctly implement innovation capabilities to develop and utilize an innovation strategy that enables them to fulfill the current demands of Industry 4.0. Thus, they can respond to the development and growth of the latter by adequately using tools and technologies such as hyper-connectivity and super-intelligence (Im et al., 2018).

It is necessary to understand that, in addition to the previously described aspects, Industry 4.0 is also based on tools and technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), Enterprise Architecture (EA), and

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Enterprise Integration (EI) (Dalenogare et al., 2018); other technologies such as blockchain, data science, and quantic computing; trends such as the orange economy (which are implemented, supported, and developed by the ICT sector); and topics such as digital economy, big data, and artificial intelligence (Bustamante & Guillén, 2017). Organizations in the ICT sector should implement and develop their innovation and R&D strategies based on these technologies (Otles & Sakalli, 2019; Fernández et al., 2024). Based on the above, the literature shows that Industry 4.0 is composed of eight constituent variables that are influenced by multiple causal variables (García & Macías, 2023).

3. RESEARCH METHODS

3.1. Data compilation

To compile the data, the ICT sector in Medellín was characterized based on information obtained from the database of the Departamento Administrativo Nacional de Estadística (DANE) in Colombia (García & Macías, 2023). As a result, a new database was created in Excel, where the data were classified using the CIIU code (version 4) and filtered using codes 61, 62, and 63, which correspond to companies that provide ITSM. Three other Colombian databases were consulted: Registo Único Empresarial (RUES), DIAN, and MUISCA. Data such as age, size, status, and registration city were used to confirm that the selected companies were medium-sized, complied with their legal obligations, and were actively operating. Applying the previous criteria, a total of 26 companies registered in Medellín were found.

Subsequently, considering a 95% confidence level and an error margin of 10%, the sample final sample included 21 companies. However, only 16 of them participated in the process by taking an online survey composed by 42 questions with a Likert scale. This instrument, which was previously validated by 16 experts in the field of ICTs, was administered to executives and project managers at the companies studied here.

3.2. Design of the structural equation modeling (SEM)

SEM can identify the effect and type of relationship between different variables. With this information, causal relationships between latent and measurement variables can be determined. (Escobedo et al., 2015). In other words, structural equation models present causal relationships between observable variables in a set, as well as between observable and non-observable variables (Álvarez & Vernazza, 2017). According to Escobedo et al. (Escobedo et al., 2015), these models resulted from the combination of two different perspectives, i.e., prediction and a psychometric approach, and their objective is to model concepts using latent (non-observable) variables and infer multiple observed measurements (manifest variables).

In this study, a path diagram (measurement sub-model) was created, and the model was established and defined in AMOS software. Afterward, a statistical descriptive analysis was conducted using SPSS Statistics software, and the factors were verified. Multiple can be applied strategies to identify the model; one of them is the degrees of freedom (DF) rule, where the following formula is used:

$$DF = \frac{(\#\, of\ observed\ variables) * (\#\, of\ observed\ variables\ +\ 1)}{2} - \#\, parameters\ to\ estimate \quad (1)$$

According to this, if the DF equal zero, the model has zero degrees of freedom and it is an identified model. However, although it presents an optimal fit for this study, it does not present significant relevance because the model cannot be generalized. An overidentified model is one in which the DF are greater than zero because its matrix presents more data than parameters to be estimated; this indicates positive degrees of freedom and that the model can be generalized (Cupani, 2012). In contrast, DF lower than zero mean that the model has not been fully identified and that the user is trying to estimate more parameters than there is information in the matrix. Therefore, the model should be applied constraints and reformulated (Ruiz et al., 2014).

4. RESEARCH RESULTS

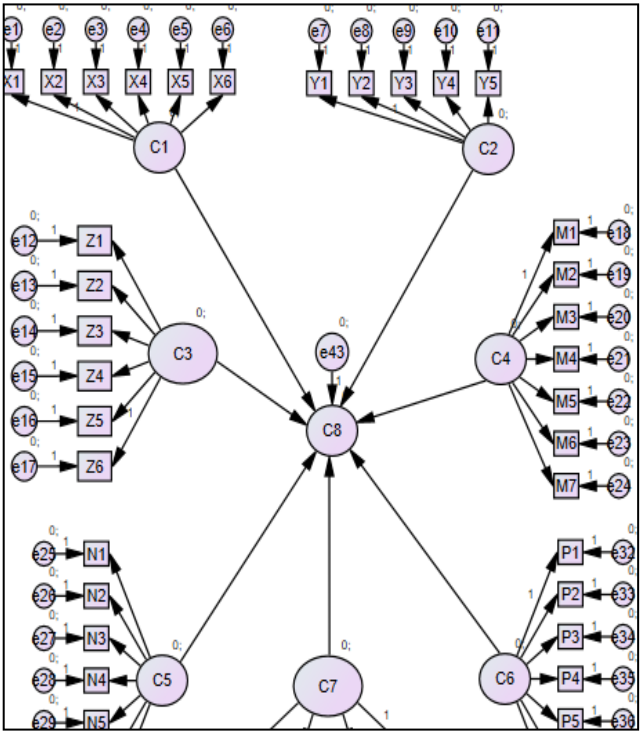
The results reported in this section were obtained by following the steps described in the methodology:

4.1. Model specification

The Structural Equation Model (SEM) designed here is based on the variables found in the literature. Said variables and their relationships were established to design the model in Figure 1, which shows eight latent endogenous variables and 42 observable variables. The model is composed of eight latent variables. Seven of them correspond to the innovation capabilities that were defined in previous sections, and the eight one represents innovation capability as a whole. The variables were named using the Ci set (from C1 to C7), as follows:

C1 = Learning capability
C2 = R&D capability
C3 = Resource allocation capability
C4 = Manufacturing capability
C5 = Marketing capability
C6 = Organizing capability
C7 = Strategic planning capability
C8 = Innovation capability

Figure 1. Measurement sub-model of the structural equation model



Source: Created by the authors

In addition, the 42 observable variables were distributed among the Ci, as follows:

The following observable variables, which have a causal relationship with C1, are in the Xj group (from X1 to X7):

X1 = Education
X2 = Innovation capability
X3 = Knowledge transfer
X4 = Intellectual capital
X5 = Obsolescence
X6 = Technology prospecting

The following observable variables, which have a causal relationship with C2, are in the Yj group (from Y1 to Y5):
Y1 = Technological innovation capability
Y2 = Social innovation
Y3 = Innovation performance
Y4 = Industry 4.0 technologies (blockchain, data science, and quantic computing)

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Y5 = Research and development (R&D) capability

The following observable variables, which have a causal relationship with C3, are in the Zj group (from Z1 to Z6):

Z1 = Adapting tools to market needs
Z2 = Activities to improve corporate profitability
Z3 = Additional financial investment
Z4 = Acquisition of external resources
Z5 = Collaboration with other actors
Z6 = Full use of technological tools

The following observable variables, which have a causal relationship with C4, are in the Mj group (from M1 to M7):
M1 = High-performance informatics
M2 = ICT tools
M3 = Productivity
M4 = Flexibility and agility
M5 = Modularity (optimization and automation)
M6 = Digitalization and integration
M7 = Orange economy

The following observable variables, which have a causal relationship with C5, are in the Nj group (from N1 to N7):

N1 = Product personalization
N2 = Systems for after-sales services
N3 = Knowledge of market segments
N4 = Digital communication channels
N5 = Monitoring goal achievement
N6 = R&D&I strategies
N7 = Evaluation of corporate brand

The following observable variables, which have a causal relationship with C6, are in the Pj group (from P1 to P7):

P1 = Dynamic capabilities
P2 = Organizational performance
P3 = Risk and safety management policies
P4 = Sustainable development
P5 = Maturity model
P6 = IT systems

P7 = Social responsibility

The following observable variables, which have a causal relationship with C7, are in the Oj group (from O1 to O4):

O1 = Collaboration
O2 = Improvisation capability
O3 = R&D&I policies
O4 = Action plans

Model identification

The following data were obtained using Equation 1 to identify the structural equation model:

$$DF = \frac{(42)*(42+1)}{2} - 92 = 811 \quad (2)$$

This indicates that the model is overidentified because the value is greater than zero.

4.2. Parameter estimation and fit evaluation

In order to apply a structural model, it is necessary to verify that the data follow a normal multivariant distribution because one of the main conditions to apply a SEM is that the observed variables follow said distribution regarding the data. Otherwise, the suggested estimators would not be optimal, and the individual contrasts and global fit parameters would not be appropriate (Levy et al., 2006). With a sample of N = 16 and a confidence level of 88%, we calculated the mean and deviation of each variable. To validate the normal multivariant distribution of the data, we used asymmetry and kurtosis methods with their respective common errors. Said data show a mean, variance, and deviation of a Likert scale that ranges from 1 to 5 in each variable.

Values greater than indicate extreme asymmetry (García, 2011), which does not apply in this case because no value is higher than that. Regarding kurtosis, values greater than indicate significant normality problems, while values between and indicate extreme kurtosis (García, 2011). In this case, five variables present extreme kurtosis, i.e., X1, M1, M2, M3, and P3, whose values range between 8 and 14.

Kolmogorov–Smirnov–Lilliefors and Shapiro–Wilks normality tests were also applied. The former is a modification of Kolmogorov–Smirnov goodness-of-fit contrast for the case in which the contrast distribution is a normal distribution of unknown parameters (which is the most common situation) (Levy et al., 2006). The latter measures the degree of fitness of the observations in the sample to a straight line, which is represented in a normal probability plot (Levy et al., 2006).

Given that the sample to obtain these data was composed of less than 50 observations, more attention is paid to Shapiro–Wilk significance. In the latter, the results obtained show that only seven variables have values higher than 0.05: Y1, Y3, N6, N7, P4, O2, and O3. This indicates that the data do not follow a normal distribution. Therefore, it is necessary to conduct a variable correlation analysis using Spearman's Rho coefficient because applying Pearson's coefficient is not advisable for a non-normal case. Said analysis confirms the existence of an important correlation structure between the observed variables (García, 2011).

According to the results of the correlation, it can be determined that there is not a high degree of association between the observable variables because, in terms of the Sig. (2-tailed), most variables present values greater than 0.05 (shown as cells highlighted in red). This indicates that the correlation is not very strong. Therefore, if one of the variables increases, it does not really affect the other. Furthermore, it can be said that, because some of the results of the correlation coefficient present negative values, there is not a direct relationship.

However, the exploratory factor analysis using the unweighted least squares method shows that the communalities (or common variance) present values higher than 0.30 although the correlation matrix is not positive. According to these results, it is not necessary to extract any of the items from the model. This indicates that although the study was applied to a small sample, the variables included have the necessary values to support the model and it is not necessary to extract any of them.

Regarding total explained variance, Table 1 indicates that eight factors explain 88.762% of the model. It can be said that the variables fulfill the statistical criterion needed for the analysis because at least 60% is required for a valid result in the total variance. This indicates that the variables included in this study can explain the seven general variables that are being studied and that therefore can be included in the future in a general framework for evaluating the innovation capacity of ICT organizations. In the same way, these variables serve as support in the generation and analysis of strategies for innovation.

Table 1. Total explained variance

Total explained variance						
Factor	**Initial eigenvalues**			**Extraction sums of squared loadings**		
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**
1	20.961	49.906	49.906	20.867	49.683	49.683
2	4.710	11.214	61.120	4.599	10.949	60.632
3	3.448	8.210	69.330	3.311	7.884	68.516
4	2.549	6.069	75.399	2.420	5.762	74.278
5	2.155	5.131	80.530	1.991	4.740	79.018
6	1.745	4.154	84.684	1.652	3.933	82.952
7	1.378	3.281	87.964	1.262	3.006	85.958
8	1.276	3.037	91.002	1.178	2.804	88.762
9	.958	2.281	93.283			

10	.719	1.713	94.996
11	.666	1.585	96.581
12	.544	1.294	97.875
13	.409	.975	98.850
14	.323	.770	99.620
15	.160	.380	100.000
16	2.973E-15	7.079E-15	100.000
17	6.538E-16	1.557E-15	100.000
18	6.171E-16	1.469E-15	100.000
19	4.415E-16	1.051E-15	100.000
20	4.123E-16	9.817E-16	100.000
21	3.846E-16	9.157E-16	100.000
22	2.908E-16	6.924E-16	100.000
23	2.863E-16	6.816E-16	100.000
24	2.545E-16	6.060E-16	100.000
25	1.820E-16	4.333E-16	100.000
26	1.068E-16	2.543E-16	100.000
27	1.013E-16	2.411E-16	100.000
28	6.350E-17	1.512E-16	100.000
29	-3.558E-18	-8.472E-18	100.000
30	-3.333E-17	-7.935E-17	100.000
31	-5.561E-17	-1.324E-16	100.000
32	-9.130E-17	-2.174E-16	100.000
33	-1.496E-16	-3.563E-16	100.000
34	-1.572E-16	-3.744E-16	100.000
35	-2.013E-16	-4.793E-16	100.000
36	-3.369E-16	-8.022E-16	100.000
37	-3.473E-16	-8.270E-16	100.000
38	-4.053E-16	-9.650E-16	100.000
39	-5.001E-16	-1.191E-15	100.000
40	-5.489E-16	-1.307E-15	100.000
41	-1.505E-15	-3.582E-15	100.000
42	-4.509E-15	-1.074E-14	100.000

Extraction method: unweighted least squares

Source: Authors' own work using SPSS Statistics software.

The results obtained from the reliability analysis of the data using the Cronbach's alpha method. Said results indicate that the data are very reliable because, according to the theory, the closer the Cronbach's alpha index is to 1.00, the more reliable the data. In this case, the resulting index was 0.969. This indicates that, although it is necessary to carry out the study applied to a larger sample, it is a basis for future studies, since the results demonstrate reliability in the variables under study.

In addition, the results in Table 2 were obtained by analyzing the Cronbach's alpha of every element. Said table shows that, if variables Z4, Z5, and P4 were eliminated, the Cronbach's alpha index would improve from 0.969 to 0.971, 0.970, and 0.970, respectively. Therefore, it is not necessary to eliminate any of the items to improve the reliability index because the difference would not be very significant.

Table 2: Improvement in reliability index if each element was eliminated.

Total-element statistics					
	Scale mean if the element was eliminated	**Scale variance if the element was eliminated**	**Corrected total correlation of elements**	**Square multiple correlation**	**Cronbach's alpha if the element was eliminated**
X1	155.7500	1032.467	.402	.	.969
X2	155.4375	1009.729	.774	.	.967
X3	155.9375	1019.263	.674	.	.968
X4	155.0625	1006.329	.883	.	.967
X5	155.3750	999.183	.906	.	.967
X6	155.1250	1004.517	.921	.	.967
Y1	156.1250	1004.383	.778	.	.967
Y2	156.6875	1030.363	.459	.	.968
Y3	155.8125	1001.763	.771	.	.967
Y4	155.7500	1001.133	.785	.	.967
Y5	155.5625	1005.329	.668	.	.968
Z1	155.6875	1020.363	.600	.	.968
Z2	155.3750	1003.583	.892	.	.967
Z3	155.7500	1012.333	.671	.	.968
Z4	156.3750	1072.117	-.121	.	.971
Z5	156.0000	1060.933	.053	.	.970
Z6	155.5000	1023.467	.591	.	.968
M1	155.0000	1013.067	.772	.	.967
M2	154.9375	1016.729	.714	.	.968
M3	154.7500	1007.133	.880	.	.967
M4	155.2500	1017.533	.691	.	.968
M5	155.6875	1001.029	.794	.	.967
M6	155.6875	997.429	.745	.	.967
M7	155.7500	1009.267	.794	.	.967

N1	155.8125	1019.096	.486	.	.969
N2	155.3750	1007.317	.655	.	.968
N3	155.3750	1013.317	.744	.	.967
N4	155.4375	1013.863	.657	.	.968
N5	155.3125	1008.363	.756	.	.967
N6	155.8125	1020.696	.529	.	.968
N7	155.8750	1013.450	.648	.	.968
P1	155.3125	1014.096	.564	.	.968
P2	155.7500	1000.467	.731	.	.967
P3	154.8750	1009.317	.831	.	.967
P4	156.2500	1053.533	.116	.	.970
P5	155.7500	1006.733	.832	.	.967
P6	155.3750	1002.250	.817	.	.967
P7	155.5625	1040.796	.290	.	.969
O1	156.7500	1029.000	.363	.	.969
O2	155.9375	1010.596	.720	.	.967
O3	156.1250	1003.983	.716	.	.967
O4	155.8750	1013.583	.646	.	.968

Source: Authors' own work using SPSS Statistics software.

Based on the above, the data obtained indicate that it is not necessary to eliminate any item because the difference would not be very significant in terms of improvement in the Cronbach's alpha. For example, if one of the elements with a high index is eliminated, i.e., Z4, the Cronbach's alpha would increase from 0.69 to 0.71, which is a 0.02 difference. Thus, it is convenient to maintain all the items.

The reliability statistics calculated using Friedman's chi-square test, where Lambda ranges from 0.945 to 0.973, indicating a high reliability and confirming the previous results. Afterward, the variances were analyzed based on Friedman's chi-square test, a non-parametric test that requires more than two related samples in order to determine if the variables share the same continuous distribution of their origin (Berlanga & Rubio, 2012). Therefore, the variables should be measured in an ordinal scale, there should be more than two related samples, and the level of statistical difference should be significant. According to this, the results in Table 3 show a significance level of 4.341E-12, which indicates that there is a very small probability of error if the null hypothesis is rejected. The null hypothesis and the hypothesis in this study are the following, respectively:

H0: The set of selected variables are not causal of the group of seven capabilities that facilitate innovation capability.

H1: The set of selected variables are causal of the group of the seven capabilities that facilitate innovation capability.

Table 3: ANOVA with Friedman's chi-square test

		Sum of squares	DF	Quadratic median	Friedman's chi-square test	Sig
Inter-subject		380.284	15	25.352		
Intra-subject	**Between elements**	128.132[a]	41	3.125	135.838	.000
	Remainder	490.653	615	.798		
	Total	618.786	656	.943		
Total		999.070	671	1.489		

ANOVA with Friedman test

Global mean = 3.7961

a. Concordance coefficient of W = .128.

Source: Authors' own work using SPSS Statistics software.

According to the above, the critical point for a chi-square distribution with 41 degrees of freedom, for a quadratic mean of 3.125, is 135.838. Given the high value obtained in the chi-square and that a significance level of 0.05 is necessary to reject the null hypothesis, the latter can be rejected based on the high chi-square and the results obtained. Thus, H1 can be confidently supported because the set of selected variables are causal of the group of seven capabilities that facilitate innovation capability.

The results presented in the previous tables, allow to affirm that the variables included and used for the construction of the model are adequate to evaluate the innovation capacity of ICT organizations, in addition to being replicable in other types of technology-based organizations given the results in the degrees of freedom of the model and of the chi-square. This is significant given that by not having to eliminate any of the variables, it allows future studies and organizations greater scope and freedom for the analysis of innovation capacity, since they have a greater variety in the selection of factors or items. to be studied, allowing more diverse results in the analysis of said capacity. Finally, the model was not respecified because the statistic results of the model and the data obtained were significant. This reason is sufficient to say that the model is valid to evaluate the proposed variables, which were found to be causal based on the literature review about innovation capabilities of medium-sized enterprises that provide information technology service management in the ICT sector in Medellín.

5. Discussion of the Results

First, these latent and observable variables have been previously acknowledged and discussed by multiple authors, some of which were cited in this paper. As a result, the model has enough theoretical support to be proposed here, and its design is saturated. In relation to descriptive statistics, it was found that the asymmetry values were not higher than in any of the cases. However, the kurtosis values were higher than , which indicates that the data do not follow a normal distribution. This indicates that the mean, median, and mode can differ.

Despite the above, the data normality tests, which were mainly based on the results of the Shapiro–Wilk test due to the sample size, show that only seven variables obtained results lower than 0.05: technological innovation capability, innovation performance, R&D&I strategies, evaluation of corporate brand, sustainable development, improvisation capability, and R&D&I policies. That is, the non-normality could have occurred specifically in these variables. In addition, a correlation analysis using Spearman's Rho coefficient was necessary due to the data abnormality. As a result, it was found that said abnormality was not very strong, which had not been taken into account when the model was designed. Therefore, the model only considers relationships between latent and observable variables and not between variables of the same type.

Although the sample was small, the data and variables facilitated the validation of the model using different descriptive statistics and fit and reliability measures of the proposed model. Thus, it was found that, as it had a great number of observable variables, the model was saturated. The result of the degrees of freedom indicates that the model is overidentified and it can be used in a general manner for other types of companies in the sector. The values of the communalities calculated using the unweighted least squares method range between 0.7 and 1.0, which indicates that the items were valid and that it is not necessary to extract any of them to improve the results of the model. Likewise, the data can be considered reliable enough because the Cronbach's alpha was 0.969 and the evaluation of each item separately resulted in similar values. This confirms the reliability of the data of the model and indicates that it is not necessary to eliminate any of the items considered here, which was confirmed by the Lambda results in the reliability statistics.

Regarding the total explained variance, the results indicate that eight factors explain 88.762% of the model, which confirms once again the validity and reliability of the data. In addition, the results of the chi-square statistic in terms of significance level were so low that the null hypothesis can be rejected. This means that at least some of the causal variables found in the literature and can and that have been detailed in the methodology section, in the model specification can explain the development of the seven capabilities that compose innovation capability: learning capability, R&D capability, resource allocation capability, manufacturing capability, marketing capability, organizing capability, and strategic planning capability.

Although the model was not re-specified, considering that this is a new proposal based on a thorough theoretical review, the results indicate that the items included here can be valid to explain the generation and development of the seven capabilities proposed by Yam et al. (2004a) as components of innovation capability, specifically at enterprises offering ITSM in the ICT sector in Medellín. The decision not to re-specify the model was justified by these results and the fact that this scale and factors were proposed here for the first time. Thus, this is considered an initial investigation of these variables and an exploratory analysis. In addition, as mentioned in the study by Adeosun & Shittu (2021), the development and promotion of innovation capacities in the ICT sector is more than adequate to achieve an improvement in the development of the territory and social inclusion, this given the improvement significant that the sector has had in different developing countries such as Colombia.

6. CONCLUSIONS

The results presented in this article can serve as a framework to guide the identification of innovation capabilities. In addition, to allow from the results presented here the design and implementation of strategies aimed mainly at innovation in processes and services in different companies in the ICT sector, focused especially on aspects such as; the capacity for technological innovation, performance in innovation, R + D + i strategies, corporate brand evaluation, sustainable development, improvisation capacity and R + D + i policies.

In conclusion, this paper can guide the assessment of the current state of organizations regarding innovation and innovation capabilities, which can be a valuable tool to review and reconsider strategies to improve these aspects and therefore their competitiveness. Future studies can define guidelines based on the proposed model and a confirmatory analysis that includes a larger sample of this sector.

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